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Emergence of cooperation in congested road networks using ICT and future and emerging technologies: A game-based review

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ABSTRACT

Information and communications technologies (ICT) and future and emerging technologies (FET) are expected to revolutionize transportation in the next generation. Travelers' behavioral adaptation is a key to their success. We discuss the notion of managing traffic congestion by enhancing cooperation in road networks enabled with ICT and FET. Cooperation is an emergent social state related to the dynamics and complexity of road traffic and reinforced learning. Game theory and research in behavioral economics show that cooperation can be leveraged to efficiently solve social dilemmas similar to traffic congestion. We review the applicability of behavioral economics and game theory concepts to route, mode and departure time choice problems. Beyond advancing theory, research on cooperation in the context of transportation is still in its infancy. We discuss state-of-the-art methodologies and their weaknesses and review the unexplored opportunities inherent in game-based methodologies. A behavioral-technological research agenda for FET is also discussed.

1. Introduction

Future and emerging technologies (FET) are expected to revolutionize the ways people use vehicles and roads. The assimilation of ubiquitous computing capabilities and pervasive Information and Communication Technologies (ICT) into both the software and hardware of vehicles and transportation infrastructures introduces innovative opportunities to improve personal mobility, including a safer, more convenient, more efficient and greener travel experience (Spieser et al., 2014). Presently, ICT applications tackle congestion mainly with "software" developments intended to enable a better flow of information about traffic. Advanced Traveler Information Systems (ATIS) such as variable message signs (VMS) (Emmerink et al., 1996) and, more recently, real time mobile navigation applications (apps) such as Waze©, assist travelers in their spatial decision making, e.g., route, mode of travel, destination choice (Mokhtarian and Tal, 2013). These changes signal a move from an era in which travel information was experiential, obtained by trial and error, to an era of descriptive, and today prescriptive, travel information enabled via ICT mediums. Moreover, it is anticipated that the more the individual traveler benefits from such sources of information, the greater the aggregate benefit will be for the entire transport system.

This overwhelmingly positive outlook regarding the benefits that new technologies are expected to confer on travelers as a whole, however, is based foremost on critical assumptions about human travel behavior and how it is related to the behavior of the transport system, a relation characterized by high complexity. That is, the behavior of the whole is not

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simply extrapolated from the behavior of the individuals but rather, the two are linked in a co-evolutionary process. Although under perfect competition, supplying consumers with more information helps them maximize utility, the effect of incorporating more information in road networks is not straightforward. In fact, some studies showed that increased amounts of information can engender possibly adverse outcomes under both recurring and non-recurring (i.e., associated with random incidents or accidents) traffic congestion (Ben-Akiva et al., 1991; Emmerink et al., 1995a, 1995b; Lindsey et al., 2014; Lu et al., 2014).

The potential effects of information availability and accessibility can be examined from the perspective of the theoretical case of perfect information. Here the corresponding lack of uncertainty results in a stable traffic state known as User Equilibrium (UE) (Wardrop, 1952), whereby travelers have, by definition, perfect information on the state of the network and on the optional routes. It is also assumed that they behave rationally and selfishly, and thus, that they choose the near-state shortest path (in terms of time or generalized cost) between any given origin and destination. Similar to a Nash equilibrium (Nash, 1951), this state is stable, as it is unlikely that travelers will change their route choices given that they know that all other options are most likely worse. In heterogeneous and nonsymmetrical networks, UE is usually a suboptimal routing solution that reflects travelers' average travel costs. In contrast, the System Optimum (SO) is a secondary traffic state where the travel costs of all travelers combined are minimized, thereby reflecting their marginal travel costs. The gap between these two concepts can be quantified using the price of anarchy (Mak and Rapoport, 2013; Roughgarden, 2005).

The behavioral assumptions on which the UE prediction is based, i.e., rationality and selfishness, were borrowed from orthodox microeconomic theory. However, behavioral economists and psychologists alike, e.g., Simon (1982, 1955) and Kahneman and Tversky (1979), criticized those assumptions as poor representations of cognitive reality. In particular, behavioral economists question the extent to which selfishness is a determinant of behavior, citing the effects of other important behavioral traits such as other-regarding and social preferences (Bolton and Ockenfels, 2000; Fehr and Schmidt, 1999). While the mobility literature is aware of these critics of rationality (Avineri and Ben-Elia, 2015; Ben-Elia and Avineri, 2015a, 2015b) and has even recently discussed the importance of social influence (Abou-Zeid and Ben-Akiva, 2011), the issue of selfishness has been left practically untouched, as recently testified to by Daniel McFadden, regarded as the "forefather" of travel behavior modeling: "new results challenge the standard assumption of maximization of individualistic utility, indicating that social networks as information sources, reciprocity, and altruism enter human behavior and cannot be ignored" (McFadden, 2013, p. 37). People, among whom are the travelers, are not necessarily selfish Homo economicus, but instead can be understood as Homo sociologicus, a social animal (Hirsch et al., 1987).

Advances in ICT and expected developments in FET offer new opportunities that could promote the manifestation of unselfish behavior in road networks by introducing and enforcing the notion of travel behavior based on cooperation strategies. This could be done in conjunction with the deployment of Intelligent Transport Systems (ITS) and the associated vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) architectures. Indeed, it is anticipated that traffic congestion management efforts will eventually receive substantial support from ICT, particularly with the establishment of the Internet of Things (IoT or Internet 3.0) and technological breakthroughs in Connected Autonomous Vehicle (CAV) deployment. In the short run, CAVs will be able to communicate and exchange information via the IoT network, which will enable them to adopt routing strategies that will contribute to increased route reliability and decreased non-recurring congestion (incidents), perhaps ultimately transcending UE to attain SO network states. In the long run, a collectivized fleet of CAVs could be the foundation for the establishment of a demand responsive public transit system (e.g., Quadrifoglio et al., 2008) based on the mass uptake of ridesharing (e.g., Nourinejad and Roorda, 2016), a move that will generate wide savings in terms of reductions in cruising time for parking and in the time vehicles remain idle (Le Vine and Polak, 2015). More importantly, such a demand responsive system will provide travelers with a spatiotemporally relevant public transit system that is not necessarily fixed according to rigid routes or timetables. Furthermore, once CAVs are mobilized and effectively shared among the traveler population, the number of conventional vehicles in operation, as the principal generators of recurring congestion, could be significantly reduced (Fagnant and Kockelman, 2014; Spieser et al., 2014).

Although a CAV-dominated future has significant potential to solve many of our most pressing traffic problems, its success will depend foremost on whether travelers can be persuaded to learn to cooperate with each other. In the absence of cooperation, CAVs could instead become detrimental to traffic flow, as a recent simulation study demonstrated for a metropolitan-size transportation system in which carsharing practices (single driver with pooled vehicle fleet) crowded out public transit, leading to an increase instead of a decrease in traffic congestion (Martinez et al., 2015). Undoubtedly, much more research, in which the methodologies of existing theories are reconsidered, is required before these ideas can become part of everyday reality.

In this paper, we show how the combination of simple theoretical principles based on game theory, on the one hand, with emerging game-based methodological approaches, on the other, can create entirely new research avenues that will provide valuable insight into the cooperative nature of travel behavior and how this knowledge can be applied with FET to improve congestion management strategies. The rest of the paper is organized as follows. Section 2 presents the behavioral foundations of cooperation based on the theoretical literature from behavioral economics, game theory, and cognitive and social psychology. Section 3 examines strategies, including the use of ICT, for enforcing cooperation on road networks. In Section 4 we discuss research methodologies for evaluating the impacts of FET. Section 5 concludes this review paper and suggests a future research agenda for transportation researchers interested in the behavioral aspects of ICT and FET.

2. Theoretical foundations of cooperation

2.1. Game theory and behavioral economics

In contrast to selfishness, according to which each person seeks to maximize their own utility, the action of working together to maximize collective utilities, i.e., cooperation, does not seem to conform with rational behavior. However, this notion is challenged by everyday situations in the domain of social dilemmas, where individual players acting in rational-maximizing fashion are later collectively worse off. Game theory was established to study such situations, examining players' strategies and the social consequences of their actions. It is common in game theory to distinguish between two-player games and multiplayer (or N-player) games. Usually the game's potential outcomes are tested initially with two players and then extended to investigate multiplayer situations. As two-player games are more intuitive, we focus mainly on them.

In two-player games that have a 2×2 strategy setting, the nature of the interaction between the players can be used to differentiate the games into three types: (1) **win – win games**, where the rational outcome of the game is that both players are better off, and therefore, cooperation works as a natural consequence, (2) **zero-sum games**, where there is no way that one of the players can cooperate with the other, since the potential gains of one player are counterbalanced by the potential losses of the other, and (3) social dilemmas, which, insofar as they are especially relevant to understanding transportation-related problems, are discussed further below.

As defined by Dawes (1980), a social dilemma has two main characteristics: (a) each player is better off defecting (i.e., behaving selfishly), regardless of the choice of the other player and (b) all players are better off if they all cooperate than if they all defect. In game-theoretic terminology, a social dilemma occurs when the Nash Equilibrium is not Pareto optimal.[1] The most prominent example for such a dilemma is the Prisoner's Dilemma (PD) (Table 1). The PD describes a situation in which players receive a reward (R) if both cooperate, punishment (P) if both defect, and, if one player cooperates and one player defects, the defector receives the temptation (T) payoff and the cooperator receives the saint or sucker (S) payoff.[2]

2.1.1. The Prisoner's Dilemma

In the PD, it is assumed that T > R > P > S, so the rational strategy for the players is to defect, the Nash equilibrium is (Defect, Defect) and the payoff (P,P) is Pareto inferior to (Cooperate, Cooperate), whose payoff is (R,R).

Although the possibility of cooperation in social dilemmas such as PD is threatened by pure rationality, the economics and psychology literature suggest ways of overcoming this barrier. One of the earliest solutions is attributed to Thomas Hobbes, whose treatise "Leviathan" acknowledges that PD, or war of all against all, is a threat to societal order. Thus Hobbes proposed that cooperation be coerced by using a third party (a benevolent dictator) who threatens the players with a larger punishment if they choose to defect. Hardin (1968) applied this idea to the "tragedy of the commons" and eliminated anti-social behavior like pollution. However, these solutions entail autocracy or severe limitations of individual liberties. Moreover, they only bypass the social dilemma by changing the scenario in which it is placed rather than confronting it directly. History teaches that similar attempts to solve static, one-shot PDs often failed, suggesting that the PD has no real rational solution.

Conversely, when the PD becomes a repeated, dynamic game comprising several player interactions, it seems that cooperation can emerge. If players are expected to interact twice, cooperation during the first interaction is a possible outcome. But because the players in the framework of the standard PD know they will encounter each other again in the second (final) interaction, both will defect, a fact that will encourage them, via backward induction logic, to also defect in the first interaction. However, if the players encounter each other a sufficiently large number of times, it seems that cooperation will emerge. The Folk Theorem (Friedman, 1971) states that a Nash equilibrium exists in repeated games in which sufficiently patient players achieve Pareto optimal payoffs. In the PD, it is possible to maintain cooperation as a Nash equilibrium, thus making repeated cooperation a rational strategy. However, two conditions are necessary to maintain cooperation in the iterated PD: (a) the game has to repeat an infinite number of times (infinite time horizon), or it should at least entail an unknown number of player interactions (i.e., periods). This ***"shadow of the future"*** (Axelrod, 1984) convinces players to continue cooperating. Many experiments (Engle-Warnick and Slonim, 2006; Feinberg and Husted, 1993; Murnighan and Roth, 1983; Roth and Murnighan, 1978) have verified that cooperation can exist in the shadow of the future (see Bó (2005) for review); (b) the players have to be sufficiently patient, i.e., the **discount factors** must be high enough to sustain cooperation (Shubik, 1970).

Because application of the folk theorem is theoretic, strategies – or heuristics – are formed to simplify players' decisions. The literature recognizes three main heuristics to encourage cooperation: (a) in infinitely repeated games, the **grim trigger** heuristic is shown to sustain cooperation (Rubinstein, 1979). For example, player A starts by cooperating and continues doing so until player B defects. Once player B has defected, player A should defect from then on. The "unforgiveness" (or inflexibility) embedded in this strategy ensures that both players strive to avoid defection. (b) The **tit for tat** heuristic (Axelrod and Hamilton, 1981) dictates that player A begin by cooperating until player B defects. In response, player A should defect and continue to do so until player B resumes cooperation, and so forth. While tit for tat is forgiving, nice (never

[1] As identified by Mak and Rapoport (2013), this definition does not relate to games with mixed equilibria or with multiple equilibria.

[2] These letters symbolize the expected payoffs of all 12 known symmetrical 2×2 games. We use them in this sense throughout the paper.

Table 1
The Prisoner's Dilemma. Assuming T > R > P > S according to rational utility maximization, both players should choose the defection strategy, which is also the equilibrium of the game.

		Player 2	
		Cooperate	Defect
Player 1	Cooperate	R, R	S, T
	Defect	T, S	P, P

punishing in the first round) and retaliatory (Axelrod, 1984), it is suitable only for small groups, as reciprocal altruism is restricted to small sized groups. Indeed, for cooperation to prosper, a cheater detection mechanism (i.e., reputation) must exist, and this mechanism is more difficult to implement as group size increases (Boyd and Richerson, 1988). (c) The **win-stay, lose-shift** heuristic is a strategy that directs the players to stick with the defect or cooperate strategy as long as they win. Once the players loses a round, they should change their behavior. The win-stay lose-shift strategy was shown to outperform tit for tat, especially insofar as the former exploits all cooperative strategies without resorting to extended, drawn out cycles of retaliatory defections, as is the case in tit for tat (Nowak and Sigmund, 1993).

Although rationality and selfishness are crucial traits of human nature in which psychological insights from the domain of social preferences are combined, many more ways can be devised to achieve cooperation. Rabin (1993) suggested the concept of the 'Fairness Equilibrium', which relies on the assumption of fairness. Accordingly, people are willing to be kind to those who they believe will be kind to them in return, but they are also willing to punish those who they believe will be unkind to them. This notion suggests that the utility of cooperation increases to the extent that it becomes another Nash equilibrium (R > T), and therefore, it is possible for the players to cooperate. In an experimental example of "conditional cooperation", Fischbacher et al. (2001) carried out a one-shot public goods experiment[3] in which they prompted players to specify their contributions given all possible average contributions of other players. Their study revealed that while 30% of players were free riders, 50% were willing to contribute amounts that were roughly equal to the average level of contribution given by other players. This shows that the predictions by the fairness equilibrium about behavior are corroborated in empirical findings.

Experiments in behavioral economics have revealed a variety of scenarios in which cooperation can prosper. Fehr and Gächter (2002) conducted a public goods experiment that included the option to punish other players, but at a certain cost. Costly punishment deterred players from not contributing and led to higher rates of cooperation. Andreoni (1995) showed that positive **framing**[4] of the public goods game yields greater cooperation than negative framing. Rege and Telle (2004) showed that **social approval** encourages cooperation (i.e., when the contributions of players are transparent to other players) and makes them contribute more. In contrast, the greater the **heterogeneity of group composition**, the lower the extent of cooperation in the public goods game (Smith, 2011). This experimental field has transcended pure behavioral research to enter the field of **neuroeconomics**, where the activity of the participant's brain is monitored while the person engages in, for example, economic decision making tasks (see Fehr and Camerer (2007) and Declerck et al. (2013) for extensive reviews).

2.1.2. Battle of the Sexes, Leader and the Route Choice Game

Beyond PD, which is considered the classic social dilemma, other social dilemmas require different solution concepts. We discuss three different 2×2 games – Battle of the Sexes (BoS), Leader and the Route-Choice Game (RCG) – and their possible cooperative solutions. In the highly similar games BoS (T > S > R > P) and Leader (T > S > P > R), players choose between two actions that must be anti-coordinated to maximize payoff (i.e., [cooperate, defect] or [defect, cooperate], which are also the Nash Equilibriums). However, each player prefers one outcome over the other. If their actions are coordinated, then both players receive lower payoffs. In the case of BoS, the outcome of mutual cooperation is better than that of mutual defection. In contrast, the opposite is true for the Leader game, namely, the outcome if both defect is better than that if both cooperate.

However, BoS and Leader are not classic social dilemmas since the Pareto optimum for each is the same as the Nash equilibrium. Because the players cannot coordinate their actions, it is possible that they will both cooperate or defect, which will ultimately result in a suboptimal outcome. As a possible solution to this coordination problem, Aumann (1987, 1974) suggested correlated equilibrium, according to which the players base their choices of action on their joint observation of a random variable value. The players then choose their strategies, according to the variable value they observed. If neither of the players deviates from their assigned strategy, a correlated equilibrium is achieved in a solution design that helps both players achieve better payoffs while remaining rational and selfish.[5]

[3] The public goods game is the N-player version of the prisoners' dilemma. In the game, subjects decide whether to contribute to the public good or not. If they choose to contribute, their contribution is multiplied by a number between 1 and 1/n, so that if all contribute, they receive a larger payoff than if none contributed. The rational solution for this game is similar to the prisoners' dilemma—we expect all not to contribute.

[4] Framing is a cognitive bias that predicts that people's reactions to a dilemma will depend on how it is presented to them, i.e., using positive or negative values (Plous, 1993).

[5] A correlated equilibrium exists only when there is a mixed Nash equilibrium. Moreover, it requires that signals be shared between the players, which means that it is not a viable solution to the PD.

A different solution to the BoS and Leader games is alternating reciprocity. Achieved by teaching the players to anti-coordinate their moves, alternating reciprocity can thus lead to optimal payoffs for both players. Browning and Colman (2004) show that this can be done without communication between the two players.

The RCG (T > P > S > R) differs slightly from the other 2×2 games, in that defecting when the other player cooperates generates the highest payoff, which is higher than that for mutual cooperation, and therefore, the expected outcome of the RCG is mutual defection. For transportation dilemmas, this game has profound consequences that we explore further in Section 3. Table 2 presents the payoff matrix in a two-player RCG.

Because the two-player RCG has only one pure Nash equilibrium, correlated equilibrium is not applicable, and therefore, it is impossible for players to coordinate their actions. However, an RCG that satisfies the condition S + T > 2P enables a Partial Cooperation Dilemma (PCD) through which, Stark (2010) suggests, players can anti-coordinate their actions to maximize their payoffs even though they neglect the Nash equilibrium. Laboratory experiments in two and four-player games verified that players are able to maximize their payoff across an iterated RCG[6] (Helbing et al., 2005, 2002; Stark et al., 2008).

2.2. Behavioral and social motivations

2.2.1. Intrinsic and extrinsic motivations

In addition to an understanding of game-theoretical mechanisms, it is also important to understand what motivates individuals to behave cooperatively or pro-socially. Psychologists assert that the motivation to cooperate can be either intrinsic or extrinsic. **Intrinsic motivation** functions via social preferences, and it extends the narrow, selfish economic model to include preferences that depend on the utility of others.

Different types of social preferences have been reported in the literature (Fehr and Fischbacher, 2002). The first, reciprocal fairness, is built on the expectation that one should treat others with the same kindness they show to everybody else (Rabin, 1993). The second, inequality aversion, is based on the assumption that some people are averse to the existence of disparities between themselves and others. Efforts to maximize their utility, therefore, focus on creating a more equitable environment (Bolton and Ockenfels, 2000; Fehr and Schmidt, 1999). The third is altruism, or unconditional kindness toward another person, and it can be pure, such that a person can benefit from the utility of the subject of the altruism (Becker, 1974), or impure, i.e., a person can enjoy the "warm glow" felt as a result of the mere act of giving to others (Andreoni, 1990). The fourth social preference, efficiency, refers to the desire of the individual to achieve the most efficient state possible, in which the aggregated (i.e., societal) utility is maximized (Charness and Rabin, 2002; Engelmann and Strobel, 2004). Societal utility can be maximized in two ways – via either a Kaldor-Hicks efficiency, which refers to a simple maximization of utility, or Pareto efficiency, where it is impossible to increase the utility of one individual without decreasing the utility of another. Although social preferences constitute an intrinsic utilitarian motivation to cooperate, motivation can be derived from a moral-deontological domain. The categorical imperative of Immanuel Kant – "treat others the way you want to be treated" – guides most people to behave cooperatively and to reject utilitarian considerations. Hofstader (1983), who suggests that superrationality accounts for the categorical imperative, states that the options open to a supperrational player are symmetrical when playing against another superrational player.

As stated, cooperation can also be driven by **extrinsic motivation**. Nowak (2006) describes five mechanisms through which extrinsically motivated cooperation is possible in systems, including cells, genomes, social insects and human society. These mechanisms mitigate the fierce competition fundamental to natural selection to create a stronger system. For example, **kin selection** is based on an act of altruism between two individuals who are "genetically" related, i.e., in biological terms. In the frame of Hamilton's rule, kin selection is expressed as an equation ($r > c/b$), in which the coefficient of relatedness r must be greater than the cost (c) to benefit (b) ratio of the altruistic act. Another mechanism, **direct reciprocity** or reciprocal altruism, explains cooperation between two unrelated individuals motivated by the expected strategic reciprocity of the other player when the probability w of another encounter between the two individuals is larger than the cost to benefit ratio of the cooperative act ($w > c/b$). It differs from fairness in that it is driven by strategic considerations and not embedded in one's intrinsic preferences. **Indirect reciprocity** extends the model of direct reciprocity to strangers (i.e., the players need not be the same individuals in repeat encounters). Whether cooperation is established depends on the reputations of the individual players, which must be positive. If q, the probability of knowing someone's reputation, exceeds the cost to benefit ratio of the cooperative act ($q > c/b$), cooperation will be realized. **Network reciprocity** restricts the assumption of natural selection that populations exist in well-mixed environments. In reality, populations are not well mixed, as the social networks or spatial structures that are in place cause certain individuals to encounter each other more often than they encounter others. Each individual is represented on a graph by a vertex, and the connections between individuals who encounter each other are represented by edges. To establish cooperation in a network, the benefit to cost ratio of the cooperative act must exceed the average number of neighbors per individual (k): $b/c > k$. Finally, **group selection** differentiates between the dynamics of cooperation within a group vs. between groups. Because within a group noncooperation is a dominant strategy, a group made up of only cooperators is likely to succeed more than a mixed group. If n is the maximum group size and m is the number of groups, then group selection allows for the evolution of cooperation provided that $b/c > 1 + (n/m)$.

[6] The same is also true for PD when S + T > 2P.

Table 2
The Route Choice Game. Assuming T > P > S > R according to rational utility maximization, both players should choose the defection strategy (Route 2; 2,2 = UE), which is also the user equilibrium of the game. The system optimum (S + T)/2 occurs when players take turns on each route in sequence.

		Player 2	
		Route 1	Route 2
Player 1	Route 1	R, R	S, T
	Route 2	T, S	P, P

2.2.2. Social motivators

To enable the emergence of cooperation, people must be able to recognize whether the other side (i.e., player) will defect. One way to accomplish this is to establish a **cheater-detector**, i.e., a tool that helps one recognize a cooperating player and to remember the interaction history with that player (Cosmides and Tooby, 1992). Also referred to as **trust** (Van Vugt and Van Lange, 2006), this cheater detector motivates people to make sacrifices for their group as long as they know that other group members will also cooperate (De Cremer and Vugt, 1999). Likewise, a betrayal of people's trust will elicit harsh retaliation (Fehr and Fischbacher, 2003). **Commitment**, which refers to the long-term orientation of the cooperative relationship, is another important motivational trait. Insofar as it strengthens the social exchange via altruistic means, commitment perpetuates the viability of the relationship even when it becomes less profitable for both sides. Moreover, commitment is a signal for other players that the player is interested in preserving the relationship (Rusbult, 1983). Finally, **empathy** is a strong facilitator of cooperation, as it promotes altruism toward complete strangers. Although the issue of whether empathy is directly related to altruism has been questioned – that is, empathy may be motivated by egoistic reasons such as the "warm glow" (Andreoni, 1990)- it is still a means of achieving cooperation (Batson and Powell, 2003).

While these three motivators are necessary conditions for cooperation to emerge at the dyadic level, they are insufficient to mobilize cooperation within larger groups. To facilitate large-scale cooperation also requires **social norms**, including fairness and morality, which regulate social exchange and promote harmony (Tyler and Smith, 1995). Cooperation is more difficult to achieve the larger the **group size** (Olson, 2009). Indeed, cooperation is negatively affected by the anonymity and lack of responsibility more common in larger groups (Van Vugt and Van Lange, 2006). Moreover, evolutionary studies showed that reciprocal cooperation is harder to achieve with increases in group size (Boyd and Richerson, 1988), where the optimum is groups comprising between five to eight people. In addition, **group stability** is also important for cooperation to evolve. If people are uncertain about the lifespan of the group, they are less likely to take part in cooperative exchanges. For example, more people cooperate in groups with fixed memberships than in those in which memberships are fluid (Van Vugt and Van Lange, 2006).

3. Cooperation in road networks

Congestion management strategies have typically attempted to encourage optimal mode and route choice by implementing a pricing system for private car use and improving the quality and reliability of public transit (May et al., 2010). But at the same time, both of these strategies impose a deadweight utility loss on society, and they suffer from a problem of equity (Viegas, 2001). To help recover this deadweight loss and to increase efficiency as well as equity, these congestion management strategies can be integrated with the cooperative solutions mentioned above. Although these solutions require a large degree of coordination between travelers, today such coordination, even in larger groups, is greatly facilitated by using ICT powered mediums, e.g., in shipment logistics (Christiaanse and Kumar, 2000), crisis response (Gonzalez, 2008), healthcare (Cucciniello et al., 2015), and, most apparently, social media, which played a critical role in launching the Arab Spring revolutions of 2011 (Howard et al., 2011).

As travelers, we make a wide array of decisions that can be summarized with five questions: What is my origin? What is my destination? Which mode of transport should I use? Which route should I take? And when should I depart? These questions are ordered according to the permanency of the decision, from high to low permanency: origin is related to the decision about where to live (high permanency, usually decided only few times during a lifetime), destination is related to the choice of where to work or study (medium to high permanency, decided a few times during a lifetime) or of where to shop or spend leisure time (low permanency, changing daily/weekly), mode choice is related to private car ownership (medium to low permanency, people replace their cars every 5–10 years, but on a daily basis they can decide whether to use public transit), and route and departure time are related to one's daily schedule of activities, e.g., work – will I be late for work? (low permanency, changing daily). These decisions are also parallel to the activity-based transportation planning modeling approach.

Travelers contemplate these questions when they consider the behavior of other travelers. As the permanency of a decision increases, however, other external considerations are taken into account, thereby reducing the importance of considering the decisions of other travelers and negatively affecting the potential for cooperation. The strategic nature of some of these questions makes their solution compatible with game theory. Solutions from the realm of game theory has been proposed for various transportation topics, such as equilibrium in freight networks (Xiao and Yang, 2007), paradoxical network reliability (Szeto, 2011), lane-changing behavior in a connected environment (Talebpour et al., 2015), the nature of equilibrium (Dixit and Denant-boemont, 2014), value of traffic information (Denant-Boèmont and Hammiche, 2010; Denant-Boèmont and Petiot, 2003) and public transport crowding (Bouman et al., 2016) to name a few.

Therefore, the question arises – is it possible for travelers to strategically cooperate even with regard to low permanency decisions, such as those about mode, route, and time of departure choices? If so, what intervention measures are necessary, in terms of travel behavior and ICT mediums, to facilitate the emergence of sustainable cooperation?

3.1. Mode choice

Mode choice entails different demand schemes for available road capacity, as a road network on which the demand for private transport is high while that for public transport is low will likely be prone to congestion. Hence, the cooperation engendered by decreasing the demand for the former and increasing the demand for the latter could mitigate congestion. However, studies show that mode choice is highly stable and invariable almost everywhere (Friedrichsmeier et al., 2013; Innocenti et al., 2013) and that it may be affected by both symbolic and affective motives (Steg, 2005). Thus, in terms of private car use, the greater the stability of the decision to travel by private vehicle, the more formidable the barrier to cooperation based on mode choice behavior. Likewise, a high demand for private transport will lead to low patronage of the public transit system, which will negatively influence the profitability of the latter and necessitate that the state direct large subsidies into its public transportation system to maintain adequate levels of service (Ida and Berechman, 2009).

From a game theoretic perspective, mode choice can be modeled as a PD: Consider two people traveling from home (A) to work (B) on route AB. The transportation options open to them – public transit and private car – entail different costs, so here we relate only to the most relevant ones. Both transportation options involve a cost of the time (t) needed to travel from A to B by the quickest route. Furthermore, the more private cars that are in use on the chosen route, the greater the congestion, and therefore, travel time is increased by multiplying time by a congestion factor ($c > 1$). Additional time costs entailed in public transit that are irrelevant to private vehicle use include the delays to pick up passengers (p) and the boarding times at bus stops (s). The payoff matrix in Table 3 illustrates this scenario. In a one shot interaction between the travelers, assuming $-\mathrm{tc} > -\mathrm{t} - \mathrm{p} - \mathrm{s} > -\mathrm{tc}^2 > -\mathrm{tc} - \mathrm{p} - \mathrm{s}$, it is predicted that both will choose the private car and neither will use public transit, which is also the Nash equilibrium of the game and the UE of the network. Alternatively, the SO is attained when both travelers use public transit, and as a result, both their travel times are shorter than that for a private vehicle.

However, if the game is repeated an infinite number of times, it is reasonable to assume that according to the folk theorem (and with assumptions about high discount factors and a long shadow of the future), cooperation could emerge, i.e., both travelers will learn to use public transit. This reasoning can also be applied for larger numbers of players, as shown by Sunitiyoso et al. (2011), who demonstrated (albeit in a small group) that social learning (i.e., when individuals learn from others' experiences) positively influences the emergence and sustainment of cooperation when players must decide whether to use public transit or private cars. Using the aforementioned heuristics (i.e., grim trigger, tit for tat and win-stay lose-shift) will elicit the same result. However, for large groups it is difficult to generalize this behavior (Boyd and Richerson, 1988).

From the perspective of the PCD framework, there are other setups in which cooperation may prosper. For example, when $2\mathrm{tc} + \mathrm{p} + \mathrm{s} > 2(\mathrm{t} + \mathrm{p} + \mathrm{s})$, the average utility per traveler achieved over two periods of the (transit, transit), (transit, transit) outcome is lower than that achieved in the (car, transit), (transit, car) outcome. It seems that PCD is a possible solution in certain mode choice scenarios. However, some type of communication may be required between the travelers to coordinate their actions. Indeed, the literature from the field of social psychology connects the social value orientations of individuals with their mode choices, stating that the more pro-social the individuals, the more likely they prefer using public transit than private cars (Joireman et al., 1997; Van Lange et al., 1998; Van Vugt et al., 1996, 1995). Accordingly, assuming travelers are able to communicate and coordinate a carpool, their utilities could change as depicted in Table 4. As can be seen, the utilities in this case are higher than in the original public transit vs. private car example (illustrated in Table 2), as the rideshare option lacks the time cost assigned for boarding at stops. Consequently, the probability that both travelers will rideshare increases in a repeated game and since the benefit for ridesharing is greater than that for classic public transit, ridesharing could be a more successful form of cooperation in larger groups. A similar logic based on cost reduction is the driving force behind several mobile apps that support ridesharing, e.g., Uber, Ridewith and Lyft, (Chan and Shaheen, 2012).

The conscious redesign of ICT applications may be part of the solution to the motivational problem inherent in large groups. Behavioral economists, who advocate the use of '*choice architecture*' to influence behavior change, describe how

Table 3
Game payoff matrix for a mode choice scenario between private car and public transit. If $-\mathrm{tc} > -\mathrm{t} - \mathrm{p} - \mathrm{s} > -\mathrm{tc}^2 > -\mathrm{tc}$, the game resembles a PD and the static one-shot outcome is (car, car).

		Traveler 2	
		Public transit	Private car
Traveler 1	Public transit	$-t - p - s, -t - p - s$	$-tc - p - s, -tc$
	Private car	$-tc, -tc - p - s$	$-tc^2, -tc^2$

Table 4
Game payoff matrix for a mode choice scenario between a private car and ridesharing.

		Traveler 2	
		Rideshare	Private car
Traveler 1	Rideshare	$-t-p$, $-t-p$	$-tc-p$, $-tc$
	Private car	$-tc$, $-tc-p$	$-tc^2$, $-tc^2$

'*nudges*', small features incorporated in the choice environment, help individuals overcome cognitive biases. As such, nudges highlight the better choices without restricting freedom of choice and without significantly changing the physical environment, the set of choices, or the economic attributes of the choices (Thaler and Sunstein, 2008). In transportation, Avineri and Waygood (2013) show how information designed with loss framing can motivate carbon reducing travel options like bicycling and public transit. We argue that nowadays, ICT is a better way to design and apply choice-architecture as a source for behavior persuasion and social norm activation. Perceiving computers as social entities has been identified by Fogg (2002) in relation to persuasive technologies. Persuasive technologies thus work on the basis that humans feel that they must reciprocate when treated favorably by their computers. This "favor" then allows the ICT applications to request that they behave in certain ways, thereby applying persuasion. From the perspective of Fogg's insights, personal travel assistant (PTA) applications could be programmed to suggest a short commute to work in exchange for the traveler's agreement to cooperate, e.g., by complying with a recommended travel option, for example, public transit, or by raising social awareness of the system costs of choosing a typical mode.[7]

3.2. Route choice

Similar to mode choice, route choice can also be modeled with a two player game that obeys the condition $T > S$, $T > R$, $S > P$, which allows the formation of traffic congestion to be modeled in a binary route choice problem. Assume that there are two players who want to drive from A to B and who must choose between two routes, a main road (M) and a side road (S), that differ in that the free flow time (f) on M is smaller than that on S ($f_m < f_s$). A feature common to both routes is that when the two travelers use them simultaneously, traffic congestion forms and travel time increases. The two roads use different congestion coefficients (i_m, i_s) that are multiplied by the number of travelers taking the route (n_m, n_s). Table 5 illustrates the two-player dynamics.

Using different parameter settings generates different types of games. As long as ($T > P > S > R$), we are dealing with the route-choice game (RCG), which has only one Nash equilibrium (M,M). In a one-shot game, the prediction in the RCG is that both drivers take Route M, which is also the UE of the network, and hence, traffic congestion is a natural consequence. However, repeating the encounter over a long period of time with ($f_m + f_s < 2(f_m + i_m)$) enables a PCD solution of the alternating coordinated strategy ((M,S), (S,M)), which results in higher gains for both players. In this case, the dominant strategy is that one driver takes route M on even days (when the other driver takes route S), while on odd days, the opposite holds. This outcome is also the SO of the network. The robustness of this result was corroborated in lab experiments where in most of the sessions, cooperation was achieved after 200 iterations even without any form of communication between the two players (Helbing et al., 2005, 2002; Stark et al., 2008). However, when the group size was expanded from 2 to 4 players, although cooperation was achieved, the emergence of coordination took much longer. This suggests that as the number of players increases, finding an analytical solution becomes extremely difficult, even in a binary network. Numerical simulations, including agent-based models, could be a viable approach to finding stable, optimal solutions as shown by Levy and Ben-Elia (2016).

The BoS and Leader games have two Nash equilibriums ((M,S) and (S,M)), which is also constitute the SO of the road network. However, when two players make simultaneous decisions, it is possible that both will choose the same strategy, since each player thinks that the other will choose the opposite route. This coordination problem may result in both drivers taking the same route, M or S, which will lead to a suboptimal state. In this case, alternating reciprocity is a viable solution that helps ensure that the players do not stray from the Nash equilibriums. If both drivers consistently play the same Nash equilibrium, the player who is worse off may "threaten" the other player by intimating that she will also take the second route, thereby leading to an inefficient result. Only by alternating the routes between the players does this threat dissipate. Although correlated equilibrium may also help solve this coordination problem, it will not necessarily hold under repeated interaction due to the element of luck (in contrast to the fairness introduced by alternating reciprocity).

A similar analysis can be applied to road pricing. This intervention aims to mitigate traffic congestion by imposing on the road network a Pigouvian tax (toll) that is proportional to the level of congestion on the different routes. Such a tax forces drivers to reconsider their travel choices according to their respective values of time and willingness to pay for congestion delay mitigation measures. Returning to the route-choice payoff matrix in Table 5, the imposition of a toll (t) on route M alters the utilities (Table 6).

[7] Application examples include: Peacox - Schrammel et al. (2013); Quantified traveler Jariyasunant et al. (2015); and Matkahupi - Jylhä et al. (2013).

Table 5
Game payoff matrix for a route choice scenario. Different parameter settings generate different types of games, including the route-choice game if (T > P > S > R).

		Driver 1	
		S	M
Driver 2	S	$-f_s - i_s, -f_s - i_s$	$-f_s, -f_m$
	M	$-f_m, -f_s$	$-f_m - i_m, -f_m - i_m$

To prevent the formation of congestion, the toll must always be sufficiently high such that this interaction will be modeled according to BoS or Leader (where the Nash equilibriums are coordination of usage of route M and S, respectively) rather than as RCG (where the Nash equilibrium is mutual defection and congestion on route M). However, such coordination is likely achieved when the tolls will influence travelers differently, i.e., when the travelers' value of time is heterogeneous, which implies that social inequality is required for road pricing to succeed (Cervero, 1998). This solution is therefore worse than alternating reciprocity where, because the toll is not required, the solution is more equitable. Note that Pareto-improving road pricing is possible in a routing game, as shown by Wu et al. (2011) and Lawphongpanich and Yin (2010), by using a manifold suboptimization algorithm. However, alternating reciprocity is still the superior outcome, as it enforces a bounded-rational solution that does not incur tolls, and therefore, its SO is higher.

Cooperation and coordination between travelers could be further enhanced by exploiting ICT to prime travelers prior to their journey with information about their travel options to direct them toward the system-optimal solution. This scenario, however, elicits a new problem, namely, travelers might not trust other travelers to act accordingly. This problem is also known as "cheap talk", a game-theoretical concept according to which if the cost of sending a communication message is negligible, then if one pure equilibrium exists (as in PD and RCG), the true value of this message will be too small to have any major effect on players' decisions.

The problem of trust can be solved by adding another vital system attribute – fairness. If travelers know they will be treated fairly, i.e., their average travel times on a weekly/monthly scale are equal, then they will be more willing to cooperate and accept the provided guidance or intervention. One such example of fairness that was first implemented on state route 91 in California in 1995 is the concept of high occupancy toll (HOT) lanes, on which high occupancy vehicles (e.g., carpools) and public transit travel for free while low occupancy vehicles pay a toll (Boyles et al., 2015; Lou et al., 2011). Another idea suggested in the literature is fast and intertwined regular or FAIR lanes (DeCorla-Souza, 2000), a road-pricing intervention based on compensating (e.g., subsidies or discounts to low income) drivers who agree to drive in the slower lanes or who carpool, while the car drivers who occupy the faster lanes pay the full toll. In the case of FAIR lanes, therefore, equity issues are substantially diminished, and traveler awareness that they are being treated fairly encourages trust in the system. Similar to the concept of FAIR lanes is the "fast lane" at the southeastern entrance to Tel Aviv, Israel. The toll collected from fast-lane users is effectively redistributed to the benefit of drivers who do not use the fast lane, i.e., drivers who exploit park-and-ride schemes, by funding for these drivers free shuttles that drive on the same fast lane. Likewise, carpools and public transit can use the fast lane free of charge.

Social punishment can also motivate cooperation by inducing trust and reinforcing long-term commitment. The operationalization of social punishment can be either centralized or decentralized.[8] In the former, the system provides prescriptive information (as opposed to experiential or descriptive information) that prompts travelers to use the most socially optimal route rather than the quickest route. Helbing et al. (2005) suggest that intermittent penalties and rewards could be designed in a way that guides travelers toward the system optimum through reinforced learning. In this scenario, non-complying travelers will pay a penalty proportional to the extra costs they created for the rest of the road users, and that money is then redistributed to reward complying travelers. In an infinitely repeated game setting, over time most travelers are expected to learn that defecting is too costly. Therefore, the amounts of the sums that are redistributed between defectors and cooperators should converge toward zero in the long run, and the network remains in a stable state of system optimum.

The notion of social punishment is also exploited, together with fairness, by travel credit and travel permit trading systems (Fan and Jiang, 2013; Tian et al., 2013; Verhoef et al., 1997; Wang et al., 2014; Xiao et al., 2013; Yang and Wang, 2011 and see recent review by Grant-Muller and Xu, 2014). In such trading systems, a central network planner distributes travel credits, the number of which is determined by the available road capacity, to all eligible travelers who can then choose to buy or sell credits in a free market. In this way, travelers with higher values of time pay premiums to travelers with lower values of time and fairness is preserved. Punishment can also be imposed in a decentralized manner, by the travelers themselves, e.g., through social media outlets (e.g., "shaming" anti-social behavior). This kind of punishment discourages defection and free riding by focusing on travelers' reputations and emphasizing social norms, as mentioned earlier. However, the use of social punishment may create a new problem, insofar as it distinguishes between cooperators who punish and those who

[8] While punishing non-cooperative travelers could contradict the universal right to mobility (Cresswell, 2006) according to Martens (2012) transportation commentary on Michael Walzer's "Spheres of Justice" (Walzer, 2008), it is possible to redistribute the good of accessibility without necessarily conforming with the right to mobility.

Table 6
Game payoff matrix for a route choice scenario, with tolls.

		Driver 1	
		S	M
Driver 2	S	$-f_s - i_s, -f_s - i_s$	$-f_s, -f_m - t$
	M	$-f_m - t, -f_s$	$-f_m - i_m - t, -f_m - i_m - t$

do not. The latter are considered "second degree free riders", as they avoid bearing the costs of punishment (Helbing et al., 2010).

3.3. Departure time choice

The choice of departure time can also be modeled as a two-player game. Let us assume that each traveler can leave for work either early (*E*), on time (OT) or late (L). They lose sleep (*s*) by leaving too early, take a chance of being fired (*f*) by leaving (and arriving) late, and risk congestion delays (*c*) by choosing the same departure time as other travelers. Table 7 shows a possible payoff matrix.

The outcome of this interaction is dependent on the values of s, f and c. Assuming $c < s < f$, the result of a one-shot game will likely be that both travelers will choose OT, while the UE outcome is that they will risk congestion delays and late arrival to work. This outcome is similar to the bottleneck model (Arnott et al., 1990; Vickrey, 1969), where rational travelers who try to economize on their travel costs tend to depart at the same time, thereby overloading the capacity of the single route. Vickrey's well-known solution, to impose a time varying toll proportional to the buildup of congestion, implies that travelers will organize their travel needs according to their respective values of time. This means that travelers with larger incomes will depart on time whereas those with smaller incomes will depart earlier or later than their preferred departure times. Thus, inequality is a necessary outcome of this type of intervention. A similar analysis can be made of Singapore's Area License Scheme, which was initially intended to mitigate congestion only during peak hours. Other ICT-enabled interventions aimed at influencing departure time choices based on a similar kind of segregation of travelers according to their willingness to pay include highway slot reservations (Edara and Teodorović, 2008; Kim and Kang, 2011; Liu et al., 2013, 2015; Su et al., 2013; Su and Park, 2015), freeway booking policies (Chung et al., 2012), highway voting systems (Lin and Lo, 2015) and lottery-based incentive mechanisms (Merugu et al., 2009; Rey et al., 2016).

However, as was shown for mode and route choice, additional options exist to foster cooperation in choice of departure time. Returning to the payoff matrix, when $s > f$ and $2s < c$, an optimal PCD solution of ((E, OT), (OT, E)), in which travelers alternate between early and on-time departure, can be realized in the system. Alternatively, if $f > s$ and $2f < c$, it is possible to achieve the optimal PCD solution of ((OT, L), (L, OT)). Nevertheless, the differences between individuals in terms of s and f may render this kind of interaction difficult to model. The cooperation-inducing measures discussed for route choice, such as persuasive technologies, fairness and social punishment, could also be applied to departure time.

4. Methodological considerations

The question of how to facilitate cooperation in road networks without implementing coercive measures like tolls remains largely hypothetical. The potential applicability of FET to such traffic management issues is enormous, but these nascent technologies are still under development or too new to have been widely adopted by travelers, and therefore, it is still too early to investigate their impact. Indeed, although a number of mobile apps that support ridesharing already exist, their use by the entire traveler population is not sufficiently widespread, and therefore, their global effect on road networks is still too limited to have an impact on congestion levels. Furthermore, apps that enable cooperation in route and departure time choice do not yet exist, and would require a large share of the population to actually use them in order to investigate their potential impact. Lastly, rather than adding travel alternatives, the introduction of cooperation presents travelers with a new technology, to which they must also adapt. This makes investigating cooperation even harder to manage. We now turn to discuss the problems associated with existing methodologies and then continue to discuss the opportunities we envision in game-based methods.

4.1. Drawbacks of existing methodologies

4.1.1. Problems related to RP– and SP–based methodologies

Contemporary methods for examining innovations in transportation use either stated preferences (SP) or revealed preferences (RP) data (and many times both). Because RP is largely irrelevant in predicting the success of new products, SP is commonly used to investigate hypothetical states (Hensher, 1994), such as activity travel choice behaviors (Arentze and Timmermans, 2004; Timmermans et al., 2002). However, some researchers have questioned whether SP is capable of replicating real situations, i.e., does SP suffer from the risk of hypothetical bias (HB)? HB is evident when responses from subjects suffer from under- or overestimation due to problems associated with a lack of concreteness in the subject's decisions

Table 7
Game payoff matrix of game theory for a departure time choice scenario.

		Traveler 2		
		E	OT	L
Traveler 1	E	$-(s+c), -(s+c)$	$-s, 0$	$-s, -f$
	OT	$0, -s$	$-c, -c$	$0, -f$
	L	$-f, -s$	$-f, 0$	$-(f+c), -(f+c)$

(Brownstone and Small, 2005). The use of SP, and especially of stated choice experiments, is very common in travel behavior research, particularly to investigate people's preferences regarding innovative travel alternatives.

The awareness among travel behavior researchers that HB is a problem is relatively high, and therefore, various measures are usually implemented in their studies to reduce its influence: (1) Cheap talk – in addition to asking study subjects about their preferences, researchers use the questionnaire to inform the subjects about the existence and potential problem of HB, in light of which they then asked the subjects to provide an as-real-as-possible answer. Cheap talk has been found to decrease HB (Fifer et al., 2014). (2) Opt-out – questionnaires from some earlier studies that examined mobility choices did not allow subjects to opt out of answering a question. Inclusion of the option to opt out has also been found to decrease HB (Hensher, 2010). (3) Certainty calibration – because a hypothetical question may "confuse" subjects and elicit from them an uncertain answer, questionnaires can include a certainty calibration scale on which subjects can mark the level of certainty they have about their choices. Higher certainty in SP choices was found to be more strongly correlated with RP (Champ et al., 1997). (4) Incentive compatibility – although a survey can be designed to elicit true answers by making truth revealing answers a rational strategy, i.e., making a survey incentive compatible, this measure works well mainly with binary choices that are non-repeating, and as such, it is of limited use in travel behavior research (Carson and Groves, 2007).

None of the four measures leveraged to reduce the influence of HB relates directly to dynamic environments, whereby the experiences of people regarding their travel alternatives also reinforce their future choices. Araña and León (2013) examined customer preferences for corporate social responsibility and found that although HB was low in first-stage assessments, later stages of a complementary RP method revealed that willingness to pay for the product had changed over time. Moreover, a panel study regarding the use of an electric vehicle that combined stated choice and attitudinal effects showed that real life experience changed user preferences after respondents used an electric vehicle for three months (Jensen et al., 2014). People who are asked hypothetical questions are not introduced with the opportunity to actually explore and experience the innovation at hand. Thus, simple SP designs will often fail to take learning into account.

To bypass the HB problem, transportation researchers make use of simulations and agent based models (ABM). ABM work around HB by simulating behavior on real road networks, and in so doing, they try to predict the effect of changes to agent or environment attributes to reveal an optimal solution. Recent years have seen significant growth in the potential of ABM in the social sciences (Helbing and Balietti, 2013; Levy et al., 2015; Levy and Benenson, 2015) as manifested in especially powerful simulations like MATSim, the multiagent transportation simulation environment (Balmer et al., 2006), which is capable of simulating complex multimodal transportation network dynamics. However, any attempt to use ABM to predict the network response to FET is bound to suffer from acute HB, especially if the rules for the agents' behavior are deduced from SP surveys, which themselves suffer from HB. If agents' behaviors are deduced by assumptions made by the ABM designer, the model is inherently weaker, as strict and simplistic decision rules will probably fail to predict the complexity of travel behavior. For ABM to predict network dynamics after the diffusion of new technologies, a more dynamic and robust approach is required.

4.1.2. The drawbacks of the technology acceptance model

A known approach for evaluating technological innovations is the technology acceptance model (TAM), which examines the actual use of technological innovations and the attitudes towards them as a function of the perceived usefulness and perceived ease of use of those innovations (Davis, 1989). The use of TAM to examine new hypothetical concepts is widespread in the realm of transportation. Indeed, TAM-based methodologies were exploited to study the adoption of electronic toll collection (Chen and Chao, 2011; Chen et al., 2007; Holguín-Veras and Preziosi, 2011), urban transport strategies (Schade and Schlag, 2003), and advanced driver assistance systems (Son et al., 2015) as well as the use of travel information (Lin et al., 2014; Xu et al., 2010). We argue that in terms of cooperation in road networks, the use of TAM is problematic both generally and specifically. Criticism of TAM in the literature revolves around its supposed flawed implementation and some of its theoretical characteristics. Problems associated with its implementation are (a) the actual use of technology is self-reported by subjects, a scenario that renders the dependent variable a subjective measure that is thus less reliable, (b) the subjects of most of the studies are students, who are not always the target audience of innovations, thus hampering external validity, and (c) use of the innovations in these studies is voluntary as opposed to mandatory reflecting a study design that may yield different results (Chuttur, 2009). From the theoretical side, critics further suggest that (a) TAM has meaningless indicators, as it does not verify actual behavior (Barki, 2007), (b) it is overly simplified, and (c) it does not describe the behavioral mechanism behind the acceptance of technology, as it uses meaningless indicators (Bogozzi, 2007). In addition, in the context of hypothetical road network cooperation, because its theoretical framework is static rather than dynamic, TAM does not enable learning.

4.1.3. Gaps between experience and description-based decisions

A prominent problem of contemporary choice experiment methods is related to the gap between making a decision from description (DFD) and making a decision from experience (DFE). Contemporary literature in experimental decision making discovered the description-experience gap, which refers to the observation that people tend to overweight the probability of rare events when those are described to them and to underweight the probability of rare events when they are experienced among a sample of several events (Hertwig and Erev, 2009). Several reasons for this gap have been speculated, including (a) sampling error in DFE – due to small samples, subjects under-sample rare events or do not sample them at all, and therefore, underweighting is natural (Fox and Hadar, 2006), (b) recency – people's memories of experiences tend to be limited to recent events, and therefore, rare events are underweighted, and (c) tallying – differences in how subjects sample events, either each event in its turn or both events intermittently, affects the size of the gap (Hills and Hertwig, 2010). Although these explanations show that a DFE may suffer from biases, the DFE nevertheless simulates day-to-day situations and learning scenarios better than a DFD, and therefore, the former has stronger external validity. Transportation studies that exploit DFE are relatively scarce. Recent contributions include Avineri and Prashker (2006) and (Ben-Elia et al., 2008) concerning route choice; (Ben-Elia and Ettema, 2011) concerning departure time; and Innocenti et al. (2013) concerning mode choice.

4.2. Opportunities of game-based approaches

Given the multiple methodological difficulties described above, we advocate that a new methodological approach is desperately needed. One approach that has a strong potential to overcome many of the problems and drawbacks discussed above comprises using serious games and game-based modeling to investigate the emergence of cooperation with ICT and FET.

4.2.1. Serious games

A game is defined as a virtual system of play where players engage in an artificial conflict that is defined by rules and that has a quantifiable outcome (Salen and Zimmerman, 2004). Any game possesses four coexisting elements: roles, objectives, rules that shape player behavior, and constraints that limit the players' virtual world (Meijer, 2009). Serious games (SGs) promote the achievement of a defined purpose, formulated by the game's designer, other than pure entertainment (Michael and Chen, 2005). These include: improving policy, education and scientific research (Mayer et al., 2014). Inferring behavior from games is not particularly new. Behavioral economists frequently apply classroom market entry games, public goods games and coordination games (Camerer and Loewenstein, 2004). Role playing games are common in public policy and natural system management research methods (Barnaud et al., 2007; Barreteau et al., 2001; Castella et al., 2005; Cleland et al., 2012; Dumrongrojwatthana et al., 2011; Mayer et al., 2004; Meijer et al., 2012). In transportation research, however, games are not very common. If is important to distinguish between serious games and gamified studies – whereas serious games have been employed in transportation research for more than a decade, mainly in the realm of multiplayer-economic routing games (Chidambaram et al., 2014; Helbing et al., 2005; Innocenti et al., 2013; Jotisankasa and Polak, 2006; Lu et al., 2014; Rapoport et al., 2014, 2009, 2006; Rey et al., 2016; Selten et al., 2007; Ziegelmeyer et al., 2008), gamified studies, in which elements of a game appear (Deterding et al., 2011), are still quite novel in transportation research.[9] Table A1 in Appendix A summarizes these studies, and Table A2 classifies them according to type of game and transportation choice.

Serious gaming possesses substantial advantages for behavior inference in the case of innovations: (a) SGs elicit the formation and stabilization of preferences through the dynamics of reinforced learning (Erev et al., 2010) and reveal the elusive decision semantics and cognitive characteristics of individuals' decision rules. (b) Multiplayer games provide an opportunity to extract the rules of collective behaviors and social interactions as well as the evolution of the group (Bainbridge, 2007). SGs create competition between individual players, but at the same time, they support learning, reciprocity and the establishment of a stable form of cooperation (Helbing et al., 2005). (c) The environment in an SG can be easily programmed to generate various constraints and degrees of uncertainty directly correlated with individuals' choices (Rapoport et al., 2009). (d) embedding the SG engine in a real geographical database can make it spatially explicit (Miller, 2013) and completely suitable for representations of a real-world transport system. (e) The SG can generate interest and participant involvement and avoid boredom in repetitious experimental tasks, and it can even be used for hypothesis generation, e.g., Foldit game (Good and Su, 2011).

Three specific properties – interaction, immersion and persuasion – make SGs particularly advantageous to better understand hypothetical choice situations that involve dynamic behavior change. Interactive animation provokes the imagination and so shifts mental tasks from cognitive to perceptual activity, freeing up cognitive processing for application tasks (Card et al., 1999). To achieve this, SGs can be merged with virtual reality (VR) and developed as high-fidelity, imaginative, interactive and immersive simulations that mirror real-world domains (Zyda, 2005). SGs also hold strong potential for behavior persuasion, i.e., enforced motivation to change behavior through incentives and generated social awareness. Persuasion can be 'gamified' by gaining points on 'good' and losing points on 'bad' behavior (Zichermann and Cunningham, 2011).

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[9] Recent examples include: The IC-DEEP project studying the ergonomics of in-vehicle information systems (Gonçalves et al., 2012); the two-city congestion charge collaborative game (Shepherd and Balijepalli, 2015); the artificial transport system agent-based game engine developed by Miao et al. (2011); urban parking behavior that is based on a serious "ParkGame" (Ben-Elia et al., 2015).

SGs must be well-designed, planned, and validated. The internal validity is based on four criteria – psychological, structural, process and predictive (Peters et al., 1998) Psychological validity necessitates a game environment that evokes natural, real-life participant behavior. Structural validity demands that the relevant elements of reality, such as actors, information, data, rules, and norms, be reflected in the game. Process validity requires that the processes that occur in reality, such as flows of information or resources, interactions between actors, and negotiations, be reflected in the game. Predictive validity dictates that the game be able to predict real outcomes or to reproduce a historical outcome. The extent to which games meet all four validity criteria prevents mistakes when translating reality to games and game results back to reality. The use of SGs in research, however, is hindered by the high expense and the exorbitant amount of time associated with their preparation. These shortcomings can be overcome by platforms, such as z –Tree (Fischbacher, 2007) and NodeGame (Balietti, 2014), created to ease the creation of interactive and multiplayer SGs. Moreover, the costs of gaming hardware (e.g., Oculus Rift 3D head mounted displays) have recently decreased considerably, and user-friendly platforms for game design and software development (e.g., Unity 3D) have improved significantly.

4.2.2. Game-based models

The fusion of ABM simulations and SG in a unified framework is known as a Game-Based model (GBM) (Riensche and Whitney, 2012). We argue that GBMs are especially useful for analyzing road and transportation networks and the complex adaptive interaction between the physical transport infrastructure and the behavior of human-agent travelers when agent behaviors collectively influence the service level of the system (i.e., congestion), which, in turn, influences travelers' behavior and so forth (Mayer et al., 2010). To properly model road networks, a game must include multiple and diverse travelers and transportation system elements, rules that structure social interaction and that are flexible enough to evolve, proper representations of players' decisions and their consequences, and the ability to register emerging processes in the final state (Bekebrede, 2010). In this context, the GBM fills the methodological gap between an analytical-based inference of behavior, such as RP-SP derived discrete choice models, and ABM simulation. GBMs also allow behavior evolution to be examined and simulated in a representation of the real world that has agents who behave and adapt in a manner similar to human players. The synergy between the game and the ABM is guaranteed by a shared, conceptual model and by their concomitance of use. The concomitant use of game and model enables simultaneous validation of the system's dynamics and of the behavioral rules of the system's constituents, i.e., the human players (Barreteau et al., 2003; Nikolic and Dijkema, 2010; van Os, 2012). By allowing autonomous agents to react to the actions of human players and vice versa and by comparing the outcomes of human agents in a GBM simulation, we are able to learn two important facts: First, at a global systemic level, whether our game-based formalization of human behavior rules is able to generate the likely dynamics of the entire system. Second, at the level of individual behavior, whether this formalization is sufficiently rich to make humans and artificial agents indistinguishable to an external "observer". In this respect, a GBM realizes the imitation game in Turing's Interrogation Test (Turing, 1950), whereby human players and an external observer should not be able to distinguish between the human player and the program agent that is part of a machine. Failure of the observer in the distinguishing task implies that the GBM is properly validated and provides behaviorally consistent predictions.

We conclude that SG and GBM provide fertile ground for research investigating the potential of future and emerging technologies to change low permanency travel decisions such as departure time, route and mode choice behaviors. Moreover, the dynamic structure of GBM facilitates the formalization of consistent hypotheses for investigating FET, such as the introduction and proliferation in the road network over time of CAVs. In conclusion, GBM are a perfect research environment to study emergent social phenomena like cooperation and the measures and strategies that can help sustain it in perpetuity on the road networks of the future.

5. Conclusions and a future research agenda

In this paper, we reviewed the potential inherent in ICT and associated FET that could enable the emergence and sustainment of cooperation in road networks. Using hypotheses based on game theory, we analyzed different types of travel behavior including route, mode and departure time choices. Different economic and behavioral mechanisms from the perspective of game theory that mitigate congestion through cooperation were discussed and compared to current strategies for tackling congestion. In addition, the necessary traits for facilitating and perpetuating cooperation (e.g., fairness, reciprocity, punishment and trust) were addressed. The limitations of current state-of-the-art research methodologies were discussed as was the potential of new approaches based on emerging game-based methods, e.g., serious games and game-based models.

What should a future research agenda for cooperation and FET include? First, we believe more research is required on understanding travelers' motivation and persuasion to cooperate and deeper investigation to the conditions, factors and mechanisms that support the emergence of cooperation in road networks. In this sense, integration of route, mode and departure time choices is paramount. In addition, studies on travelers' satisfaction under cooperation should be carried out, e.g., by adapting the STS framework proposed by Ettema et al. (2011). In addition, standard national and metropolitan surveys regarding travelers behavior should give attention to the use of mobile apps based on gamified and persuasive technology principles that can foster cooperation, as well as to other forms of ICT-enabled travel behaviors.

Second, we consider that an integrative complexity approach is required to fully understand and forecast future mobility trends and transportation system performance. In particular, co-evolutionary processes of change of both individual travelers and the attributes of the system need to be investigated. These should consider different scenarios for proliferation of FET like CAV while testing different cooperation enabling mechanisms we reviewed such as centralized intermittent penalties and rewards (Helbing et al., 2005), raising social awareness influence through persuasive technologies (Du et al., 2014), and even possibly through trading in travel credits (Grant-Muller and Xu, 2014), to name a few. These mechanisms could work in different ways to solve the social dilemmas based on game-theoretic principles and could be implemented by embedding V2V and V2I telecommunication architectures in CAV in the future.

Third, research should look more closely at forecasting key phase transitions in the operations of the road network. These indicate that the entire system is co-evolving toward a new phase of operations. A major aspect is when cooperation becomes "viral", i.e., what are the properties of the system, the environmental conditions and the underlying enabling mechanisms when a key threshold is passed and travel behavior does not relapse into selfishness (e.g., driving alone in a shared car). In this respect, it is important to consider the fleet mix of the vehicles, as it is expected that CAV gradually proliferate and replace conventional vehicles. Thus only when a certain share of the fleet is connected will cooperation succeed and

Table A1
Summary of multiplayer-economic experiments.

Study	#participants	#sessions	#rounds	Type of game	Transportation choice	Description	Results
Chidambaram et al. (2014)	204	34	18	Route choice game	Mode	Mode choice experiment which examines Pigovian interventions and public coordination	Pigovian interventions have bigger effect over network dynamics than public coordination
Helbing et al. (2005)	2(4)	24(12)	300	Route choice game	Route	Route choice experiment which examines the possibility of cooperation	Cooperation often achieved after a long learning phase
Iida et al. (1992)	80	2	20/21	Route choice game	Route	Route choice experiment which examines convergence to user equilibrium	Convergence to equilibrium does not occur smoothly
Innocenti et al. (2013)	62	3	50	Route choice game	Mode	Mode choice experiment which examines mode stickiness	People have preference for car and inclination to mode stickiness
Lu et al. (2011)	12	2	120	Route choice game	Route	Route choice experiment which examines the effect of information over network dynamics	Partial real time information increases network efficiency
Lu et al. (2014)	128	8	120	Route choice game	Route	Route choice experiment which examines the effect of information over network dynamics	Partial real time information increases network efficiency
Rapoport et al. (2009)	Two experiments, each 108	6 Each	80 Each	Prisoners' dilemma (public goods game)	Route	Route choice experiment which examines network dynamics in a Braess network	Adding a route in Braess network increase travel time
Rapoport et al. (2014)	200	10	160	Route choice game	Route	Route choice experiment which examines the effect of information over network dynamics including incidents	Real time information can possibly increase travel time
Rey et al. (2016)	60	6	80	Route choice game	Time of departure	Time of departure choice experiment which examines lottery based incentive mechanisms	Lottery based incentives push road users from choosing pick strategy to off peak strategy
Selten et al. (2007)	108	6	200	Route choice game	Route	Route choice experiment which examines the effect of information about foregone payoffs	Foregone payoffs have little effect over network dynamics
Sunitiyoso et al. (2011)	9	1	30	Prisoners' dilemma (public goods game)	Mode	Mode choice experiment which examines social learning	Social learning exist in mode choice
Ziegelmeyer et al. (2008) (two experiments)	1st: 128 2nd: 64	1st: 8 2nd: 1	1st: 40 2nd: 25	Battle of the sexes	Time of departure	Time of departure choice experiment which examines public information on congestion	Information is unable to mitigate congestion

Table A2
Classification of multiplayer-economic experiments by type of game and transportation choice.

	Mode	Route	Time of departure
Prisoners' dilemma (public goods game)	Sunitiyoso et al. (2011)	Rapoport et al. (2009)	–
Battle of the sexes	–	–	Ziegelmeyer et al. (2008)
Route choice game	Chidambaram et al. (2014) and Innocenti et al. (2013)	Helbing et al. (2005), Iida et al. (1992), Lu et al. (2014, 2011), Rapoport et al. (2014), and Selten et al. (2007)	Rey et al. (2016)

remain sustainable. These questions need answering soon to develop flexible and effective traffic management strategies long before CAV become an everyday reality.

Lastly, more research is needed to explore the emerging methodologies aimed at examining complex systems. Here we suggested serious games, virtual reality and possibly their integration with agent-based simulations (i.e., game-based models) to obtain flexible, dynamic and robust methods that permit investigations of complex systems, co-evolutionary processes and different game-theoretic enabling mechanisms for cooperation. Despite their immense potential, such emerging methods also entail high risks of failure that must be carefully and meticulously examined. No doubt the future holds major surprises for our understanding of transportation, and as such, to be better prepared for tomorrow we should start asking the right questions today.

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Appendix A

See Tables A1 and A2.

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