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Agent-behaviour and network influence on energy innovation diffusion

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ABSTRACT

An agent-based model is developed for investigating the role of individual behaviour and network influence on energy innovation diffusion. Behaviour is based on how agents value specific attributes of a technology, and network effects are disaggregated into indirect influence through exposure to a larger population, and direct influence through personal contacts. We find that network influence can have a positive effect on accelerating the diffusion of new energy innovations, but can be counteracted by risk adverse behaviour. Combined direct and indirect network effects can have as strong an influence on adoption behaviour as personal preferences. Interestingly, we find that indirect influence from the larger population can have a greater effect than direct personal contacts on an individual. This implies a feedback between population and sub-population level signals on adoption behaviour which warrants further exploration as a mechanism to induce individual level change.

1. Introduction

Global sustainable energy and environmental policies have increased the need to understand how new energy innovations diffuse into the market [1]. A central uncertainty is whether the market for new energy innovations can be sustained into the future. Although lessons have been learned from previous attempts to develop green technology markets in general and alternative fuelled vehicles (AFVs) in particular, policymakers often overlook this question [2]. Policy needs to be better informed about the necessary conditions for successful market introduction and penetration of new energy innovations [3]. This will depend on understanding the behaviour of highly heterogeneous consumers and the underlying mechanisms by which innovations spread throughout society.

There is growing empirical evidence that adoption of new energy innovations, such as hybrid electric vehicles (HEVs) can be reinforced by adherence to group behaviour and social norms [4,5]. Adopters can be geographically clustered constituting a sub-population or social network [6,7]. Theoretical and empirical research shows that adoption behaviour is a function of both individual preferences [8–10] and social network influence [6,11]. There can be a feedback effect between decision-makers that can reinforce particular behaviours over time [12] implying that a strong enough feedback effect could accelerate diffusion [13]. This has important implications for energy policy where decarbonizing the transport sector is contingent on rapid diffusion of AFVs [14]. Although energy policy has been informed by macro level modelling [15–19] there is need to develop disaggregated techniques to assess how individual behaviour can be influenced, or reinforced by network processes.

Personal preferences and network effects influence adoption behaviour yet those two factors are not typically integrated into diffusion modelling. Advanced methods for modelling individual-level behaviour, such as discrete choice analysis generally assume that individuals do not account for how their choices affect others [13,16]. Recent efforts have begun to

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address this gap by integrating social influence into choice modelling [12,13,20–23]. However, assumptions are still often imposed to make social effects consistent with individual utility maximization [20].

Adoption behaviour and social influence have a history of being modelled at the aggregate level [24–28]. Although aggregate diffusion models have been successful in forecasting market trends, they do not capture heterogeneous behaviour, a central feature of diffusion processes [29]. Aggregate modelling techniques show diffusion to be a smooth logistic *S*-curve, which can miss the high degree of variability, particularly during the early phases of diffusion [29,30]. Fig. 1 shows empirical diffusion curves for various AFVs in the US indicating different trends. This variability can be caused by multiple diffusion processes occurring simultaneously via inter-market competition, and inherently random consumer behaviour not captured by aggregate techniques [29,31]. This implies the need for considering how consumers make trade-offs when faced with different available market options and other non-linearity such as multiple diffusion processes occurring simultaneously.

Adoption behaviour is governed by non-linear interactions between heterogeneous agents. There is much potential for analysis from a complex systems perspective [29,33,34]. The objective of this paper is to develop a complex systems approach that builds upon earlier research by integrating individual choice behaviour and network influence using an agent-based modelling (ABM) framework. The flexibility of an ABM can relax many of the assumptions implicit in conventional diffusion models [29]. We proceed by assessing empirical data to inform our modelling framework, derive the ABM and give data, present simulation results, and conclude with limitations and further research.

2. Empirical analysis of agent choice and network influence

2.1. Agent choices and preferences

Empirical analysis indicates that adoption behaviour proceeds in various stages including: (1) acquiring information through social interaction, (2) forming an individual attitude, (3) making a decision to adopt; and (4) implementing and (5) confirming the decision [33]. In the second stage potential adopters develop a general attitude towards an innovation based on their perception of its characteristics. Perceived innovation characteristics are an important explanation for the rate of adoption [5]. Fig. 2 shows the top factors for adoption between HEV and conventional vehicles.

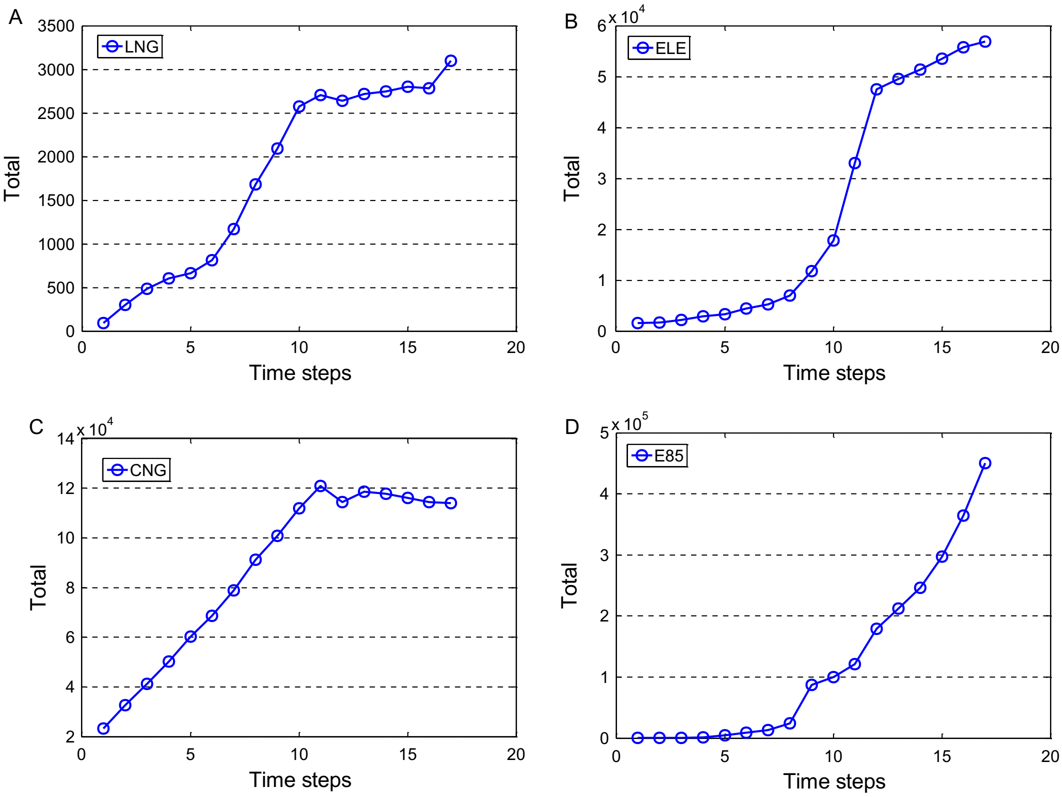

Fig. 1. Cumulative adoption curves for (A) liquefied natural gas (LNG), (B) full battery electric, (C) compressed natural gas (CNG), (D) ethanol-85 (E85), US 1992–2008. *Notes*: Cumulative vehicles in use, less retirements at end of each calendar year. Data from [32].

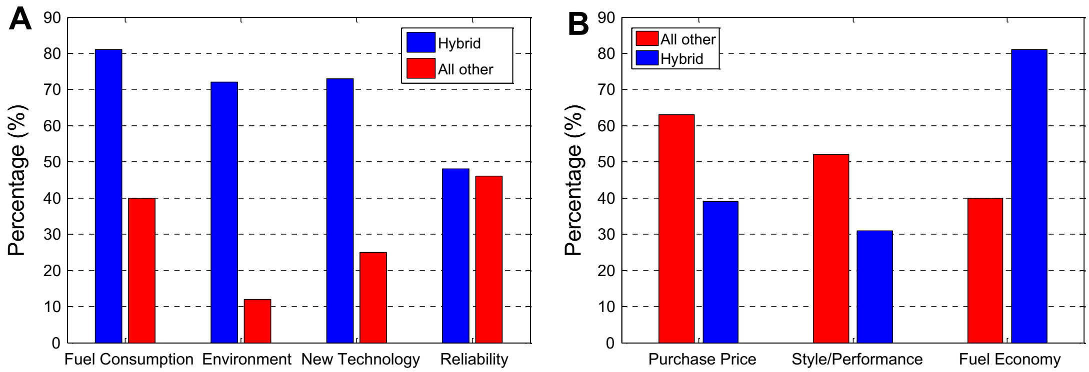

Fig. 2. (A) Top factors for HEV adoption relative to all other buyers; (B) major differences in reasons to adopt between all other and HEV buyers. *Notes*: Arithmetic mean across US (N = 25,244), Germany (N = 16,300), France (N = 14,000), UK (17,000). Data from [35].

When looking at mean values across regions the top factor for HEV adopters was fuel consumption (81% HEV versus 40% for all others); second, interest in new technology (73% HEV versus 25% for all others), third, environmental appeal (72% for HEV versus 12% for all others) and fourth, reliability (48% for HEV and 46% for all others). Although reliability features as a common purchasing motivation, factors that most influenced non-HEV adopters were notably different. The largest differences in important adoption factors were >63% of all other buyers cite purchase price versus 39% for HEV, ~52% of all others cite vehicle styling versus 31% for HEV, and only 40% of all others cite fuel economy, far less than the 81% for HEV buyers [29]. This suggests that adoption behaviour is characterized by highly heterogeneous consumer preferences across populations.

2.2. Social network influence on adoption behaviour

Innovations can diffuse through communication channels over time among members within a social system [24,33]. Empirical research on the purchasing motivations of HEV adopters indicate that a strong motivating factor was compliance to the social norms of a community with adopters geographically clustered [5]. This type of localization can create an ideology or perception that hybrid car ownership reflects a particular community's values and norms [6]. Fig. 3 shows the percentage of adopters that claimed they were first among their social group to be attracted to new innovations. The percentage of HEV adopters that made their decision relative to how they perceived themselves within a larger social network was higher than for buyers of incumbent technologies. This suggests a feedback mechanism where individual behaviour could be influenced or responsive to signals sent from the group at large and vice versa. If a social group perceives an individual to be an early adopter, this could reinforce the propensity of that individual to continue to fill that role. In turn, the social group would be better informed and attracted to a particular innovation since it is valued by a peer within the group.

Across different markets, individual choices were made within the context of a larger network. More direct evidence of network influence was found in France where 30% of respondents indicated that an important factor to adopt an HEV was a preference to buy things that friends or neighbours approved of [35]. Empirical research in the UK also indicates that social networks played an important role in familiarizing potential adopters to the benefits of HEVs which led to adoption [5]. Conversely, 43% of HEV buyers in Germany disagreed that their purchasing decision was to gain the approval of friends and neighbours [35]. Network influence can therefore vary greatly across different populations, which should be accounted for in policy formulation and industry marketing campaigns. In summary, extensive research indicates that agents not only

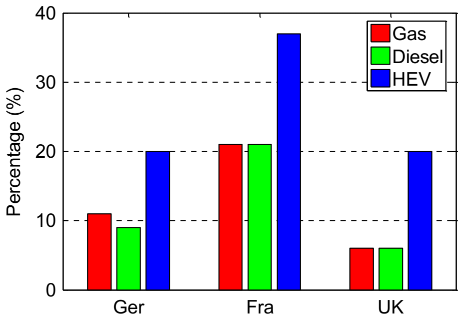

Fig. 3. Factor that influenced purchasing decision: percentage (%) of survey respondents that claim 'I'm always one of the first of my friends to try new products/services. Data from [35].

make a distinction between personal preferences and social network influence, but consider those internal and external influences in the decision making process [24,25,28,33]. In making the decision to adopt an individual takes stock of internal preferences and weighs that against their perception of social norms of the larger group. This balancing of individuality and social acceptance suggests people adopt new products based on a need for both assimilation and differentiation depending on the level of desire to be distinct from others, similar to the group, and on the size of the perceived group [36].

3. Methods and materials

3.1. Model derivation

We develop a flexible agent-based modelling (ABM) framework to examine adoption behaviour. ABM's have been used to study a number of product diffusion processes [37–41] including AFVs [42]. Our work builds on those studies, but also differs because we account for individual preferences. This allows us to assess how agents make trade-offs as a function of personal preferences when faced with multiple options. Network influence will also vary for different options. For instance, social network influence proved to be a stronger motivating factor for HEV adoption than for petrols. So by combining individual choice behaviour and network influence into a single model, we can assess the full range of options available to individuals and the different levels of network influence associated with each option. Conventionally, innovation diffusion has been modelled as a function of communication processes beginning with the Bass [25] model:

$$\frac{dn(t)}{dt} = [M - n(t)] * [p + \frac{q}{M} n(t)], \quad n(0) = 0 \tag{1}$$

where $n(t)$ is the number of individuals that adopted the product by time t, and M is the population size. The parameter, p captures external influences on the likelihood of adoption such as mass media and, q represents the influence of other individuals who have already adopted. While the model has been successful at forecasting aggregate market trends considerable effort has since been made to model individual level behaviour to capture agent heterogeneity [43]. In the marketing literature, among the first of these were ABM's developed in [29,31,34] such as the following binomial formula:

$$\mathrm{Prob}(t) = 1 - (1 - p) * (1 - q) \wedge k(t) \tag{2}$$

where $\mathrm{Prob}(t)$ is the individual probability of adoption at time, t and, $k(t)$ are the number of previous adopters that the individual interacts with while, p and q are the parameters specified in the Bass model. The ABM algorithm [31] specifies that in the initial condition $t(0)$ no individual has yet adopted; in time step, $t + 1$ the probability function, $\mathrm{prob}(t)$ is applied to each agent and stochasticity is introduced to capture random behaviour where a random number, U is drawn from a uniform distribution, $[0,1]$. If, $\mathrm{prob}(t) > U$ than adoption occurs and the agent is assigned a value of 1. By summing the number of one's over period, $t + n$ cumulative adoption is determined. In our simulations we repeat this process for, $t + 1000$ and analyze both short term, $t < 100$ and longer term, $t = 1000$ diffusion patterns.

3.1.1. Agent choice

Although we maintain the ABM framework and implementing algorithm given above, we reinterpret Eq. (2) as:

$$\mathrm{Prob}(t) = 1 - (1 - P_{ij}) * (1 - Q_{ij}) \wedge K_{ij}(t) \tag{3}$$

where P_{ij} captures individual choice in the adoption process [33]. We follow a discrete choice modelling framework used for evaluating consumer decision-making [44–46]. The probability to adopt is motivated by the perceived utility that a consumer derives from the technology based on valuation of technology attributes [47]. The model captures heterogeneity in an individual's sensitivity to different attributes of a particular innovation [33]. The probability to adopt motivated by individual preferences takes the following form [48]:

$$P_{ij}(\theta) = \int_{-\infty}^{+\infty} L_{ij}(\beta) f(\beta|\theta) d(\beta), \quad L_{ij}(\beta) = \exp(\beta' x_{ij}) / \sum_j \exp(\beta' x_{ij}) \tag{4}$$

where P_{ij} is the probability that individual i chooses option j. The vector x_{ij} are observed variables specific to individual i and option j and β represents parameters which are random draws from a density function $f(\cdot)$ and theta θ is a vector of underlying moment parameters characterizing $f(\cdot)$. The random-coefficients structure specified as the utility U_{ij} that individual, i associates with option, j is

$$U_{ij} = \beta_i' x_{ij} + \varepsilon_{ij}, \tag{5}$$

where x_{ij} is a vector of exogenous attributes β_i is a vector of coefficients that varies across individuals with density $f(\beta)$, and ε_{ij} is assumed to be an independently and identically distributed (iid) across alternatives type I extreme value error term. With this specification the choice probability of alternative j for individual i is given by Eq. (4). While several density functions can be used for $f(\cdot)$ we use the normal and lognormal distributions, which are the most common [48–50]. A lognormal distribution is used to specify a beta (β) coefficient having the same sign (±) for all individuals. This allows us to assume global preferential behaviour for specific attributes under different scenario assumptions. For example, a negative coefficient for purchase price is used assuming all consumers are negatively influenced to adopt from high vehicle costs, or we can simulate early adopters by giving preferential weighting for a low CO_2 emitting vehicle attribute such as battery electric vehicles (BEVs). Eq. (4) does not have a closed form so is numerically integrated using Monte Carlo simulations following an algorithm [50]: Take a random draw, R of β's from a density $f(\beta|\theta)$ such that,

$$(\beta_n) \sim f(\beta_n|\theta) \tag{6}$$

Calculate the conditional probability, L_{ij}

$$L_{ij} = e^{\beta' i * X_{ij}} / \sum_{j=1}^{J} e^{\beta' i * X_{ij}} \tag{7}$$

Repeat R times such that

$$P_{ijn} = \frac{1}{R} * \sum_{r=1}^{R} L_{ij}(\beta^r) \tag{8}$$

as R increases variance decreases, and average at each time step, n. P_{ijn} is the simulated probability of agent i adopting option j in time step n based on individual preferences given by $f(\beta)$ for a vector of attributes x_{ij} associated with option j. The flexibility of the choice model allows us to develop scenarios where we can assume different preferences for specific technology attributes capturing consumer heterogeneity.

3.1.2. Network influence

The external network effect on potential adopters is a function of the total number of previous adopters in a population [24,25]. Previous adopters can influence potential adopters through indirect exposure amongst the larger population, or direct exposure from an agent's personal network [29]. Network effects can be captured [30] where a product's value, V depends on the number of users, N in a total population, Nt according to some function, $F(x)$ such that,

$$V(N) = V(p) = F(x) \tag{9}$$

where p is the fraction of the population that has already adopted the innovation giving

$$V(p) = N/Nt \tag{10}$$

The potential to adopt is than based on an agent's estimate of, V. Although agents do not know the exact number of adopters in a population, $V(p)$ if we assume that each person is exposed to, n other people in a local population, they can estimate the fraction of adopters in that local population. Therefore person, k's estimate of the fraction of adopters in a local population is,

$$p_k = n_k/n, \tag{11}$$

where n_k is the number of previous adopters in a local population that, k is exposed to. Network influence from a local population therefore enters our model as,

$$Q_{ij} = V(p_k), \quad p_k = n_k/n \tag{12}$$

where Q_{ij} is the indirect network influence upon agent, i to adopt innovation, j as a function of the number of previous adopters, n_k out of a local population, n that the agent is exposed to. We reinterpret from [33] that an agent, k is connected to, n other people as, k being exposed to a local population comprised of, n other people. That is, our Q_{ij} parameter reflects, q in the Bass model (Eq. (1)), which represents the indirect influence by other individuals out of a population, M who have already adopted.

Along with indirect exposure diffusion processes are strongly influenced by direct network interactions where current adopters can persuade or entice non-adopters [11]. Direct network influence can be captured by a contagion model where an individual's likelihood of adoption increases as the proportion of users in his/her personal network increases. Direct network exposure from non-random mixing is given by

$$E_i = \sum w_{ij} y_i / \sum w_i \tag{13}$$

where E_i is the proportion of personal contacts that have adopted based on, w which is a social network weight matrix and, y is a vector of adoptions [11]. When network exposure is measured on direct contacts it can capture social influence through overt transmission of information, persuasion or direct pressure. Exposure can also be calculated by transforming the social network, w to reflect other social influence processes [51]. We specify, w as the proportion of personal contacts that have already adopted an innovation and are able to exert direct influence upon an agent that has not yet adopted. Therefore, direct network influence, K_{ij} for agent, i to adopt innovation, j is a function of the proportion of an agent's personal network of contacts that has already adopted in time, t given by,

$$K_{ij}(t) = E_i = \sum w_{ij} y_i / \sum w_i \tag{14}$$

Therefore the master function is,

$$\mathrm{Prob}(t) = 1 - \left(1 - \left[\frac{1}{R} * \sum_{r=1}^{R} L_{ij}(\beta^r)\right]\right) * (1 - [n_k/n]) \wedge \left(\sum w_{ij} y_i / \sum w_i\right) \tag{15}$$

3.1.3. Modelling limitations

The model implies three distinct but inter-related factors that influence adoption behaviour including individual choice, P indirect network influence from a local population, Q and direct network influence from personal contacts, K. One can see from equation 15 that the model assumes feedback between all of those parameters but the structure of personal networks in a social system can vary considerably [34]. Previous research has shown the importance of rewiring (making new friends) and network growth (population increase) [52,53]. But empirical findings on exact network structure are scarce leaving researchers to make simplifying assumptions to assess how individual behaviour might aggregate to a larger social system [52,54]. We therefore make simplifying assumptions and develop different scenarios to execute the ABM. Although we parameterize the model with empirical data where possible, the analysis is mostly based on synthetic output data from the model. To ensure robustness we conduct sensitivity analysis on all model parameters.

3.2. Data and scenarios

3.2.1. Agent choice scenarios

We first run the individual preference algorithm to show varying types of adoption behaviour under different scenario assumptions. Table 1 summarizes the technology choice set and vector of attributes that the agent is faced with. We assume petrol, diesel, and hybrids (HEVs) have 100% access to refuelling opportunity i.e. no range anxiety. A recent US survey [55] implies that 39% of respondents have access to home charging facilities, so we conservatively set plug-in hybrid (PHEV) charging at 30%. The main constraint for short range full battery electric (BEV) and H_2 fuel cell (FC) is on-road refuelling availability, which is currently marginal so we arbitrarily set refuelling availability at 1% relative to ICEs. All vehicle attributes, X_{ij} are normalized and indexed against petrol vehicles to assess the relative performance of alternatives against petrols (Table 2). Consumer preference heterogeneity is simulated by changing the distributions of $f(\beta|\theta)$ under different scenario assumptions. Four choice scenarios are developed to reflect different agent behaviour including: mass market, early adopter, trade-offs, and exogenous effects.

Mass market – industry survey data [63] indicates purchase price and reliability are important factors for vehicle buyers. Another key barrier for AFV adoption is the lack of refuelling infrastructure [64]. We therefore give preferential weighting to purchase price and refuelling availability by specifying $f(\cdot)$ as lognormal suggesting that consumers are negatively influenced by high purchase prices and lack of refuelling infrastructure to adopt AFVs. Normal distributions are used for all other

Table 1
Vehicle technology attributes.

Technologies	Purchase price (2011 USD)	Fuel price (USD/ 160 km)	Fuel consumption (L/100 km)	Performance (acceleration 0-100 km/h in seconds)	Range (Km on 1 tank/ charge)	Environment (annual WTW GHG CO_2-eq emission, metric tonnes)	Refuelling availability (%)
Petrol	16,640	12.9	8.1	6.5	567	5.9	100
Diesel	20,180	11.5	6.9	8.7	714	5.7	100
HEV	26,155	8.45	4.7	10	862	3.9	100
PHEV	40,280	7.63	4.5	12	764	4.0	30
BEV	32,780	3.74	2.4	11	117	3.6	1
FC	100,000	5.00	3.9	12	384	3.2	1

Data and assumptions: fuel price, consumption, range and emissions and range [56,47,62]; FC purchase price [58,59]; acceleration: petrol, diesel and BEV from company websites and [57], HEV [60], PHEV and FC [61]; refuelling availability is a relative measure of range anxiety and does not imply number of refuelling stations.

Table 2
Model input parameters. All values normalized and indexed against petrol.

Technologies	Purchase price (PP)	Fuel price (FP)	Fuel consumption (FC)	Performance (Perf.)	Range (Rang.)	Environment (Env.)	Refuelling availability (RA)
Petrol	1	1	1	1	1	1	1
Diesel	1.21	0.90	0.85	1.34	1.26	0.97	1
HEV	1.57	0.66	0.58	1.54	1.52	0.66	1
PHEV	2.42	0.59	0.56	1.85	1.35	0.68	0.3
BEV	1.97	0.29	0.29	1.69	0.21	0.61	0.01
FC	6.00	0.39	0.48	1.85	0.68	0.54	0.01

Table 3
Sensitivity analysis on all parameters.

Simulations	P	Q	K
1	0.1	0.1	0.1
2	0.9	0.1	0.1
3	0.1	0.9	0.1
4	0.1	0.1	0.9
5	0.1	0.9	0.9

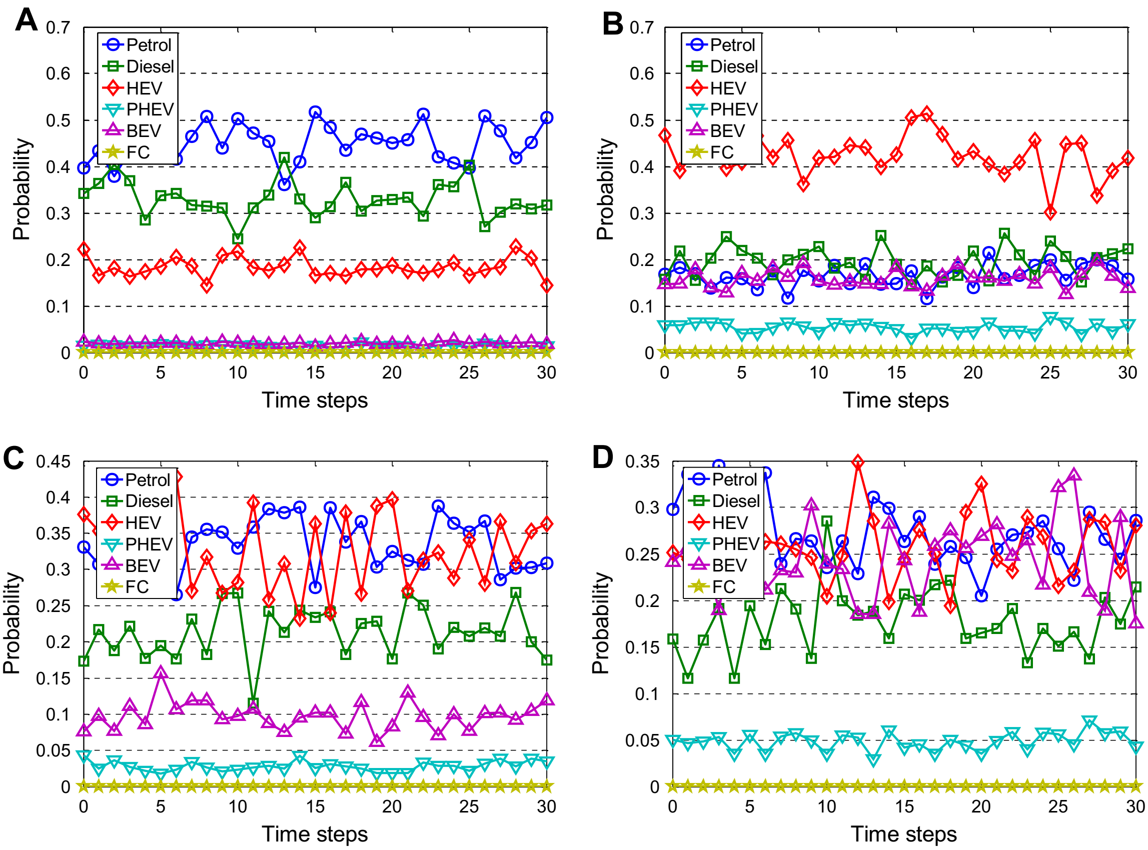

Fig. 4. Adoption behaviour as functions of heterogeneous agent preferences over time: *A* = mass market, with sensitivity to purchase price and overall reliability (proxied by refuelling availability); *B* = early adopter, with sensitivity to economic and environmental factors i.e. improved fuel economy and CO_2 emission; *C* = trade-off, where agents weigh attributes of AFVs equally against attributes of ICEs i.e. preferential weighting for performance, proxied by acceleration; *D* = exogenous effects, where adoption behaviour is influenced by increasing levels of refuelling availability for AFVs: PHEV (80%), BEV (80%), FC (50%).

attributes indicating greater heterogeneity in agent preference for the remaining attributes. For all simulations normal distributions have a mean value that fluctuates around zero, for lognormal distributions ∼1.4 and both distributions have a standard deviation of one.

Early adopters – improved fuel economy and environmental performance were strong motivating factors for HEV adopters [5,35]. We therefore give preferential weighting to lower fuel prices, better fuel economy and lower CO_2 emissions. We assume that HEV early adopter characteristics can give insight into early adoption for other AFVs. The negative effects on adoption of purchase price and refuelling availability are also maintained in order to compare potential early adopters against the mass market.

Trade offs – although some agents may favour environmental performance and the financial benefits of improved fuel economy, we also know from empirical studies that those same people are also not entirely willing to sacrifice technological performance and style [64]. We therefore develop a choice situation that accounts for an agent that weighs those different factors against each other in the adoption process. We proxy performance and style with vehicle acceleration. While AFVs outperform conventional vehicles (ICEs) in fuel economy and environmental performance, advanced petrols have better acceleration and customers typically associate high-performance specification vehicles as petrol vehicles. By giving preferential weight to acceleration, this choice simulation levels the playing field between ICEs and AFVs.

Exogenous effects – empirical and theoretical work shows that consumers are heterogeneous reflecting different personal tastes, values, and perceptions. Those factors can all potentially influence the decision-making process leading to different outcomes, even when agents are faced with the same set of options [24,33]. But the value or utility of an innovation perceived by an agent will also be influenced by exogenous factors such as supporting infrastructure for the technology. For instance, consumers consistently indicate that they would not be willing to adopt AFVs unless refuelling availability is comparable to the incumbent system [63]. We therefore develop simulations with increasing penetrations of refuelling infrastructure and specify the refuelling parameter for PHEVs and BEVs at 80% each and FCs at 50% relative to ICEs. All other parameters from the Trade-off scenario are held constant to give an indication of how AFVs might compete against ICEs with better support infrastructure. The agent therefore now weighs the inherent attributes of each technology along with exogenous factors such as support infrastructure when formulating an overall opinion of the technology.

3.2.2. Network influence scenarios

The results of each choice simulation are used as input values (P_{ij}) into the ABM framework (Eq. (15)). Since we are interested in assessing how network influence will be weighed against individual preferences for diffusion of a new energy innovation, we use the mean probability, P_{ij} values for BEVs. From the four choice scenarios the lowest and highest, P_{ij} values are selected to assess the range of effects on adoption when considering network influence. The ABM algorithm is then implemented (Prob($\underline{t}$) > $U[0,1]$: yes → adopt (1); no → do not adopt (0); iterate $t + 1000$; sum 1's; end). In the first network simulations indirect (Q) and direct (K) influence is held constant to see the effects of varying agent choice preferences on both short term ($t = 100$) and long-term ($t = 1000$) diffusion patterns. We also consider how different network structures can influence diffusion dynamics. Two cases are considered: (1) random mixing in the local population and (2) network clustering characterized by small world effects [65,66].

Random local mixing – for random mixing we arbitrarily assume an agent is exposed to, $n = 100$ individuals in their local population at any given time, and in the case of a new innovation a minority 30% has adopted ($n_k = 30$) thus assigning a value of, $Q_{ij} = 0.3$. The individual's personal network, w is specified as a smaller fraction ($w/n < n$) of the larger population and arbitrarily set the personal network, $w = 10$ or 10% of the local population. We can also assume that an individual's personal network lags behind the larger population in willingness to adopt for any variety of reasons. For example, the group does not share the values and norms of the larger population, individuals might be more risk averse which reinforces a typical behaviour within the group, or simply there is a weak feedback effect between the larger population and the individual's personal network. In the first set of simulations we can simulate some of those sub-network structures by specifying personal network adopters, $y_i = 1$, and therefore assign a value, $K = 0.1$.

Network clustering – originating with Milgram's [65] study it was speculated that a 'small world' was a network with a surprisingly few degrees of separation between agents despite people tending towards cliquish social networks. It was subsequently shown that small-world networks constituted a distinct class of networks that have short average path lengths (L) and high clustering coefficients (CC); where, L measures the degrees of separation between two agents in a network and, CC measures how many contacts are connected to each other [66]. In the context of diffusion, shorter average path lengths infer that people, ideas and resources are closer to each other in a network, and high clustering suggests greater exposure to those ideas and resources. Many real world social networks are characterized by people's friends also being friends of each other (triads). This means that a typical social network has high clustering because the probability of neighbouring nodes being connected is relatively higher than the probability of non-neighbouring nodes being connected. Conversely, in random networks, neighbouring nodes and non-neighbouring nodes have the same probability of being connected [67].

We use a simple example of network clustering where adoption behaviour spreads more efficiently between individuals that have a higher potential of interacting with each other following [30]: Consider a local population of agents, $n = 100$. Assume the population is split into two subpopulations where there is a relatively higher probability that people from the same subpopulation come into contact or are otherwise exposed to each other. We can specify that the probability that two people from the same subpopulation interacting is 50% ($p_1 = 0.5$), and the probability that two individuals from different subpopulations interacting is arbitrarily lower at 10% ($p_2 = 0.1$). If $n = 100$, the average total probability, $\hat{p}_t$ for interactions on any given node in that network is $\hat{p}_t = p_1 + p_2 = (0.5 * 50 + 0.1 * 50 = 30)$. If we equate adoption behaviour as a function of exposure through interactions on a local network such that, $\hat{p}_t = p_k = n_k/n$, where $n = 100$ we can assign a value, $Q_{ij} = 0.3$. This gives our original value assignment for, Q_{ij} from random local mixing. Both specifications of Q_{ij} are equal suggesting few long-range interactions. However, if we now consider small world effects characterized by short path lengths, L and high clustering, CC we can assume that there are more long-range interactions between people from different subpopulations and increase their probability of interacting. In the second set of simulations we therefore hold, p_1 constant but specify p_2 = 30%, 50%, 70% and 90% to simulate increasing small world effects. This transforms value Q_{ij} = 0.4, 0.5, 0.6, 0.7. We run simulations with the new Q_{ij} values and hold K_{ij} constant at 0.1 to see the influence of increasing small world effects. We than re-run the simulations but now assume that the agent's personal network reflects the larger population and specify K_{ij} = 0.4, 0.5, 0.6, 0.7 in order to see combined indirect and direct network effects on adoption.

Table 4
Mean preferences (P_{ij}) for adoption per technology for each simulation (%).

Simulations	*A*	*B*	*C*	*D*
Petrol	45	17	33	27
Diesel	33	20	21	18
HEV	18	42	33	26
PHEV	1.5	5	3	5
BEV	2.0	16	10	25
FC	0	0.0001	0.0001	0.0001

Notes: Number of random draws for all simulations N = 1000; Beta coefficient distributions for each simulation (*n* = normal, log = lognormal): *A* = PP (−log), FP (*n*), FC (*n*), Per (*n*), Rang (*n*), Env (*n*), Refuel (+log); *B* = PP (−log), FP (−log), FC (−log), Per (*n*), Rang (*n*), Env (−log), Refuel (+log); *C* = PP (−log), FP (−log), FC (−log), Per (−log), Rang (*n*), Env (−log), Refuel (+log); *D* = PP (−log), FP (−log), FC (−log), Per (−log), Rang (*n*), Env (−log), Refuel (+log). Refuelling assumptions *A*–*C*: Petrol (100%), diesel (100%), HEV (100%), PHEV (30%), BEV (1%), FC (1%); *D* = Petrol (100%), diesel (100%), HEV (100%), PHEV (80%), BEV (80%), FC (50%).

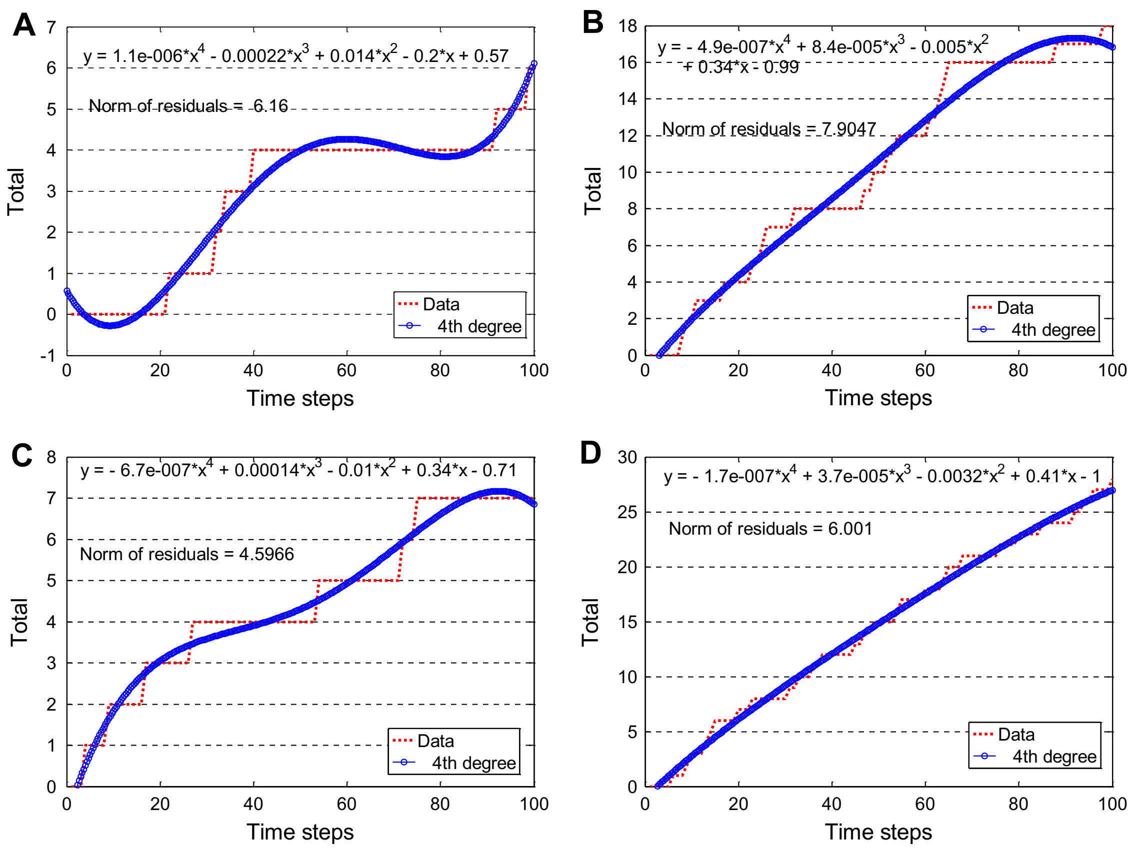

Fig. 5. Cumulative adoption patterns during the early stages of diffusion, time step (t = 100), with different individual BEV preferences (Panels A: P = 0.02, B: P = 0.16, C: P = 0.10, D: P = 0.25) and network effects held constant (Q = 0.3, K = 0.1). P values for simulations *A*–*D* correspond to BEV mean preferences P1-4 (Table 4). Curves were fitted to each simulation iteratively to decrease the norm of residuals while avoiding over fitting, converging on 4th degree polynomials. The curves are not intended to be forecasting models but to show the variability in diffusion trends during early stages of adoption. >25 model runs for each simulation (*A*–*D*) were performed showing random patterns for cumulative adoption in early time steps (t = 100).

3.3. Sensitivity analysis

In the final set of simulations we conduct sensitivity analysis on all parameters, *P*, *Q*, and *K* using five different parameter settings (Table 3). We conduct 10 model runs for each simulation to assess a distribution of results for each setting. We look at the cumulative effects on adoption behaviour over the long term (t = 1000).

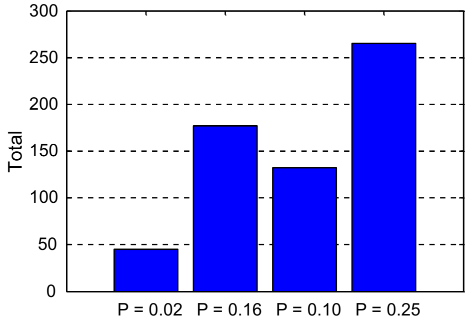

Fig. 6. Cumulative adoption over the long-term ($t = 1000$). As consumer preferences (P) increase cumulative adoption increases. Indirect (Q) and direct (K) network influences are held constant in these simulations.

4. Results and discussion

4.1. Agent-choice

Fig. 4 plots the probability of adoption based on agent preferences over time ($t = 30$) and Table 4 gives the mean preference, P_{ij} values for each technology in each simulation. The overarching story is that a variety of behaviours can be captured by the model. The model captures random individual behaviour shown by the high levels of fluctuations at each time step, but a pattern emerges over time showing which technology is most favoured under each simulation (*A–D*). The mass market (*D*) simulation shows that agents prefer the incumbent technology system of petrols (45%) and diesels (33%) with HEVs (18%) also competitive, while the remaining AFVs cannot compete. In the early adopter (*B*) simulation, HEVs (42%) are the most preferred while BEVs (16%) are competitive with ICEs. Interestingly, early adopters prefer BEVs over PHEVs despite having less refuelling capability, which is likely due to lower cost, superior fuel economy and lower emissions as compared to the mass market simulation where BEVs and PHEVs are nearly on par. When agents have to trade-off (*C*) desirable qualities specific to each technology, there is no clear winner, with only HEVs (33%) and petrols (33%) having a small edge over diesels. However, when we consider exogenous effects (*D*) such as increasing refuelling capability, BEVs (25%) become competitive with the incumbent system.

While individual preferences may appear non-deterministic at discrete time steps, over the longer-term, a trend emerges shown by average behaviour over time. This of course depends on the initial model parameters, but dynamic vectors for technology attributes, $x_j(t)$ or agent preferences, $\beta_j(t)$ could be introduced into the probability function, $P_{ij}(t)$. The key point is that the model is able to capture a variety of individual level behaviour, which could be informed by detailed empirical data. And importantly, various assumptions could be made to simulate how individual behaviour may change under different scenarios, such as evolving technological attributes or how different social norms may affect preferences for specific innovations over time.

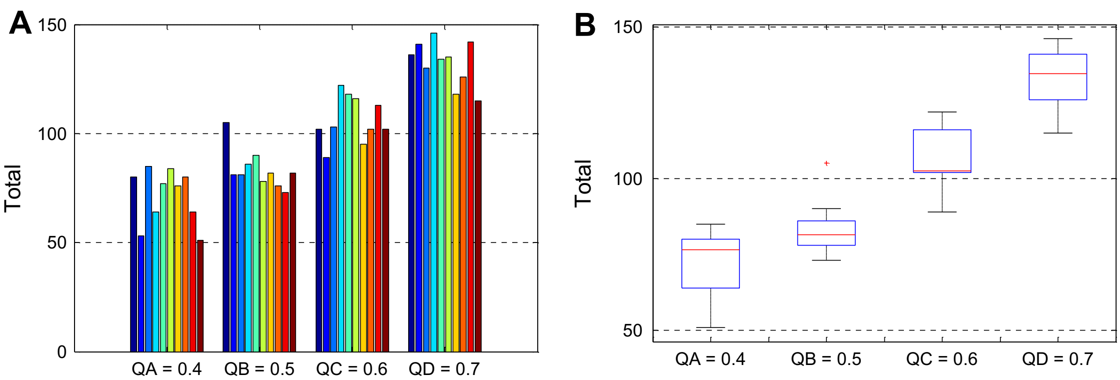

Fig. 7. Increasing indirect network effects (Q) on cumulative adoption of BEVs. Panel (A) Sensitivity analysis with increasing parameter Q: $A = 0.4$, $B = 0.5$, $C = 0.6$, $D = 0.7$. Reference case $P = 0.02$ (low individual preferences for BEV) and $K = 0.1$ (low direct personal network effects) are held constant to show adoption sensitivity to only indirect network effects Q. Simulation run time = 1000. For sensitivity analysis on parameter Q: *A–D*, 10 simulations are performed to show possible distribution of outcomes. Panel (B) Box plot for each sensitivity analysis of Q shows distribution of adoption outcomes. Central mark on the box plot is the median, edges of the box are the 25th and 75th percentiles, and whiskers extend to most extreme data points not considered outliers, outliers are plotted individually.

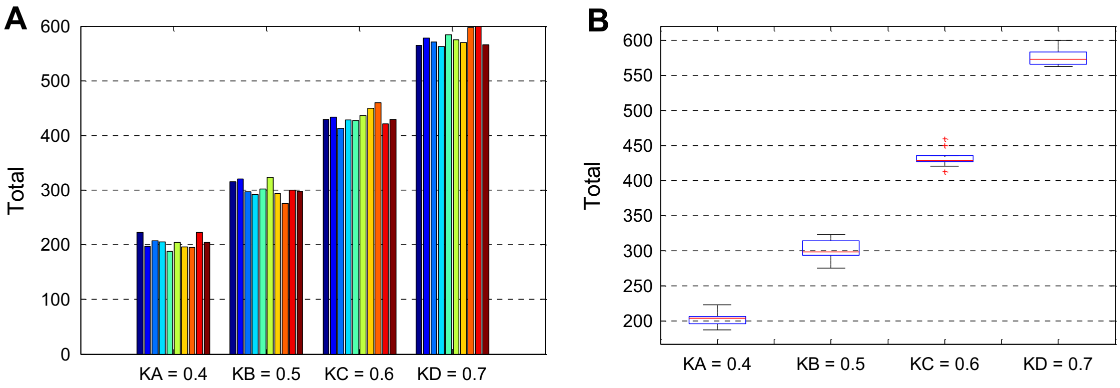

Fig. 8. Increasing indirect (Q) and direct (K) network effects on cumulative adoption of BEVs. Panel (A) sensitivity analysis with increasing parameter K: $A = 0.4$, $B = 0.5$, $C = 0.6$, $D = 0.7$. Reference case $P = 0.02$ (i.e. low individual preferences for BEVs) and Q parameters as above in Fig. 7. The assumption is that an individual's personal network reflects the larger population of adopters, that is, direct influence from personal network increases proportionally with the indirect influence from the larger population. Simulation run time ($t = 1000$). For sensitivity analysis on parameter K: A–D, 10 simulations are performed to show possible distribution of outcomes. Panel (B) Box plot for each sensitivity analysis of K shows distribution of adoption outcomes. Central mark on the box plot is the median, edges of the box are the 25th and 75th percentiles, and whiskers extend to most extreme data points not considered outliers, outliers are plotted individually.

4.2. Random network influence

We now pass individual choice preferences (P_{ij}) for BEVs into the ABM framework to assess the influence of random network influence on short and long-term diffusion patterns. We can see how different individual preferences for BEVs are influenced by random mixing in a local population (Q_{ij}) and personal network (K_{ij}) influence. Short-term diffusion patterns are shown in Fig. 5 and long-term cumulative adoption is given in Fig. 6.

What the diffusion patterns reveal in the short-term is a high degree of variability (Fig. 5). This variability is not a function of the different input parameter, P_{ij} for each simulation, but the stochasticity introduced into the ABM, meant to capture random behavioural effects. These results differ from aggregate diffusion models, which show the early phases of diffusion as a smooth process, which does not reflect real world behaviour. The ABM is better able to capture variable adoption patterns during the early phases of diffusion.

Over the longer term we can see the clear influence that individual preferences combined with network influence have on cumulative adoption (Fig. 6). The exogenous effects scenario with high BEV preferences ($P = 0.25$) from increased refuelling infrastructure (Fig. 4D) results in six times greater cumulative adoption compared to the mass-market scenario with low BEV preferences ($P = 0.02$). While in the early stages of diffusion, it appears uncertain how individual preferences will influence the adoption trend, over the long-term high individual preferences makes an important difference in cumulative adoption. This has implications for capturing a particular market in the early phases of diffusion and sustaining interest in an innovation over the longer term, despite early signs that may give unclear signals. For instance, the diffusion curve may dip indicating to investors or policy makers declining market interest, which could negatively affect further investment during the crucial early stages of diffusion. But the curve may quickly continue its previous growth trajectory as shown in Fig. 5A. This can also be explained by a 'saddle effect' where an aggregate market trend may be misleading because it is actually comprised of two consumer segments adopting simultaneously, where early adopters lose interest showing a dip, but then the growth curve takes off again due to increased interest form late adopters [29].

4.3. Network clustering

We now see the effect of different network structures on adoption behaviour. We use mass-market preferences for BEVs ($P = 0.02$) to show how network influence may affect cumulative adoption even with low individual preferences. Fig. 7 shows

Table 5
Parameter settings and cumulative adoption results for each simulation.

Parameters	S1	S2	S3	S4	S5
P	0.1	0.9	0.1	0.1	0.1
Q	0.1	0.1	0.9	0.1	0.9
K	0.1	0.1	0.1	0.9	0.9
Cumulative adoption range	100–150	850–950	250–300	150–200	850–950

Notes: Simulation assumptions, S1: reference case, S2: high individual preferences, S3: high indirect network influence, S4: high direct network influence, S5: high combined network influence. Cumulative adoption range over time step ($t = 1000$).

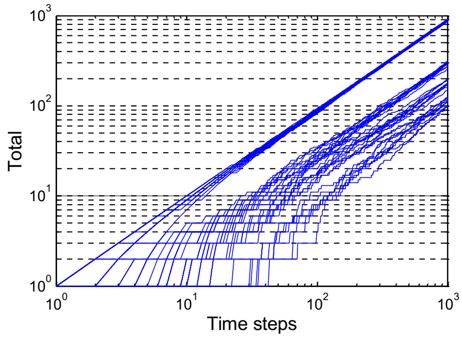

Fig. 9. Sensitivity analysis on *P*, *Q* and *K*. Each simulation is run 10 times for a distribution of results.

increasing indirect network influence due to clustering, with low direct personal network effects held constant. Fig. 8 gives the results of proportionally increasing indirect and direct network effects.

Fig. 7 shows that high clustering (Panel A, QD = 0.7) results in 134 total adoptions, 3 times greater than the 45 cumulative adoptions from local random mixing ($Q = 0.3$). Fig. 8 shows that when further accounting for increasing influence from an agent's personal network that reflects the behaviour of the larger population, the effect on cumulative adoption is non-linear resulting in 576 total adoptions over the same period (Panel A, KD = 0.7). Our results imply that even if an individual does not have a strong personal preference for a particular innovation, network influence can have non-trivial effects on cumulative adoption. This is because individuals could gain increased exposure through certain social structures, such as small world networks, where information and other influencing factors can spread over a large population through just a few intermediaries. Those structures are common for various social communication networks [68,69]. Additionally, since a person's group of friends also interacts with the larger population, and then directly transmits information or influence to the individual, this can have a magnifying effect on a person's behaviour. Our modelling results support empirical evidence that HEV adopters were influenced by their peer group and also imply that individual-level behaviour can change over time from social influence. Recent empirical work in the US indicates that people were more amenable to developing new pro-societal perspectives of PHEVs, which might encourage adoption over time, if there was positive feedback from their social network [4].

4.4. Sensitivity analysis

Table 5 provides the results of the sensitivity analysis, which indicates that in comparison to the reference case, individual preferences have the strongest influence on adoption behaviour with ~10 times increase in cumulative adoption. Indirect influence alone can also strongly influence adoption but is outweighed by individual preferences with ~3 times difference in cumulative adoption. Interestingly, the model suggests that direct influence from a personal network has slightly less influence (~1.5 times) than exposure to a larger public, which implies an influence through numbers effect. That is, the influence of an impersonal public through higher numbers is weighted more by a person than a minority opinion even though it may arise from a personal group of friends. Although personal networks exert influence, if group behaviour does not reflect the population at large, it has less of an effect on an individual. This implies that individuals weigh public opinion against the opinion of their personal friends in deciding on a course of action, pointing to an important feedback between sub-group and mass-group behaviour on individual level decision-making. Our results also indicate that the combined influence of indirect and direct network influence can have equal weight to individual preferences, but does not exceed it. That has implications for potentially influencing highly risk adverse individuals that may at first be unwilling to adopt a particular innovation, but could be persuaded over time by high network feedback.

Fig. 9 plots the range of cumulative adoptions from the sensitivity analysis. The double log plot emphasizes high variability during the early phases of diffusion. Over time, a clearer pattern emerges in cumulative adoption, which could reveal market forerunners depending on the combination of individual preferences, and network influence for a given technology. This has implications for policy and investment. For instance, if a policy target is set, despite potentially negative signals, which may only reflect inherent market variability in the short-term, the initial policy course of action should be maintained, or even reinforced to achieve longer-term results. Incentives and other interventions could be used to provide positive feedback to early adopters since this may have multiplicative effects through network influence on the rest of the population leading to further adoption. We know from empirical and theoretical studies on network contagion, that there is often a threshold level, whereby a critical mass of adopters has to be reached for diffusion to become self-sustaining [70]. Unpredictability during the early stages of diffusion should not discourage decision-makers since understanding the non-linear effects of social network interactions could lead to more targeted policy interventions, rather than blanket approaches. For example, if there are known positive feedbacks among clustered sub-populations that reinforces pro-environmental behaviour, those groups could be incentivised first, in order to reach the necessary threshold point for others to place a sufficient value on an innovation to trigger adoption.

5. Conclusions and further research

Conventional diffusion models can be unreliable where non-linear behaviour is not captured. Over the longer-term, mean-field techniques often based on differential equations can converge on average system-level behaviour with good predictive ability. Although an ABM can capture behavioural variability, it is not necessarily better at forecasting. There can also be challenges for calibrating ABMs, especially when there is scarce data during the early phases of a diffusion process. However, one potential advantage an ABM has is the ability to provide a distribution of possible outcomes. This could be useful for decision-makers to evaluate a range of scenarios and develop multiple response strategies. In this regard, ABMs can capture human variability, or other non-linear processes providing a range of possibilities, rather than locking into a single pathway which may later prove misleading [71,72].

Our empirical analysis and model simulations suggest that network influence can play an important role in accelerating energy innovation diffusion. What is encouraging is that network topologies that can amplify behavioural signals such as small worlds and scale free networks are commonly found in the real world [68,69]. However, we should note that social influence might not be the only diffusion force at work. Empirical research has also found that homophily can account for a great deal of what first appears to be a social contagion [73]. This should encourage more detailed analysis of different network topologies. Importantly, a gap exists in understanding how individual-level behaviour can be shaped by feedback from both personal contacts and a larger population. Our simulation results stimulate some interesting questions in this regard and infer possible avenues for further research.

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