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Eran Ben-Elia[a] & Erel Avineri[b]

[a] Department of Geography and Environmental Development, Ben-Gurion University of the Negev, PO Box 653, Beer-Sheva 8410501, Israel

[b] Department of Engineering and Management of Infrastructure Systems, AFEKA, Tel-Aviv Academic College of Engineering, 38 Mivtza Kadesh St., Tel Aviv 6998812, Israel

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ERAN BEN-ELIA*§ AND EREL AVINERI**

**Department of Geography and Environmental Development, Ben-Gurion University of the Negev, PO Box 653, Beer-Sheva 8410501, Israel; **Department of Engineering and Management of Infrastructure Systems, AFEKA, Tel-Aviv Academic College of Engineering, 38 Mivtza Kadesh St., Tel Aviv 6998812, Israel*

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ABSTRACT *Innovation in information and communication technologies (ICTs) is providing us with a myriad of travel information sources. Knowledge on the influence of information on human travel behaviour (mainly route and mode choice) and their implications on network levels of service remains fragmented. We distinguish between experiential, descriptive, and prescriptive information sources. We draw on recently developed theoretical concepts in behavioural and cognitive sciences to examine the state of the knowledge on information and travel behaviour. Key theoretical concepts used to explore the relationship between information and travel behaviour include: reinforced learning; framing; risk and loss aversion; probability weighting; affect; anchoring and ambiguity aversion; and regret aversion. We review studies focusing on individual travel behaviour as well as network studies involving collective behaviours. While information seems to assist individual travellers in coping with uncertainty, the impacts relating to collective behaviour on networks remain unclear. Many open questions remain, yet research provides important insights and suggests that ICTs will enable the design of persuasive information systems that motivate cooperative and efficient use of the transportation network beyond what is possible today.*

1. Introduction

We live in the midst of a telecommunications revolution. The rise of the Smart City (Schaffers et al., 2011) will bring about the integration of ubiquitous computing and pervasive information and communication technologies (ICTs) in many urban systems including transport. A main goal of ICTs is the supply of accurate and reliable travel information (Mokhtarian, 1990, 2009; Salomon, 1986). To help the reader characterise travel information, we apply, throughout the paper, a simple typology comprising three main categories: two of which are *ex ante* (prior to a choice action) while one is *ex post*. *Experiential information* (EI) is retained in memory and gained by learning reinforced from feedbacks of past experiences. *Descriptive information* (DI) includes information describing the prevailing travel conditions such as current or predicted travel times. DI can be provided either before departure (pre-trip) or once on the move (en route). Both can be based on historic and or real-time estimates. *Prescriptive information* (PI) includes a

§Corresponding author. Email: benelia@bgu.ac.il

suggestion, guidance, or a recommended alternative (e.g. the quickest path in real time from A to B). Sometimes a fourth category is considered if *ex post* information is provided on a foregone alternative (a non-chosen alternative).

Conceptually, Travel Information is not uniquely a telecommunications-age phenomenon. Travellers intuitively acquire EI by cognitive means — memorising the knowledge they learn from previous travel experiences. DI is physically printed on formal notice boards or road signs, including variable message signs (VMS). It can also be obtained informally, communicated via word of mouth which continues to be a vital source for information though transcending to more technologically orientated forms of expression via social media platforms (Bartle, Avineri, & Chatterjee, 2013). The rise of the Internet has brought about widespread availability of travel information. Initially, travellers in the physical proximity to wired computers could acquire information via online web-based portals, namely pre-trip information for planning trips (e.g. *OV9292* in the Netherlands or *Transport Direct* in the UK). Phasing in of wireless telecommunications (mobile telephony and local Wi-Fi routers) provided connected travellers accessibility to real-time information, anytime and anywhere while stationary or on the move through modified mobile portals using personal specialised portable devices such as laptops, mobile phones, and sat-navs. High-speed broadband connecting smartphones have now allowed information to be channelled through specialised applications (apps). Apps have decentralised the generation and supply of information. No longer restricted to public agencies and their designated infrastructures (e.g. embedded loops under road surfaces or public transport vehicles equipped with GPS or RFID[1]); private enterprise is outsourcing information freely from the crowd and communicating it back to customers.[2] Rather than lacking information, nowadays travellers are facing a growing problem of how to assemble these myriad decoupled sources of information into one user-friendly ensemble.

While the supply side of travel information has benefitted from technological innovation, scientific knowledge about its demand side, that is, travellers' responses and consequently on network level of service, remains rather fragmented. This corresponds to the duality embedded in travel information, being generated by aggregation of individual travel choices while simultaneously influencing them. Reviewing these knowledge gaps is the aim of this paper. We review mainly recent studies (the last decade or so).[3] Although travel behaviour includes both generation (the choice to travel or not) and destination choices, we relate mostly to route and mode choices as these are the most studied behaviours in response to travel information.[4]

1.1. *Scope and Organisation*

A common notion is that travel information supply will solve many transport-related problems, namely traffic congestion (e.g. Levinson, 2003). However, decision-making theories emerging in the cognitive psychology and behavioural economics literature (discussed in Section 2) suggest that this view is problematic. While studies of individual behaviour (Section 3) point that information is beneficial in coping with uncertain travel context, studies of collective behavioural response in networks (Section 4) suggest that adverse effects of information are not entirely hypothetical. Moreover, information can bring about strange patterns of collective behaviour, better categorised by system complexity (Section 5).

Luckily, advances in ICT coupled with information architecture could be used for shaping travel behaviours, leading to development of proactive and persuasive mobility management regimes (Section 6). The paper concludes (with Section 7) by providing an outlook for future research and innovation.

2. Theoretical Overview: Choice and Behaviour under Uncertainty

Transport theory has traditionally developed with strong behavioural links to neoclassical economics and its fundamental decision-making paradigm — rational choice. Conceptually, a choice maker is said to behave rationally if given information on all the attributes of all the relevant alternatives in her choice set, she will choose the alternative which maximises her utility. Utility represents a hedonic abstraction characterised by diminishing sensitivity. It describes an ordinal relationship between consumption of goods and personal benefit (or pleasure). In transport theory, utility is often related to the attributes of travel alternatives (e.g. the cost and time of travelling by a mode or route, its level of comfort and its environmental friendliness among others). This interpretation of utility has been extensively implemented in random utility-based choice models (Ben-Akiva & Lerman, 1985; Train, 2002) — the main workhorse of travel behaviour models (Prashker & Bekhor, 2004).

The transport system is a choice environment associated with uncertainty as no traveller ever knows for certain, once departed the exact time of arrival (or any other journey attribute). Uncertainty by definition suggests travellers face imperfect information. A rational choice maker will assign values for probabilities to risky choice outcomes and consider the product of utility and probability of each alternative to arrive at its expected utility value. Expected utility theory (EUT), first introduced by Bernoulli in 1738 and later extended formally by Von-Neumann and Morgenstern (1944) and Luce and Raiffa (1957), is thus a natural extension of rational choice for risky prospects (where probabilities are assumed to be known). Accordingly, a rational choice maker is assumed to be risk averse — preferring alternatives with more certain outcomes compared to a risky gamble of equivalent expected value (e.g. £500 is better than £1000 if a tossed coin falls on heads and 0 otherwise).[5]

Economists (e.g. Friedman, 1953) have embraced rational choice as a proper representation of human decision-making, contributing to a large body of empirical behavioural research (e.g. Chater, Oaksford, Nakisa, & Redington, 2003). However, rational choice has been widely criticised, specifically in transport studies (Gärling & Young, 2001) as providing a narrow description of travel behaviour and its motivations. Psychological research has unveiled systematic violations of the fundamental axioms of rational choice in laboratory-based experiments. Criticism focuses on the limitations of human cognition. Simon (1955, 1982) states that individuals are rationally bounded, that is, they cannot acquire and process complete information on all alternatives and all their attributes. Instead, they hold limited choice sets and focus on the most important attributes, apply simple heuristics to solve ad hoc problems, and compromise on the alternative which is satisfactory and sufficient. In the same line of thought, Kahneman (2011) illustrates two abstract cognitive systems — one slow, thorough, and reasoned, but carries a high caloric tag and so put to work only when absolutely necessary. The other is blazing fast, energy lean, working automatically (often unconsciously and intuitively), but is prone to make mistakes. It is the latter that systematically 'misbehaves' in an irrational manner. In contrast to the script-like optimisation algorithm of rational choice epitomised in 'System 2', human cognition comprises an adaptive toolbox of problem-solving heuristics. Heuristics share key traits — fast, frugal, and computationally cheap — rather than consistent, coherent, and general. Heuristics are an evolutionary necessity, allowing the organism to respond rapidly to survival risks in the uncertain environment. Heuristics are context dependent; different ones are applied for solving different problems in different choice environments (Gigerenzer & Selten, 2001). Moreover, heuristics give rise to decision rules that can generate contradictory behaviour. Recently, Hess, Stathopoulos, and Daly (2012) provided evidence to a large degree of heterogeneity in decision rules applied in a travel choice context. This heterogeneity is one explanation for lack of consistency with predictions based on rational choice maximisation.

A wide range of decision rules are documented in the behavioural and cognitive sciences literature. No full-fledged theory of individual's responses to information has yet been suggested. However, some theoretical frameworks have been discussed and applied in transport research. Of specific relevance to understanding travellers' response to information under uncertainty is prospect theory (PT) (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). As PT has attracted much interest from transport researchers,[6] we further elaborate concepts related to or associated with PT and its extensions including: framing, risk and loss aversion; probability weighting; anchoring, and ambiguity aversion. Another theory that has grown in importance in the area of transport is Regret Theory (Loomes & Sugden, 1982) and its extension in the form of Random Regret Minimisation (Chorus, Arentze, & Timmermans, 2008).[7] Other decision rules that are unrelated to the previous theories are also discussed, including: reinforced learning, affect, and beliefs.[8]

2.1. *Framing and Risk and Loss Aversion*

PT (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) asserts that in static ('one-shot') decisions, choice makers tend to frame uncertain outcomes as prospective gains or losses relative to some reference point rather than final end-states, as suggested by EUT (Kahneman & Tversky, 1984). PT assumes diminishing sensitivity similar to EUT. Contrary to EUT, however, instead of consistent risk aversion, risk-averse behaviour is predicted in the domain of gains, whereas risk-seeking behaviour is predicted in the domain of losses.[9] *Loss Aversion* (i.e. sensing a loss looming larger than any equivalent gain) motivates people to stick to known states. This status-quo bias happens when the disadvantages of moving to an ambiguous situation appear larger than its advantages (Kahneman, Knetsch, & Thaler, 1991).

Although PT has been largely discussed in the context of choice under risk or uncertainty, there are several dimensions of behavioural responses that are relevant for understanding the response to information that it does not capture. Some critical views discuss the shortcoming and limitations in applying PT to modelling of travel choices (albeit not in studies of travel information). These pertain specifically to capturing the alluding reference point (e.g. Rose & Masiero, 2010; Schwanen, 2008; Schwanen & Ettema, 2009; Timmermans, 2010). Moreover, loss aversion has been exhibited in a range of behaviours (in general and transport contexts), tested mainly in 'one-shot' settings, with limited feedback on the consequences of choices. Yet some recent studies have questioned its validity, mainly in dynamic settings (repeated decisions) that feature experiential (feedback) information (Avineri & Prashker, 2005; Erev & Barron, 2005; Erev, Ert, & Yechiam, 2008; Post, Van den Assem, Baltussen, & Thaler, 2008). These studies identify risk attitude reversals in repeated contexts: decrease in risk aversion for gains and increase for losses.

2.2. *Probability Weighting*

While EUT assumes linearity in probabilities, PT predicts overweighting of small probabilities (Kahneman & Tversky, 1979), that is, rare events are perceived as more likely than they really are. Consider lottery tickets where a huge prize is presented to the ticket buyer. Yet the probability of winning is miniscule and still people buy lottery tickets even though their expected value is worth less than the price of the ticket. Conversely, with learning underweighting is common (Camilleri & Newell, 2011; Hertwig, Barron, Weber, & Erev, 2004). Think about insurance policies that once required removing the front panel of a car's CD player when not present in the vehicle. Most people will have done so for a few days until they realised that the chance of their car would be burgled is quite low. In fact, their risk perception became too low, leading them to ignore an objective risk. Sure enough, once in a while a burglary will occur, but this is already too late for the policy holder who is left with a void insurance due to personal negligence.

2.3. *Anchoring and Ambiguity Aversion*

Although not incorporated formally in the PT framework, these two concepts describe situations where decision-makers might fail to take into account relevant information and are influenced by contextual effects. The estimation of subjective probabilities is severely biased by anchoring. Anchoring occurs when people rely on apparently unreliable information to solve problems. Tversky and Kahneman (1974) asked subjects to estimate the number of African member states in the United Nations while the subjects were given the winning number derived from a spinning roulette. Surprisingly, many subjects relied on the unrelated information to derive their answer. Ambiguity aversion, that is, the preference of something known over unknown, is the motivation behind this odd problem-solving heuristic (Ellsberg, 1961). Ambiguity aversion is context dependent and driven by comparative ignorance, that is, by the comparison with more familiar events or more knowledgeable peers (Fox & Tversky, 1995; Fox & Weber, 2002).

2.4. *Reinforced Learning*

In situations of repeated choice (like daily commuting), individual decision-makers use their experience to choose or avoid certain actions based on their consequences. In line with the 'classic' law of effect (Thorndike, 1898), the probability of repeating a choice yielding a good (bad) outcome is expected to increase (decrease), facilitating (impairing) the collection of information concerning a specific alternative. However, there is inherent asymmetry between impressions of good and bad experiences: bad impressions tend to last longer compared to good ones, resulting in avoidance behaviour (Denrell, 2007; Denrell & March, 2001). A noisy choice environment, associated with uncertainty in the choice attributes, impedes learning and results in choices becoming more random. A 'payoff variability effect' occurs when the choice maker relies on feedback from past experience to form knowledge on the probability distribution of outcomes (Erev & Barron, 2005). Learning depends to a large degree on how much information is acquired. As information acquisition is a function of sampling EI from retained memory, biased estimates are typical (Tversky & Kahneman, 1974).

2.5. *Regret Aversion*

Regret Theory postulates that behaviour is affected not only by the attractiveness of a considered alternative as in EUT and PT, but also from the anticipation of sensing regret for not choosing a foregone alternative (Loomes & Sugden, 1982; Quiggin, 1994). Regret Theory predicts regret aversion (i.e. convexity of the regret function is assumed). This implies that large regrets loom disproportionately in the mind when compared to small regrets.[10] However, repetition and experience can influence this sensation of regret (Zeelenberg, Beattie, Van der Pligt, & De Vries, 1996). While regret can be triggered by *ex ante* reflections on the outcomes of alternatives, evidence from experiments suggests that people compare 'what is' with 'what might have been', mainly by learning, *ex post*, 'what might have been' implies. The difference between *ex ante* and *ex post* regret reflections is subtle. Information about what definitely would have occurred has a greater potential to generate regret than abstract knowledge of what was statistically likely to occur (Larrick, 1993). Thus, anticipated rejoice or regret depends on whether the choice maker can unveil what is the current state-of-the-world through *ex post* feedback: is it one where the foregone alternative is better off or not (Humphrey, 2004).

2.6. *Affect*

Enjoyment, liking, and sensing of pleasure is related to affect. Affect sometimes clouds better judgement. The affect heuristic lures people into risky behaviours by the prospects of fun and excitement (Slovic, Finucane, Peters, & MacGregor, 2007). Consider young smokers, lured into bad behaviour, who begin to contemplate the health risks only after starting to smoke. Similarly, the detailed caloric information printed on candy bars does not seem to convince many of us to reduce their consumption.

2.7. *Beliefs*

A different strand of psychological literature is process theories of behaviour change (belief updating and formation of intention), such as the Theory of Planned Behaviour (Ajzen, 1991), norm activation (Schwartz, 1977; Schwartz & Howard, 1981), and interpersonal behaviour (Triandis, 1977, 1980) related to habit formation. These are beyond the scope of this review and are less commonly linked to travel information response.[11]

To summarise, different theory-driven concepts regarding choice and decision-making under uncertainty have been discussed. These concepts demonstrate a wide range of seemingly unrelated or even contradictory behaviours that arise from different decision rules and their contexts. In Table 1, we present the

Table 1. Review of bounded rationality literature by choice action frequency and decision rule

Theoretical concept	Choice action frequency: One shot	Choice action frequency: Repeated
Associated with PT framework		
Framing and loss aversion	Kahneman and Tversky (1979, 1984), Kahneman et al. (1991), Tversky and Kahneman (1992)	Barron and Erev (2003), Erev et al. (2008), Post et al. (2008)
Probability weighting	Kahneman and Tversky (1979)	Hertwig et al. (2004), Camilleri and Newell (2011)
Anchoring and ambiguity aversion	Ellsberg (1961), Tversky and Kahneman (1974), Fox and Tversky (1995), Fox and Webber (2002)	
Not associated with PT framework		
Affect	Slovic et al. (2007)	
Reinforced learning	–	Denrell and March (2001), Erev and Barron (2005), Denrell (2007)
Regret aversion	Loomes and Sugden (1982), Quiggin (1994)	Zeelenberg et al. (1996), Humphrey (2004)

bounded-rationality literature by choice action frequency (one shot or repetition) and by the decision rule or heuristic. In the next two sections, we review these decision rules in explaining travellers' response to information and the implications of their collective response on the level of service in transport networks.

3. Individuals' Response to Travel Information

Individual travel choices under different information regimes are mainly studied in what we connote as non-competitive transport networks. In a non-competitive network, attribute values (e.g. travel times) are generated through an independent and random sampling process unrelated to individual behaviour. Though less realistic, these environments are useful for testing different behavioural hypotheses under controlled conditions, often using a travel simulator apparatus or numerical simulations based on synthetic data for postulating choice models. Table 2 presents reviewed studies according to the information typology and theoretical concepts. Note that some duplication necessarily does occur.

3.1. *Experiential Information*

Lacking other sources, travellers base their choices on EI. EI is sampled from retrospective memory that is generated from feedbacks acquired from experience with previous choices. Thus EI is directly related to dynamic choice contexts. EI reinforces learning, while over time its internalisation stabilises habitual travel behaviour (Gärling & Axhausen, 2003). Adaptive learning was first utilised by Horowitz (1984) to explain dynamic route choice based on a utility maximisation framework. Arentze and Timmermans (2003) also proposed a framework of dynamic travel choice making that incorporated reinforcement learning. Avineri and Prashker (2003, 2005) show the existence of a payoff variability effect

Table 2. Reviewed studies of individual response by information type and theoretical concept

Theoretical concept	Information type: Experiential	Descriptive	Combined (E + D)	Prescriptive
Associated with PT framework				
Framing, risk and loss aversion, probability weighting	Abdel-Aty, Kitamura, and Jovanis (1997), Avineri and Prashker (2003)	Katsikopoulos, Duse-Anthony, Fisher, and Duffy (2002), Avineri and Prashker (2004), Avineri and Bovy (2008), Gao, Frejinger, and Ben-Akiva (2010), Avineri and Waygood (2013), Kemel and Paraschiv (2013)	Avineri and Prashker (2006), Ben-Elia, Erev, and Shiftan (2008), Ben-Elia and Shiftan (2010), Ramos, Daamen, and Hoogendoorn (2013)	Ben-Elia, Di Pace, et al. (2013)
Ambiguity aversion		Kemel and Paraschiv (2013)		Ben-Elia, Di Pace, et al. (2013)
Not associated with PT framework				
Reinforced learning, decaying memory and recency effect	Avineri and Prashker (2003, 2005), Arentze and Timmermans (2003), Ben-Elia et al. (2008)		Avineri and Prashker (2006), Ben-Elia et al. (2008), Ben-Elia and Shiftan (2010), Ramos et al. (2013)	Ben-Elia, Di Pace, et al. (2013)
Anticipation adaptation		Ettema and Timmermans (2006), Chorus, Walker, and Ben-Akiva (2013), Razo and Gao (2013)		
Affect	Innocenti, Lattarulo, and Pazienza (2013)	Farag and Lyons (2010, 2012)		
Regret aversion		Chorus et al. (2008), Chorus (2014a, 2014b)	Chorus, Molin, Van Wee, Arentze, and Timmermans (2006), Ben-Elia, Ishaq, and Shiftan (2013), Ramos et al. (2013)	

reinforced by travel time feedback. They demonstrate that preference for an alternative route grew when its travel time variability had been increased. Ben-Elia et al. (2008) corroborated this finding by demonstrating explicitly that uncertainty in the environment brings choice shares closer to parity. This behaviour can be likely explained by the Recency effect and decaying memory. Here the effect of recent outcomes outweighs outmoded ones. Repeating the choice of an alternative that is positively associated with recent outcomes replicates a classic learning curve (Ben-Elia & Shiftan, 2010). Bogers, Bierlaire, and Hoogendoorn (2007) further demonstrated that enriching EI with feedback information on foregone alternatives greatly expedited the learning process compared with a treatment without such information.

3.2. *Descriptive Information*

As explained in the Introduction, DI can be delivered pre-trip or en route. Most studies conducted on DI apply a one-shot choice design, neutralising the effect of EI. The dominant behavioural paradigm is utility maximisation (e.g. Arentze & Timmermans, 2005; De Palma & Picard, 2005). Researchers commonly postulate a choice model to explain and predict behaviour and then either empirical or synthetic data are used to corroborate or refute it. Three main issues arise in the literature. First, what is the influence of DI on travellers' perceptions? Ettema and Timmermans (2006) use numerical simulations to show how DI changes travellers' expected (mean) travel time estimates thus reducing their perceived scheduling costs. A second issue involves DI acquisition. Chorus et al. (2013) estimated a discrete-choice rational expectation model for information acquisition and its perception. They postulated that travellers acquire DI based on the utility of the anticipated *ex post* choice situation. DI alters travellers' perceptions of the number or variability of known travel alternatives and their attributes. Once acquired choices are reconsidered from an altered choice set containing the option for additional information acquisition and available travel alternatives. Model estimates were based on travel simulator data and revealed that people adhere to myopic behaviour in the joint task for information acquisition and travel choice upon it. A third issue involves strategic behaviour and planning ahead (Bonsall, 2004). Here, a link downstream with an installed VMS can become more attractive, becoming more concentrated, as demonstrated by Razo and Gao (2013). Using a travel simulator, they estimated a rank-dependent utility model for explaining the choice among risky routeing policies. Route attributes are dependent on the occurrence of stochastic incidents leading the traveller to consider not only the route but also the probability that an incident may occur on the way. As only proximity to a VMS resolves this uncertainty, a VMS-installed link becomes more attractive and strategic behaviour arises.

Framing, Loss aversion, and probability weighting effects have also been verified with DI. Katsikopoulos et al. (2002) showed how a riskier route is preferred when the range of travel times (i.e. the difference between maximum and minimum) is presented. In their driving simulator experiment, a route perceived as a relative expected loss was preferred when its travel time range was greater compared with the reference route, indirectly implying risk seeking. Avineri and Prashker (2004) and Avineri and Bovy (2008) found empirical evidence for framing effects and loss aversion when risky prospects are described in travel time terms with explicit known probabilities. Avineri and Waygood (2013) found similar results for DI describing CO_2 emissions. Gao et al. (2010) postulated and show numerically that strategic planning can also be consistent with PT. Kemel and Paraschiv (2013) demonstrate how probability weighting can be found in the valuation of joint time and money prospects which becomes more accentuated under ambiguous conditions. Notwithstanding, a main caveat of PT-based models is the arbitrary selection of the perceived reference point which poses a considerable challenge for modellers — since it is not well defined in the literature. Moreover, this reference point is not necessarily stationary but possibly dynamic changing from one context to the other and over time, implying that DI provided in different stages of the decision process, for example, pre-trip or en route, may well have different behavioural outcomes.[12] While, unrelated to travel information, Li and Hensher (2011) advocate against a fixed reference point in specifying PT-based choice models. We argue that more research is necessary in this issue.

Regret Theory has been suggested as an alternative description-based model to both PT and EUT. Chorus et al. (2008) developed a model based on regret minimisation rather than utility maximisation. The Random Regret-Minimisation model explains information acquisition when travellers face uncertainty. They used data from a travel simulator, where subjects choose between travel alternatives with risky travel times and costs, as well as information acquisition. Semi-compensatory decision-making and choice set composition effects like the compromise effect emerge as Random Regret-Minimisation model features. Chorus, Molin, Van Wee, Arentze, et al. (2006) integrated Bayesian updating into a regret-based framework of mode choice using numerical simulations. They show that the perceived value of acquiring DI on public transport is limited when a traveller has an overall preference for car travel. Furthermore, even in the case where public transport DI is acquired, and the message is favourable to public transport, its impact on mode choices will likely remain limited because of regret aversion.

3.3. *EI and DI in Combination*

A main weakness in pure DI studies is that despite acquiring information and change in perceived anticipation regarding the expected outcomes of travel alternatives, without EI people have no real ability to learn what is actually better or worse. Long-term effects of EI are hence overlooked while the inter-relationships between DI and EI remain unresolved. In reality, travellers will acquire DI in order to base their choices, and their outcomes will in turn reinforce subsequent choices. Moreover, the influence of DI on behaviour may well depend on the manner by which it is received, that is, whether it is pre-trip or provided en route. Consequently, several key issues emerge in the literature: What is the influence of information on risk aversion, loss aversion, and regret aversion? What are the affective attributes of information? And what are the perceptions of its reliability?

3.3.1. *Framing and risk and loss aversion*. In a travel simulator experiment, Abdel-Aty et al. (1997) asserted that travellers will tend to exhibit risk aversion when faced with DI for pre-trip travel time. Avineri and Prashker (2006) corroborate this find in a learning scenario. They also compared between a treatment (with DI and EI) and control (EI only) group. The treatment group received pre-trip information regarding the mean travel times of two possible routes (one riskier). Based on travel simulator data they found that respondents in the treatment group were more risk averse and preferred a more reliable route compared with the control group. Conversely, Ben-Elia et al. (2008) provided respondents in their treatment group with pre-trip DI regarding the routes' travel time ranges (a measure for variability) rather than just the mean. Based on travel simulator data they find that respondents provided with such DI were faster to recognise the route with a shorter mean compared with the control group, that is, learning was expedited.[13] In addition, they found DI was associated with risk seeking (i.e. preferring a shorter and riskier route) in the short run. This tendency dissipated in the long run, as EI became more dominant, whereas the control group showed more risk-averse behaviour from the start. Respondents in the treatment group also switched routes more often while the average payoffs (total network travel times) were not much different. Thus, DI did not have much impact on the overall network costs. Fujii and Kitamura (2000), who investigated DI effects in a real-life road closure field study, found greater sensitivity to DI than to EI in the short run, brought about by the high risk of delays that diminished over time. In a follow-up paper, Ben-Elia and Shiftan (2010) use a panel-data discrete-choice model to explain that this behavioural difference arises from different mental processes associated with formation of long-term memory (estimated using a recursive harmonic mean specification). Whereas the control group had only EI to rely on leading to a Recency effect, DI allowed the treatment group to gradually memorise previous outcomes and improve sampling from long-term memory as a consequence. Framing and loss aversion effects appear to weaken in learning scenarios, similar to Erev et al. (2008), Ben-Elia and Shiftan (2010) show that reference dependency (specified as mean travel time) does not improve model fit. Neither were real differences between gains and losses nor evidence for loss aversion identified. However, given that only one reference point definition was tested, there is insufficient evidence to generalise on the robustness of loss aversion in dynamic travel contexts. As noted, more research into reference point dynamics is required.

3.3.2. *Regret aversion*. Using a discrete-choice model estimated from their previous travel simulator data, Ben-Elia, Ishaq, and Shiftan (2013) revealed that provision of DI increases regret aversion, while with only EI regret aversion estimates were lower. This anomaly can be explained if DI improves the ability to learn the possible traffic states that can occur, whereas the control group which only relies on EI is less able to resolve this — resulting in lower regret aversion. Moreover, while regret aversion is generated from EI as asserted by feedback-conditioned regret theory, its effect seems to be amplified by DI provision. Farag and Lyons (2010, 2012) had similar conclusions in a field-based study regarding the acquisition of DI on public transport. They found that acquiring DI is influenced by the propensity to consider using public transport rather than information influencing mode choice. Furthermore, positive past experience (i.e. EI) with public transport and positive beliefs had the strongest effect on acquisition of public transport information. However, similar to Chorus, Molin, Van Wee, Arentze, et al. (2006), respondents tended eventually to travel more often by car rather than by public transport after consulting information. A possible explanation for this behaviour is regret aversion.

3.3.3. *Affect*. Affective attributes of information are accentuated when combining both types of information. Innocenti et al. (2013) studied mode choice between car and public transport in a travel simulator. They found a marked preference for cars with a strong recency effect leading to mode stickiness. The strength of affective dominance was apparent even when the car performed significantly less well than the public transport alternative. Apparently, affective dominance neutralises the positive benefits of information, for example, encouraging mode changes. Cars are often perceived as symbols of status and freedom (Steg, 2005). Costs are often underestimated and a strong label effect for the car mode is often found (verified in the choice model's alternative specific constant).

3.3.4. *Perceptions of reliability*. The combination of information sources raises a further important issue which is the influence of EI on the perceived reliability of DI. Ben-Elia, Di Pace, Bifulco, and Shiftan (2013) asserted that previously reported behavioural differences attributed to pre-trip information can be explained by difference in reliability perceptions. As Ben-Elia et al. (2008) designed EI to be consistent with DI (drawn from within the travel time range), no cognitive dissonance seems to have been perceived between the two, leading to greater confidence in the DI. In contrast, perceived discrepancies between EI and the pre-trip mean DI, as in Avineri and Prashker (2006), could lead to confidence loss in the received information and consequently greater risk aversion. The two aforementioned studies illustrate the possible associations that could exist between the perceived reliability of information on the one hand and changes in travellers' risk attitudes on the other hand. This issue justifies more research.

3.3.5. *Heterogeneity*. While previous studies applied one particular form of decision rule either in static or dynamic choice contexts, there is growing evidence for different people applying different decision rules in similar contexts (Hess et al., 2012). Using the route-choice data of Bogers et al. (2007), Ramos et al. (2013) show the ability of decision rule mixtures to explain behavioural differences in a repeated choice setting. Clearly, heterogeneity is an issue which needs to be better researched in the future.

3.4. *Prescriptive Information*

The key issue in studies with PI is the compliance rate with suggestions. Chorus, Arentze, and Timmermans (2009) using a Bayesian utilitarian approach (i.e. travel time probabilities are conditional on DI) and numerical simulations show that compliance is negatively associated with the perceived unreliability of the information and the uncertainty regarding the travel time differences between (two) alternative routes. Ben-Elia, Di Pace, et al. (2013) use a mixed logit model estimated from travel simulator data combining all three types of information. They assert that PI had the largest effect on route choice, that is, a suggested route is also more likely to be chosen. However, reducing reliability (i.e. the suggested route is not always the eventual quickest route) shifted choices not only in the direction of risk aversion as seen previously, but also choosing a useless alternative. In line with the comparative ignorance postulation, travellers will prefer to rely on information even if they sense that it is not very helpful due to anchoring and ambiguity aversion. We argue that more research is needed on the topic of perceived reliability and learning.

4. Collective Response to Travel Information

The response of collectives or aggregates to travel information is studied in a competitive (game-like) transport network, either with human subjects or artificial agents or field observations. The performance or level of service of the network is determined by individuals' collective decisions (Balakrishna, Ben-Akiva, Bottom, & Gao, 2013). Competitive networks directly emulate traffic on the network and are therefore useful for understanding system dynamics and the formation of congestion.

Historically traffic assignment models have been used extensively to understand network behaviours (Daganzo, 1983; Daganzo & Sheffi, 1977). One key issue is the perfect information assumption (specifically in route-choice). Although stochastic models better reflect uncertainty in traffic conditions (e.g. Cascetta & Cantarella, 1991), to evaluate the effects of information the perfect information assumption needs to be reconsidered. In this respect, Ben-Akiva, de Palma, and Kaysi (1991) and Mahmassani and Jayakrishnan (1991) have hypothesised three adverse network effects related to information provision: (1) concentration when travellers make too similar choices that exacerbate congestion; (2) overreaction when travellers fail to anticipate how other travellers will react and collectively respond too much to information; and (3) oversaturation if drivers are faced with too much information, and become overwhelmed resorting to heuristic decision rules.

Stability is a second issue involving network studies. Both static and dynamic simulation models work on the principle of convergence towards some kind of stable user equilibrium (UE) (Arnott, de Palma, & Lindsey, 1991, 1996, 1999). First defined by Wardrop (1952) and elaborated by Beckmann, McGuire, and Winsten (1956), UE is a network condition whereby choices do not change as there is no possibility to gain any advantage by changing. However, UE is often a suboptimal network state as overall time or costs are not minimised. Unlike UE which is a user-optimal condition related to average travel costs, achieving the social optimum (SO) is desirable. However, it is more complicated, as it requires travellers to recognise their external cost on other travellers (marginal travel costs) and behave in a way that is not user optimal and contradictory to their self-interest.

The SO also tends to violate the third assumption applied in network analysis — competition. Competition can be directly related to rational choice whereby travellers are inherently selfish, striving to maximise (minimise) individual payoffs (costs). Unless tolled, infrastructure is characterised as a public good and so competition results in a social dilemma similar to Hardin's tragedy of the commons (Hardin, 1968). Competition therefore determines endogenously volumes and travel times (level of service) on network links and their spatiotemporal distribution. Utility maximisation has been the main workhorse also in network studies. However, recently studies testing bounded-rationality concepts, mainly in experiments with human subjects have appeared. These studies focused exclusively on car traffic (route-choice) and involved either EI or a combination of EI and DI. Studies involving PI are scarcer and focus on compliance in agent-based simulations. Table 3 presents network studies by type of information and theoretical concepts tested. As can be seen, there are still wide gaps in the knowledge base, especially in relation to PI and combining various sources in network dynamics. Moreover, compared with Table 2, the influence of affect and ambiguity

Table 3. Reviewed studies of collective response by information type and theoretical concept

	Information type			
Heuristic/ decision rule	Experiential	Descriptive	Combined (E+D)	Prescriptive
Associated with PT framework				
Framing, risk and loss aversion		Avineri (2006), Connors and Sumalee (2009), Tian, Huang, and Gao (2012)		
Not associated with PT framework				
Reinforced learning	Nakayama, Kitamura, and Fujii (1999, 2001), Nakayama and Kitamura (2000), Selten, Chmura, Pit, Kube, and Schreckenberg (2007), Rapoport, Kuglar, Dugar, and Gisches (2009), Lu, Gao, and Ben-Elia (2011), Lu, Gao, Ben-Elia, and Pothering (2014), Helbing (2004)	Fujii and Kitamura (2000)	Lu et al. (2011, 2014), Rapoport, Gisches, Daniel, and Lindsey (2014)	Helbing, Schönhof, and Kern (2002)
Anticipation adaptation		Emmerink, Axhausen, Nijkamp, and Rietveld (1995a, 1995b), Mahmassani and Liu (1999)	Lu et al. (2011, 2014)	Levinson (2003), Leontiadis et al. (2011)
Regret aversion		Chorus (2010)		
Neural networks				Dia and Panwai (2010)

aversion are entirely missing in network studies. Much more research is needed in this respect to fill these gaps.

4.1. *Networks with EI*

The key issue preoccupying the literature is how reinforced learning influences traffic dynamics in the long run. Nakayama et al. (1999, 2001) and Nakayama and Kitamura (2000) studied behaviour and network dynamics in agent-based simulations with maximisation under utility thresholds. They assert that EI assists agents to adapt to uncertain travel times. Selten et al. (2007) found similar results in an experiment with human subjects. In both studies, network traffic was more volatile compared with assignment model predictions and UE was not always attained. These fluctuations can result in large inefficiencies and energy wastage when the network's topology results in a Braess' paradox, as shown by Rapoport et al. (2009). Whereas in simulations this paradox is seen as an unstable state relapsing towards UE, human subjects often fail to learn that a paradox is occurring, resulting in larger fluctuations and route switching. However, since these networks were rather simplistic, homogeneous, and had different topologies gaining concrete conclusions remains hard.

4.2. *Networks with DI*

Stability is a key issue that appears in the literature regarding how DI affects route switching. In an experiment with human subjects, Mahmassani and Liu (1999) found that pre-trip or en-route DI increases route switching at the location of provision (at the origin or downstream). Travellers become more prone to switch when they perceived late arrival compared with an early arrival. This behaviour can be explained by risk-seeking in the face of a potential loss. *Information penetration* is a second issue of concern. Based on simulated dynamics of a two-route network with recurring and non-recurring congestion, Emmerink et al. (1995a, 1995b) concluded that if the information penetration rate exceeds 20% of the agents, adverse effects due to concentration and overreaction are expected, as suggested by Ben-Akiva et al. (1991). The critical penetration rate can depend on the type of information provided, and the degree of inertia (stickiness) in agent response (Emmerink, Verhoef, Nijkamp, & Rietveld, 1998). Lindsey, Daniel, Gisches, and Rapoport (2014) assert that adverse effects of information are not entirely hypothetical. Using a transport economics framework of average and marginal costs and numerical examples, they show that information is more likely to be beneficial when free-flow travel costs differ appreciably, travel cost functions are convex, shocks are similar in size on the routes, and route conditions are strongly and positively correlated (e.g. bad weather). Information is likely beneficial only in uncorrelated conditions (e.g. accident on a specific route) and when differences in free-flow travel times are small (i.e. the network topology is close to symmetry). These studies were based on utility maximisation principles.

PT-led concepts have also been applied in network models. Framing and loss aversion and the effect of the reference point value on UE are investigated (e.g. Avineri, 2006; Connors & Sumalee, 2009; Tian et al., 2012). A UE concept based on *Regret Aversion* was also developed by Chorus (2010). These works are more theoretical or numerical and empirical data are lacking. For example, the functional forms of PT apply parameter values obtained from non-transport contexts (such as Tversky & Kahneman, 1992), while for Regret Theory, numerical methods are used in the sensitivity analysis to determine potential regret aversion values. More empirical work is still needed in this respect.

4.3. *Networks Combining EI and DI*

Studies involving learning, information provision, and network dynamics remain rather rare. Lu et al. (2011) introduced en-route DI on the occurrence of a non-recurring incident, EI, and foregone feedback information in a network experiment with human subjects. Their findings show that DI reduced overall network travel time and increased travel time reliability. Less switching was observed with foregone feedback compared with the EI-only condition. However, information on foregone alternatives was also counterproductive and resulted in efficiency loss as the network costs were closer to theoretical UE values. Similar results were obtained by Selten et al. (2007) in their second treatment (the first was EI-based only). The results suggest that with more complete information, travellers simultaneously learn which routes are preferable. This outcome paradoxically expedites the network's convergence towards UE. Thus the prophesy of the traffic assignment model under perfect information appears to becomes true.

In a follow-up study (Lu et al., 2014), strategic behaviours were investigated when DI was provided to human subjects downstream at a branch node. In comparison to EI, DI reduced network costs but route switching did not decrease as expected. Instead of switching at the origin node subjects learned that switching at the branch node was a better strategy. This implies concentration could occur on links where travel time ambiguity is potentially resolved. One interpretation for this behaviour is reducing regret aversion. Importantly, without information on foregone alternatives, equilibrium is harder to reach and efficiency remains higher. Moreover, information did not bring the network towards the SO. Rapoport et al. (2014) empirically corroborate the findings of Lindsey et al. (2014) by representing a road network as an n-player non-cooperative game (implying a social dilemma situation). They show that information allows participants to generate decentralised coordination without resorting to direct communication thus bringing the network closer to UE. However, as predicted by Lindsey et al. (2014), under correlated conditions, information increases overall travel costs. One cautionary note is that such results are highly dependent on specific network topology. Heterogeneity in individual response could also be relevant. Evidently, more studies of experimental networks and underlying behavioural concepts are required here.

4.4. *Network Studies with PI*

These studies focus on network dynamics in relation to compliance rates to distributed route suggestions. The research framework is often based on operation research and the behavioural content remains rather limited. We note here the few exceptions. Dia and Panwai (2010) model compliance to route suggestions, comparing formulations of discrete choice with artificial neural networks. They suggest that artificial neural networks are able to deal better with complex nonlinear relationships, are fault tolerant in producing acceptable results under imperfect inputs, and are suitable for modelling reactive behaviour with imperfect information. Helbing et al. (2002) develop an analytical framework based on fractional provision of PI to switch routes together with EI. They demonstrate how such a framework can bring the network closer to UE in an agent-based model where agents learn to coordinate using information as a guide. Given that PI is now abundant in real-world settings more research is required to determine the conditions for it to be useful.

5. Changing Travel Behaviour Using Information Architecture and Persuasion

Network studies have mainly focused on the benefits and disadvantages of information in a dynamic traffic context. However, there is growing debate arguing that the provision strategy of information neither seems to generate greater efficiency to the network nor bring it closer to an optimal state. Rather, information only provides a temporary reprieve to individual travellers facing ambiguity. It follows that although useful in helping individual travellers avoid non-recurring incidents and excessive delays due to bottlenecks in uncorrelated conditions, information provision might seem as no more than marketing an illusion — a sense of self-control over ambiguous travel conditions — and a powerful motivation for DI acquisition. However, it is plausible that in large heterogeneous networks, information can allow redistribution of travel costs in a way that is more efficient. Furthermore, an important remaining question is who are the true beneficiaries of information? Especially when information services are commoditised equity considerations become highly relevant.

Nevertheless, some innovative thoughts for changing this status quo are starting to appear, sometimes outside the mainstream transport literature in psychology and social physics. First, the assumption that humans are unequivocally selfish maximisers has been questioned by leading economists like 2009 Nobel laureate Elinor Ostrom. She investigated the motivations for trust and reciprocity (Ostrom & Walker, 2003) as did behavioural economists (see the review by Metcalfe & Dolan, 2012). Criticising maximisation applies not only to axioms of rational choice, but also to the fundamentals of PT and Regret Theory. Psychological studies show empathetic behaviour, altruism, and cooperation emerging in social dilemmas like the Prisoners Dilemma (Kim, 2011). This view has been neatly expressed by one of the great forefathers of the choice modelling field: "new results challenge the standard assumption of maximisation of individualistic utility, indicating that social networks as information sources, reciprocity, and altruism enter human behaviour and cannot be ignored" (McFadden, 2013, p. 37). Bartle et al. (2013) describe how cyclists are willing to freely exchange information on traffic conditions through social networks without apparent extrinsic rewards. Crowdsourcing apps like WAZE allow customers to share information with the larger user community regarding incidents. Helbing, Schönhof, Stark, and Hołyst (2005) demonstrate experimentally how individuals in small groups of 2 or 4 travellers can learn to take turns on alternative routes through a self-interested strategy of alternating cooperation, thus bringing the network closer to SO. However, as noted by the great economist Olson (1965), decentralised cooperation in larger groups would be very difficult to maintain and can take a very long time to achieve without external direction.

Second, information provision strategies can be designed in order to persuade travellers to change behaviour. Thaler and Sunstein (2008) advocated the use of 'Choice Architecture' to influence behaviour change. They illustrate how 'nudges', small features designed in the choice environment, help individuals to overcome cognitive biases, elucidating the better choices without restricting their freedom of choice, and without making big changes to the physical environment, the set of choices, or the economic attributes of the choices (Avineri, 2012). Avineri and Waygood (2013) show this empirically when presenting information with loss framing-motivated carbon-reducing travel choices. Based on the results of Helbing et al. (2002), Helbing (2004) raises a conjecture that fractional PI could be designed to achieve the SO if a punishment cost can be inflicted on defectors for non-cooperative behaviour while an equivalent reward can be provided for cooperative behaviour. Given loss aversion, such a design might work. A field experiment conducted in the Netherlands has recently demonstrated how rewards can motivate travellers to avoid commuting during the peak hours, thus demonstrating some cooperative behaviour in congestion management (Ben-Elia & Ettema, 2011). Regarding mode changes, Sunitiyoso, Avineri, and Chatterjee (2011) suggest conformity and social learning as a possible strategy. They showed experimentally that communication can help travellers to cooperate and coordinate decisions on the use of a bus alternative rather than the car.

These are still emerging ideas supported by advancements in ICT capabilities, but they elucidate the innovative potential embedded in ICT to move mobility management from passive provision of information to a new more proactive role of behaviour persuasion. Fogg (2002) suggested that Persuasive Technologies[14] could endorse cooperation through reciprocity (favour exchanges) between computers and humans. Such technologies are being tested in gamified mobile apps, intended to motivate a voluntary behaviour change, via personalised feedback on travel choices.[15] Gamification consists in game-thinking and game mechanics to engage people and is adopted for influencing human motivation and behaviour (Zichermann & Cunningham, 2011). These ideas now present planners and designers with new research challenges — how to encourage, through the design of content (text and images) and context of travel information, pro-social and sustainable travel choices. We argue that information architecture can facilitate the emergence of cooperation and optimal self-organisation without necessarily resorting to unfair measures like pricing and tolls.

The development of peer-to-peer information exchange (Internet 2.0 e.g. Twitter), crowdsourcing, and the expected emergence of Internet of things (Internet 3.0) for operations of autonomous connected vehicles will have major implications on information provision, its reliability, and its credibility. Leontiadis et al. (2011) designed a decentralised crowd-source system allowing to dynamically reroute cars based on individually collected information. Their system was tested in a simulation and a case study and showed ability to avoid concentration due to overreaction to identical information (e.g. avoiding a closed road can congest the obvious second best road). Solutions in the case of network disruptions and emergency evacuation could be designed using peer-to-peer cooperative strategies. Cooperation is of utter importance for implementing schemes for automated vehicle routeing, car-sharing and ridesharing in the future. Serious games and gaming simulations (Hofstede & Meijer, 2008; Michael & Chen, 2006) are emerging as methodological approaches to study how to manage collective behaviours in systems characterised by complexity (where individual decisions influence collective outcomes recursively like travellers and transport networks). For example, Rossetti, Almeida, Kokkinogenis, and Gonçalves (2013) report on a serious gaming app in the design of in-vehicle support systems.

6. Conclusions and Future Outlook for Research and Innovation

In this paper, a rather large body of literature on the behavioural response to travel information has been reviewed. Understanding how information influences travel behaviour requires investigating some of the fundamental behavioural assumptions used in transport research and practices. In addition to rational choice which remains the dominant stream, some of the leading alternative theoretical concepts such as: reinforced learning, framing, risk and loss aversion, affect, regret aversion, and ambiguity aversion have been discussed, including their manifestation in travel behaviour studies. The review suggests that both the type of information and the choice environment are relevant to understand the information effects. Most of the behavioural research has been conducted on individual response. Network studies of collective behavioural response to information are scarcer. As depicted in the tables, in both cases there are still considerable gaps in the literature that could be filled, providing a vast and rich pasture for future research. These include more research on the behaviour of networks with individual response governed by bounded-rational theories and more attention to reinforced learning and to affect. Studies relating to PI are particularly missing in the behavioural literature. Given that many travel assistance apps now provide suggestions, it is disturbing that we still know relatively little about their implications.

From the individual's perspective, we can conclude that information assists travellers to learn through EI how to contend with ambiguous travel conditions, particularly in the short run. In the long run, behaviour becomes more habitual due to internalisation of learning effects and sensitivity to information decreases. DI (and PI) seem especially beneficial in the face of non-recurring incidents (accidents or bad weather) allowing the individual traveller to avoid excessive delays. Information increases sense of self-control and would be likely positively associated with subjective well-being.[16] However, a full understanding of individual response to information remains elusive. Behaviour differences appear in relation to applied decision rules (utility maximisation, framing, regret aversion risk attitude, and affect), information type (EI, DI, PI, and their combinations as well as foregone feedback), manner of provision (pre-trip or en route), and location (e.g. fixed VMS or universally distributed). Thus, modelling individual response to information is not at all trivial and remains an open and rich research agenda.

From the perspective of the transport network, the effect of information appears to be less obvious. The claim that more information is necessarily better for the network remains speculative. Adverse effects are possible but the results are topology sensitive. Learning from experience does not seem to result in greater stability in collective response. Conversely, more DI, particularly with foregone feedback, brings collective behaviour closer to UE. Ambiguity aversion and anchoring seem to keep compliance rates with PI unexpectedly high. This problem could be turned to an opportunity if we can design information systems that guide towards SO through cooperative strategies. More research is necessary in more elaborate heterogeneous networks with simulation models considering different decision rules and combinations of information types. Research on the beneficiaries of information provision and equity effects when information is commoditised is required in addition to systemic efficiency effects.

Perhaps the main caveat of current information provision strategies is failure in making substantial changes from competitive maximisation to cooperative travel behaviour. However, looking forward, pervasive peer-to-peer communication between travellers, vehicles, and physical infrastructure can provide new opportunities to optimise mobility through cooperative strategies. ICT, the Cloud, and crowdsourcing are becoming the basis for designing information architectures that motivate cooperative behaviours through persuasive technologies. Cooperation will be a main issue for research in the development of evacuation policies, and more importantly the gradual integration of autonomous connected vehicles. New methodologies beyond discrete-choice models and simplified agent-based simulations are also of need. Neural networks, gaming, and simulations seem to be inspiring directions to investigate.

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Notes

1. RFID is the acronym for radio-frequency identification device.
2. Google's recent purchase of the social navigation start-up company WAZE, for a colossal sum of more than $1.3 billion, elucidates the lucrative aspects of this new market. See *Google Maps and Waze, outsmarting traffic together*. Posted on 11 June 2013. Retrieved on 12 December 2014. http://googleblog.blogspot.co.il/2013/06/google-maps-and-waze-outsmarting.html.
3. Readers interested in the literature preceding this period will find an excellent review by Chorus, Molin, and Van Wee (2006).
4. Regarding information effects on generation and destination choice, the interested readers can find an elucidating account in Mokhtarian and Tal's (2013) book on ICT and travel behaviour.
5. Note that random utility models (RUM) is not derived from EUT as it usually overlooks uncertainty or risk per se. Any uncertainty included in RUM is attributed to the analyst not behaviour. Michea and Polak (2006) provide an example where EUT is integrated within an RUM specification.
6. Van de Kaa (2010a, 2010b) examines PT applications in transport studies and presents a meta-analysis of different studies.
7. Ramos, Daamen, and Hoogendoorn (2014) recently published an excellent review on the contribution of random utility, prospect theory, and regret theory for understanding travel behaviour under uncertainty.
8. Kaplan and Prato (2012) discuss the use of semi-compensatory decisions rules in route-choice choice set formation and selection but without specific reference to travel information.
9. To illustrate this peculiarity consider the choice problem 'choose between: (A) there is an 80% chance of losing $4000', and (B) 'lose 3200$ with certainty (100%)'. Although the expected values are identical most people prefer the gamble or risky prospect because it provides a chance of avoiding the unpleasantness of a sure loss.
10. For a discussion of risk aversion, regret aversion and travel choice inertia, and translation into a model of ex-ante and ex-post information, see Chorus (2014a, 2014b).
11. The interested readers can find more on the relation of such theories to travel information in the editorial by Ben-Elia and Shiftan (2013).
12. The difficulties of selection of one or more reference points have been recognised in the travel behaviour literature, albeit not in studies of travel information (Avineri, 2009; Rose & Masiero, 2010; Schwanen, 2008).
13. Ben-Elia, Ishaq, and Shiftan (2013) reveal significant differences in learning effects based on group scales' estimates and their evolution over the experiment.
14. Fogg (2002) suggests seven types of persuasive tools: tailoring, reduction, self-monitoring, tunnelling, suggestion, surveillance, and conditioning.
15. Examples of such applications include: Peacox — Schrammel, Busch, and Tscheligi (2012); Quantified traveller — Jariyasunant et al. (2014), and Matkahupi — Jylhä, Nurmi, Sirén, Hemminki, and Jacucci (2013).

16. A travel satisfaction scale has been developed by Ettema et al. (2011) but does not relate to availability of information.

ORCID

Eran Ben-Elia http://orcid.org/0000-0002-4169-7129

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