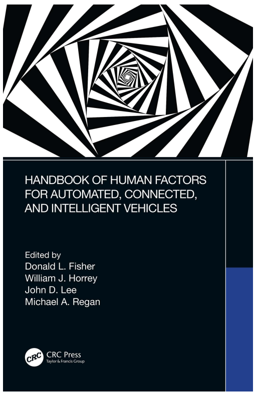

Handbook of Human Factors for Automated, Connected, and Intelligent Vehicles

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Congestion and Carbon Emissions

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20 Congestion and Carbon Emissions

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CONTENTS

KEY POINTS

- Unless people completely surrendered driving control to ACIV, researchers must understand the effects of vehicle intelligence, connectedness, and automation on driver behavior.
- Interventions that aim at behavior modification only—such as congestion pricing or techniques of nudging—without boosting underlying processes and competencies, might fail to promote pro-environmental driving-related behaviors.
- Reasoning and decision-making, regarding one’s own or others’ driving, seem to be predicted by simple rules of thumb.
- The use of simple rules of thumb for parking can increase system efficiency, compared with standard game-theoretic proposals.
- Driving-related moral and social dilemmas, induced by automation, have been investigated, but more work remains to be done.

- Life cycle assessment of automated vehicles has found that they could decrease greenhouse gases emissions by 9%, but this is not taking into account possible rebound effects such as increased driving.
- Pro-environmental driving-related behaviors are tailored by personal as well as contextual factors: Being motivated towards decreasing carbon emissions is not enough to undertake a pro-environmental behavior.
- Carbon-emission information may have an impact on driver's decisions when it is provided clearly, but other criteria (e.g., fuel price, safety, time) should also be satisfied.

20.1 INTRODUCTION

According to the U.S. Bureau of Transportation Statistics (2007), the road transportation sector accounts for approximately one-third of U.S. carbon emissions from the use of energy. Previous studies have shown that congestion wastes time and money, and it also increases emissions of greenhouse gases and localized pollutants such as particulate matter (Barth & Boriboonsomsin, 2008). Can roads be de-congested, and emissions be reduced, by changing the transportation infrastructure?

One might expect that building more roads should relieve traffic congestion. Think again. Duranton and Turner (2011) conclude that increased provision of interstate highways and major urban roads is unlikely to relieve congestion. These researchers used the economic theory of supply and demand coupled with the statistics of logistic regression to estimate the elasticity of vehicle-kilometers traveled with respect to the lane kilometers in U.S. metropolitan areas between 1983 and 2003. This elasticity was estimated to be 1.03, which means that there is more driving when there is more road to drive on, with the increase in traffic being 3% in excess of the corresponding increase in road.

Decades ago, such results have been expressed by the umbrella term of a *fundamental law of road congestion* (Downs, 1962). With the benefit of hindsight, it is not very surprising that people increase the consumption of road when more road is made available to them—such behavioral adaptations are ubiquitous; haven't we all had the experience of eating more just because more was served to us? This suggests that before looking for physical interventions for decreasing congestion, one might want to look for psychological ones.

Since the publication of Thaler and Sunstein's (2008) *Nudge*, psychological interventions are often identified with behavioral ones. However, these two types of intervention are not the same. The distinction we have in mind is that in the latter, an effort is made to directly change behavior without necessarily enhancing the underlying psychological processes and their associated competencies. For example, individuals might end up eating fruits and vegetables if those are exhibited at eye level in their work cafeteria, without learning and understanding that eating fruits and vegetables (in general) enables the body's healthier function. From a human-factors perspective, this is a tricky issue as any gains from purely behavioral interventions may be transient, fail to generalize to other contexts, or could create dissonance and disappointment because it is not clear that the receivers of a nudge actually want to make the choices they are nudged toward (Sugden, 2017).

This chapter follows the *Boost* approach to making psychological interventions (Bond, 2009; Katsikopoulos, 2014; Hertwig & Grüne-Yanoff, 2017). This approach aims at first *understanding* the psychological processes—such as cognitive, motivational, and social ones—underlying behavior, and then attempting to enhance these processes so as to increase *competency* and lead to empowerement. We will not delve into conceptual discussions of these two approaches in this chapter, although we will return to the relevance of psychology in enhancing pro-environmental behavior (Bortoleto, 2014), as it relates to reducing emissions while driving, in Section 20.3.

Section 20.2 focuses on reducing congestion and, as a result, reducing carbon emissions. Unless people completely surrender driving control to automated, connected, and intelligent vehicles (ACIV), researchers must understand how driver behavior is affected by vehicle intelligence, connectedness, and automation. The next section reviews such work.

20.2 REDUCING CONGESTION: DRIVER BEHAVIOR

20.2.1 Effects of Vehicle Intelligence on Driver Behavior

Guide signs display up-to-date information useful to drivers, such as travel time on a route to a popular destination or the number of parking spots available in a busy lot. They can be located inside or outside the vehicle. Such signs can affect driver behavior (Kantowitz, Hanowski, & Kantowitz, 1997). Thus, they also represent an opportunity to alleviate traffic congestion. For instance, if one knew the percentage of drivers who, after reading a particular piece of travel time information, decided to divert to the surface streets—as opposed to staying on the highway—one could intelligently switch the sign on and off to control traffic. What do we know about the effect of information displayed on guide signs on driver decision-making?

A series of experiments run on a mid-level driving simulator (Katsikopoulos, Duse-Anthony, Fisher, & Duffy, 2000; 2002; Figure 20.1)[1] investigated the choices that highway drivers made between two routes to a common destination when information about travel time on the routes was given, as shown in Figure 20.2. The experimental instructions emphasized that I–93 was the default route in the sense that participants were currently driving on it. Thus, the choice was framed as staying on the default route or diverting to the alternative, which was Route 28.

In the first experiment, the default route always had a certain travel time (100 minutes) while the alternative route had a range of travel times (from 70 to 120 minutes; Figure 20.2). The average travel time of the alternative was taken to be the midpoint of the interval: (70 + 120)/2 = 95 minutes. The range of this interval is

[1] The University of Massachusetts at Amherst driving simulator (see Figure 20.1) was used, which, at the time, consisted of a car (Saturn 1995 SL 1) connected to an Onyx Infinite Reality Engine 2 and an Indy computer (both manufactured by Silicon Graphics, Inc.) The images on the screen subtended 60° horizontally and 30° vertically, might have been artificial or natural, and were developed using Designer's Workbench (by Centric). The movement of other cars on the road was controlled by Real Drive Scenario Builder (Monterey Technologies, Inc.). The system was assembled by Illusion Technologies.

FIGURE 20.1 Driving simulator used in the route and parking choice experiments described in the text (located at the University of Massachusetts at Amherst).

Estimated Travel Time to Downtown Boston	Route
100 min	I–93
70–120 min	Route 28

FIGURE 20.2 Sign with travel time information, to guide route choice.

120 − 70 = 50 minutes. By crossing three levels of average travel time (95, 100, 105) with five levels of range (20, 30, 40, 50, 60), 15 route choice scenarios were generated.

The results showed that a risk-averse driver is less likely to divert to the alternative route as the range increases while the average remains the same. For example, a risk-averse driver was less likely to choose Route 28 in the example in Figure 20.2 when the travel time ranged from 70 to 120 minutes than when the travel time ranged from 80 to 110 minutes (the average, in both cases, equals 95 minutes). On the other hand, a risk-seeking driver was more likely to choose the 70-to-120-minute route.

An early claim in economics was that people are risk averse. The psychological literature, however, suggests that people are risk averse when the choice belongs to the domain of *gains* but risk seeking when the choice belongs to the domain of *losses* (Kahneman & Tversky, 1979). In route choice, scenarios in which the alternative has a shorter average time than the default belong to the domain of gains. The scenario in Figure 20.2 where the alternative route ranges from 70 to 120 minutes is in the domain of gains because the average equals 95 minutes, which is less than the default of 100 minutes. If the alternative route ranged from 90 to 120 minutes, the choice

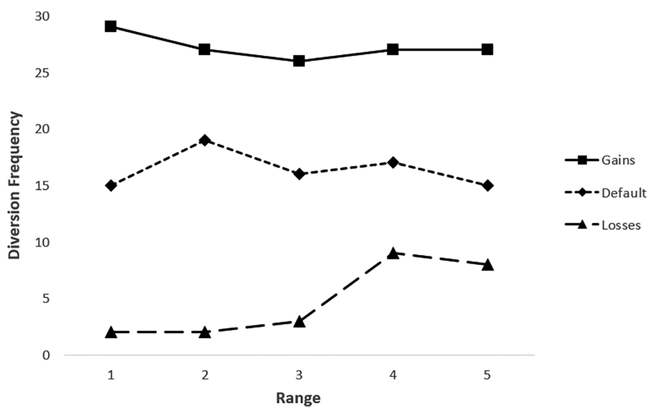

FIGURE 20.3 Number of participants diverting to the alternative route as a function of its range of travel time. On the *x*-axis, 1 means a range of 20 minutes, 2 means 30 minutes, etc. and 5 means 60 minutes.

would be in the domain of losses because the average would equal 105 minutes, and that is more than the default of 100 minutes.

Past research on route choice had only tested scenarios in the domain of gains. Katsikopoulos et al. (2000) tested route choices framed as losses. So what happened in the experiment? Figure 20.3 shows the number of participants (out of 30) that diverted as a function of the range of travel time of the alternative route (on the *x* axis, 1 means a range of 20 minutes, 2 means 30 minutes, etc. and 5 means 60 minutes). There is a decreasing trend for gains indicating risk aversion, a roughly flat line for the case where the alternative route has the default average (indicating risk neutrality), and an increasing trend for losses indicating risk seeking.

Expected utility theory (von Neumann & Morgenstern, 1947) and its modification, prospect theory (Kahneman & Tversky, 1979), are often used to model human choice in economics and psychology. According to such theories, people compute the "worth" of a decision option by summing up its possible outcomes, where each outcome is weighted by its probability. Then, people choose the option with the maximum worth. If outcomes and probabilities are taken at face value, this is the expected value theory. In expected utility theory and prospect theory, outcomes and probabilities may be translated by multi-parameter mathematical functions. A problem with such theories is that they are probably too complicated to be describing the underlying cognitive processes; rather, they are meant to be as-if representations of behavior (Katsikopoulos & Gigerenzer, 2008). In as-if theories, the claim is not that people really translate outcomes and probabilities and then sum and weight them, but rather that they make decisions "as-if" they did so.

In an alternative theory, the driver takes a *single* sample to estimate the travel time along the alternative route (where s/he perceives that the travel time of the alternative route is following a normal probability distribution over the interval of possible travel times), and chooses to divert if this estimate is less than the reference travel time. This modeling incorporates two themes of behavioral theory

(Katsikopoulos & Gigerenzer, 2008): (1) the driver is tuned to the probabilistic nature of decision-making and (2) the driver uses one piece of information to make a decision (one sample of travel time). This simple rule of thumb accounts well for a host of effects on route choice, including effects that could also be modeled by prospect theory, such as the effects of gains and losses, and effects that could not be modeled by prospect theory, such as the effects of an uncertain reference point (Katsikopoulos et al., 2002).

Such rules of thumb have been put forth for predicting parking choices as well. Hester, Fisher, and Collura (2002) ran a driving simulator study with parking scenarios where a utility model and a simple rule of thumb made different predictions. It was found that actual parking choices were more consistent with the rule of thumb than with the utility model. For instance, only 10% of the participants made all parking choices consistent with utility theory, whereas 35% of the participants made all choices consistent with the simple rule of thumb.

20.2.2 Effects of Vehicle Connectedness on Driver Behavior

Many acts of driving involve *interaction*—cooperation or competition—with other drivers. Obvious examples of interactions are when a number of drivers arrive at an intersection without traffic lights or when they are driving inside a parking lot waiting for spots to become available. Presumably, connected vehicles can support such interactions. Vehicle connectedness can, for example, utilize wireless networking technologies and mobile social applications running on smartphones, which can collect, share, and present real-time information about parking demand and availability to drivers.

The behavioral sciences, such as economics and psychology, are dominated by models of interactive situations, or *games* as they are called, that propose that people are "rational," which means that people aim at maximizing the value they receive from the game. In this sense, game theory is analogous to expected utility theory, which was discussed in the previous section. But it is even more complicated. This is so because in games, one's value depends on others' decisions, and thus "rational" decision-making needs to take into account this complexity as well. Game theory aims at discovering decisions that are mutually "optimal" for all people who play a particular game (von Neumann & Morgenstern, 1947).

Mainstream transportation theory employs game theory in order to describe and prescribe the behavioral aspects of traffic management systems, including parking management systems. Nevertheless, as noted above, it might be that parking behavior is better described by simple rules of thumb (Hester et al., 2002). More surprisingly, it might also be that such simple parking behavior in fact leads to better system performance than the purported "optimal" parking behavior suggested by game theory, as the following study found.

Karaliopoulos, Katsikopoulos, and Lambrinos (2017) consider a game where multiple drivers are competing over two types of parking resources—on-street parking and a parking lot. On-street parking is assumed to be cheaper and more easily accessible than lot parking. There is an additional excess cost for parking at the lot after searching for parking on the street (this cost expresses, among other things, additional fuel consumption). Assuming estimates of the number of drivers, the number of spots in each parking resource, and the various costs—which can be made available to ACIV drivers—Karaliopoulos et al. (2017) compared the performance of the system when drivers behave according to (1) an "optimal" equilibrium computed by game theory and (2) the following simple rule of thumb:

Step 1. If the best-case costs of the two alternatives (on-street and lot parking) differ by more than a percentage of the overall worst-case cost one may incur, then search for on-street parking (because it has much smaller best-case cost);

Step 2. Otherwise, consider the probabilities incurring the two best-case costs: If their difference exceeds a threshold, then choose the alternative with the larger probability of best-case cost;

Step 3. Otherwise, choose the alternative with the smaller worst-case cost (independently of how small the difference between the two worst-case costs is).

To see how the simple rule works, say that there are currently two drivers on the road and there is one parking spot available on the street and three in the lot. In this case, the unit costs for on-street and lot parking are 1 and 5.5 respectively, and the excess cost is 2. Assume that for one of these drivers the percentage in Step 1 equals 10% and the threshold used in Step 2 equals 0.1. Then, the difference of the best-case costs is 5.5 – 1 = 4.5 which is larger than 0.75 (10% of 5.5 + 2), and thus this driver would search for on-street parking. If this driver's percentage parameter were 60%, however, Step 2 of the rule would be used. In Step 2, the difference of the probabilities—assuming that the other driver chooses one of the four parking spots randomly—of the best-case costs equals 1.0 (for the parking lot) – 0.75 (for on-street parking) = 0.25, which is larger than 0.1, and thus the driver would go to the parking lot.

The rationale for considering this particular rule of thumb is that it might be descriptive of how people choose where to park. A reason to expect so is because the rule is analogous to a rule that predicted people's majority choices better than expected utility theory and prospect theory (Katsikopoulos & Gigerenzer, 2008). Consistently, Karaliopoulos et al. (2017) provide the results of a survey of 1,120 participants, which found that the parking choices of those drivers who always park on the street or always park on a lot—19% of all participants—can be well described by this simple rule. It is not clear how to apply expected utility theory or prospect theory in this case, because it is not clear how to reliably estimate their multiple parameters.

Regarding system performance, Karaliopoulos et al. (2017) analytically derived conditions under which game-theoretic equilibrium behavior incurred larger total costs and resulted in a larger percentage of drivers competing for on-street parking than behavior consistent with the simple rule presented above. For instance, say that there are 60 drivers on the road and the number of available parking spots is 10 on the street and 15 in the lot, the unit costs for on-street and lot parking are 1 and 5.5, respectively, and the excess cost is 2. Then, it turns out that the total cost at equilibrium equals 280, whereas under the simple rule, it equals 220. And, the number of competing drivers at equilibrium is 55, whereas under the simple rule, it is 35.

In general, conditions under which the simple rule improves system performance are fulfilled for a broad range of scenarios concerning the fees charged for parking resources and their distance from the destinations of the driver's trips. This result also holds for more complicated parking games, including more than one lot. Finally, one might expect that the simple rule of thumb is more transparent than game theory to drivers, parking managers, and other stakeholders such as local authorities.

20.2.3 Effects of Vehicle Automation on Driver Behavior

As also discussed in Chapter 4, the effects of vehicle automation on driver behavior are strongly moderated by people's trust in automation. It is sometimes thought, or implied, that the more people trust automation, the better, and thus design should "invite" people to rely on automation. This, of course, cannot always be true. As Lee and See (2004) point out, the point is to design for appropriate reliance. These authors also suggest that appropriate reliance could be achieved "by making the algorithms of automation simpler or by revealing their operation more clearly" (Lee & See, 2004, p. 74). Endsley (2017) also makes the same point (Chapter 7), worrying about the opaqueness of now routine deep-learning algorithms. Such algorithms are often not even transparent to their own designers (Townsend, 2008). This point follows from the sections above and emphasizes the need for simplicity and transparency in researchers' understanding of human behavior. In particular, if the automation is going to suggest, say, following the speed limit on a smart motorway during periods of congestion, the automation needs to provide that information in a way that makes it possible for the human driver to use simple rules to come to a decision about what to do.

The design of the human–machine interface (HMI) and, in particular, how information on congestion is displayed will also influence driver's choices. Chapter 4 provides an exposition of how psychological theories of motivation, emotion, and personality, as well as the associated concepts of traits and attitudes, can inform such automation design and its customization. Additionally, Chapters 7 and 15 are also relevant, as they argue for the need for improved HMI design for automated vehicles. Endsley (2017) describes her six-month experience of driving the Tesla Model S and the challenges she faced in interacting with the automation interface. Beyond these chapters, we do not have much to add on automation here, except for the following outline of a new direction in behavioral research on automation and congestion.

Bonnefon, Shariff, and Rahwan (2016) placed Foot's (1967) classic trolley problem in the context of automated driving. The researchers presented participants in multiple surveys with questions such as the following: Should an automated-driving algorithm protect its passengers at the cost of running over pedestrians? Should such an algorithm change its course so as to run over a smaller number of pedestrians? An interesting result was that people said they want utilitarian automated vehicles (i.e., vehicles saving a larger number of people) on the road, but also seemed hesitant to buy such vehicles (and bear responsibility for their associated moral stance). Whereas it is not clear whether (1) the automated vehicles built in the future will actually have to solve dilemmas like this, and if (2) stated, hypothetical responses represent people's actual behavior (in this experiment, participants were paid only

25 cents to answer a question), such work surely needs to be followed up. It is also relevant to congestion when there is a choice between two routes and the risk of injury or fatality to other drivers and vulnerable road users is relatively high (say by a factor of four) for one route, but the travel time is shorter (say by a factor of half).

20.3 REDUCING CARBON EMISSIONS: VEHICLE CAPACITY AND DRIVER READINESS TO USE

20.3.1 Vehicle Capacity to Reduce Carbon Emissions

Today's vehicles could help reduce carbon emissions to an extent that a layperson might find surprising. For example, Berners-Lee (2011) argues that driving 10,000 miles could make a difference from 35% to 250% in emissions, depending on the type of car and how it is driven. As instances of this claim, consider the following.

About 50% of the carbon impact of driving a car comes out of the exhaust pipe, 10% comes from the fuel, and 40% is associated with the manufacturing, operating, and maintenance of the car. Small and efficient cars can save 50% of emissions compared with average cars. Accelerating and decelerating gently, and avoiding braking, save 20% of emissions under urban conditions. Driving at 60 miles per hour on highways and freeways saves 10% compared with driving 70 miles per hour. It follows from these figures that automated driving—to the extent that it is done in the right way—can make a big difference on carbon emissions.

Now, a life cycle assessment of automated vehicles showed that sub-systems could initially increase vehicle primary energy use and greenhouse gases emissions by 3%–20% due to increases in power consumption, weight, drag, and data transmission. But when potential operational effects of these vehicles are included (e.g., eco-driving, platooning, intersection connectivity), automated vehicles can lead to an overall decrease of 9% in both energy use and greenhouse gases emissions (Gawron, Keoleian, De Kleine, Wallington, & Kim, 2018).

Additionally, Igliński and Babiak (2017) argue that carbon emissions reductions will only occur after automated vehicles become very popular, and this, they say, requires developers to achieve the fifth level of automation. Of course, doing so could also lead to rebound effects such as increased driving, but this has not been estimated yet.

20.3.2 Driver Readiness to Use Carbon-Emissions-Reducing Vehicles

In a review of the literature, Stern (2000) showed that pro-environmental behavior is dependent on personal as well as contextual factors. That is, being motivated towards decreasing your carbon emissions is not enough in order to undertake a pro-environmental behavior. For instance, the behavior may be beyond your reach for a number of reasons. It may not be facilitated locally or might be costly, or it could be faced with barriers that are too difficult to overcome.

One example is the decision of buying a car. Consider a single man living in Copenhagen, Denmark. He can avoid buying a car since public transportation is comfortable enough to reach any area within the city. Besides, the city is biking-friendly.

Now, consider the same man living in Rio de Janeiro, Brazil. The overcrowded public transportation does not reach all of this city's areas, most of the roads do not even have a biking lane, and local violence should also be considered. Can the man now easily avoid buying a car in this situation? Also, what if he has three children, or lives far away from his work?

A recent survey conducted by ReportLinker in the United States (ReportLinker, 2017) found that 62% of the respondents would buy an autonomous vehicle. The following are the main reasons for doing so: using it for long-distance travel (18%), becoming able to multitask (12%), increasing the safety of roads (10%), not having to park (6%), and helping to reduce energy consumption (5%). On the other hand, 33% of the respondents said that safety was their top objection to buying an automated vehicle.

More generally, consumers have said that they would favor items with a lower carbon footprint if they were given clear information (Camilleri, Larrick, Hossain, & Patino-Echeverri, 2019). Carbon footprint labels have been suggested as a simple and clear intervention for increasing the understanding of energy use and greenhouse gases emissions for a diversity of products, thus helping to reduce environmental impacts. In Finland, 90% of consumers have stated that carbon-footprint information would have at least a little impact on their buying decisions. But this is so when other purchasing criteria (e.g., price of fuel or travel time) were satisfied (Hartikainen, Roininen, Katajajuuri, & Pulkkinen, 2014). Moreover, 86% preferred carbon labels that allowed comparisons of carbon emissions to be made across products.

20.3.3 Eco-Driving

Eco-driving is one area where the human factors issues dominate the discussion. Much more is known about these issues in the last ten years. They include everything from pre-trip eco-driving planning, to actual eco-driving during the trip, and finally to post-trip presentation of energy use (Barkenbus, 2010). A recent book has focused on one aspect of the actual driving task, in particular the presentation of in-vehicle information to the driver as the trip unfolds (Mcllroy & Stanton, 2018). The authors argue for an ecological design of the interface (e.g., Rasmussen & Vincente, 1980), one which supports the interaction of the driver with the driving task across skill-based, rule-based, and knowledge-based behaviors.

The authors of the book depart in an interesting way from the above discussion on congestion, which emphasizes the primacy of boosting underlying competencies and processes as in addition to improving actual behaviors. With eco-driving it turns out to be important to automate the decision, which is a skill-based behavior, not a knowledge-based behavior, in part because the cognitive load imposed by eco-driving needs to be minimized. The cognitive load needs to be minimized because eco-driving requires continuous input whereas route choice is engaged in sporadically and often when the driver chooses to do so. As Mcllroy and Stanton (2018) state: "the *expert* eco-driver performs the task in a way that approaches automaticity, that is, they are performing at the skill-based level of cognitive control." We refer the reader to their text for an enlightening and much more detailed discussion.

20.4 CONCLUSION

Traffic congestion increases emissions of greenhouse gases and localized pollutants such as particulate matter (Barth & Boriboonsomsin, 2008). Life cycle assessment of automated vehicles has found that automated vehicles could decrease greenhouse gases emissions by 9% (Gawron et al., 2018; although this figure does not take into account possible rebound effects). Furthermore, vehicle intelligence and connectedness are expected to bring additional efficiency gains.

This chapter reviewed research on (1) the effects of vehicle automation, intelligence, and connectedness on driver behavior and on (2) the capacity of automated vehicles to reduce carbon emissions and the readiness of drivers to use such vehicles, and (3) the strategies needed to achieve eco-driving. Related to (1), it seems that drivers tend to interface with vehicle technology by relying on the simple rules of thumb. With regards to (2), it seems that people's motivation to reduce carbon emissions is not enough for them to engage in pro-environmental behavior, but rather, informing the drivers is key. Moreover, with respect to (3) once a driver decides to purchase an environmentally friendly vehicle, it becomes important at that point to focus on the development of the actual skills required to make eco-driving a reality.

We end with a note on research methodology. Work on (1) has utilized formal analyses and driving simulation experiments, where tradeoffs encountered while driving was made explicit and controlled experimentally. In contrast, work on (2) has used engineering analyses and surveys, where tradeoffs between engaging in pro-environmental behavior and possibly giving up some convenience have not been studied in controlled laboratory settings. For example, we do not know if and to what extent people would buy a vehicle reducing carbon emissions at the expense of increased travel time (Huang, Ng, & Zhou, 2018). Finally, work on (3) has used all methods. However, the effects of eco-driving training appear to attenuate over time. How to maintain these effects is an issue of considerable interest. Investigating such questions would be a promising research direction.

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