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Improving the behavioural realism of integrated assessment models of global climate change mitigation: a research agenda

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1 INTRODUCTION

1.1 Overview of Report

Models of the global energy-economy are widely used to evaluate the costs, potentials, and consequences of greenhouse gas emission trajectories over the medium to long-term. Energy-economy models are increasingly coupled to atmospheric, land use, agricultural, forestry and other sectoral models: hence, 'integrated assessment models' (IAMs).

This report concerns the behavioural realism of global energy-economy IAMs. Specifically, we are interested in whether IAMs endogenise or reproduce key features of human behaviour. This is important because empirical research shows that behavioural features exert a strong influence on energy and emission outcomes. Consequently behavioural realism contributes to the usefulness of IAMs for climate policy analysis (Rivers and Jaccard 2006).

The objective of this report is to set out a conceptual and empirical basis for improving the behavioural realism of IAMs which is often related to the representation of critical heterogeneities . The research summarised in this report was conducted as part of Work Package 3 in the EU FP7-funded 'ADVANCE' project, whose aim is to develop improved models for climate change mitigation analysis.

The report is structured as follows. Section 1 provides a basic overview of IAMs, defines behavioural features, and sets out the importance of trying to improve the behavioural realism of IAMs by incorporating behavioural features and heterogeneity. Section 2 sets out a detailed typology of behavioural features that serves as a conceptual framework throughout the report. Section 3 maps current best practice in a sample of eight IAMs against the typology of behavioural features, and discusses the main approaches to behaviourally-realistic modelling in IAMs. Section 4 then reviews the strength of the evidence base in a particular domain that is influential on IAM analysis: vehicle adoption. Two bodies of literature are systematically reviewed: discrete choice studies; and studies of social influence. Section 5 concludes by drawing together insights from the conceptual framework, the mapping of IAMs, and the review of the evidence base, into a research agenda for improving the behavioural realism of IAMs.

1.2 Global energy-economy IAMs: purpose and applications

We begin by introducing the main applications and design features of global energy-economy IAMs, referred to hereafter as simply: IAMs.

From the outset, it is important to stress that IAMs are neither designed nor used to predict the future. Their representation of the global energy-economy is inevitably stylised, simplified, selective, parsimonious and partial. Their purpose is to derive robust, predominantly qualitative insights on the consequences of policy choices (Krey 2014). These insights are generated by exploring possible futures contingent on scenario assumptions, either descriptively (*what if*?) or normatively (*how to*?).

The recent IPCC assessment report provides a comprehensive synthesis of policy-relevant findings across a family of 30+ widely-used IAMs (Clarke et al. 2014). Many of the studies reviewed in the

IPCC assessment originate from inter-model comparison studies in which modelling and scenario protocols are coordinated to examine the robustness of between-model findings on important policy questions. Krey (2014) provides an extensive summary. Recent examples of multi-model studies managed from the EU include AMPERE (Riahi et al. 2013) and LIMITS (Tavoni et al. 2014); from the US, EMF27 (Weyant and Kriegler 2014); and focusing on Asia, the AME (Luderer et al. 2012b).

1.3 Global energy-economy IAMs: design features

The IAMs used in such studies have much in common, and important differences. In common, they all have a representation of the energy system and its interactions with the economy, some level of regional disaggregation, a medium-to-long term time horizon (2050 to 2100) in five to ten year time steps, and the ability to evaluate the effect of global climate policy (particularly carbon taxes and emissions limits).

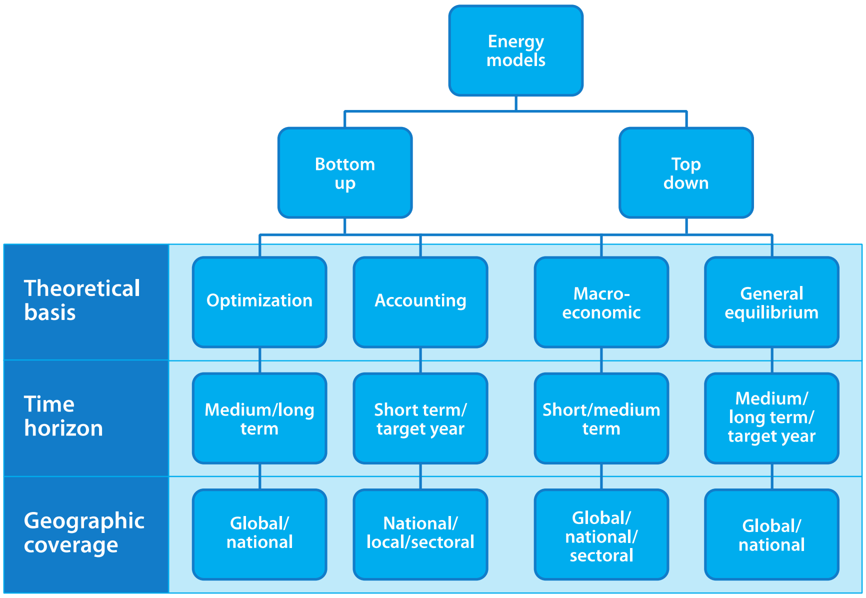
IAMs also have important differences, both structurally (e.g., endogenous processes, technological and spatial granularity) and functionally (e.g., computational algorithms). Sathaye and Shukla (2013) identify eight main factors differentiating IAMS. These include: purpose; economic rationale; level of disaggregation of decision variables; degree of endogenisation; sectoral coverage; time dynamics; and applied mathematical techniques.

IAMs have traditionally been grouped as either top-down or bottom-up (Figure 1). Top-down models have a highly aggregated representation of economic and endogenisation effects, a limited characterisation of technologies, and are well suited to assess the macroeconomic impact of market-based energy and climate policies (Sathaye and Shukla 2013). Common top-down models include computable general equilibrium (CGE) models.

In contrast, bottom-up models have a disaggregated representation of the energy-economy and a relatively more detailed characterization of technologies, and are well suited to assess the impact on energy supply and demand of technology-based and other policies (van Vuuren et al. 2009). Common bottom-up models include optimisation and accounting models which represent the energy sector in great detail but treat the rest of the economy exogenously and so solve only for partial equilibrium (Kriegler et al. 2014).

Increasingly, IAMs are combining the macroeconomic consistency of top-down models with the technological resolution of bottom-up models: hence, hybrid models. Hybridisation is blurring traditional distinctions between top-down and bottom-up models (Hourcade et al. 2006; Krey 2014).

FIGURE 1. CLASSIFICATION OF ENERGY-ECONOMY IAMS (SATHAYE & SHUKLA 2013).



Krey (2014) distinguishes IAMs along three main dimensions: (1) the 'mathematical solution concepts' - optimisation or simulation, partial or general equilibrium, limited or perfect foresight; (2) system boundaries - sectoral, regional, temporal; and (3) the level of detail or heterogeneity - technological, spatial (urban/rural), income.

Inter-model comparison studies are useful for identifying how these distinguishing features of model design influence results. For example, van Vuuren et al. (2009) explain different IAM estimates of mitigation costs and technology portfolios in terms of the optimisation or simulation techniques used as solution algorithms, and what these imply for the optimality of solutions. IAMs using optimisation to develop a baseline will automatically find climate policy incurs costs. Conversely, simulation models that describe the energy-economy on the basis of a set of rules that do not necessarily lead to full equilibrium may find climate policy results in net lower costs (van Vuuren et al. 2009).

In another inter-model comparison study, Edenhofer et al. (2010) conclude that model outcomes are "*a function principally of each model's assumptions about available technologies, learning rates, and resource prices*" (p26). Sathaye and Shukla (2013) take a broader view. They summarise the main sources of variation across model structures and assumptions that yield differences in results: (1) energy demand drivers (e.g., population, GDP); (2) resource costs and technology performance parameters; (3) technology growth constraints; (4) base year calibration; (5) regional resource bases and endogenous competition (e.g., biofuels, land); (6) endogenous technological change; (7) trade restrictions (e.g., fossil fuels, bioenergy); (8) solution algorithms (e.g., intertemporal optimisation, myopic with recursive dynamics).

However, the central design features of IAMs identified in these studies can not always explain divergent results. Kriegler et al. (2014) develop a set of diagnostic indicators to characterise how IAMs respond to a harmonised set of carbon price scenarios. These indicators describe the magnitude and speed of emission reductions, the relative contributions of supply-side decarbonisation and demand-side efficiency improvements, the cost of abatement, and so on. Characteristic model 'fingerprints' are then used to classify IAMs as high, medium or low response to carbon prices. This descriptive classification of model responsiveness to an exogenous forcing (climate policy) is not simply explained by the partial equilibrium (mainly bottom-up) or general equilibrium (mainly top-down) design of the models (left-side or right-side of Figure 1).

A comprehensive mapping of IAM structure and function to IAM results is impractical given the manifold design possibilities.

1.4 <u>Representations of behaviour in IAMs</u>

Krey (2014) finds that mitigation scenarios and the IAMs that generate them are increasingly being designed to be more 'realistic' by incorporating features observed in the real world. Such real world features include delays in concerted global action (e.g., Riahi et al. 2013), fragmented policy approaches (e.g., Tavoni et al. 2014), and the political or social rejection from mitigation portfolios of specific low carbon technologies or resources such as nuclear power or biofuels (Riahi et al. 2012).

Another important set of real world features relates to human behaviour. Part of the stylised and parsimonious way in which IAMs represent the real world is in their representation of consumer or end-user decisions through simplified economic relationships: energy demand as a function of price; technology investments to minimise levelised costs; and so on. The emphasis throughout this report is on consumers or end users (ie, demand-side heterogeneity), but the same basic arguments apply equally to producers or firms (e.g., Laitner et al. 2003). (Note also that we use the term 'behaviour' in a modelling context to refer to the choices and decisions of consumers and firms, not to describe the general performance and results of a model).

Mundaca et al. (2010) review the representation of end-user decision making in IAMs, focusing on households in technologically-explicit (bottom-up) models. They find that IAMs commonly assume end-users have clear and known preferences and all the necessary information to make their decisions. Preferences are narrowly expressed for financial attributes. And end-users make optimal decisions, typically by minimising costs.

A microeconomic understanding of consumer choice provides the conceptual foundations of IAM representations of decision making at different nodes in the energy system. With their necessary levels of aggregation, IAMs do not represent individual interacting decision makers, but rather 'representative agents' describing aggregate behaviour at the mean (Laitner et al. 2000). Models describing the mean representative decision maker not heterogeneity across the population are acceptable reductions if the tails of the distribution are neither fat, nor influential on macro-dynamics (Conlisk 1996).

Taking a simple example in the optimisation model MESSAGE, representative decision makers selecting which type of power plant to build in response to rising electricity demands will estimate the levelised cost of alternative generation technologies using a fixed discount rate, and will select the lowest cost option subject to resource and capacity expansion constraints. The representative decision makers have perfect (global) knowledge of all technologies' capital and operating costs, conversion efficiencies, other technical parameters, as well as perfect (long-term) foresight of future cost trends. The heuristic process is thus lowest cost optimisation, turning inputs (technologies, costs, constraints, discount rates) into outputs (investments, capacity expansions). The outputs constitute the observable behaviour. Although this example is specific to optimisation models, Laitner et al. (2000) discusses very similar issues in CGE-type IAMs.

Representative agents act '*as if*' they were perfectly rational. Rational choice implies: (1) decision makers with known and fixed preferences (2) maximising utility by using optimising heuristics, (3) based on perfect information about all decision alternatives and their attributes. A further constraint is that preferences are self-regarding, i.e., expressed over attributes which affect the outcome for the decision maker. Other-regarding preferences are not commonly factored in.

Laitner et al. (2000) refer to a canonical statement of '*as if*' rationality by Milton Friedman. Although with reference to firms rather than consumers, Friedman argues: "*individual firms behave as if they were seeking rationally to maximise their expected returns … and had full knowledge of the data needed to succeed in this attempt*" (pp21-22, Friedman 1953).

The importance of the *as if* reasoning is that models describing aggregate behaviour using representative decision agents do not (and need not) imply that actual agents are perfectly rational, they just behave - at the population level - as if they were.

1.5 Lack of behavioural realism in IAMs

IAMs represent homogeneous and 'unboundedly rational' investment decisions and technology choices (Mundaca et al. 2010). Yet even within economics there is widespread recognition of the many observable deviations from rational choice (McFadden 1999).

Gillingham et al. (2009) review the behavioural features of energy-related end-user decisions from a microeconomic perspective. They emphasise the important difference between market failures and 'behavioural failures'. Market failures presuppose individual rationality and focus on the conditions surrounding interactions among economic heterogenous agents. In contrast 'behavioural failures' are inconsistent with utility-maximisation. Behavioural failures include: (1) asymmetric responses to losses and gains associated with loss aversion; (2) bounded rationality; (3) non-optimising, heuristic decision making (Shogren and Taylor 2008). The field of behavioural economics has amassed extensive empirical evidence for these features of real-world decision making that deviate from the axioms of rational choice (Kahneman and Tversky 2000; Camerer et al. 2004).

From an entirely different standpoint, empirical research on the 'energy efficiency gap' has shown that end-users do not adopt energy-efficient technologies based solely on a cost-effectiveness criterion (using levelised costs at market discount rates) (Jaffe and Stavins 1994; Gillingham et al.

2009). Explanations and perspectives vary, but most tend to invoke 'barriers' to otherwise cost-effective technology adoption decisions (Brown 2001). "*If there are profits to be made, why do markets not capture these potentials? Certain characteristics of markets, technologies and end-users can inhibit rational, energy-saving choices …*" (p148, Levine et al. 2007).

But what to an engineer or an economist may be barriers to optimality, to a psychologist or sociologist may be inherent characteristics of real world behaviour and decision-making. To paraphrase the psychologist, Paul Stern, we end-users are not just cost-minimisers or profit-seekers, but consumers with desires for non-financial benefits, people who express our values through our actions, social animals who are influenced by our peers, easy-goers who want to minimise effort and hassle, creatures of habit who follow deeply embedded patterns of behaviour, and we act differently in different contexts (Stern 1986).

The complexities of end-user decisions are illustrated by Mundaca et al. (2010). They review the empirical literature to identify the key determinants of technology choices in the cases of household appliances, building efficiency measures, and light bulbs. End-user preferences are expressed for a whole range of non-financial and non-energy attributes include size, brand, comfort, noise, aesthetics, timing, design, compatibility, performance, quality, and safety. Moreover preferences expressed for these attributes use non-optimising heuristics, and are based on imperfect information (Mundaca et al. 2010).

Other research shows the importance of decision makers' attitudes and socio-demographic characteristics (Guerin et al. 2000). The status and position of decision makers within social networks is also influential as technology adoption signals status and prompts social recognition.

Mundaca et al. (2010) conclude that "*the literature shows that … capital and operating costs … represent only a part of a great variety of determinants that drive consumers' energy-related decisions regarding technology choices … even in the presence of perfect information, a larger set of determinants can still lead to irrational utility maximization decisions*" (p317).

1.6 The importance of behavioural realism in IAMs

Laitner et al. (2000) ask: "*the crucial question is whether the behaviour that is actually carried out by the economic agents has different consequences for economic modelling of climate policy than the 'as if' presumption of maximisation"* (p19).

They answer their own question with a tentative yes. We would answer yes more forcefully. Behaviourally-realistic models of many different forms similarly show the influence of behavioural assumptions on policy-relevant outcomes (e.g., Rivers and Jaccard 2006; Sun and Tesfatsion 2007). And a mass of empirical evidence has accumulated on behavioural influences on energy use, end-use technology adoption, and resulting emissions (e.g., Lutzenhiser 1993; Ayres et al. 2009).

As characteristic 'real world' features of human behaviour are notably absent from IAMs, Rivers and Jaccard (2006) argue that this limits the models' usefulness to policy makers as they can not realistically simulate the effect on energy efficiency of different policy instruments.

In sum, there are four reasons for trying to improve the behavioural realism of IAMs in terms of how they represent end-user behaviour and decision-making, particularly with respect to technology adoption and use:

1) Empirical evidence clearly shows that end-user behaviour has many features that are not captured by representations of unbounded rationality (Stern 1992; Lutzenhiser 1993; Gillingham et al. 2009).
2) Theories and concepts of behaviour and decision-making across the social sciences variously emphasise the many influences on end-user behaviour beyond costs and prices (Wilson and Dowlatabadi 2007).
3) Models lacking behavioural realism are limited in their ability to evaluate energy efficiency policies and other influences on end-user demand. Consequently, models are limited in their usefulness to policymakers (Rivers and Jaccard 2006).
4) Improving the behavioural realism of models substantially affects policy-relevant model analysis of climate change mitigation.

1.7 Examples of behaviourally-realistic energy modelling

Some IAMs explicitly aim to improve their behavioural realism (Rivers and Jaccard 2005). The CIMS model of the Canadian energy-economy has the same explicit representation of energy system technologies as a bottom-up model with the same basic formulation of utility-maximising end users. But CIMS then draws on empirical research explaining the way in which end users have made, or might make, technology choices in real-world situations (Rivers and Jaccard 2005; Jaccard and Dennis 2006). Empirical studies of either observed market behaviour or stated preferences in discrete choice surveys are used to estimate intangible costs and benefits, end-user heterogeneity, and non-market discount rates. Intangible costs and benefits reflect end-users' preferences for the non-financial attributes of competing technologies. The heterogeneity of end-user decisions is simulated by multinomial logit functions allocating market shares to competing technologies. Non-market discount rates capture the end-users' strong aversion to delayed financial benefits. Parameters describing these behavioural features are context-specific to different decision nodes in the model (vehicle purchase, commuting mode, building renovation, heating system, industrial heat, and so on) (Rivers and Jaccard 2006).

Among energy-economy IAMs, CIMS is the exception not the rule (Mundaca et al. 2010). It is also worth noting that CIMS is national rather than global. It is not clear if the efforts of the CIMS modelling team towards behavioural realism is 'globalisable': parameterising the non-monetary preferences in utility functions at multiple decision nodes for heterogeneous consumers in multiple regions world-wide would be a formidable empirical challenge. (As shown in Section 4, empirical studies and data sets are sparse in their geographical coverage).

An alternative, more localised approach in IAMs is to distinguish several 'representative agents' to capture some element of heterogeneity but only at particular decision points or in particular sectors. For example, Ekholm et al. (2010) introduce heterogeneous end-user preferences for cooking appliances in less developed economies to improve the modelling of energy access.

Other forms of modelling than IAMs are more readily suited to behaviourally-realistic analysis of energy and used to analyse energy-related problems.

Agent-based models (ABMs) offer a computational approach which allows for heterogeneous and interacting decision agents using non-optimising decision rules and acting on local information. By relaxing a narrow microeconomic framing of choice, ABMs aim for greater micro-level behavioural realism, and so greater exploratory *and* explanatory power of macro-dynamics.

Typical behavioural features of consumers or end users in ABMs are:

- <u>other-regarding preferences</u>: *i.e.*, inclusion of social preferences related to the prevalence and/or social desirability of an alternative;
- <u>bounded rationality</u>: *i.e.*, constraints on the availability of information about an alternative or on the ability of a decision maker to process that information; includes alternative heuristics to optimisation.

There are many examples of ABM representations of choice and consumer preference that illustrate these behavioural features in an energy and environmental context (Axelrod and Tesfatsion 2006). One approach is based on consumer agents in a co-evolutionary model of technological change and product innovation (Janssen and Jager 2001; Janssen and Jager 2002). These agents have both personal and social needs, corresponding to self-regarding preferences for intrinsic goodness and other-regarding herding instincts. Agents' preferences are heterogeneous, change as a function of experience and socialisation, and are expressed through a range of different heuristics including repetition, imitation, social comparison, and deliberation (Janssen and Jager 2001; Janssen and Jager 2002). Safarzynska and van den Bergh (2010) develop an alternative model of co-evolving production and consumption to explore the phenomenon of lock-in. Their consumers' utility functions also have self-regarding preferences for a good's quality and price, as well as other-regarding preferences as a function of peer-group behaviour and network effects (imitating, positioning, conforming). Malerba et al. (2008) develop a "history-friendly" model of the evolution of semi-conductors and the computer industry. Their consumer agents have self-regarding preferences (for performance or cheapness) as well as social or other-regarding preferences in the form of a bandwagon effect for products of greater market shares. Consumers are also bounded by imperfect information, a heuristic bias towards habituation and brand-loyalty, and a sensitivity to marketing (Malerba et al. 2008).

Many other ABMs exist with varying specifications of consumer choice. As a general rule, the more behavioural features incorporated, the more complex the interpretation of emergent macro-dynamics becomes. Moreover, imbuing decision agents with particular behavioural features presents formidable parameterisation problems and a highly selective approach to behavioural realism. ABMs thus face the same tension as IAMs between parsimony and interpretability on the one hand, and empirical calibration and behavioural realism on the other. Simplified, stylised systems ('abstract ABMs') are used to explore and explain emergent phenomena in a what-if mode, yet resist application to particular contexts, datasets, or policies. Detailed, multi-featured systems (‘appreciative ABMs’) can better calibrate to empirical data and reproduce observed behaviour but in so doing risk losing explanatory power and generalizability (Axelrod and Tesfatsion 2006).

1.8 The challenge of improving behavioural realism in IAMs

Improving the behavioural realism of IAMs is extremely challenging. Behavioural realism itself is a slippery term, interpreted through different theoretical, empirical, and methodological lenses. Even ‘behaviour’ itself is a contested term, central to economic and psychological research (Ajzen 1991; Thaler and Sunstein 2008; Klöckner 2013), but questioned as a meaningful object of enquiry in some sociological research (Røpke 2009; Shove 2010).

As a result, there are important epistemic issues with trying to improve the behavioural realism of IAMs. Shipworth (2013) captures this vividly in his description of building energy models as “*epistemic sausage machines*”, mixing, matching, and packaging up seemingly incompatible views of the world. Shipworth goes on to quote Winsberg (2009) in describing simulation models as “*motley in that they draw on a wide variety of sources. These include theory, but also physical insight, extensive approximations, idealizations, outright fictions, auxiliary information, and the blood, sweat, and tears of much trial and error”* (p837). The development of complex models such as global energy-economy IAMs draws on a wide range of insights, data, relationships from different bodies of theory and analysis. IAMs thus amalgamate different forms of knowledge about the world into outputs “*of indeterminate epistemic character*” (Shipworth 2013). Hence the sausage machine analogy: the models combine “*inputs of all qualities and types into outputs of homogeneous and indeterminate quality and type*”.

The obvious absence of a grand unified theory in the social sciences is testament to the incommensurability of different theoretical and methodological approaches to understanding behaviour (Abell 2003; Gintis 2006). IAMs are interested in particular types of behaviour affecting energy and emissions. Here too, diverse theoretical approaches offer competing accounts of behaviour (Wilson and Dowlatabadi 2007). IAMs almost exclusively enshrine one particular account, characterised by a physical, technical and economic model (PTEM) of behaviour that centres on costs (prices), technologies, markets, and investments (Lutzenhiser 1993; Lutzenhiser 2014).

Central to this IAM epistemology are implicitly-represented representative decision makers whose decisions can be modelled as discrete, heuristic processes subject to an identifiable set of predominantly financial influences. By heuristic processes, we mean ones that are defined by simple rules for turning inputs (decision influences and decision-maker characteristics) into outputs (behaviour).

Our definition of ‘behavioural realism is intentionally consistent with the understanding and representation of the world enshrined in IAMs. We therefore acknowledge from the outset that we sidestep critical epistemological reflections. The aim of this report is to explore how the behavioural realism of IAMs can be improved, given their current structure and function. We are aiming for incremental improvement, not radical disruption.

Yet this requires a careful eye on the appropriate interpretation of findings. Efforts to improve the 'realism' of models and scenarios can create seemingly sets of conditions. As an example, an IAM may be set up to generate an optimal pathway from an inter-temporal social planner's perspective (with perfect system knowledge) but under non-optimal conditions. Yet the results remain clearly interpretable as the best solution in a second-best world.

To conclude this introduction, we follow Mundaca et al. (2010) who note that improving the behavioural realism of IAMs is important, only partially feasible, inherently selective, and needing empirical support. These are the challenges addressed in this report.

> *It has been long argued that bottom-up energy models provide an unrealistic portrait of microeconomic decision-making frameworks for technology choice. The key question is to what extent a better representation of empirically estimated determinants of choice is actually feasible in energy modeling. Which determinants are more workable than others in improving such tools? How can one assess the specific influence of certain parameters on technology choice? With the exception of the work done by Jaccard and Dennis (2006), no other reviewed modeling work attempts to answer these types of questions. Nevertheless, one has to acknowledge that even if modelers are sometimes fully aware of the need for a better representation of microeconomic decision-making frameworks, there is still limited empirical work and practical research on how to handle and convert qualitative knowledge about household behavior into a set of quantitative parameters … Quantitative simulation of household behavior is as yet very limited and complex, but it is nonetheless highly necessary to improve the modeling and evaluation of policies."* (p333-336, Mundaca et al. 2010).

2 TYPOLOGY OF BEHAVIOURAL FEATURES

2.1 What do we mean by 'behavioural features'?

Improving the behavioural realism of IAMs means improving their ability to reproduce observable real-world dynamics that deviate from narrow prescriptions of economic rationality. A microeconomic representation of rational choice can be simply characterised as describing utility-maximisation under a budget constraint. Sources of utility in principle can be anything, but in practice are often financial or monetary.

Any 'behavioural feature' added to this representation of end-user decision making within the IAM epistemology would therefore constitute a move towards improved behavioural realism. Our working definition of 'behavioural features' in IAMs is therefore "*anything beyond price-responsiveness under income constraints"*. This obvious simplification is generous. Essentially, any non-monetary preference as a source of utility would be included as a 'behavioural feature'. Although not explicitly referenced in the definition, any non-optimising, bounded, or information-deficient heuristic for processing decision inputs into behavioural outputs would also be included as a 'behavioural feature'. Any constraint on choice that is not income would also be included as a 'behavioural feature'. This might include constraints on choice placed by memory, experience, physical infrastructure, social norms, and so on.

2.2 Four main types of 'behavioural features'

Working within the IAM epistemology, we accept the representation of 'as if' individual decision makers using heuristic routines to process information and influences into observable outcomes. As noted, behavioural features are "*anything beyond price-responsiveness under income constraints"* that could be included in this 'as if' representation of decisions.

We develop a simple typology that distinguishes three types of behavioural feature according to whether they relate to individual decision making, social influences, or broader contextual conditions within which decisions are made. Individual decision making refers to features that are endogenous to the representation of decisions. Social influences and contextual conditions refer to features that are exogenous to the decision but influence, constrain or otherwise shape decision outcomes.

We also include heterogeneity as a fourth type of behavioural feature that cuts across the three other types. Allowing for heterogeneity in decision preferences or influences enables other types of behavioural feature to be considered. For example, it is not possible to have social influence without distinguishing early adopters from later adopters, as the one exerts social influence on the other. Heterogeneous adoption propensities among end users are therefore an enabling feature for social influence. Figure 2 illustrates the basic relationship between the four types of behavioural feature in our typology.

FIGURE 2. RELATIONSHIP BETWEEN BEHAVIOURAL FEATURES.

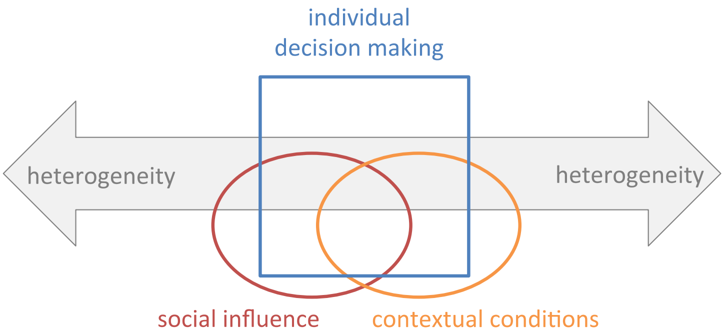


Table 1 provides a detailed overview of the typology, with a breakdown of each main type of behavioural feature. A short summary of each type of feature, including some key references, is included in the sections below. A basic distinction is made between decisions and behaviours, with decisions meaning the expression of preferences over decision alternatives (based on some level of information processing) behaviours meaning the observable outcomes of those decisions. This is particularly relevant for the social influences and contextual influences in Table 1 as these can act directly on behaviours as well as their antecedent decisions.

The typology shown in Table 1 is descriptive in that it groups behavioural features according to the relationship they have with individual decision making without reference to theory, disciplines or methods. No overarching theory sets out the decision contexts in which particular behavioural violations of rational choice apply, and to what extent. Nevertheless, certain fields of study link more closely to particular behavioural features. Microeconomic and behavioural economic research provide much of the evidence for bounded rationality, non-optimising heuristics, and non-market discount rates. Social psychology distinguishes heterogeneous personal characteristics from contextual influences on decisions. Diffusion theory is interested in social influence as information is transmitted through social networks. Game theory is concerned with how strategic decision making is affected by interactions. Sociology situates individual decisions within highly localised contexts of action, emphasising contextual conditions (Guy and Shove 2000). The links between fields of research and insights into human behaviour are vast and varied. As noted above, the aim here is not to use a disciplinary lens to compare and contrast insights (see (Wilson and Dowlatabadi 2007) for an example), but to describe key findings in a form commensurate with IAM representations of decision making and behavioural outcomes.

TABLE 1. A TYPOLOGY OF BEHAVIOURAL FEATURES CONSISTENT WITH IAMS' REPRESENTATION OF DECISIONS.

	Behavioural Feature	Description	Examples
Heterogeneity	***Heterogeneous decision makers***	End users are different in their preferences for decision outcomes.	- Differences in sources of utility or weighting of variables in decision functions. - Heterogeneous propensity for technology adoption (e.g., innovators, early adopters, followers). - Heterogeneous risk preferences (e.g., technologies, markets, portfolios) and time preferences. (See also under '*Non-market discount rates*'). - Heterogeneous socio-economic characteristics (e.g., income, age, education) influencing responsiveness to price or other variables. - Heterogeneous other-regarding preferences and social behaviour. (*See also under 'Social influence'*).
Individual	***Bounded rationality***	Decisions are made based on incomplete, partial, or local information.	- Costly search for and acquisition of information on decision alternatives and outcomes (transaction costs, myopia). - Uncertain expectations of outcomes as future is unknown (temporal myopia, limited foresight). - Unknown prospective behaviour of others (collective outcomes). - Errors in decision process (stochasticity, randomness).
	Non-optimising heuristics	Decision rules other than optimisation or maximisation are used in specific decision contexts.	- Decisions in familiar, repeated contexts influenced by past experience (habit, path dependence, inertia, loyalty). - Reliance on, and preferential use of, certain types of information (availability, salience, recency heuristics). - Tendency to follow 'default option' (status quo bias). - Limited capacity to remember and learn from outcomes of past decisions (memory, forgetting).
	Non-monetary preferences	End users value non-financial attributes of decision alternatives.	- Wide range of non-monetary attributes of decision alternatives and non-monetary outcomes of decisions. - Non-monetary preferences specific to decisions and contexts. - e.g., home renovation decisions: comfort, convenience, responsiveness, disruption, reliability. - e.g., vehicle purchase decisions: aesthetics, brand, status, functionality, performance, refuelling.
	Context-dependent preferences	Decision context or experience with decision influences preferences.	- Decision preferences strongly context-dependent (e.g., effort-minimisation at home, cost-minimisation in the workplace). - Decision preferences affected by experience, time, or others' behaviour (reinforcement, memory, learning). - Potential for social learning from collective outcomes. *(See also under 'Bounded rationality' and 'Non-optimising heuristics').*
	Non-market discount rates	End-users' discount rates are higher than market rates and non-constant.	- Implicit discount rates estimated from market behaviour are significantly higher than interest rates, and can be non-constant over time. - High implicit discount rates (up to 400%) for the purchase of energy efficient goods. - Constant discount rates inadequately describe strong immediacy effects (aversion to delayed gains) with low discounting of distant future. - Empirical and theoretical support for discount rate functions (e.g., hyperbolic discounting) distinguishing short and long-term time horizons.

Social	***Social influence & information networks***	Decisions and behaviours are influenced by others.	- Other-regarding preferences for decision outcomes. - Descriptive social norms: what others are doing. - Injunctive norms: what others approve of. - Imitation (herding, bandwagon, network externalities). - Distinction (status-seeking, snob effects, opinion leadership). - Social learning. - Intensity and frequency of social interaction through social networks transmits social influence. - Neighbourhood effects linked to visibility of others' behaviour. - Mass media, campaigns.
	Strategic decision making	Strategic interactions with others influence decisions.	- Strategic interactions combine self-regarding preferences with expectations about others' decisions. - Influential features of the decision context (e.g., anonymity, one-off or repeated interactions, sanctions). - Explored extensively by game theory.
Contextual	***Contextual conditions***	Decisions and behaviour are influenced by contextual conditions.	- Behaviour is heavily influenced, shaped, constrained, or determined by contextual conditions. - e.g., physical infrastructure (transport modes, heating fuels). - e.g., supply chains influence availability of technologies to end users (home renovation measures, power plant installations). - e.g., social norms influence market heterogeneity - e.g., design and compatibility influences how technologies are used (light bulbs, vehicles) - many more examples!
	Political and social institutions	Decisions and behaviour are influenced by political and social institutions.	- Institutions and culture shape decisions and behaviour through social norms, availability and type of choices. (*See also under 'Social influence'*). - Governance institutions (e.g., electoral mandate, policy instrument preferences, institutional histories, modes of rule). - Centralisation vs. decentralisation. - Concerns for equity and distributional impacts. - Legitimation and legitimacy. - Participation, social movements, civil society.

2.3 Behavioural features (1): Heterogeneity

Heterogeneity - variation or differences between end users - is an inherent characteristic of many of the other behavioural features. As noted earlier, varying propensities to adopt new technologies are central to diffusion theory (Rogers 2003). Bounded rationality implies the use of partial, localised information that will vary across contexts (Simon 1990). Decision preferences affected by experience or memory will similarly vary (Safarzynska and van den Bergh 2009). Decision makers' attitudes and socio-demographic characteristics will influence their energy-related decisions (Guerin et al. 2000).

Heterogeneity may thus apply to individual decision preferences (e.g., what's valued), individual decision processes (e.g., which heuristics are used), individual decision contexts (e.g., how much experience). Heterogeneity may also apply to the exogenous social and contextual influences to those decisions (see Figure 2). Examples include adoption propensities, density of local neighbourhoods, access to physical infrastructure in urban or rural areas, and so on. Heterogeneity is thus an enabling feature for other types of behavioural features to be considered.

More fundamentally, introducing heterogeneity among consumer (and producer) decision agents is essential for addressing the problems with mean representative agent assumptions. With reference to general equilibrium IAMs, Laitner et al. (2000) argue that "*… the device of the representative agent is highly questionable … even if one accepts the utility-maximising consumer as a model for individual decision making, it is not valid for aggregate decision making … [unless] one makes the explicit assumption that consumers are virtually identical. But this is clearly at odds with reality*" (p26, our emphasis). Heterogeneous end users are therefore central to the behavioural realism of IAMs. Modelling heterogeneity is also computationally tractable (Rausch and Rutherford 2010).

2.4 Behavioural features (2): Individual decision making

Behavioural features endogenous to individual decision making can relate to the underlying decision process (how the decision is made) or to decision preferences (why the decision is made, and with what outcome). Bounded rationality and decision heuristics relate to the decision process, and challenge a narrow interpretation of rational choice. Non-monetary preferences, context-dependent preferences, and non-market discount rates relate to decision preferences are how these are expressed over alternatives (see Table 1).

Bounded rationality and heuristic decision making are two of the main themes to have emerged from behavioural economics (Shogren and Taylor 2008). Bounded rationality describes the cognitive constraints faced by otherwise rational decision makers. This typically means that decision makers use only partial, local, accessible information when making choices (Simon 1956). Heuristic decision making is closely related. It describes how simplified rules are used to search for and process information about decision alternatives (Chater et al. 2003). Like bounded rationality, heuristics are a response to the cognitive burden of rational choice, which requires an optimising heuristic using complete (exhaustive) information on all decision alternatives and attributes. An example of a non-optimising heuristic is 'satisficing': searching through alternatives until a minimum acceptability threshold is reached (Kahneman and Tversky 2000). A non-optimising heuristic associated with habit would be 'choose the one I chose last time'. Heuristics are associated with common forms of bias (or deviations from rational choice). The availability heuristic, for example, means that salient, memorable, readily accessible information is disproportionately influential on decisions (Baron 2008).

Non-monetary preferences and context-dependent preferences suggest that the sources of utility and their relative weight in making decisions is broader, more varied, and less fixed than is commonly assumed in microeconomic representations of choice. (Jaccard and Dennis 2006), for example, include 'comfort' as a non-monetary preference in the utility functions of homeowners making decisions about energy efficient home renovations. Yet the three other sources of utility were all monetary, and no reference was made to the numerous other attributes relevant to renovation decisions, including aesthetics, disruption, functionality, reliability, disruption, performance, quality, and so on (Wilson et al. 2013). These non-monetary preferences will be strongly context-dependent. As a simple example, decisions made by facility managers in an energy-intensive work environment may be strongly influenced by cost savings, whereas energy costs in a domestic environment may have low salience and so be only marginally influential on homeowners' decisions.

Non-market discount rates are included separately in Table 1 as they feature prominently in the energy efficiency literature. Both stated preference studies and observed market behaviour 'reveal' or imply that end users apply discount rates well above market interest rates when investing in energy efficient technologies (Train 1985; Ruderman et al. 1987). These discount rates (up to 400%) are implicit because they are estimated from market behaviour rather than observed directly. They are interpreted in terms of time preference, revealing an aversion to delayed gains and uncertain benefits (a literal interpretation of the discount rate). However, they are also consistent with a host of other 'behavioural features' that may result in end users eschewing cost-effective technologies. It can not, therefore, be assumed that high implicit discount rates imply inefficient market behaviour that could potentially be corrected by providing information on energy efficiency to overcome aversion to delayed gains (Mundaca et al. 2010). Omitted variables may actually explain the high discount rates. Examples of omitted variables include transaction costs relating to the search for and processing of information (Sioshansi 1991; Moxnes 2004), and mis-estimations of costs and benefits (Attari et al. 2010).

2.5 Behavioural features (3): Social influences

The end-user decisions of most relevance to IAMs relate to technology adoption and subsequent use. The dominant theoretical framework used in the analysis of technology adoption is Rogers' 'diffusion of innovations' (Rogers 2003). Innovations diffuse as information on their attributes and the costs and benefits of their use is communicated among members of social groups linked by inter-personal networks. Social influence among heterogeneous technology adopters is a central feature of diffusion theory, and so an important type of behavioural feature.

There are many different types of social influence (see Table 1) and it is a coarse generalisation to group them as one. Examples of social influence identified in the literature include descriptive and injunctive norms (Cialdini et al. 1991), imitation effects (also herding behaviour and bandwagon effects), localised neighbourhood effects, and status-seeking (Griskevicius et al. 2010). Axsen and Kurani (2012) review five different research perspectives on how social influence affects the diffusion of innovative technologies and behaviours. They distinguish: (1) diffusion of functional information; (2) conformity; (3) social marketing of public goods by organized, resourceful groups; (4) translation of consumers' perceptions between social groups; (5) individuals' continual search for self-identity and expression through lifestyle practices. These distinctions in the literature are covered in more detail in Section 4.3 of this report.

Table 1 includes strategic decision making as a separate form of social influence as it draws on a distinct literature using game theory to explore (among other things) the effect of interactions between decision makers. Research on strategic decision making includes many domains relevant to IAMs including the management of common resources (Vollan and Ostrom 2010; Janssen and Anderies 2011) and the evolution of energy systems (Safarzynska and van den Bergh 2009).

2.6 Behavioural features (4): Contextual conditions

The final type of behavioural feature is also the broadest. Contextual conditions that can influence, constrain, or otherwise shape behaviour are many and varied. Examples given in Table 1 include physical infrastructure, supply chains and technology designs, but the list could also include climate, the natural environment, urban form, historical experience, and so on. To some extent, contextual conditions is a catch-all category for behavioural features that do not fit within the individual decision making or social influences categories.

Stern (2000) includes contextual influences as one of the four causal explanations of environment-related behaviour. The other three are attitudinal factors, personal capabilities, and habit. Lutzenhiser (1993) and Wilson and Dowlatabadi (2007) provide reviews of empirical studies in the energy field whose emphasis is not on individual decisions or the characteristics of decision makers, but on the context-dependent and often strongly habituated nature of energy-using behaviours. The 'socio-technical' perspective on technological change sees behaviour and technology as tightly entwined, each shaping one another in a co-evolutionary process (Geels 2004). (Shove 2010) contrasts psychological representations of individual behaviour influenced by contextual factors with sociological perspectives on behaviour as endogenous to different contexts. As noted above, our typology of behavioural features is consistent with IAM epistemology and so places contextual conditions as exogenous to individual decisions. Nevertheless, these contrasting lens on energy-related phenomena point to the wide variety of relevant influences.

Table 1 includes political and social institutions as a separate type of contextual influence in recognition of the issue faced by global IAMs in generalizing across very different regions, cultures, and political systems. Regional disaggregation in IAMs is typically between a few and 30 regions, a resolution that is substantially coarser than country-level analyses (Krey 2014). Culture, social and civic institutions, historical experience, and governance institutions will all shape behaviour at the aggregate and also individual levels (Urry 2008; Rudel et al. 2011).

2.7 Using the typology of behavioural features

The typology of behavioural features set out in Table 1 organises, characterises and exemplifies the main ways in which IAMs may currently represent end-user decision making and behaviour "*beyond price responsiveness under income constraints*". The next section of this report describes a mapping of best practice in 8 global energy-economy IAMs against the behavioural features set out in Table 1.

To improve IAMs' behavioural realism beyond current best practice requires not just modifications to IAM design and parameterisation, but also a robust evidence base. The typology in Table 1 also provides a framework for searching through and annotating the empirical literature across many different disciplines and fields. Section 4 provides two examples of how a systematic search of empirical studies can map the evidence base onto the behavioural features set out in Table 1.

3 BEHAVIOURAL FEATURES IN CURRENT IAMS

3.1 Behavioural features in energy-economy integrated assessment models (IAMs)

Section 11 set out a typology of behavioural features that go beyond a narrow microeconomic representation of rational decision agents responding to prices under income constraints. This typology includes many forms of heterogeneity, decision processes and preferences, social influences, and a range of contextual conditions. In this section we assess the extent to which global energy-economy IAMs include any of these behavioural features either explicitly or implicitly in their endogenous representations of end-user decisions.

Mundaca et al. (2010) review 20 studies that use bottom-up models to evaluate policy instruments for improving energy efficiency in households. They find that these models commonly represent homogeneous end users making unboundedly rational investment decisions. No behavioural features are included, with one exception: some models use high (above market) discount rates as a means of reproducing sub-optimal adoption rates of cost-effective energy-efficient technologies.

Laitner et al. (2000) focus their critique on the behavioural realism of top-down, general equilibrium models (see Figure 1). Through the device of representative agents who utility maximise, such models similarly characterise decision making in the aggregate as consistent with rational choice. The behavioural features of individual decision making are excluded. Social and contextual influences are to some extent factored in, albeit hidden in the econometric estimation of parameters such as income and price elasticities, or the elasticities of substitution between capital, labour and energy. But there is no explicit recognition nor endogenisation of social influence and contextual conditions.

We develop these critiques by mapping our typology of behavioural features against a sample of ten IAMs that are widely used for long-term mitigation analysis. The key features of these IAMs are set out in Table 2. This sample of IAMs covers a wide range of design features, different modelling approaches, technological resolution, and responsiveness to carbon price (Kriegler et al. 2014).

TABLE 2. KEY CHARACTERISTICS OF IAMS. BASED ON: (KRIEGLER ET AL. 2014).

Model	Modelling approach	Equilibrium type	Time horizon	Resolution of energy supply	Response to carbon price [a]	Key reference
DNE21+	inter-temporal optimisation	partial	2050	high	low	(Akimoto et al. 2008)
GCAM	recursive dynamic, simulation	partial	2100	high	high	(Calvin 2011)
IMACLIM-R	recursive dynamic, simulation	general	2100	medium	low	(Sassi et al. 2010)
IMAGE-TIMER	recursive dynamic, simulation	partial	2100	high	high	(Van Vuuren et al. 2007)
iPETS	inter-temporal optimisation	general	2100	low	(high) [a]	(O'Neill et al. 2012)
MESSAGE-MACRO	inter-temporal optimisation	general	2100	high	high	(Riahi et al. 2007)

REMIX	optimisation	partial	2050	high	-	(Scholz 2012)
REMIND	inter-temporal optimisation	general	2100	high	high	(Luderer et al. 2012a)
TIAM-UCL	inter-temporal optimisation	partial	2100	high	-	(Anandarajah et al. 2013)
WITCH	inter-temporal optimisation	general	2100	low	low	(Bosetti et al. 2006)

Table notes: [a] Not included in Kriegler et al. (2014) diagnostic evaluation study, so response to carbon price is estimated for comparative purposes only.

3.2 Mapping the behavioural features of ten IAMs

Within the context of the ADVANCE project, each of the modelling teams for the ten IAMs described in Table 2 completed a questionnaire that asked whether each of the behavioural features in our typology was represented in their models, and if so, how. This could be a model-wide approach, or a sector-specific or decision-specific modelling approach. IAMs resolve the upstream, conversion, and end-use sectors in the energy-economy. Consequently, there are many different types of decision represented in IAMs, from power plant investment decisions to home heating decisions. These may be represented explicitly, e.g., a lifecycle cost minimisation formulation for power plant investment decisions. Or decisions may be represented implicitly, e.g., an aggregate relationship expressing household energy demand as a function of price.

The principal decisions affecting energy and emission outcomes that are modelled in IAMs are as follows. Most of these decisions relate to technology adoption. Decisions in the buildings and transport sector are made mainly by end-users or consumers (individuals, households). Decisions in the industry and energy supply sectors are mainly made by firms or producers.

- buildings end-use sector: efficiency investments (retrofits, new builds); appliance adoption and use; levels of demand for energy services (heating, lighting, cooking).
- transport end-use sector: vehicle purchase; mode choice; levels of demand for energy services (mobility).
- industry end-use sector: furnace type (iron and steel).
- energy supply sector: upstream (resource extraction investments), conversion: power plant investments.

The results of the mapping exercise of current IAM modelling against our typology of behavioural features are shown in Table 3. This includes both sector-specific or decision-specific approaches, as well as general, model-wide approaches. Details of specific modelling approaches are summarised in the text below. (A full mapping of IAMs' current practice against the typology of behavioural features is available in spreadsheet format on request. The WITCH and REMIX modelling teams reported no current modelling of behavioural features and so do not appear in Table 3).

TABLE 3. MAPPING OF BEHAVIOURAL FEATURES IN TEN IAMS. BLANK CELLS INDICATE NO MODELLING APPROACH REPORTED.

	Buildings	**Transport**	**Industry**	**Supply**	**General**
	- efficiency - appliances - service demand	- vehicles - modes - service demand	- furnaces	- upstream - power plants	- model wide - all sectors
Heterogeneous decision makers	iPETS MESSAGE	MESSAGE			*discount rates:* DNE21+, TIAM *logit calibration:* GCAM, IMAGE
Bounded rationality					implicitly within discount rate formulations (DNE21+, TIAM), and logit calibrations (GCAM, IMAGE)
Non-optimising heuristics					
Non-monetary preferences	IMACLIM IMAGE MESSAGE	GCAM MESSAGE TIAM			
Context-dependent preferences	IMACLIM MESSAGE REMIND	MESSAGE			
Non-market discount rates	MESSAGE	MESSAGE			
Social influence & information networks					
Strategic decision making					
Contextual conditions	MESSAGE	GCAM MESSAGE		GCAM	
Political and social institutions					

3.3 General, model-wide approaches for modelling behavioural features

Four modelling teams provided information on general, model-wide approaches to behavioural realism. These were substantially different between the inter-temporal optimisation type models (DNE21+, TIAM-UCL) and the recursive dynamic simulation type models (GCAM, IMAGE-TIMER).

The technology-rich bottom-up IAMs using inter-temporal optimisation (DNE21+ and TIAM-UCL) reported using varying discount rates as a general approach to modelling heterogeneous end-user behaviour and context-dependent preferences. Discount rates (or investment hurdle rates) were varied as a function of income, technology characteristics, or adoption context (e.g., country or region). The DNE21+ team noted that discount rates were used as a proxy measure of many different behavioural features, and should not be interpreted solely in terms of time preference.

In contrast, the simulation models with limited temporal foresight and a recursive dynamic modelling approach (GCAM, IMAGE-TIMER) reported using multinomial logit functions to model heterogeneous end-user preferences and resulting market shares of competing technologies. These logit functions were calibrated to empirical data. The calibration parameters were thus used as a proxy for all the non-monetary preferences and other behavioural features influencing observed adoption behaviour during the historical calibration period. As the calibration of the logit functions requires historical data, this general modelling approach does not apply to new technologies. The calibration parameters for existing technologies are held constant, implying that the influence of non-monetary preferences on adoption behaviour persists over the 100 year model time horizon. This is in contrast to the CIMS modelling approach discussed earlier that assumes the influence of non-monetary preferences decreases as the technology becomes more widely adopted (Rivers and Jaccard 2006).

3.4 Decision-specific or sector-specific approaches for modelling behavioural features

Some IAMs use formulations representing behavioural features that are specific to particular decisions or particular sectors. This is in contrast to the generic formulations summarised in the previous sections that are integral design features of four of our sample of ten IAMs.

These decision or sector-specific formulations are summarised here, organised according to the behavioural feature from our typology with which they most closely correspond.

Heterogeneous decision makers

Buildings: iPETS varies preferences for technology adoption as a function of socio-demographic characteristics. MESSAGE varies price elasticities of electricity use and preferences for technology adoption as a function of income. In the case of MESSAGE, this is specific to less developed economies as part of work on energy access (Riahi et al. 2012).

Transport: MESSAGE includes disutility cost factors that vary by consumer group and vehicle technology. Consumer groups distinguish adoption propensity (early adopter, early majority, late majority), spatial characteristics (rural, suburban, urban), and annual levels of service demand for mobility (low, medium, high).

Recall also the general approach to modelling heterogeneous end-user preferences in GCAM and IMAGE.

Non-monetary preferences

Buildings: IMACLIM uses fixed intangible costs as a proxy for non-monetary preferences for energy-efficient technologies (e.g., disruption and hassle associated with insulation retrofits). MESSAGE uses inconvenience costs as a proxy for non-monetary preferences and barriers to adoption for stove-fuel combinations in less developed economies. REMIND similarly use income-dependent preferences for stove choices.

Transport: GCAM includes the average value of time in transit as a non-monetary preference in both mode choice and total service demands. The value of time in transit is derived from vehicle speed, the wage rate, and an exogenous multiplier reflecting consumers' stated value of time in transit for each mode. IMAGE and MESSAGE include time budgets (and speed) as an influence on mode choice. In both cases, this is related to transport infrastructure.

Recall also the general approach to calibration parameters in GCAM and IMAGE that implicitly include non-monetary preferences for existing technologies.

Context-dependent preferences

Buildings: IMACLIM decomposes aggregate energy consumption into technology adoption (quantity and quality of retrofits) and technology use (level of service demand). Preferences for technology use are therefore conditional on technology adoption in households. MESSAGE modelling of energy access issues recognises specificity of adoption preferences in less developed economies.

Transport: MESSAGE applies a risk premium to new technologies to capture the context of early market deployment, also related to heterogeneous adoption propensities among end-users (see above). These two behavioural features are the necessary basis for modelling social influence on the diffusion of innovations through interpersonal communication.

Non-market discount rates

Buildings: MESSAGE uses high implicit discount rates to annualise costs of lighting and cooking equipment in less developed economies.

Transport: In MESSAGE, the parameterisation of disutility costs implicitly captures variable and non-market discount rates.

Contextual conditions

Buildings: IMAGE and MESSAGE endogenise the influence of infrastructure availability on capital investment decisions; in the case of IMAGE, this is specific to hydrogen infrastructure.

Transport: GCAM exogenously reduces the market shares of alternative-fuel vehicles due to infrastructure-related constraints. MESSAGE partially captures the influence of refuelling infrastructure through disutility cost factors for limited vehicle range and refuelling station availability (which vary by consumer group and vehicle technology).

Energy Supply: GCAM lowers the capital cost recovery factors for renewable technologies to represent the favourable financing conditions due to government support programmes (mostly in the OECD at present)

3.5 Key findings on the behavioural features of IAMs

Various general observations can be made based on the reported data from the ten modelling groups.

Current modelling of behavioural features is relatively sparse.

More cells in Table 3 are empty than are filled. This could in part be due to missing data and incomplete reporting from the modelling teams in our survey of these ten IAMs. However, the evidence clearly indicates that endogenising behavioural features or otherwise improving the behavioural realism of IAMs has not to-date been of central concern.

Model-wide formulations aggregate behavioural influences.

Current modelling efforts in our sample of ten IAMs are dominated by two general, model-wide approaches: variable discount rates in two optimisation IAMs (DNE21+, TIAM), and market share calibration parameters in two simulation IAMs (GCAM, IMAGE). Both approaches are notable for being grounded in empirical data that aggregate many different potential behavioural influences on technology adoption and use to explain apparent deviations from rational choice. Although most closely associated with non-market discount rates, these behavioural features also include bounded rationality, non-optimising heuristics, non-monetary preferences, and context-specific preferences. Tuning discount rates or market heterogeneity parameters so that modelled adoption behaviour fits empirical observations is a simple, tractable, and readily implementable means of improving models' behavioural realism. But it is also analytically problematic as it masks the underlying behavioural features that explain the adoption behaviour in the first place. As a result, these modelling approaches may be able to reproduce more faithfully what we have observed historically in terms of adoption behaviour, but they are constrained in their ability to explore prospectively why we have observed it and so how policy may be able to shape it.

The same basic argument applies to the sector-specific approach in IMACLIM and MESSAGE of using intangible, inconvenience, or disutility costs as proxies for non-monetary preferences. Although ostensibly describing non-monetary preferences, as they are empirically-estimated they could also be capturing bounded rationality, non-optimising heuristics and so on.

Some behavioural features are not currently modelled.

Several of the behavioural features identified in our typology (see Table 1) are not currently modelled by any of the ten IAMs in our sample. These include: the effect of social influence on decisions; strategic decision making among interacting decision agents; the effect of political and social institutions on decisions.

In addition, none of the IAMs are currently modelling *explicitly* the effect of bounded rationality or non-optimising heuristics on decisions. As noted, discount rate or market share parameters based on empirical data *implicitly* bundle together all behavioural influences on technology adoption choices.

Current modelling of behavioural features is concentrated in consumer end-use sectors.

Current modelling of behavioural features in our sample of ten IAMs is almost exclusively concentrated in the buildings and transportation end-use sectors. No industry-specific behavioural features are being modelled. The only example of an upstream behavioural feature is in GCAM, which approximates the effect of favourable contextual conditions for power plant investments created by policy programmes. Current modelling of behavioural features in IAMs thus focuses on end-users (consumers) not firms (producers).

4 EVIDENCE BASE FOR IMPROVING BEHAVIOURAL REALISM IN IAMS

4.1 Reviewing the evidence base

The mapping of current modelling practice against the typology of behavioural features set out in Table 3 reveals significant opportunities for improving the behavioural realism of IAMs. As noted by Laitner et al. (2000), one of the key challenges in this research agenda will be the strength of the evidence base from empirical studies that identify, isolate, and quantify the influence of specific behavioural features. This is particularly salient for those behavioural features that no IAMs currently endogenise or otherwise represent. Social influence is one such example.

This section synthesises the results of two systematic literature reviews of empirical studies from the last 30 years. The first review covers discrete choices studies of alternative vehicle purchases. The second review covers studies of social influence on vehicle adoption and use. The rationale for each is set out further below. Both reviews are additionally concerned with the main sources of heterogeneity in vehicle-related decisions.

The main objective of these reviews is to determine the strength of the evidence base for endogenising behavioural features in IAMs, and the type and magnitude of behavioural influences on end-user decisions. The systematic nature of the reviews also allow comparison of studies geographically and over time, both of which are relevant to IAMs exploring energy transitions globally over 100 year time frames.

4.1.1 Focus of reviews: end-user decisions

The body of empirical literature on decision making and behaviour is vast, spanning the various disciplines of social science. To be manageable, the reviews needed to focus on specific end-user decisions and specific behavioural features.

The range of end-user decisions implicitly represented in IAMs was set out in Section 3.2. We selected vehicle purchase as the focus for the reviews. End-user choices of vehicle are important for many reasons.

Vehicle purchase is a technology adoption decision that strongly influences energy and emission outcomes in IAMs (Girod et al. 2013). Transportation is arguably the hardest end-use sector to decarbonise making end-user vehicle choices a critical determinant of low emission futures (Riahi et al. 2012). Mobility is an energy service that is written in to the fabric of social and economic activity, is strongly associated with development and modernity (Urry 2008), and involves a wide range of socio-economic actors (Marletto 2014). Vehicle preferences are highly heterogeneous, and vehicles are socially-visible technologies with many non-financial attributes. The behavioural features identified in our typology (see Table 3) are likely to be relevant.

Vehicle purchase and use is strongly dependent on transportation infrastructure, leading to relatively inert and strongly path-dependent change (van Bree et al. 2010; Riahi et al. 2012). Alternative fuel vehicles (e.g., electric, hydrogen) are exemplars of chicken-and-egg problems between investments in refuelling infrastructure and end-user vehicle purchases (Tran et al. 2012). Behaviourally-realistic modelling can provide insights into this impasse (Anable et al. 2012).

Vehicles are relatively short-lived capital assets (compared to buildings or energy supply infrastructure), so multiple generations of vehicles resulting from successive adoption decisions occur within long-term IAM projections. Behavioural influences on decisions would therefore propagate over time, allowing the path-dependent relationship between vehicles and infrastructures to be explored.

Finally, the availability of national or regional data sets on vehicle registrations increases the likelihood of large sample size analysis with robust effect sizes.

All these characteristics make vehicle choice an appropriate focus for the two systematic literature reviews to establish whether there is a sufficient evidence case for improving the behavioural realism of IAMs.

4.1.2 Focus of reviews: behavioural features

The two systematic literature reviews conducted take different approaches to identifying behavioural features.

The first review focuses on a particular analytical approach: discrete choice studies. Discrete choice studies use formal models of decision making to quantify the relative influence of different choice attributes under assumptions of utility-maximisation. They are well suited to identifying both heterogeneous preferences and also non-monetary preferences (depending on the study designs). As noted in Sections 1 and 3, these characteristics of discrete choice formulations make them directly implementable in IAMs (Rivers and Jaccard 2006). Discrete choice studies drawing on both stated preference (survey) data and observed market behaviour have been long been used to model vehicle purchase decisions. More recently they have been applied to alternative fuel vehicles as an important feature of low carbon transitions. This is the focus of the first review.

The second review focuses on a particular behavioural feature in our typology: social influence. As noted in Section 2, social influence is a pervasive characteristic of decision making and behaviour across all the end-user decisions represented implicitly in IAMs. Social influence is central to understanding technology adoption and diffusion (Rogers 2003), particularly for publicly visible technologies like vehicles. Moreover, it is strikingly absent from the behavioural features that IAMs currently represent (see Table 3). Social influences on vehicle adoption are the focus of the second review.

The first review of discrete choice studies draws mainly on microeconomic, consumer choice, and marketing studies with a singular view of utility-maximising consumer choice. Studies are broadly comparable in design and analysis, albeit with different variables and choice contexts. In contrast, the second review of social influence studies includes a wide range of theories, data, and methodologies. Results are not directly commensurate. This allows similarities and divergence between insights from different fields to be compared, and insights to be linked to research designs.

4.2 Synthesis of discrete choice studies of alternative fuel vehicles

4.2.1 Discrete choice experiments

This section synthesises the findings of a systematic review of 16 peer-reviewed articles that examine preferences for alternative fuel vehicles (AFVs) using discrete choice experiments (DCE).

DCEs use stated preferences in structured survey instruments. Unlike observations of market behaviour, they allow individuals' responses to new, unfamiliar technologies to be tested. This makes DCEs useful for examining behavioural influences on AFVs whose current rates of market penetration are low.

DCEs are distinctive in their design. They represent individuals as rational actors making deliberative choices based on their preferences for a given set of alternatives described by a number of attributes. This disaggregated approach captures the relative influence of various attributes on choice at the individual level. Derived within a random utility framework, decision makers are assumed to utility maximize by choosing the alternative (in this case, vehicle fuel type) with the highest utility. In discrete choice models this utility is captured by observing certain attributes of the alternatives (often derived from open-ended qualitative studies). In choice models for AFVs, common attributes for which preferences are estimated include price, operating cost, CO_2 emissions, engine power, range and refuelling availability.

There are other factors that affect utility that are not observed directly in the DCEs. Models vary according to both the assumptions made about the distribution of unobserved utility and the independence of choice alternatives. These assumptions are apparent through the functional form on which the model is based. These include logit, nested logit, mixed logit, and probit functions. Discrete choice models are distinct in that they are primarily concerned with relative utility: the main effects typically reported in empirical papers describe increases or decreases in utility for observed attributes holding other effects constant.

4.2.2 Inclusion criteria for empirical studies

Disaggregated models of vehicle choice appear in the wider transportation literature from about 1975. These empirical studies tended to concentrate on stated preferences for vehicles according to the function and form of the vehicle. Experimental studies looking at choice between fuel types appeared much more recently from about 1985. This is the literature included in the review.

Full details of the search and inclusion criteria used are provided in [Appendix A, Table A1]. A total of 16 papers met these criteria and were included in the synthesis. Reviewed studies are included in a separate bibliography with numbered references. A full annotated bibliography of all the studies including effect sizes accompanies this report and is available from the authors on request.

4.2.3 Methodological divergence between studies

Although the studies incorporated into this synthesis were similar in design, they varied in terms of sample size, modelling approach, and choice alternatives. Full details are provided in [Appendix A, Table A2].

The studies also varied in terms of the country from which data were sampled. This provides useful insights into spatial heterogeneity that may be relevant to global IAMs. However, studies were concentrated in North America (9 of 16 studies) and Europe (6 of 16 studies), with only 1 non-OECD country represented (South Korea). This lack of global coverage is a limitation of the small number of studies identified and compromises the generalisability of findings to other regions.

Studies mostly take a purposive approach to sampling potential AFV buyers, representing drivers, dealerships, student populations, commuters and new vehicle owners. A few studies suggest there may be within-sample bias towards the inclusion of males and higher income households.

Choice alternatives tested in studies vary from direct comparison of conventional vehicles (CVs) to AFVs as a generic vehicle class, to multi-choice experiments across the whole range of potential AFV vehicle types. These include: gas-fuelled vehicles, either liquefied petroleum gas (LPG) or compressed natural gas (CNG or NGV); hydrogen fuel cell vehicles (FCEV); electric vehicles, either battery electric (BEV) or plug-in hybrid electric (PHEV); and biofuel vehicles (BV).

4.2.4 Methodological convergence between studies

Methodological convergence is examined by comparing common attributes against which utility is measured. Table 4 groups attributes according to whether they are monetary or non-monetary.

TABLE 4. VEHICLE ATTRIBUTES COMMON TO STUDIES.

	Attribute	n	References in bibliography
Monetary attributes	Vehicle purchase price	14	All apart from [12] [13]
	Fuel or operating costs	16	All studies
	Government or financial incentives	1	[3] [11] [15]
Non-monetary attributes	Vehicle range	8	[5] [6] [7] [8] [9] [11] [12] [14]
	Body type or size of vehicle	2	[2] [7]
	Engine power	12	[1] [3] [4] [5] [6] [7] [8] [9] [12] [13] [14] 16]
	CO_2 emissions	12	[1] [2] [4] [5] [6] [9] [10] [11] [12] [13] [14] [16]
	Refuelling availability	11	[1] [4] [5] [6] [9] [11] [12] [13] [14] [15] [16]
	Behavioural features	*15*	*All apart from [7]*

A DCE design typically allows no more than 6 attributes to be compared. All studies examined monetary attributes as endogenous to the decision: fuel or operating costs (all studies, n=16); vehicle purchase price (n=14). Three studies (n=3) examined financial incentives as endogenous to vehicle choices. Both price and operating costs were consistently found to decrease utility, and financial incentives to increase utility. A range of non-monetary attributes were also included as endogenous to decisions (Table 4). The most common were: engine power (n=12), CO_2 emissions (n=12), and refuelling (n=11).

The effects of a range of behavioural features were examined mostly as exogenous effects. In all studies these effects are incorporated either as interaction terms or, in a few cases, as alternative treatment groups. We use the typology of behavioural features set out in Section 2 to classify studies according to whether they examine: (1) heterogeneity; (2) individual effects; (3) social influence effects; (4) contextual influence effects. Full details of this classification are provided in [Appendix A, Table A3].

Ten studies (n=10) measured heterogeneity, the majority as broad socio-demographic characteristics including age, gender and education. Although these characteristics enter models as exogenous to vehicle purchase decisions, different methods have been used to classify or group individuals according to a common set of traits. Methods include factor analysis and latent class analysis. In one study two consumer groups are identified distinguishing 'electric vehicle orientated' or 'gasoline vehicle orientated' adopters [11].

Two studies attempted to capture heterogeneous propensities for technology adoption by measuring ownership of other technological products and services, but neither study reported significant effects [4, 11].

Contextual constraints are modelled as both endogenous to decisions (e.g., availability of public refuelling infrastructure) and as exogenous effects (e.g., plug in facilities / parking at home).

4.2.5 Annotated bibliography

An annotated bibliography accompanying this report contains detailed findings from all 16 studies, including effect sizes across monetary and non-monetary attributes, and interaction effects from all behavioural features. Each study is annotated using the following framework: summary of findings, model fit or explained variance, location of sampling, date of sampling, sample characteristics, design and analysis, measurement issues, functional form, dependent variable or choice alternatives, other treatment group criteria or choice scenarios, explanatory variables. The annotations also record the attribute coefficients (ßs) for choice alternatives, treatment groups, choice attributes and explanatory variables, as well as any post-estimation calculations or simulations using the logit coefficients (e.g., willingness to pay). It is important to emphasise that these standardised ß coefficients should not be directly compared between studies as study designs, sample populations, alternatives and attributes are not the same. A screenshot illustrating the annotated bibliography is provided in [Appendix A, Table A4].

4.2.6 Synthesis of findings on behavioural features

In line with systematic reviews (Gough et al. 2012), the main findings of our systematic literature review are presented here as thematic summaries.

Table 5 summarises the findings on heterogeneity. Respondent age was consistently reported as significant in AFV choice with younger people more likely to choose different types of gas, electric, biofuel, and fuel cell vehicles. Propensity to choose an AFV varied for men and women, moderated not by price and costs, but vehicle performance. Loss of vehicle performance associated with AFVs reduced vehicle utility more for men than women. People more environmentally aware are more likely to choose an AFV, with a further increased likelihood for those actively as opposed to passively concerned.

TABLE 5. THEMATIC SUMMARY OF FINDINGS: HETEROGENEITY.

	Description	Key Findings	Refs
Heterogeneous decision makers	Heterogeneous socio-economic characteristics	Higher fuel consumption reduces vehicle utility for both men and women across all age groups but reduction greatest for men over age 50. Younger people more likely to choose AFVs (compared to CVs); consistent for all different AFV types.	[8] [4] [1] [4] [11]
		A top speed (100 miles per hour) increases vehicle utility but significant only for men aged 18-29. As price and capital costs increase, overall utility decreases - there is little or no heterogeneity reported if gender and age are examined. Overall probability of young women choosing EV nearly 10% higher than men.	[8]
		Highly educated people more likely to choose EV, BVs.	[5] [6]
		People for whom over 60% of driving involves city trips more likely to choose EV, interaction effects not significant for BV or PHEV.	[11]
	Heterogeneous preferences	Utility gains from reductions in CO_2 are greater in people who are more environmentally aware.	[12]
		Refuelling time, driving range, price and capital costs matter less to people identified as 'electric vehicle oriented': younger/middle age; university degree; expect higher gas prices in next 5 years; have made some greener lifestyle change; have somewhere they could install an EV outlet at home; likely to buy small/medium sized passenger car on next purchase; have tendency to buy new products that come onto the market; take at least one drive per month longer than 100 miles.	[12]
		People with high environmental awareness more likely to choose an AFV; consistent across studies with interaction effects for different AFV types. Some evidence of distinction between people more actively concerned and those more passively concerned in terms of environmental attitudes. Gains in utility from expanded service station network higher in people with a high propensity to drive a conventional vehicle.	[1] [11] [9] [16] [12]

Table 6 summarises the findings on behavioural features describing individual decision making. Eight studies including these behavioural features indicate that the availability of refuelling and service networks increases vehicle utility. However, effects are non-linear and likely to reduce as infrastructure improves. Moreover effects are heterogeneous as the availability of refuelling matters less to people identified as 'electric vehicle oriented' [11]. In general there are concerns about driving range and battery time with eleven studies finding significant effects.

TABLE 6. THEMATIC SUMMARY OF FINDINGS: INDIVIDUAL BEHAVIOURAL FEATURES.

Behavioural Feature	Description	Key Findings	Refs
Non-monetary benefits	Aesthetics, functionality, performance, refuelling	Expansion of the service network increases vehicle utility, but effects are non-linear, i.e., utility gains reduce as market share of vehicle technology increases.	[1] [4] [5] [6] [11] [12] [13] [16]
		Greater driving range, reduced battery time, warranties and fuel cost savings increase utility.	[1] [2] [3] [4] [5] [6] [7] [11] [13] [15] [16]
		Reductions in CO_2 emissions increases utility but this is more in environmentally aware individuals.	[1] [4] [5] [6] [10] [11] [16]
pe nd en t pr	Heterogeneous	Heterogeneity in private discount rates for HEVs vary	

	discount rates as function of market penetration	according to market penetration rates from 21% when market share=0.03% to 49% when market share=20%	[15]
Non-market discount rates	High implicit discount rates for the purchase of energy efficient goods	Decrease in vehicle range from 300 to 225 miles must be compensated for by a reduction in purchase price of $2000. A range of only 100 miles cuts the odds of choosing a vehicle by more than half. Individual willingness to pay per mile of added driving range is $35 to $75, diminishing at higher distances. Willingness to pay per hour reduction in charging time is $425 to £3250 (for a 50 mile charge).	[6] [9] [12]

Table 7 summarises the findings on behavioural features describing social influences and contextual conditions.

Where social influences were included in studies they were significant. Our analysis shows that people are more likely to choose an AFV if they have information that their peers are doing likewise. Two studies evaluated the effects of changing market conditions by including treatment groups with varying information on the market share of AFV compared to conventional and all effects observed were significant. Physical infrastructure is an important convenience but the availability of home charging where examined did not significantly affect choice.

TABLE 7. THEMATIC SUMMARY OF FINDINGS: SOCIAL INFLUENCES AND CONTEXTUAL CONDITIONS.

Behavioural Feature	Description	Key Findings	Refs
Social Influences & information networks	Information on the behaviour of others	People more likely to choose HEVs if they have information suggesting their peers are doing likewise.	[10]
	Changing characteristics of the marketplace	Utility gains from increases in driving range and decreases in price reduce as HEVs become more widespread. However, gains to utility from government subsidy and warranty remain the same.	[15] [3]
Contextual conditions	Physical infrastructure	Density of refuelling stations increases vehicle utility but gains are not linear. Gains are also higher in people who are oriented towards gasoline vehicles.	[1] [4] [5] [6] [11] [12] [13]
	Design and compatibility	Added convenience increases utility but gains weaken as technology becomes more popular. Studies that examined home charging did not produce significant coefficients within the modelling frameworks used.	[4] [5] [15] [16]

The relatively small number of studies reviewed (n=16) and the differences in research designs mean that directly comparing effect sizes is non-representative and likely to be misleading. As an alternative approach for synthesising insights on the evidence base for behavioural features, Table 8 compares the frequency of studies and the frequency with which they report significant effects

(Gough et al. 2012). The results presented in Table 8 should not be used as an isolated quantification but rather as a qualitative assessment within the context of all other findings in this report.

TABLE 8. THEMATIC SYNTHESIS EVALUATING FREQUENCY AND SIGNIFICANCE OF FINDINGS.

Behavioural Feature	Description	n of studies	Frequency of non-sig. effects	Frequency of sig. effects	Range of effect sizes (log odds) between studies
Heterogeneous socio-economic characteristics	Age	5	2	12	-0.001 to -1.0879 [a]
	Gender, age	1	5	13	-1.59 to -4.676 [b]
	Education	2	3	4	0.272 to 0.549 [c]
Heterogeneous preferences	Orientation (towards electric vehicles)	1	0	12	-0.35 to 0.53 [d]
	Driving practices	3	6	7	-0.2881 to 0.3685 [e]
	Environmental awareness	3	2	13	-0.525 to 0.8658 [f]
Non-monetary preferences	Refuelling network	8	4	18	0.0046 to 3.01
	CO_2 emissions	7	0	10	-0.002 to 0.849 [g]
	Range, battery time, warranties	11	0	13	0.0008 to 2.69
	Vehicle range	3	0	10	n/a [h]
Social influences	Neighbourhood effects	3	0	19	-0.00110 to 9.04 [i]
Contextual conditions	Refuelling availability	1	0	4	-0.0009 to 0.00658 [j]
	Refuelling location	1	4	5	n/a [k]
	Incentives	4	0	6	0.000029 to 0.1637

Table notes: [a] Larger coefficient reported against choice of generic AFV whereas smaller coefficients reported against specific types of AFV. [b] Comparison is within study but between various vehicle attributes (purchase price, performance/speed, fuel costs). [c] Probability of choosing AFV if respondent has degree ranges from 56% to 63%. [d] Comparison here is within study but between various vehicle attributes (fuel cost, refuelling time, driving range and capital costs). [e] Probability ranges from 56% to 59%. [f] Negative coefficient compares low awareness to high and positive coefficient high awareness to low. [g] Positive coefficient reported here for CO_2 emissions as a fraction of current vehicle. [h] Decrease in range of 75 miles compensated for by $2000 decrease in price. [i] Largest effect is seen for increase in refuelling infrastructure when hypothetical market share is very low. [j] Reported here as interaction effect with type of AFV but overall qualitative effect based on significance of earlier findings on refuelling density. [k] More than six times more important than purchase price.

4.2.7 Conclusions: Systematic review of discrete choice studies of AFVs

We reviewed 16 studies that used discrete choice modelling to examine preferences for AFVs. These studies span the period 1985 to 2013. We found strong evidence that DCEs are primarily focussed on explaining AFV choices in terms of monetary and non-monetary preferences expressed by optimising individuals. This is consistent with the underlying microeconomic representation of consumer choice. Although DCEs incorporate heterogeneity through interaction effects with choice outcomes, the majority of studies reviewed only captured heterogeneous decision maker characteristics such as gender, age, education and environmental awareness. Some studies tried to capture heterogeneity in terms of innovativeness (or adoption propensity) but effects were mainly insignificant within the modelling frameworks used.

Not all studies report model fit statistics. If reported, McFadden's R^2 was generally in the region of 0.15 – 0.17 suggesting relatively poor model fit. Hensher et al. (2005) suggest a good model fit for DCEs is in the range of 0.3 - 0.4. This indicates that AFV choices are influenced by other sources of heterogeneity that were omitted from the studies reviewed.

Social influences on AFV choices are poorly accounted for in DCE studies, with the exception of three studies that took account of either neighbourhood or peer effects on vehicle choice. Contextual conditions are similarly infrequently included in study designs, although this appears to be changing given 'range anxiety' issues with EVs. Infrastructural considerations such as refuelling density and convenience are increasingly being modelled as endogenous to AFV choices.

In conclusion, the comparative summary of 16 DCE studies shown in Table 8 found that:

Non-monetary benefits are very important.

All studies that measure combinations of non-monetary benefits within their design report significant effects (16 studies report 52 significant effects).

Refuelling networks for AFVs are important.

Eight studies measured the importance of refuelling networks as a direct effect on choice of AFVs in general or on specific types of AFV (8 studies report 18 significant effects).

Socio-demographic characteristics influence choices**.**

Choice of AFV is moderated by age, gender and education. Of the range of heterogeneous socio-economic characteristics included in study designs, only these three factors are reported as significant (8 studies report 29 significant effects).

Social influences are important, but are rarely modelled in DCEs.

If incorporated in study designs, effects of social influence are significant across the range of AFVs (3 studies report 19 significant effects).

4.3 <u>Synthesis of social influence studies of vehicle adoption</u>

4.3.1 <u>Social influence studies</u>

Social influences are increasingly recognised both intuitively and conceptually as an important determinant of consumption behaviour. However, there is a marked lack of associated empirical work. Grinblatt et al. (2008) suggest that this is due to the complexity of research designs needed to incorporate, isolate and measure social influences. Only three discrete choice experiment studies in our first literature review incorporated social influences into their design. These design and measurement difficulties are also highlighted by Manski and Sherman (1980) who suggest there is an identification problem inherent in observing social influences as correlations between the behaviour of two individuals are not only explained by social interactions between them. He suggests three reasons why not. First, 'exogenous effects' describe how two people who are neighbours, friends or family members are likely to be subjected to similar contexts that influence their decisions. People living next to each other make decisions about vehicle ownership based on similar surroundings such as shared transport infrastructure, travel patterns, exposure to local media and advertising. Second, 'correlated effects' describe how friends may have similar attitudes to the environment or have similar incomes, be of a similar age so their choices are more likely to be similar than dissimilar (Manski and Sherman 1980). The third reason describes how individuals influence each other's behaviour by interacting and exchanging information. This corresponds to the social influences identified in our typology of behavioural features.

4.3.2 Inclusion criteria for empirical studies

This review broadens out from AFVs to include all types of personal vehicle (conventional as well as alternative). The aim is to observe and understand the types of research designs used to observe social influences, how effects are measured and if so, whether they have a significant influence on vehicle choice.

A variety of search terms were used in journal databases to identify relevant studies. These included: 'neighbourhood effects', 'peer effects', 'herding', 'social influence'. The inclusion criteria were mainly designed to identify empirical studies although we also incorporated modelling or simulation studies that were grounded in real world data. Full details of the search and inclusion criteria used are provided in [Appendix B, Table B1].

The literature reviewed was drawn from many different disciplines and journals in transportation, marketing, business, economics, social and behavioural sciences. Full details of the journal sources are provided in [Appendix B, Table B2]. A total of 280 studies were initially identified, reduced to 72 studies after a full text review. Of these, 44 studies met all our inclusion criteria with respect to social influences, and a further 28 studies were included because they examined heterogeneous socio-demographics and non-monetary preferences.

A total of 72 studies were therefore included in the synthesis. Reviewed studies are included in a separate bibliography with numbered references. (Note that this is a separate numbered list to the previously described review of DCE studies, so begins again from [1]). A full annotated bibliography of all the studies accompanies this report and is available from the authors on request.

4.3.3 Methodological divergence between studies

Social influence studies looking at all vehicle types have a broader geographic representation compared to discrete choice studies looking only at AFVs. Thirty five studies (n=35) sampled populations from North America, and twenty one (n=21) studies from Europe (21), but these were many different countries: UK (n=7), Greece (1), Netherlands (2), Germany (4), France (2), Finland (1), Sweden (2), Belgium (1), and Iceland (1). Eleven studies (n=11) used data collected in Asia: Malaysia (n=2), Tokyo (2), South Korea (3), Thailand (1) Taiwan (1) and China (2). Three studies (n=3) in total covered the Middle East: Tehran (n=1), Israel (1) and Iran (1).

The earliest vehicle choice study identified in our review dated to 1965 using data collected in Western USA [7]. However studies incorporating social influences into their design are all post-2000. Similar to discrete choice studies, sampled populations were derived mostly from car owners and drivers. Some samples were drawn from specialist populations or convenience samples including government workers, online panels, commuters, students or trainees in driving school. Studies that had a strong empirical focus on social networks used more purposive samples drawn from families and friends, work colleagues, individuals connected through technology (internet and social media) and through physical networks (neighbours). Full details of the sample characteristics as well as outcome measures across the 72 studies reviewed are provided in [Appendix B, Table B3].

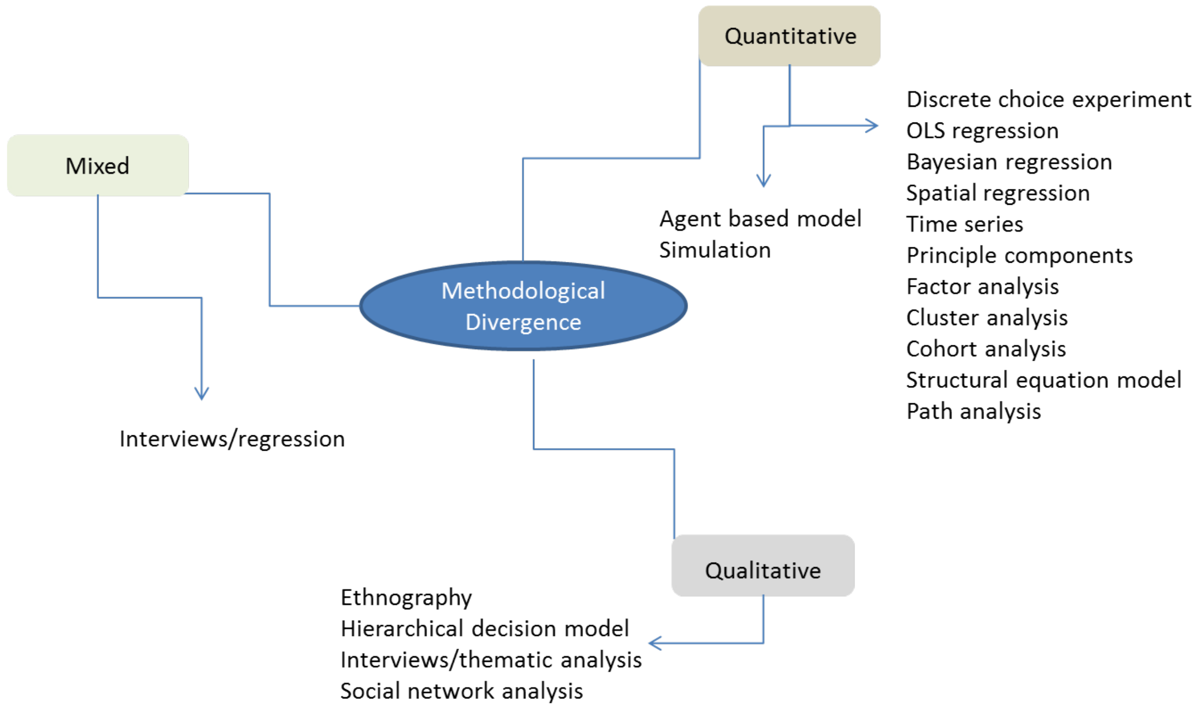
Most outcome measures related directly to vehicle choice, ownership or use with choice between alternative types the most common outcome measure. This reflects the influence of discrete choice modelling and conjoint analysis within transportation research.

Just three studies used some form of social influence measure as the direct outcome. In [48] respondents were asked to rate the influence of others on their vehicle perceptions. In [71] the outcome variable was individual propensity to influence others by word of mouth after purchasing a vehicle. In [56] a visibility index was created by asking respondents to rate the influence of their near neighbours on their own vehicle purchase behaviour.

Figure 3 summarises the different analytical approaches in the studies reviewed, distinguishing quantitative from other qualitative and mixed method studies. The range of quantitative methodologies is striking. This reflects the range of research traditions from which the studies are drawn. Full details of the analytical approaches are provided in [Appendix B, Table B4].

Although the inclusion criteria for the literature review were designed to capture all empirical studies irrespective of approach, 65 out of the 72 studies of vehicle adoption in transportation research used quantitative data and methodologies. Of these, DCEs were the most common (n=23). The use of agent-based models in transportation research also appears to be growing since 2005 when the first study reviewed was published. Although agent-based model insights are often abstracted and exploratory in nature, the parameterisation of agents with behavioural features can be grounded in empirical data, and the effect of interactions between agents can be modelled (see Section 1.7 for further discussion of agent-based models).

FIGURE 3. ANALYTICAL APPROACHES OF SOCIAL INFLUENCE STUDIES.



4.3.4 Methodological convergence between studies

In the review of DCE studies of AFV choices, all 16 studies modelled monetary preferences for AFV purchases. In contrast, only about 60% of social influence studies (n=44) in this review conceptualised vehicle choices as determined partly by monetary attributes of which fuel or operating costs were the most common. Across the full set of studies, non-monetary attributes included size, body shape, performance, functionality, comfort, appearance or aesthetics, safety, reliability (see Table 9 for a full list). Range and convenience were also included, particularly in AFV studies. Socio-demographic characteristics of decision makers included age, gender and income. Some studies looked beyond simple demographic variables into more complex constructs such as lifestyle, life stage, and family type. Other sources of heterogeneity were also included such as environmental identity and personality. Full details of the study designs are provided in [Appendix B, Table B5].

TABLE 9. VEHICLE ATTRIBUTES COMMON TO STUDIES.

	Attribute	**n**	**References in bibliography**
Monetary attributes	Vehicle purchase price	19	[2-5] [8] [12] [15-16] [21] [23-24] [26-30] [32-35] [37] [39-40] [42-43] [45] [47-50] [54-55] [57-58] [63-67] [69-70] [72-74]
	Fuel or operating costs	25	
	Government or financial incentives	2	
Non-monetary attributes	Range (AFVs only), size, body type, interior, driving experience, number of seats, age, turning radius, horsepower, manufacturer, quality of transaction, appearance, safety, design, technical features, after sales, environmental impact, convenience, shoulder room, luggage space, airbags, reliability, replacement value	46	[1-5] [8] [12-14] [21] [24] [26-32] [37-38] [40-44] [46] [48-50] [52-55] [59-63] [65-72]
	Behavioural features	*72*	*All*

4.3.5 Annotated bibliography

As with the review of DCE studies, an annotated bibliography accompanying this report contains detailed findings from all the social influence studies reviewed. Each study is annotated using the following framework: empirical focus, summary of findings, location of sampling, date of sampling, sample characteristics, design, functional form, model type, model fit, choice examined (dependent variable), measurement issues, vehicle attributes examined (explanatory variables), social characteristics or influences, reported coefficients or output. A screenshot illustrating the annotated bibliography is provided in [Appendix B, Table B6].

4.3.6 Synthesis of findings on behavioural features

In line with systematic reviews (Gough et al. 2012) and as with our earlier review of DCE studies, the main findings of our review of 72 social influence studies are presented here as thematic summaries. These summaries cover heterogeneous decision makers and social influences. (Individual decision making and contextual influences are the two other types of behavioural feature identified in our typology, but are not examined here).

Table 10 summarises the findings on heterogeneity. Both the socio-demographic characteristics and the psychological characteristics of individual decision makers explain some of the observed heterogeneity in vehicle adoption decisions. Socio-demographic characteristics include age, gender, income, car ownership. Psychological characteristics include knowledge, attitudes and perceptions towards cars, mobility, energy and the environment. Full details are provided in Table 10. One study [1] finds that 27% of the variance in intentions towards new vehicle technologies is explained by the socio-demographic and psychological characteristics of decision makers alone. Two studies [3, 33] find that attitudinal factors are stronger predictors of propensity to adopt electric vehicles than demographic factors. Income is reported as significant in a number of studies [17, 19, 25, 30, 32], but there are also indications that the influence of income on vehicle adoption is falling due to increasing market saturation and growing differentiation of vehicles [17].

TABLE 10. THEMATIC SUMMARY OF FINDINGS: HETEROGENEITY.

	Description	Key Findings with References
Heterogeneous decision makers	*Heterogeneous socio-economic characteristics (general):* age, gender, marital status, ethnicity, education, residency, employment, income, birth cohort, household life stage, family type	Men and women vary in their intentions, choices or concerns [1] [9] [10] [25] [32] [69]. Number of children, age and education are significant [10] [38]. Transit accessibility linked to residency and residential density predict type of vehicle driven [25] [32].
		Knowledge, awareness of vehicle attributes varies. Fuel efficiency and cost are commonly identified as important determinants in vehicle choice but few people know this information about their own vehicles [2] [40]. Only 20% know CO_2 emissions of their current vehicle, but 69% know fuel efficiency [2]. Households do not analyse fuel costs in a systematic manner: they know the cost of their last tank of gas but this information is rapidly forgotten [43].
	Heterogeneous socio-economic characteristics (travel-related): car ownership, commuting distances, car history	Income does predict vehicle decisions but importance varies according to household income levels [17] [19] [25] [30] [32]. Added luxury worth more to households on higher income [5]. Social influences have larger effect on decision to buy than purchase price [54].
	Heterogeneous psychological characteristics (general): environmental identity, personality, lifestyle type, personal efficacy, energy saving behaviour	Knowledge of climate change and environmental concern increase intentions towards AFVs [1] [31] [37]. Households will replace vehicles sooner if they have high levels of environmental awareness [31]. Consumers prioritise personal mobility needs over environmental concerns or social desirability [55]
	Heterogeneous psychological characteristics (travel-related): travel, attachment to cars, self-confidence in car selection, emotional or personal symbolic meaning	Attachment to current vehicle and ownership patterns are significant in determining type of future vehicle [4] [21] [28] [29]. Travel attitudes, personality and lifestyle influence vehicle choice [11]. Emotions and attitudes towards EVs are stronger predictors of purchase behaviour than peer and media effects [65]. Values, beliefs, norms and habits determine willingness to change behaviour and adopt greener innovations [22]. Car drivers vary in their scepticism towards new products [35]. Hedonic and symbolic attributes mediate between AFV attributes and intentions to adopt [40]. Inner-directed people more likely to be influenced by others [52]. Over 16% of people, particularly men, perceive that there is a risk to social status with AFV ownership [69]
	Heterogeneous propensity for technology adoption	Technological interest increases intentions towards HEVs [37]. Pro-social interpretations of PHEVs form if people have a basic understanding of the technology and if they are in a transitional state in their lifestyle practices [49].

Table 11 summarises the key findings on social influence which is the emphasis of this review. Findings are grouped into four distinct but related types.

The first type of finding describes how information transmitted by word of mouth, mass media, and interactions with other electronic media such as company websites influences vehicle choices.

Information is important in influencing vehicle assessment and choice whether it is written, verbal or online.

The second type of finding is also related to inter-personal communication but emphasises the intensity and frequency of social interaction. All studies reporting the influences of family, friends and peers report significant effects. Effects are stronger when social ties are stronger. Fathers have more influence on some purchase decisions. If tested, influences from peers are weaker than from family members. Social influences have a larger effect on the decision to buy than purchase price but people are still likely to prioritise their own personal mobility needs over the influences of others. There is also evidence of further heterogeneity in that people are more likely to be influenced by others of the same gender and in the same income group.

The third type of finding relates to neighbourhood effects and the visibility of others' vehicle choices resulting from geographic proximity. There is strong evidence to suggest that people are more likely to purchase a new car if people living around them have done so recently. These effects are seen in both urban and rural areas, but according to one study, neighbourhood effects are short lived.

The fourth type of social influence describes social norms. Acceptance of AFVs in particular strengthens as their market share rises and their purchase and use becomes normalised.

TABLE 11. THEMATIC SUMMARY OF FINDINGS: SOCIAL INFLUENCES.

	Description	Key Findings with References	Other Refs
Social Influences & information networks	Mass media campaigns, pre-purchase information and word of mouth, interactive learning	People are more likely to be influenced by the opinions of others in their social network if they themselves are better informed of the technology [48] [49]. Conversations online about new models and re-modification are strongly associated with increased sales [53]. Expert opinion is important and has a particularly strong effect on internet users [62]. Word of mouth is an important antecedent to behavioural intentions [61]. People who are more likely to use word of mouth information in their own vehicle decisions are more likely to pass on information by word of mouth [71]	[13] [15] [58] [59] [60] [72]
	Intensity and frequency of social interaction through social networks	People are strongly influenced by the opinions of others [4] [6] [7] [48] [50] [52] [55] [71] [73] [69]. Propensity to be influenced varies [48] [52] [69]. Propensity to influence others also varies [6] [71]. Some people are more outer-directed (as opposed to inner-directed) [52]. Some perceive greater social risk (to individual identity) from vehicle ownership. More men fit into this latter group than women [69]. Social influences are stronger if there are stronger ties within a relationship [6] [48]. Decisions on what car to buy influenced more by father than mother, peers or media [6].	[3] [9] [20] [63]
	Neighbourhood effects linked to visibility of others' behaviour	Strong neighbourhood effects are evident in both urban and rural communities [9] [51] [18] [19] [46] [68] [70] [74]. People are more likely to purchase a new car if people living around them have done so recently [9] [51]. Households have a higher probability of possessing a vehicle if they are surrounded by other automobile-owning households (endogenous effect) [18]. Neighbours are more likely to choose a certain type of car if their neighbours have [19] [46] [68]. Neighbour nearness is critical to social influence but these influences are short lived and stronger in more rural areas with lower population density [19] [68]. Preference inter-dependence among individual consumers reflects conformity for which geographic networks are more important than demographics [70] [74]. Increasing numbers of geographic clusters feature households with HEVs [74].	[56]
	Social norms: descriptive (what other people are doing) and injunctive (what other people approve of)	The market share of a new technology has a positive effect on choice [14] [64]. Acceptance for EVs increases when market context strengthens (e.g., increasing market penetration, rising gas prices, increasing number of electric charging stations) [14]. Social norms explain 12.6% of the variance in purchase decision of Toyota Prius [37], are less influential than emotions and attitudes [33] [65], but more influential than costs and purchase price [54]. Social position mediates the effect of social norms, with people more likely to be influenced by others in their own income group [19]. Social influences are also stronger with luxury brands such as BMW or Mercedes-Benz [68].	[1] [4] [22] [23] [40] [47] [49] [55] [57] [67] [69]

The research designs and methods used in the 72 studies reviewed are very diverse. It is not therefore possible to compare effects sizes, or report and compare coefficients for specific explanatory variables. To provide a comparative overview, Table 12 shows the number of studies that reported significant findings for each of the main types of behavioural feature.

Although a number of studies included socio-demographic factors such as age and gender, these were often incorporated as controls and so main effects were not reported. As a result, the frequencies of significant effects for these factors in Table 12 should be interpreted as a lower bound. Table 12 also includes an overall high-medium-low evaluation of each behavioural feature's influence on vehicle choices.

TABLE 12. THEMATIC SYNTHESIS EVALUATING FREQUENCY OF FINDINGS.

<table>
<tr><th>Behavioural Feature</th><th colspan="2">Description</th><th>Frequency of sig. effects</th><th>Evaluation of influence on choice</th></tr>
<tr><td rowspan="9">Hetero-geneous decision makers</td><td rowspan="6">Socio-demographics</td><td>Age</td><td>2</td><td>Low</td></tr>
<tr><td>Gender</td><td>6</td><td>High-medium</td></tr>
<tr><td>Number of children</td><td>2</td><td>Low</td></tr>
<tr><td>Education</td><td>2</td><td>Low</td></tr>
<tr><td>Income</td><td>7</td><td>Medium [a]</td></tr>
<tr><td>Information and knowledge</td><td>6</td><td>High-medium</td></tr>
<tr><td rowspan="2">Heterogeneous preferences, psychological characteristics</td><td>Environmental concern</td><td>3</td><td>Low</td></tr>
<tr><td>Emotions and attitudes towards ownership and travel</td><td>6</td><td>High-medium</td></tr>
<tr><td>Propensity for technology adoption</td><td>Technological awareness, information and understanding</td><td>5</td><td>High-medium</td></tr>
<tr><td rowspan="4">Social influences</td><td>Pre-purchase information</td><td>Word of mouth, on-line information, experts</td><td>12</td><td>High</td></tr>
<tr><td>Social proximity (friends/family)</td><td>Socio-psychological connections, relationships, physical meetings</td><td>14</td><td>High</td></tr>
<tr><td>Physical proximity (neighbourhood effect)</td><td>Characteristics of the built environment, urban density, geographical proximity to neighbours (visual and spatial effects)</td><td>9</td><td>High</td></tr>
<tr><td>Social norms</td><td>Changing characteristics of the market place</td><td>19</td><td>High</td></tr>
</table>

Table notes: [a] The explanatory value of income has diminished over time [17].

4.3.7 Conclusions: Systematic Review of Social Influence Studies on Vehicle Adoption

We reviewed 72 empirical studies that examined heterogeneity and social influences in vehicle purchase intentions, choices or motivations. Heterogeneous characteristics of decision makers were often used as controls in social influence studies, but if reported as main effects, characteristics such including age, gender, education and environmental awareness have significant effects on vehicle choice.

Overall the review identifies a surprising lack of empirical research designs incorporating social influence. From a total of 280 studies initially identified, only 44 measured social influences on private vehicle choices. Research approaches to measuring or otherwise evaluating social influences are very diverse, from constructing a visibility index to rank neighbours' perceived influence to agent-based modelling of social interaction and diffusion rates. Although it is not possible to compare effect sizes or model fits across this diverse of set of studies (not all of which are quantitative), the thematic synthesis of significant main effects shown in Table 12 provides very strong evidence that social influences are important in determining vehicle choice. It also provides an indication of which heterogeneous decision-maker characteristics are more influential in vehicle purchasing decisions: technological awareness, emotions and attitudes towards mobility, and information and knowledge.

5 APPROACHES FOR IMPROVING BEHAVIOURAL REALISM IN IAMS

5.1 Overview

This report has identified the importance of improving the behavioural realism of IAMs (Section 1) and set out a typology of behavioural features for possible endogenisation (Section 2). A mapping of current IAM designs against this typology found two main approaches to behaviourally-realistic modelling (Section 3). First, model-wide formulations aggregate all behavioural influences by calibrating modelled choice outcomes to stated or revealed preference data. Second, decision-specific representations capture non-monetary preferences of heterogeneous decision makers distinguished by basic socio-demographic characteristics such as income or technology adoption propensity.

The rationale and opportunities for improving the behavioural realism of IAMs need supporting by a strong evidence base (Laitner et al. 2000). Using vehicle choices as an example, two reviews of empirical studies established the strength and influence of behavioural features on decision outcomes (Section 4).

This concluding section draws together these various strands of research to identify next steps in a research agenda for developing the next generation of more behaviourally-realistic IAMs. Five criteria are used to prioritise behavioural features for IAM modelling teams, and some initial ideas for endogenisation are proposed.

5.2 Prioritising behavioural features in IAM developments

The first two prioritisation criteria are empirical: (a) strength of the evidence base; (b) influence of the behavioural feature. Strength of the evidence base is proxied by the number of studies in the reviews. Influence of the behavioural feature is evaluated subjectively on a three-point scale (high-medium-low) by comparing effect sizes and significance across studies. (Studies reviewed are methodologically too diverse to allow a statistical meta-analysis.)

The remaining three prioritisation criteria are modelling-related: (c) ease of implementation in IAMs; (d) link to policy levers in IAMs; (e) likely impact on IAM analysis. These three modelling criteria are subjectively assessed by the authors on a three-point scale (yes-maybe-no) based on current knowledge of IAM design and application. Ease of implementation refers to the practicality and tractability of endogenising a behavioural feature in IAMs, recognising that IAMs vary widely in their current designs (see Section 1). Link to policy levers relates to whether including a behavioural feature would enhance the ability of IAMs to analyse particular energy or climate policies as this is a key part of the rationale for behaviourally-realistic modelling (Rivers and Jaccard 2006). Likely impact on IAM analysis identifies the sensitivity of key policy-relevant outcomes to a behavioural feature.

For each behavioural feature identified in our typology, the criteria assess the breadth and depth of the evidence base, and the tractability, policy-relevance, and impact of possible endogenous formulations in IAMs.

5.2.1 Selection criteria applied to evidence from DCE studies

Table 8 summarises the breadth and depth of the evidence base for behavioural features of AFV choices from the review of *discrete choice studies*. Given the utility-maximising formulation of discrete choice models, these behavioural features emphasise heterogeneity and individual decision making. Table 13 extends this analysis by including the three additional prioritisation criteria related to modelling.

TABLE 13. PRIORITISING BEHAVIOURAL FEATURES: DISCRETE CHOICE STUDIES OF ALTERNATIVE FUEL VEHICLES.

	Criteria	**empirical**		**modelling**		
		(a)	**(b)**	**(c)**	**(d)**	**(e)**
Behavioural Feature	**Description**	**n (of 16)**	**influence**	**useable**	**policy lever**	**impact**
Heterogeneous socio-economic characteristics	Age	5	high	maybe	no	maybe
	Gender x age (interaction)	1	medium-low	maybe	no	no
	Education	2	medium-low	maybe	no	maybe
Heterogeneous preferences	Orientation (to EVs)	1	medium-low	no	no	maybe
	Driving practices	3	low	no	no	maybe
	Environmental awareness	3	high-medium	maybe	no	yes
Non-monetary preferences	Refuelling network	8	high	yes	yes	yes
	CO_2 emissions	7	high-medium	yes	yes	yes
	Range, battery time, warranties	11	high	yes	maybe	yes
	Vehicle range	3	high-medium	yes	no	yes
Social influences	Neighbourhood effects	3	high-medium	maybe	no	yes
Contextual conditions	Refuelling availability	1	high	maybe	yes	yes
	Refuelling location	1	medium	maybe	yes	yes
	Incentives	4	high	yes	yes	yes

Rows shaded grey in Table 13 indicate behavioural features ranked highly across both the two empirical criteria and the three modelling criteria. These are priority areas for improving behavioural realism as the evidence base is robust *and* IAM formulations are likely to be tractable, useful, and impactful. Three of these priority behavioural features describe the influence of non-monetary preferences on AFV choices: availability of refuelling networks; vehicle attributes including range and battery time; and CO_2 emissions. All three are closely related to consumers' perceived costs and benefits of emerging low emission vehicle technologies.

5.2.2 *Selection criteria applied to evidence from social influence studies*

Table 12 summarises the breadth and depth of the evidence base for behavioural features of all types of vehicle adoption from the review of *social influence studies*. Given the focus of the review, these behavioural features emphasise social influences and interactions between heterogeneous adopters. Table 14 extends this analysis by including the three additional prioritisation criteria related to modelling.

TABLE 14. PRIORITISING BEHAVIOURAL FEATURES: SOCIAL INFLUENCE STUDIES OF VEHICLE ADOPTION.

	Criteria	empirical		modelling		
		(a)	(b)	(c)	(d)	(e)
Behavioural Feature	**Description**	**n (of 72)**	**influence**	**use-able**	**policy lever**	**impact**
Heterogeneous socioeconomic characteristics	Age	2	low	maybe	no	maybe
	Gender	6	high-medium	maybe	no	no
	Number of children	2	low	maybe	no	no
	Education	2	low	maybe	no	maybe
	Income	7	high-medium	maybe	no	yes
Heterogeneous preferences	Information & knowledge	6	high-medium	maybe	maybe	yes
	Environmental concern	3	low	maybe	no	maybe
	Attitudes to vehicles	6	high-medium	maybe	no	yes
	Adoption propensity	5	high-medium	maybe	maybe	yes
Social influences	Information transmission	12	high	maybe	maybe	yes
	Inter-personal networks	14	high	maybe	no	yes
	Neighbourhood effects	9	high	maybe	maybe	yes
	Social norms	19	high	maybe	no	yes

As before, rows shaded grey in Table 14 indicate behavioural features ranked highly across both the two empirical criteria and the three modelling criteria. The potential implementation of social influences in IAMs is more problematic than in the case of individual decision making. The useability criteria (c) is 'maybe' in all cases as it depends on the IAM's ability to also represent heterogeneous adoption propensities, information and knowledge (in the case of information transmission via word-of-mouth and social networks) and heterogeneous spatial characteristics of adopting populations such as urban density (in the case of neighbourhood effects). Nevertheless, the robustness of the evidence base warrants efforts to improve IAMs' representation of social influences on vehicle adoption.

5.3 Endogenising behavioural features in IAMs

Laitner et al. (2000) note the relative ease of critiquing behaviourally-*un*realistic modelling but the real difficulty in providing meaningful alternatives, particularly given the time and resource investments in the IAM design, construction and parameterisation. Focusing on top-down, general equilibrium-type IAMs, they suggest various improvements in the short- and long-term. Immediate improvements, compatible with existing model designs, include: (1) sector or technology-specific investment hurdle rates which can be reduced by non-price policies and programmes; (2) non-constant price and income elasticities; and (3) co-benefits of energy technologies in decision functions. Over the longer-term, they suggest more far-reaching improvements including: (4) representative agents substituted by "*pragmatically formulated equations describing aggregate supply and demand in each market*"; (5) all-encompassing utility functions replaced with multi-criteria decision making; (6) heterogeneity introduced among agents and their interactions; and (7) establishment of the empirical grounding of the "*broader behavioural approach … [such as] bounded rationality … and the properties of psychologically-conditioned investment decisions*" (p48, Laitner et al. 2000).

Although our conceptual framing of behavioural features and our empirical review has followed very different lines, we reach very similar conclusions. Sector- and technology-specific hurdle rates (potentially varying over time) correspond to heterogeneous risk preferences; non-constant elasticities correspond to context-dependent preferences; co-benefits correspond to non-monetary preferences. The more far-reaching suggestions of Laitner et al. (2000) thus emphasise heterogeneity and robust empirical evidence, as does our analysis.

As with any new feature added to an IAM, from a technical perspective there are numerous options for how to model behaviour. At the most fundamental level, modellers must decide whether to: (a) improve existing elements within their IAM; (b) build an entirely new module; or (c) outsource the computations to an external model. The first two approaches imply that solution algorithms (e.g., optimisation or simulation) would be the same in the behavioural module as in the rest of the IAM. In contrast, this need not be the case with the third approach that sees the core IAM and the external behaviourally-realistic model being 'soft-linked'. In other words, the two models exchange key information (e.g., fuel prices, service demand levels by technology and consumer group over time, etc.) in an iterative manner. This sort of modelling arrangement is already quite commonplace within the IAM community. The MESSAGE energy-economy model, for instance, is linked to an aggregated model of the global macro-economy (MACRO), as well as air pollution (GAINS) and land-use and forestry models (GLOBIOM) (Riahi et al. 2007). In such IAMs, the distinctions between individual models within an integrated framework can become blurred, and what was originally a soft-linked module may become absorbed into the core IAM framework.

For each of these approaches, it is clear that to adequately represent behaviour IAMs will need to disaggregate end-users into heterogeneous decision agents at some level within the model structure. This could be done directly within the core part of the IAM or only in the external model, depending on the modelling arrangement. It may be possible, for instance, that following a soft-linked approach, an IAM could continue to rely on average, per-capita characteristics of end-users, while the external model could contain all of the heterogeneous detail.

As shown previously in this report, logit-type formulations are a common means of representing vehicle purchase decisions in the discrete choice literature. Hence, simulation-based models (e.g., GCAM, IMAGE), which already make use of logit functions, will be able to endogenose such information more directly within their solution frameworks. Given the prevalence of boundedly rational and non-optimising decision making (see Section 2), optimisation-based IAMs (e.g., TIAM, DNE21+) will find it more difficult to directly endogenise, so may prefer to soft-link with an external model.

The question of how much heterogeneous detail to include in a behavioural model is an important one. One view of modelling is that the more detail, the better. An alternative view is that a model should not attempt to explicitly represent more than it needs to in order to address the particular questions at hand. This is why 'policy lever' and 'impact' are included as key criteria for selecting which behavioural features to prioritise. In the case of vehicle purchase decisions, models should, if possible, disaggregate the consumers of their light-duty vehicle sectors (passenger cars, SUVs, trucks) in ways that allow for explicit representation of the most influential behavioural features identified in Table 13 and Table 14 (see rows shaded grey). These high priority areas for behavioural modelling in IAMs include attitudes toward new technology, income, incentives, vehicle range between refuelling, availability of refuelling infrastructure, and social influences such as information and knowledge exchange between peers.

5.4 Modelling heterogeneous end-users, using MESSAGE as an example

It is neither appropriate nor reasonable to propose a single, standardised approach for incorporating behavioural realism into IAMs. No two IAMs are exactly alike, and IAM modelling teams have distinct research interests and focus on different sets of policy-relevant questions. At the same time, it is generally recognized within the IAM community that there is potentially great value in having certain models experiment with new approaches or novel methodologies before applying them to other models. This has proven an effective strategy, for example, in recent IAM inter-comparison projects such as LIMITS (air pollution modelling) and AMPERE (near-term reference policy implementation). In the context of the ADVANCE project, a similar strategy has been instituted with 'pioneering' models experimenting with novel methodologies within their own frameworks, and subsequently packaging, recoding, and diffusing effective innovations to other modelling frameworks, both within and outside the ADVANCE consortium.

MESSAGE is one of the pioneering models in ADVANCE for vehicle purchase decisions. The goal of this work is to demonstrate a proof of concept that is flexible enough to be applied to IAMs of different structures and solution algorithms, yet complex enough to capture the most influential behavioural features identified in the empirical evidence base. This section proposes a research agenda for better representing vehicle purchase decisions in IAMs, as seen from the current perspective of MESSAGE.

The MESSAGE approach disaggregates light-duty vehicle demands into a heterogeneous mix of consumer groups and then assigns additional cost terms ('disutility costs') to the vehicle technologies within each of these groups. In one formulation, consumers are divided up along three separate dimensions, each with three distinct consumer types.

1. *Settlement pattern*: Urban – Suburban – Rural
2. *Attitude toward technology adoption (i.e., Adoption propensity)*: Early Adopter – Early Majority – Late Majority
3. *Vehicle usage intensity*: Modest Driver – Average Driver – Frequent Driver

The combinations possible in this 3x3x3 set-up lead to 27 unique consumer groups. All members of the entire driving population (within a particular model region) fall into one of these 27 groups. Apportionment of vehicle demand by consumer group is based on base-year statistics and projections for population (urban-rural) and GDP, among other things. Figure 4 illustrates this heterogeneous consumer group structure.

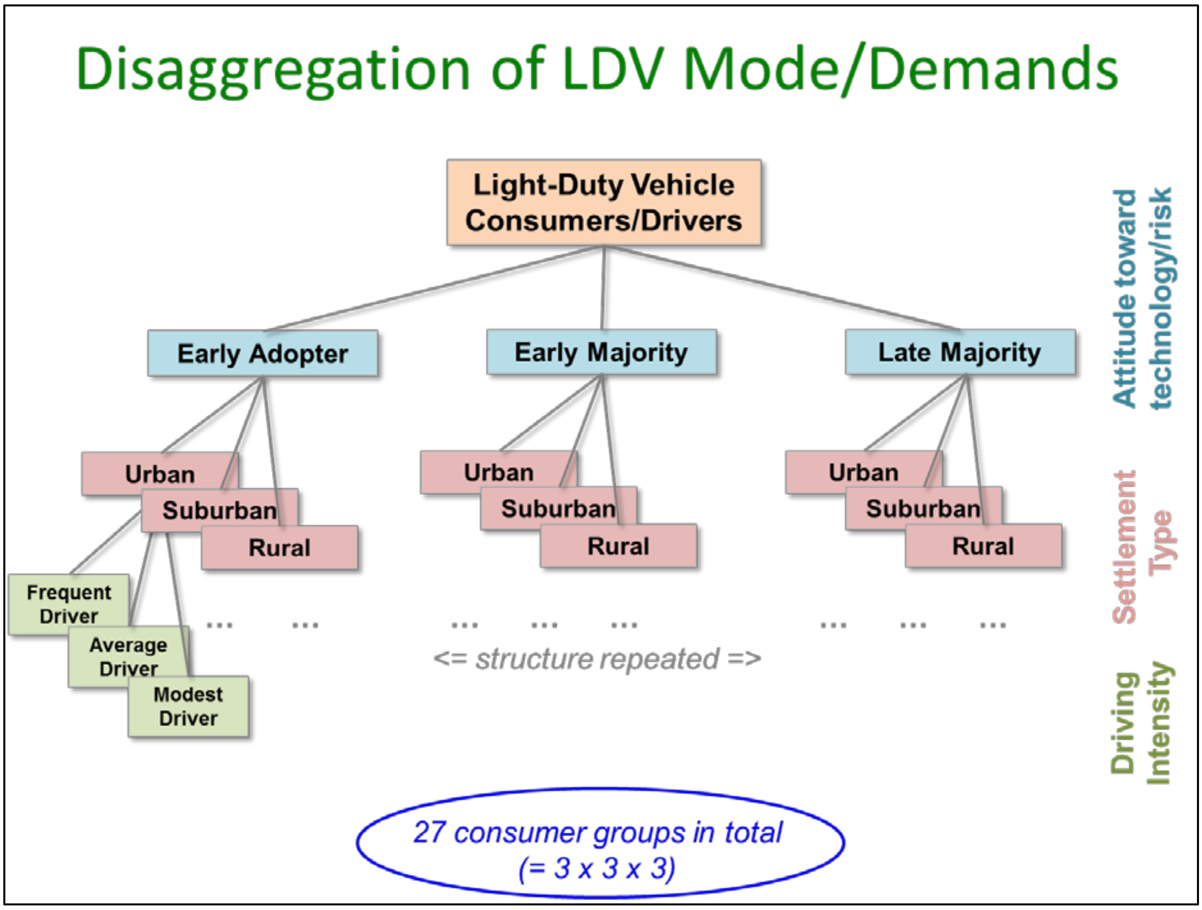


FIGURE 4. SCHEMATIC ILLUSTRATION OF THE HETEROGENEOUS CONSUMER GROUP STRUCTURE WITHIN THE LIGHT-DUTY VEHICLE MODE OF MESSAGE.

Once a disaggregated set of heterogeneous agents has been programmed into the model, the second important step is to assign disutility costs (or inconvenience costs, non-monetary costs, etc.) to each of the vehicle technologies (e.g., gasoline vehicles, battery-electric vehicles) that can potentially be purchased by a consumer within the group. These disutility costs necessarily vary by technology, by consumer group, by country/region, and over time. They are calculated through utilisation of an external discrete choice model known as MA^3T (see http://cta.ornl.gov/ma3t/ or (Lin et al. 2013) for details). The MA^3T model, developed by researchers at Oak Ridge National Laboratory, was originally intended for analyses of vehicle transitions in the US light-duty vehicle sector. The model can be extended, however, to other countries and regions as long as the underlying data is available. Because MA^3T makes use of a Nested Multi-Nomial Logit (NMNL) solution algorithm, it is soft-linked to the optimisation-based MESSAGE model. To give an illustrative example of how this linking works in practice, the disutility costs of an electric vehicle are estimated by MA^3T to be higher for a rural dweller who drives frequently and is typically a late adopter of new technologies than they are for an urban dweller who drives relatively little and is an early adopter. These differentiated costs are then added to the corresponding vehicle technology costs in MESSAGE.

The differences in disutility costs between consumer groups can actually be quite sizeable, particularly in the near term when advanced vehicle penetration remains small. And when implemented into the optimisation model, they can potentially have an important impact on choice outcomes. This is illustrated in Figure 5 for consumers with different attitudes to technology adoption (using illustrative not actual data). In this low-carbon scenario for China, electric vehicles come to dominate the light-duty market much more quickly in the early adopter group, with fossil and biofuel internal combustion engine vehicles persisting well into the second half of the century in the early majority and late majority groups. To be sure, the mere addition of disutility costs to account for non-monetary considerations will likely lead to a delay in the uptake of advanced, low-carbon technologies in an IAM's transport sector compared to a model formulation that does not recognize such considerations. This is because these behavioural considerations generally act as constraints on how quickly consumers adopt advanced vehicle technologies, making them less attractive vis-à-vis the status quo fossil technologies they might intend to replace. In other words, better representing behaviour in an IAM is likely to make the decarbonisation challenge more difficult in the transport sector.

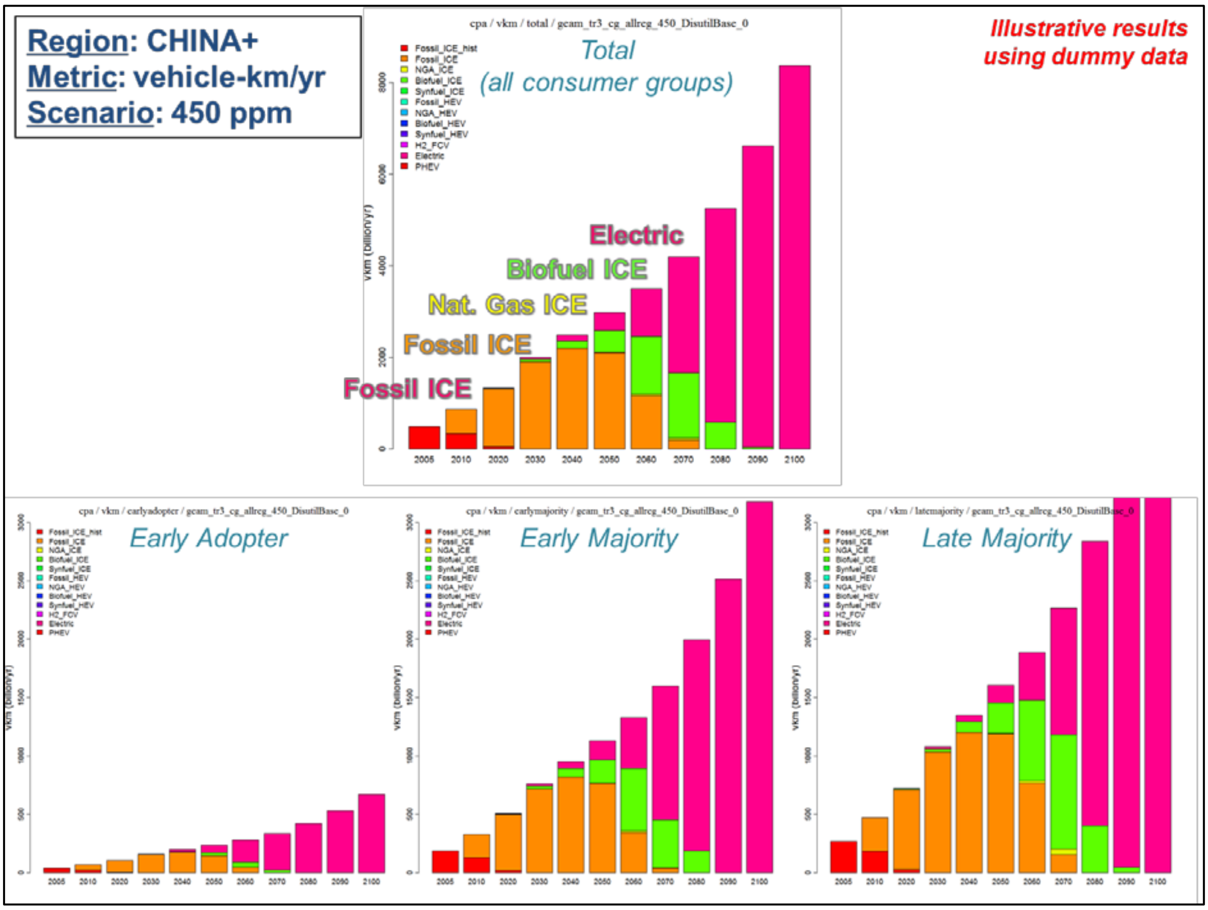


FIGURE 5. ILLUSTRATION OF POTENTIAL IMPACT OF DISAGGREGATING LIGHT-DUTY VEHICLE CONSUMERS AND IMPLEMENTING DISUTILITY COSTS IN AN INTEGRATED ASSESSMENT MODEL.

Once implemented, such an approach to modelling vehicle purchase decisions can allow IAMs to better capture consumer anxieties regarding vehicle range and refuelling and recharging station availability, as well as hesitations among some consumers to adopt advanced, though potentially unfamiliar, technologies. The next logical step would then be to analyse the impact of policies targeted at removing these barriers to technology adoption. These policies might include, for instance, publicly-funded programs to aid the build-out of new refuelling infrastructure (e.g., for hydrogen or natural gas) or the installation of a certain number of electric vehicle recharging stations throughout a metropolitan area. Other policies that can be assessed with this approach are financial incentives for vehicle purchases (e.g., subsidies or tax credits), perhaps even those which are targeted to consumers of a certain type (e.g., urban-based, infrequent drivers).

Recent model inter-comparison projects have made clear that there are notable benefits in using multiple models to address a single question. The modelling of behaviour in the transport sector is no different in this respect. For this reason, the ADVANCE project has developed and is implementing a behavioural research agenda in which the pioneering work on vehicle purchase decisions currently being undertaken in MESSAGE can subsequently be implemented in other IAMs, with a standardised set of policy-relevant scenarios being then run by each model. This would permit the identification of the most robust insights for policy makers. This report establishes the conceptual and empirical basis for this endeavour.

6 APPENDIX A. ADDITIONAL INFORMATION: DISCRETE CHOICE STUDIES OF ALTERNATIVE FUEL VEHICLES

Studies were sampled according to the following inclusion criteria:

1. Empirical studies
2. Published in peer reviewed journals
3. Examine consumer choice between conventional and alternative fuel vehicles
4. Based on discrete choice models
5. Model stated preferences and where revealed preference data is also used we report and compare the findings for stated choices only
6. Similar in overall design although varying in functional forms (logit, mixed logit, nested logit)

Table A1. Sources of studies: peer-reviewed journals.

Journal	**Number of articles included in this review**
Ecological Economics	1
Energy Economics	2
International Journal of Transport Economics	1
Journal of Public Policy and Marketing	1
Resource and Energy Economics	2
Transportation Research Parts A to D	8
Transportation Research Record	1
TOTAL	16

Table A2. Methodological divergence: country, sample, choice alternatives, and modelling approach.

Reference	**Data**	**Dependent Variable or Choice Alternatives**	**Modelling Approach**
Achtnicht et al (2012)	Germany, Aug 2007 – random sample driving age, n=600	gasoline, diesel, hybrid, LPG/CNG, BV, hydrogen, electric	Standard Logit
Ahn et al (2008)	South Korea, July 2005, car owners aged 20 to 59, n=280	gasoline, diesel, CNG, LPG and hybrid	Multiple random effects model (Bayesian)
Axsen et al (2009)	Canada and California 2006, people aged 19+ purchased new vehicle 2002 or later n=950	gasoline, HEV	Multinomial Logit
Batley et al (2004)	UK Jul 01, 179 quota sampled in shopping centre	Conventional vehicle, AFV	Mixed logit
Brownstone et al (2000)	California 1993, randomly sampled, n=4656	gasoline, NCG, methanol and EV	Multinomial Logit
Bunch et al (1993)	California 1991, n=692	Gasoline, AFV, electric	Multinomial Logit and Nested Multinomial Logit
Calfee (1985)	California members local church, n=51	EV, Gasoline	Aggregated & Disaggregated Logit
Dagsvik et al (2002)	Norway 2002, randomly sampled 18-70 yr olds, n=662	Electric, LPG, hybrid, gasoline	Models for ranking
Ewing et al (2000)	Canada 2000, random sample commuters, n=881	Gasoline, AFV	Multinomial Logit
Gaker et al (2010)	USA 2010, sample students taken from pool, n=2500	Conventional, hybrid	Logit
Hackbarth et al (2013)	Germany 2011, n=711	CV, NGV, HEV, PHEV, BEV, BV, FCEV	Mixed logit and nested
Hidrue et al (2011)	USA 2009, n=3029	Conventional gasoline, EV	Latent class random utility
Horne et al (2005)	Canada, 2002/3, n=1150	conventional gasoline, NGV, hybrid electric, FCEV	Multinomial Logit
Lebeau et al (2012)	Belgium 2011, people over 18, n=1197	Conventional vehicle, BEV, PHEV	Bayesian
Mau et al (2002)	Canada 2002 drivers, n=200	Hybrid electric, hydrogen fuel cell	Multinomial Logit
Ziegler (2012)	Germany 2007/8 potential car buyers, n=598	Gasoline, hybrid, gas (CNG/LPG), hydrogen, electric	Multinomial probit

Table A3. Behavioural features examined in studies. (For full typology see Section 2 in main report).

	Behavioural Feature	**Description**	**Constructs examined**	**Number of studies**
Heterogeneity	*Heterogeneous decision makers*	End users are different in their preferences for decision outcomes	Heterogeneous propensity for technology adoption (ownership of various technology/household products) Heterogeneous socio-economic characteristics (age, income, education, gender, children, household size, employment, residency) Heterogeneous vehicle fleet/ownership and travel behaviour (% city trips, long distances driven) Other heterogeneous preferences (attitudes towards environment, threshold purchase price, beliefs about future fuel prices)	10
Individual	*Bounded rationality*	Decisions are made based on incomplete, partial, or local information	None included	0
	Non-optimising heuristics	Decision rules other than optimisation or maximisation are used in specific design contexts	None included	0
	Non-monetary preferences	End users value non-financial attributes of decision alternatives	CO2 emissions, warranties, range, engine power, driving routines, brand image, desired form and quality of vehicle	15
	Context-dependent preferences	Decision context or experience with decision influences preferences	None included	0
	Non-market discount rates	End users' discount rates are higher than market rates and non-constant	Variable discount rates	5
Social	*Social influences & information networks*	Decisions and behaviour are influenced by others	Peer effects, neighbourhood effects, word of mouth information, expert advice, social norms	3
	Strategic decision making	Strategic interactions with others influence decisions	None included	0
Contextual	*Contextual conditions*	Decisions and behaviour are influenced by contextual conditions	Availability of infrastructure (refuelling stations, plug in facilities at home, space for plug in facilities/parking)	10
	Political and social institutions	Decisions and behaviour are influenced by political and social institutions	None included	0

Table A4. Screenshot of layout of annotated bibliography.

	REFERENCE	POST ESTIMATION/SIMULATION RESULTS (discount rates, MWP)	SUMMARY OF FINDINGS	MODEL FIT | EXPLAINED VARIANCE	LOCATION OF SURVEY	DATE OF SURVEY	SAMPLE
[1]	Achtnicht M Buhler G Hermeling C (2012). The impact of fuel availability on demand for alternative fuel vehicles. Tranportation Research D 17:262-269	Estimate marginal willingness to pay for expanded service station network. People whose car budget is less than £20k more price sensitive (their coefficient 3x as large) have lower willingness to pay for improvements in other passenger car attributes. Low vehicles emissions important but deps on env awareness. Utility value for env aware indv is affected more negatively by higher CO2 emissions. Compared to diesel AVFs are preferred by environmentally aware indvs. Other factors affect choice age, desired vehicle range, expected annual mileage. Pref for AFVs decreases with age.	Widespread adoption of AFVs highly dependent on alternative fuel stations although the marginal utility diminishes with more widespread diffusion of fuel stations (-ve coefficient of the squared term). Simulations suggest biofuel and electric cars are unpopular amongst German car buyers and that even with more widespread diffusion of service networks these cars would capture small market shares. Higher rates of diffusion indicated amongst those with high environmental awareness. Lower in older age groups. Higher price sensitivity in group expecting to pay less for next car. Higher desirability for diesel in group expecting to do higher mileage	pseudo r2=0.15	Germany	Aug 2007 to March 2008	random sample 600 German wide via CAPI (Respondents legal age to drive and possess valid drivers licence)
[2]	Ahn J Jeong G Kim Y (2008). A forecast of household ownership and use of alternative fuel vehicles: A multiple discrete continuous choice approach. Energy Economics 30: 2091-2104	Choice of gasoline fueled car is highest in all scenarios tested	Gasoline vehicles preferred followed by CNG, diesel, LPG and hybrid. Coefficients for maintenance cost and fuel cost are significant and negative.	Not included	South Korea	Jul-05	280 households, car owners aged 20 to 59

DESIGN AND ANALYSIS	MEASUREMENT ISSUES	FUNCTIONAL FORM	DEPENDENT VARIABLE | CHOICE	OTHER TREATMENT GROUP CRITERIA/SCENARIO (specific utility functions developed for these groups)	CHOICE ATTRIBUTES	EXPLANATORY VARIABLES
Stated preferences choice experiment. Primary aim to study the impact of fuel availability on demand for AFVs - 7x6 choice set using experimental design	over-representation of education indvs and under-representation of woman and indvs aged 40-49	Standard logit	Fuel type (7 different) Choice between seven hypothetical vehicles with base category=diesel		6 =purchase price, fuel costs, Engine power, CO2 emissions, Fuel availability	Age, environmental awareness, expected annual mileage, desired vehicle range, purchase price threshold
Stated preference analysis using multiple discrete continuous extreme value model (allows for multiple vehicle ownership)		Multiple random effects model (Bayesian)	Five fuel types | gasoline, diesel, compress natural gas (CNG), liquefield petroleum gas (LPG) and hybrid		5 = Body type (ordinary/RV or SUV), Engine displacement, Fuel efficiency, maintenance costs, fuel price	Annual average mileage

7 APPENDIX B. ADDITIONAL INFORMATION: SYNTHESIS OF SOCIAL INFLUENCE STUDIES ON VEHICLE ADOPTION

Table B1. Search terms and inclusion criteria

Search Terms	***Databases (n=280)***	***Inclusion Criteria 1*** ***(n=77)***	***Inclusion Criteria 2*** ***(n=44)***
Social influence OR social norms OR social networks Neighb*effect OR peer effect Or peer influences Media OR information Social diffusion OR innovation Social groups Behav* norms Behav* routines Social risk Social media Word of mouth Social herding Social conformity Personal norms Social symbol Social signal	Science Direct Scopus Google Scholar EBSCO (business source premier, psycARTICLES), marketing journals	Population: sample consists of private vehicle/car owners or potential owners (drivers/adults of driving age). All countries included Includes cars/private vehicles only ie., excludes other modes of personal travel or mode choice. Excludes studies which look at vehicle use, driving patterns, number vehicles owned, car-sharing schemes or model wider transportation systems. Includes studies where there is insufficient information to determine whether or not they fit these criteria based on title/abstract	Include empirical studies only with the exception of simulations where effects are grounded in empirical data (such as agent based models). Includes studies which measure the effects of social status or conspicuous consumption as these are conceptualised as integral to the process and dynamic of social influence, social signalling/information transmission to others. Excludes studies which focus on brand image, brand attributes which are conceptualised as product attributes which can be manipulated. Excludes studies which measure the effects of urban characteristics or characteristics of the built environment unless these are used as a proxy for neighbourhood effects or other social influences. Includes studies which examine the effects of personal norms on intentions/choices etc (as internalised social norms/expectations) Outcomes: must have examined behaviour (ownership, purchase, decision) or behavioural intentions (choice, preferences). Outcomes: can be self-reported/stated or revealed behaviour/preferences.
Vehicle OR automobile OR car AND CHOICE Vehicle OR automobile OR car AND PURCHASE Vehicle Or automobile OR car AND BUY Vehicle OR automobile OR car AND DECISION Vehicle OR automobile OR car AND OWNERSHIP Vehicle OR automobile OR car AND PREFERENCES			

Table B2. Sources of studies.

Journal Type	**Journal**	**Number of articles included in this review**
Conference Proceedings and Working Papers	Conference Proceedings	2
	Working Papers	3
Transportation Related Journals	Transportation Research Parts A – B, D	21
	Transportation Research Record	1
	Transport Reviews	1
	Journal of the Eastern Asian Society for Transportation Studies	1
	Transportation Energy Futures Series	1
Marketing and Business Journals	Journal of Marketing Research	5
	Journal of Consumer Marketing	2
	Journal of Business Research	1
	International Journal of Retail and Distribution Management	1
	Journal of Retailing and Consumer Services	1
	Journal of Marketing Management	2
	Journal of Marketing Theory and Practice	1
	Journal of Interactive Marketing	2
	Marketing Intelligence and Planning	1
	Marketing Science	1
	Journal of Product and Brand Management	1
	Journal of Production and Innovations Research	1
Economics Journals	Journal of Environmental Economics and Management	1
	Journal of Evolutionary Economics	1
	The Review of Economics and Statistics	2
	Rand Journal of Economics	1
	Journal of Urban Economics	1

	Energy Economics	1
	Ecological Economics	2
Environment or Policy Journals	Environment and Planning	2
	Energy Policy	7
Social, Applied and Behavioural Science Journals	Procedia Social and Behavioural Sciences	1
	Australian Journal of Applied and Basic Sciences	1
	Technological Forecasting & Social Change	3
	Expert Systems with Applications	2
Total		74

Table B3. Methodological divergence: data collection and sample.

	Study Characteristic	**n**	**References**
Year of data collection (if reported)	Crosses decades	2	[17] [19]
	2000 onwards	55	[1] [2] [3] [4] [6] [9] [10] [12][13] [14][15] [16] [18][20] [22] [23][24] [27] [31] [35] [36] [37] [38] [40] [41][42] [43] [44] [45][46][47][48][49][50][53][54][55] [56] [57] [58][59][60] [61][63] [64] [65][66][67][68] [69][70][71] [72] [73] [74]
	1999-1990	5	[11] [25] [29] [39] [62]
	1989-1980	3	[8] [32] [34]
	Pre 1980	7	[5] [7] [21] [26] [28] [30] [52]
Sample	Car drivers	5	[4] [35] [36] [61] [64]
	Networked Individuals [a]	6	[19] [48] [49][50] [53] [59]
	Non-specific [b]	21	[3] [10] [11] [13] [15][17] [20] [21] [23] [24] [30][42] [43] [45][46] [56] [60] [63] [66] [67] [72]
	Recent car purchasers	9	[2] [7] [9] [16] [26] [29] [32] [34] [38]
	Vehicle owners (specific) [c]	9	[5] [14] [37] [40] [41][52][57] [58][62]
	Vehicle owners (non-specific)	13	[12] [18] [22] [28] [31] [44] [47] [55] [68] [69] [70] [71] [74]
	Single vehicle households	1	[8]
	Multi vehicle households	1	[25]
	Other [d]	7	[1] [6] [27] [39] [54] [65][73]
Outcomes measured	Preference valuation or choice	29	[2] [4] [5] [8] [10] [11] [12] [14] [21] [24] [25] [26] [27] [28] [29] [30] [32] [39] [42] [43] [47] [50] [54] [58] [62] [64] [70] [72] [73]
	Purchase intentions	15	[1] [3] [13] [22] [31] [35] [36] [40] [44] [45] [46] [59] [61] [65] [68]
	Purchase motivation	10	[6] [7] [9] [20] [34] [37] [38] [52] [56] [74]
	Car ownership (size or growth)	9	[15] [16] [17] [18] [19] [23] [41][53][57]
	Driving experience	2	[49] [55]
	Diffusion, market Share, innovation resistance	5	[60] [63] [66] [67] [69]
	Social influence measure	2	[48] [71]

Table notes: [a] Includes families and friends, work colleagues, linked individuals through internet and social media, neighbours. [b] Includes samples of households or simulations of single agents which are grounded in aggregate data, or synthesis of many samples. [c] Includes small vehicle owners or groups with particular interest in EVs, owners of Toyota Prius, owners with specific patterns of use or driving experience. [d] Includes government workers, online panels, commuters, students, trainees in driving school.

Table B4. Methodological divergence: analytical approach.

	Analytical method	n	References
Quantitative Approach Only	Discrete choice experiment, conjoint analysis	23	[4] [5] [8] [10] [11] [12] [14] [21] [25] [26] [27] [28] [29] [30] [32] [39] [42] [44] [47] [50] [54] [58] [62]
	OLS regression, logit	13	[1] [16] [18] [24] [31] [38] [41][53] [65] [68] [70] [71] [73]
	Hierarchical Bayesian probability model	1	[9]
	Spatial regression model	1	[46]
	Time series models, repeated measures	3	[19] [40] [57]
	Principle components, factor, cluster analysis	3	[35] [37] [69]
	Cohort analysis	1	[17]
	Structural equation or path model	4	[36] [45] [59] [61]
	Multiple methods (mixed quantitave)	4	[3] [6] [22] [74]
	Descriptive statistics (e.g., t-tests, scales, rank orders)	2	[7] [52]
	Visibility index	1	[56]
	Simulation (grounded)	4	[63] [64] [66] [67]
	Agent-based model	5	[13] [15] [23] [60] [72]
Qualitative Approach Only	Ethnography	1	[20]
	Hierarchical decision model	1	[34]
	Semi-structured interviews	2	[43] [55]
	Multiple methods (mixed qualitative)	1	[48]
	Social network analysis	1	[49]
Mixed Method	Quantitative - qualitative	1	[2]
	Qualitative - quantitative	0	

Table B5. Research designs: 72 studies of social influence.

Ref	Citation	Sample, Data	Dependent Variable, Choice Alternatives, Outcome Variable	Analytical Approach
[1]	Aini et al (2013)	Malaysia circa 2013, n=201 government workers	Intentions towards AFV	OLS Regression
[2]	Allis et al (2013)	UK 2012, n=1005 car buyers follow up with 8 focus groups	Relative importance of fuel economy to CO2 emissions as determined by their relative priorities on ECO labelling	Qualitative/descriptive stats
[3]	Anable et al (2011)	UK 2010, n=2729 random individuals	Likelihood of purchasing Electric vehicle in 5 year period	Paired t-tests, factor analysis, stepwise regression
[4]	Baltas et al (2013)	Greece 2013, n=1622 car drivers	Stated preference for new vehicle based on size and body type	Discrete choice experiment
[5]	Beggs et al (1980)	North America 1977, n=326 multi vehicle owners who own small car	Stated preference for small vehicle based on size and age	Discrete choice experiment
[6]	Belgiawan (2013)	Indonesia 2013, 134 students who owned car	Purchase motivation	T-tests, principle component analysis
[7]	Bell (1967)	North America, n=234 new car buyers sampled through local dealerships	Purchase motivation	Summated scale to group owners into three categories
[8]	Berkovec et al (1985)	North America 1985, n=237 single vehicle households	Stated preference for new vehicle based on size and age	Discrete choice experiment
[9]	Blakely et al (2012)	North America 2012, n=1000 individuals recently purchased new car	Purchase motivation	Hierarchical Bayesian probability model (regression)
[10]	Cao et al (2006)	North America 2003, n=500 residents San Francisco Bay	Stated preference for new vehicle based on body type	Discrete choice experiment
[11]	Choo et al (2004)	North America 1998, n=1904 residents of San Francisco Bay	Stated preference for new vehicle based on size and body type	DCE/Multinomial logit
[12]	Darzianazizi et al (2013)	Tehran 2013, n=280 car owners	Stated preference for new vehicle based on brand and related attributes	Conjoint analysis
[13]	Dijk (2013)	Simulation using 1000 agents and 10 supply companies	Innovation trajectories related to conventional engines versus electric/hybrid technology	Agent based model
[14]	Eggers et al (2011)	Germany 2008, n=242 people high involvement in cars or who would buy small vehicle	Stated preferences for AFV	Conjoint Analysis
[15]	Eppstein et al (2011)	Simulation	PHEV market growth	Agent based model
[16]	Gallagher et al (2008)	North America 2000 to 2006, n=4630 sales of hybrid vehicles	Log per capita sales (based on jurisdictions varying according to tax incentives and access to HOV lanes)	Linear regression
[17]	Gallez (1994)	French National Household and Travel survey repeated data 1962, 1972 and 1977-1991	Percentage of motorised households which vary according to birth cohort	Cohort analysis
[18]	Goetzke et al (2012)	North America, n=3322 car owners	Car ownership	Binary probit including instrumental variables

				to account for unobserved heterogeneity
[19]	Grinblatt et al (2008)	Finland, car owners 1999 to 2001	Propensity to own vehicle over 3 year period based on behaviour of nearest neighbours	Pooled time series and cross sectional regressions
[20]	Heffner et al (2007)	North America 2004/5, n=25 households	Personal stories behind purchase of HEV	Ethnographic interviews
[21]	Hockerman et al (1983)	Israel 1979, n=500 HH (mix vehicle and non-vehicle)	Stated preference for first or replacement vehicle based on make, model, body type and age	Discrete choice experiment
[22]	Jansson et al (2010)	Sweden 2010, n=1832 car owners	Willingness to curtain non-green driving behaviours and willingness to adopt AFV	Principal components analysis followed by stepwise regression
[23]	Kim et al (2011)	Korea, Calibration experiment simulating diffusion of 3 vehicles within Korean car market	Mean market share error (difference between actual and modelled data)	Agent based model
[24]	Kishi et al (2005)	Japan 2002/3, n=490 individuals	Choice between conventional gas versus hybrid vehicle	Logit
[25]	Kitamura et al (2000)	North America (1993), n=1898 multi vehicle HH	Stated preference based on body type	Discrete choice experiment
[26]	Lave et al (1979)	North America, n=541 new car buyers	Stated preference based on size and price	Discrete choice experiment
[27]	Lieven (2011)	Germany, 1152 e-commerce customers	Stated preference based on choice first, second vehicle and type	Correspondence analysis
[28]	Mannering et al (1985)	North America 1978, n=3842 single and multiple vehicle HH	Stated preference based on make, model and year)	DCE/Multinomial logit
[29]	Mannering et al (2002)	North America, n=654 HH who had purchased new vehicle 1993/95	Stated preference based on make and model (financing also examined)	DCE/Nested logit
[30]	Manski et al (1980)	North America 1976, n=1200 individuals	Stated preference based on make, model and age	DCE/Multinomial logit
[31]	Marell et al (2004)	Sweden circa 2004, n=513 owners cars less than 10 years old	Propensity to replace existing car	OLS regression
[32]	McCarthy et al (1998)	North America 1989, n=1564 new car buyers	Stated preferences (based on fuel efficiency	DCE/logit
[34]	Murtaugh et al (1980)	North America 1978, n=42 new car buyers	Purchase motivations	Hierarchical decision process model (qualitative)
[35]	Oliver et al (2010)	North America, n=1083 car drivers, circa 2010	Purchase intentions (hybrid)	Cluster analysis, manova
[36]	Oliver et al (2010)	Korea, n=783 USA, n=1083 car drivers, circa 2010	Purchase intentions (hybrid vehicle)	Partial least squares structural model
[37]	Ozaki et al (2009)	UK 2009, n=1263 owners of Toyota Prius	Purchase motivations	Exploratory Factor Analysis
[38]	Prieto et al (2012)	France 2011/12, n=1,967 new car owners	Purchase motivations	Multinomial logit

[39]	Salon (2009)	North America 1997/8, n=2621 commuters	Stated preferences towards travel mode based on car ownership and residency	DCE/Multinomial logit
[40]	Schuitema et al (2010)	UK 2010, n=2728 car owners which high propensity towards EV	Purchase intentions towards AFV as primary/secondary vehicle	Repeated measures ANOVA and OLS regression
[41]	Sierzchula et al (2014)	Multi country comparison 2012, n=30 countries	National market shares of electric vehicles	OLS regression
[42]	Stephens et al (2013)	Meta-synthesis	Non cost barriers to AFV technologies	Synthesis of DCE papers
[43]	Turrentine et al (2007)	North America 2003/4, n=57 Californian households	Fuel efficiency (value and knowledge)	Qualitative Study
[44]	Wu et al (2014)	Thailand circa 2014, n=201 owned or planned to own car	Purchase intentions towards sub-compact vehicles	Conjoint analysis
[45]	Yusof et al (2013)	Malaysia circa 2013, n=250 people over age 19	Purchase intentions towards AFV	Path analysis (OLS regression)
[46]	Adjemain et al (2010)	USA 2000, n=15,064 households	Car Purchase Decision	Spatial regression model
[47]	Axsen et al (2009)	Canada and California 2006, n=943 people over 19 who purchased new vehicle 2002 onwards	Stated preferences HEV versus conventional gas	MNL model
[48]	Axsen et al (2011)	USA 2009, n=10 households and network 40 individuals	Ranking of social influences on perceptions	Multi-method, indepth interviews, social network mapping, diaries, influence ranking
[49]	Axsen et al (2012)	USA ?, n=11 households on 4-6 week trial	Behaviour and experiences of PHEV	Interviews and social network analysis
[50]	Axsen et al (2013)	UK 2010, n=500 members staff (57 taken part in BEV trial)	Preferences for BEV versus conventional vehicle	MNL Model
[52]	Donnelly et al (1974)	USA 1972, n=641 Toyota Maverick owners and control group	Purchase behaviour	Descriptive Stats
[53]	Feng et al (2012)	USA 2000, n=616 consumer reports	Vehicle sales	OLS regression
[54]	Gaker et al (2010)	USA ?, n=312 UC Berkeley Students	Choice between hybrid and conventional gas	DCE
[55]	Graham-Rowe et al (2012)	UK ?, n=40 people involved in trial BEV and PHEV	Perceptions of BEV	Qualitative Study
[56]	Heffetz (2011)	USA 2004/5, n=480	Purchase behaviour	Creation of visibility index using survey
[57]	Heutel et al (2010)	USA 2000/2006, n=?	Hybrid Sales	Fixed effects panel regression model
[58]	Hsu et al (2013)	Taiwan 2011, n=1594 experienced and inexperienced drivers	Stated preferences	DCE followed by simulation

[59]	Hutter et al (2013)	Germany ?, n=311	Purchase intention	Structural equation model
[60]	Huetink et al (2005)	Simulation (number agents?)	Rate of diffusion	Agent based model
[61]	Jalilvand et al (2011)	Iran 2011, n=341 potential customers well known auto brand	Purchase intention	Structural equation model
[62]	Kulkarni et al (2012)	USA 1999, n=886 internet and non-internet users	Choice of family sedan	DCE
[63]	Lee et al (2013)	Korea ?, n=1	Market Share	Simulation drawing on results DCE
[64]	Mau et al (2008)	Canada, n=2000	Stated preference	Simulation drawing on results DCE
[65]	Moons et al (2012)	Belgium 2009, n=1202 students	Intention to use EV	OLS Regression
[66]	Park et al (2011)	?	Diffusion of HFCVs	Simulation drawing on results DCE
[67]	Shafiei et al 2012)	Iceland 2011, n=1	Consumer behaviour and market share of EVs	Simulation based on real world data
[68]	Shemesh et al (2014)	USA 2004/2006, n=7 million	Propensity to buy luxury car	OLS regression
[69]	Wiedmann et al (2011)	Germany ?, n=480	Resistance of innovation	Factor analysis, path analysis, cluster analysis
[70]	Yang et al (2003)	USA ?, n=857 consumers	Purchase of mid size car	Auto-regressive MN probit
[71]	Yang et al (2012)	UK 2007, n=4544 people purchased car in previous 12 months	Propensity to generate word of mouth following purchase car	Bivariate probit
[72]	Zang et al (2011)	?, n=7000	Vehicle choice	Agent based model
[73]	Zang et al (2011)	China 2010, n=299 driving school pupils	Willingness to choose EV	Binary logistic regression
[74]	Zhu et al (2013	USA ?, n=15,884 households	Purchase motivation	Cluster analysis and logit

Table B6. Screenshot of layout of annotated bibliography.

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