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Driving electric vehicles' mass adoption: An architecture for the design of human-centric policies to meet climate and societal goals

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ABSTRACT

For a real "green deal" to take place, it is important that technological achievements in the realm of green mobility solutions are paired with novel sustainable and energy efficient mobility models, smart enough to answer the multifaceted needs of their users. Within this challenging context, we set the foundations of a human-centered framework for the analysis and design of policies promoting the mass adoption of electric vehicles (EVs). The proposed data-driven architecture is conceived to leverage the deep intertwining between users' attitudes, mutual influences and technological traits of EVs to support policy makers in studying the effect that individual characteristics and homophily have on the "natural" spread of EVs, and analyzing the costs and benefits of different intervention policies. By introducing the so-called *EV-adoptability DNA*, compactly representing the individual predisposition towards EVs, the proposed architecture is intended to be an actionable tool to shape a mobility of the future that is centered on the users' needs, aiding in the fight of climate change and the lack of inclusiveness in the green transition. Through extensive simulations carried out by assembling the proposed framework with a set of anonymized real mobility data, we show its potential in supporting the design of policies to foster greener mobility habits and in the analysis of their mid-term effects, even when access to social/personal information is denied.

1. Introduction

In the pre-pandemic era, 20% of the overall transport energy was consistently consumed for moving people and goods along (Docherty et al., 2017), making mobility responsible of a large share of greenhouse gas emissions. It is well-known that these emissions must be capped in response to climate change. Meanwhile, it is also well-established that Electric Vehicles (EVs) can be crucial to support a shift towards greener mobility models and, thus, to aid in the reduction of pollutants (Popovich et al., 2021). To this end, several governments all around the globe are shaping their policies to support EV mass adoption. Two notable examples are the *Next Generation EU* program for post-COVID recovery and the *Clean Energy Revolution and Environmental Justice* plan of the new US administration, both aiming at achieving a full "electrification" of public and private vehicle fleets by 2050. Nonetheless, recent works (see *e.g.*, Coffman et al., 2017; Taalbi and Nielsen, 2021; Wei et al., 2021; Hardman et al., 2017; De Gennaro et al., 2014; Krishna, 2021; Rezvani et al., 2015; Sierzchula et al., 2014; Singh et al., 2020; White and Sintov, 2017) show

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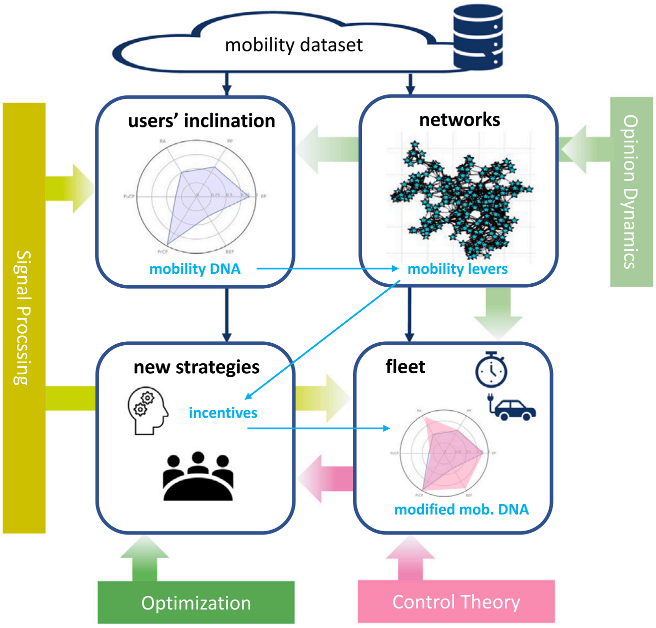


Fig. 1. A scheme of the interactions between different players and methodologies in the proposed human-centered design framework.

that there are still significant barriers that undermine EVs adoption, such as vehicle ownership costs, driving range, charging time, fuel prices, consumer characteristics, availability of charging stations, and public visibility/social norms. Therefore, the shift to a full electrification is all but a smooth and well-traced process, which can only be favored by considering the conflicting constraints arising from the limitations of the infrastructure and the technology, management issues, users' needs and mutual influences among connected individuals. Recent agent-based transportation studies (see *e.g.,* Helmus et al., 2022; Leng and Corman, 2020; Manser et al., 2020), have highlighted the importance of considering the peculiarities of individuals, their attitudes and their transportation choices in analyzing existing mobility infrastructures and designing novel mobility solutions. Meanwhile, works like McCullen et al. (2013), Delre et al. (2010), Schepers and Wetzels (2007), Lucas and Spitler (1999) already expose the impact that social contagion can have in the massive spread of new technologies, which is surely a factor that must be accounted for when designing policies to favor the adoption of EVs.

1.1. Contribution

In line with the previous considerations, in this work we present a human-centered architecture to aid policy makers in (i) analyzing EV-adoption, (ii) synthesizing intervention policies to boost EV adoption and (iii) quantitatively evaluating their costs and benefits from a set of data. A conceptual picture of the main layers constituting our framework is illustrated in Fig. 1, showing that we encompass all the different players who characterize a mobility system, namely the *users*, the *environment or network*, the *management* and the *infrastructure*.

By exploiting a set of anonymized trips of about 1000 vehicles, we progressively show how these quantitative (and neutral) information on individual mobility habits can be leveraged to extrapolate insights on the users' adaptability towards EV adoption, when merged with known limitations of the EV technology and of the available infrastructure. In the footsteps of Fugiglando et al. (2017), our contribution in this sense is the introduction of what will be referred to as the users' *EV-adoptability DNA*. This novel compact indicator groups a set of synthetic features characterizing the adaptability of each individual to an immediate switch to an EV, based on its travel habits. Differently from the users' description considered in our previous work (Breschi et al., 2020), this granular representation can help policy makers visualizing the main levers to be pulled to favor the spread of EVs, while being flexible enough to be easily augmented with additional socio-economic features of each individual (when available).

In addition, we propose an approach to use the available set of mobility data to characterize a proximity bond among agents, ultimately allowing us to assess via simulation the role played by homophily in the adoption process. This further enables us to mathematically describe the impact that individual adaptability to EVs and proximity-based relationships have on the spread of EVs over a community, thus formalizing the interplay between different layers of the proposed framework. Such a representation of the adoption phenomenon is here obtained via an *irreversible cascade model* (Acemoglu et al., 2011). This model leads to a binary representation of individual attitudes, with the (eventual) unilateral transition from one predisposition state to the other guided by *users' attributes* exceeding a *personal threshold*. Note that irreversible cascade models have already been employed in Delre et al. (2010), McCoy and Lyons (2014) to characterize the effect of social contagion on the adoption of EVs. Nonetheless, in Delre et al.

Table 1
Abbreviation index: list of the main acronyms.

Acronym	Definition	Role
EV	Electric Vehicle	–
EP	Electrification Predisposition	EV-adoptablity DNA component
PP	purchase Power	EV-adoptablity DNA component
RT	Range Trust	EV-adoptablity DNA component
PuCP	Public Charging Potential	EV-adoptablity DNA component
PrCP	Private Charging Potential	EV-adoptablity DNA component
BEF	Break Even Feasibility	EV-adoptablity DNA component
EP	Electrification Predisposition	EV-adoptablity DNA component
W	Weak-oriented policy	Policy classification
S	Strong-oriented policy	Policy classification
PC	Poorly connected-oriented policy	Policy classification
C	Connected-oriented policy	Policy classification
R	Resistant-oriented policy	Policy classification
NR	Not Resistant-oriented policy	Policy classification
OD	Overload-Density	Policy evaluation index
OT	Overload-Time	Policy evaluation index
R-CO_2	Reduction of CO_2 emissions	Policy evaluation index
I-F	Income Fairness	Policy evaluation index
C-F	Centrality Fairness	Policy evaluation index

(2010), McCoy and Lyons (2014) the individual thresholds are randomly chosen, while the user's attributes linked to these thresholds combine features regarding the individual socio-economic status, environmental awareness, information of its direct neighbors and the overall state of the network. Instead, our thresholds are directly associated with the resistance of each individual to a potential shift to the EV technology and, thus, they are connected to the EV-adoptability DNA. With a shift in perspective, in our framework the thresholds embed the minimal number of EV "accepting"neighbors required for each individual to be convinced to consider EVs as a possible mobility solution by mutual influence only. Therefore, differently from McCoy and Lyons (2014), McCullen et al. (2013), each individual is not directly influenced by the status of the overall network, but it more realistically changes opinion directly based on the inclination of its more proximal peers, while being only indirectly influenced by the rest of the agents. At the same time, we assume the resistance of each agent to be embedded in its own threshold and, thus, we allow for bidirectional communications between agents (differently from Delre et al., 2010). Another element that we have decided not to inherit from the model proposed in McCoy and Lyons (2014) is the direct dependence on time of the transition from a negative to a positive predisposition towards EVs. Such a dependence is introduced in McCoy and Lyons (2014) to induce a change in the inclination of all individuals, once the EV technology has reached the level of maturity for its potential widespread adoption. However, technological advancements might not always be paired with the socio-economic changes required for an innovation to become widely adopted (Zhang and Vorobeychik, 2019) and with an actual change of sentiment, especially in the more resistant portions of the population (McCoy and Lyons, 2014). For these reasons, we have instead decided to propose the cascade model for the analysis and policy design only over limited time periods, after which the building blocks composing our framework should be updated to better reflect the up-to-date status of the considered population. Lastly, by means of extensive simulations, we show how the presented framework can be exploited to study the evolution of users' predispositions with respect to EVs over time within a community, to test different policies fostering EV adoption, and quantitatively analyze their socio-economic and environmental impact. Our study thus allows us to examine various *policy scenarios*, differently from many studies proposed in the literature (as evidenced in Hesselink and Chappin (2019a)). We stress that the simulations presented in this work have not the intent (nor the ambition) to provide realistic forecasts on EV adoption over the considered geographical area. Instead, they are instrumental to constructively illustrate how real (yet anonymized) mobility patterns can be fruitfully used to build a human-centered framework for the design and the evaluation of adoption policies from scratch. The reader is referred to Table 1 for a list of all abbreviations used throughout the paper.

2. Dataset and preprocessing

Data are of paramount importance to set the basis of a human-centered framework for studying EV adoption over a community. In particular, direct insights on the individual socio-economic status, the predisposition towards EVs and mobility habits are particularly valuable, since they allow one to have a realistic outlook on the users' routines, needs and inclinations. Combined with well-known technological and economic barriers to a widespread EV adoption, these data-based insights are thus crucial for the complete characterization of the individual, and thus, of one building block of the framework schematized in Fig. 1. Nonetheless, depending on the performed data collection campaign, it is often true that all these information are not available at once. Indeed, socio-economic data can be gathered through extensive surveys, which generally provide only basic insights on individual mobility habits (Coffman et al., 2017). A collaboration with EV providers might instead allow policy makers to have access to users' real mobility traces, while personal information might be withheld by the providers for privacy reasons. The data used here allow us to show how the framework schematized in Fig. 1 can be constructed in this second challenging scenario.

In this work, we specifically use a set of *anonymized*[1] GPS traces already exploited in Breschi et al. (2022), collected from *internal combustion engine* (ICE) vehicles registered in the Italian province of Parma over one year (specifically from September 1st, 2017 to August 31st, 2018). These traces are uniquely linked with the time stamps associated to each data string.

This combination of information allows us to detect relevant events, such as ignitions and shutdowns, ultimately leading to insights on individual trips and stops. The *trips* are characterized by their origin, destination, distance traveled, start and ending times, while *stops* are defined by their position (in terms of measured latitude and longitudes) and duration. Once trips and stops have been characterized, zero-distance trips have been converted into stops and data have been cleaned up by removing:

- instances with no one-to-one correspondence between trips and stops;
- invalid or incomplete trips and stops;
- data associated to vehicles that are inactive within the first/last two months of observation.

By combining the remaining information on each ICE vehicle, we thus have a picture of the owners' mobility habits.[2] We remark that here only a subset of 1000 ICEs of the total tens of thousands of vehicles available in the original dataset is considered, for the sake of a more effective explanation of the proposed framework and an easier visualization of the performance of human-centered policies. Nonetheless, this subset is representative of the overall population in terms of mobility habits, since it preserves the overall distribution of the ratio between:

- *active days*, namely those in which a vehicle is actually in use;
- *critical days*, *i.e.,* the ones in which the distance traveled exceeds 300 km and no stops longer than 30 min are performed.

Note that, the traveled distance considered here to compute this ratio represents a conservative estimate of the distance that can be covered with an *electric vehicle* (EV) without recharge, while the stop duration accounts for the minimum time generally required to regain some driving range.

The insights on the trips and stops of each ICE vehicle further allow us to retrieve the position (latitude and longitude) of what we refer to as the **base stop** b_v of each vehicle v. The latter is computed for each agent as the average coordinates of a pool of *candidate base stops*, *i.e.,* those longitudes and latitudes associated with at least 50% of overnight stops of length above 7 h (similarly to De Gennaro et al., 2014). As such, the base stop can be seen as a proximal indicator of the location of each ICE owner's house. Since we are interested in studying the adoption process at the level of the city and province of Parma, all stops laying outside this area have been removed prior to the computation of the base stops. In turn, this pruning procedure leads to removing all those drivers whose base stop is outside the geographical area of interest. To be able to uniquely locate the base stop of each vehicle, we further neglect all those ICEs whose candidate base positions are located in different cities. From this additional pruning phase, we discard about 38.5% of the initial drivers, thus reducing their number of considered individuals from 1000 to 615.

3. A human-centric framework to understand and foster EV adoption

Studies on adoption behaviors have shown that people's preferences for technological innovations are not independent from those of others, and that conformity to group behaviors and mutual contagions are strong drivers in shaping individual inclinations (Ravazzi et al., 2021). The tight connection between interpersonal interference and personal predisposition is also at the core of transportation choices and travel habits (Pritchard et al., 2016; Han et al., 2019). Therefore, it is pivotal to characterize the network embedding the mutual connections between drivers and their own mobility attitudes, so as to better understand the EV adoption process. Meanwhile, given the nature of the available dataset, it is important to devise a constructive strategy that allows us to leverage on anonymized data to describe mutual interactions in the analysis of adoption mechanisms. Such an approach represents an asset of our framework, since it can be employed when information on social connections are not directly accessible by the policy maker. Towards the construction of a human-centered framework to analyze EV adoption, we now detail how the available data can be manipulated based on known technological features of electric vehicles, to characterize the personal propensity to EVs and the mutual influences among individuals belonging to the same community.

3.1. Network-based characterization of mutual influences

Since adoption processes are known to be guided by mutual imitation (Huang and Wong, 2016), (Alraddadi et al., 2019), ICEs owners (also referred to as agents) that are *proximal* in some sense are likely to influence each other. The proximity between agents can be defined by looking at different aspects, such as:

- social features, *e.g.,* age, education;
- actual social connections, *e.g.,* co-workers are more likely to influence each other opinions, since they spend several hours at tight contact;
- geographical information, such as the distance between recurrent stops of different agents;

[1] Although the data are made anonymous, the rights on them are retained by the providing company. As such, we will not publicly share them.

[2] We assume that all trips are performed by the same individual.

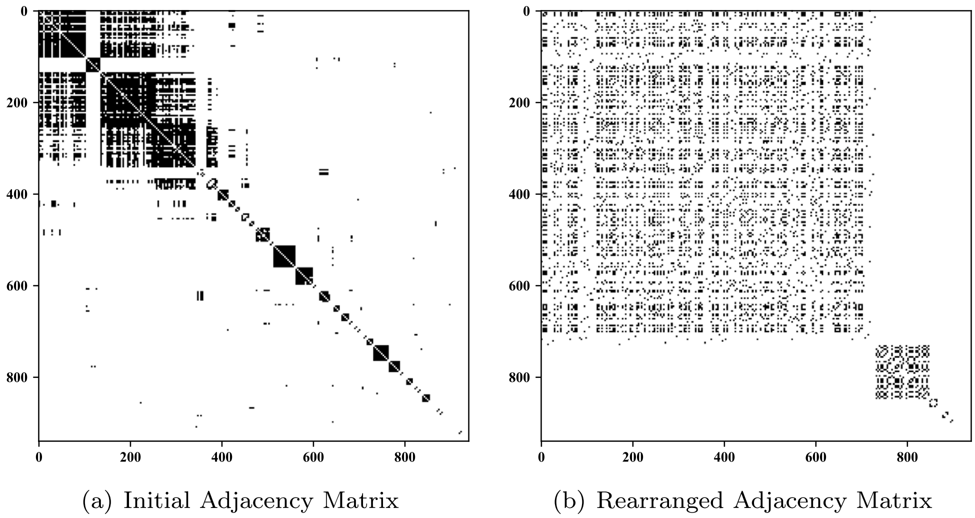


Fig. 2. Initial *vs* rearranged adjacency matrix associated with $\mathcal{G}$. Each black square indicates a couple of connected agents, while the blank spots indicate ICE owners not influencing each other.

- agents' habits, as their mutual influence can depend, among others, on the similarity between their social, working and shopping habits.

The first two features require private information or insights on social exchanges, that might not be always accessible to the policy makers due to privacy reasons. Instead, features related to geographical proximity and mobility habits require information that can be anonymized, thus being less subject to privacy issues. In this work, we establish connections between ICE owners by looking at the geographical proximity of their base stops. This choice has been driven by the inkling that ICE owners living next to EVs ones might be more inclined to become adopters themselves, since they indirectly have an experience of the potential benefits of adopting this new mobility solution. Accordingly, by considering that the average extension of a neighborhood in Parma is about 19 [kmq], we assume agents to mutually influence each other if the geodesic distance between their bases is lower than $D = 2.5$ [km].

By representing EV owners and potential adopters as a set of nodes $\mathcal{V}$, each endowed with distinguishing features, the complex relationships among them is then represented via an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. Based on our design choices, the edges $\mathcal{E}$ of $\mathcal{G}$ are dictated by the *geographical proximity* of the individual *bases* $\{b_v\}_{v \in \mathcal{V}}$, resulting in an adjacency matrix A associated to the constructed graph satisfying the following:

$$A_{v,w} = 1 \iff d(b_v, b_w) \leq D, \quad \forall v \neq w,$$

where $d(b_v, b_w)$ indicates the geodesic distance between the bases b_v and b_w. Nonetheless, as clear by looking at the pictorial representation of this matrix[3] in Fig. 2(a), the resulting proximity-driven network is still characterized by sub-communities that are barely connected among each other. Although we expected this outcome due to the geographical extension of the province of Parma, the presence of *isolated* groups in the network hinders the analysis of the "social" diffusion of new mobility habits over the whole network . Since the proposed architecture can be easily adapted to analyze the impact of individual inclinations and mutual influence on different (not connected) groups of individuals, we have decided to focus on the largest community within our network, while neglecting those disconnected ones that comprise smaller subsets of the original agents. We thus detect and keep the *largest connected component* in the adjacency matrix A associated to the obtained graph only, which is shown in Fig. 2(b). The graph $\mathcal{G}$ associated with this subset of agents comprises 582 nodes (*i.e.,* 94.6% of the agents kept after pruning) and it is *completely connected*, namely there always exists a path linking two nodes within the network. Note that, since the graph is undirected, all connected agents have an influence on each other. The resulting proximity-based network is shown in Fig. 3 , where it is superimposed over the map of the province of Parma. Clearly, most of the base stops are mainly located in the city of Parma and its surrounding belt. As shown in Fig. 4(a),[4] the proximity to the city center further entails an higher normalized in-neighbor degree (*i.e.,* number of incoming edges), with agents being progressively less influenced by others as the distance from Parma increases. The connectivity histogram in Fig. 4(b) further highlights that, despite the graph being fully connected, there is still a relevant percentage of drivers whose opinion will be clearly more difficult to change based on mutual influences only, if they are not already well disposed towards EVs.

[3] All operations and simulations are carried out in Python, using standard libraries and the NetworkX package (Hagberg et al., 2008).
[4] The network is plotted over an unlabeled Cartesian plane.

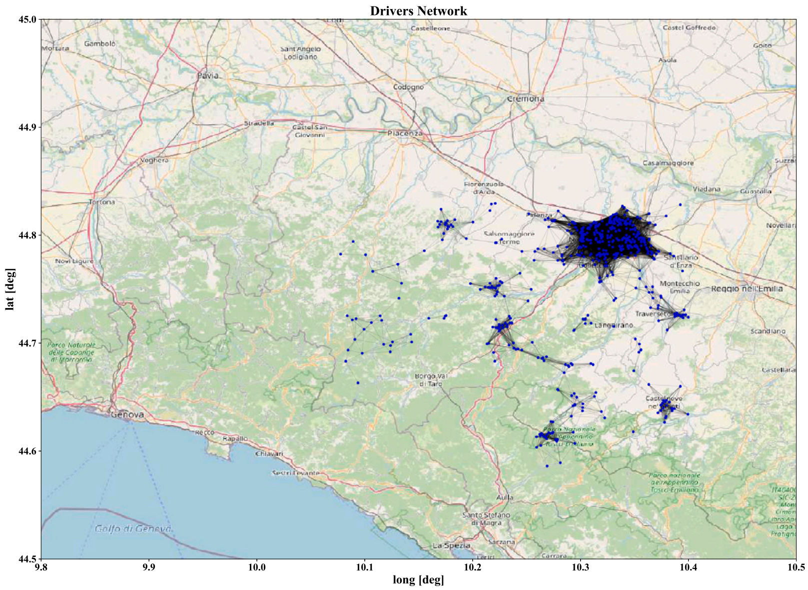
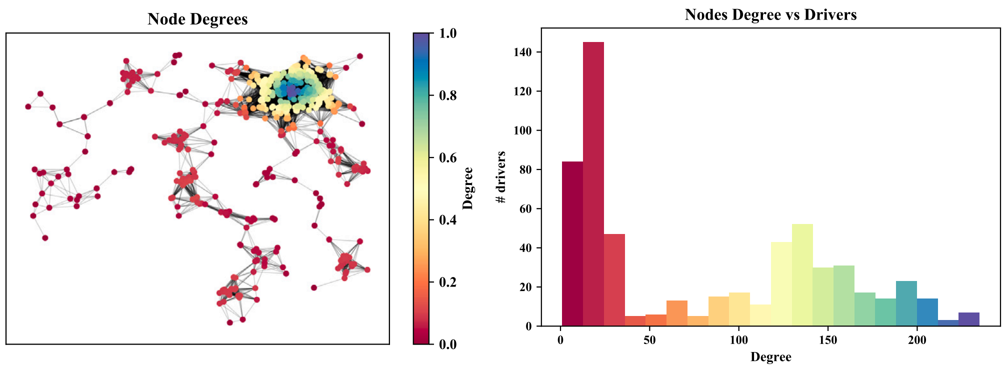


Fig. 3. Data-driven proximity-based network, with $|\mathcal{V}| = 582$. The blue dots spotlight the base positions of the drivers, while the black edges depict connection between agents whose basis are geographically proximal. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

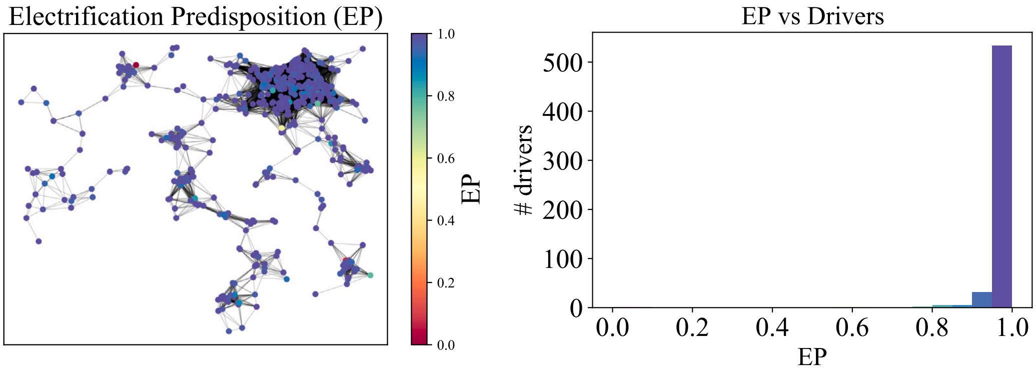


(a) Normalized degrees over the network. (b) Distribution of the in-neighbors degree.

Fig. 4. Connections within our proximity-based networks: normalized node degrees and distribution of in-neighbors.

3.2. A pattern-based description of individual inclinations

With the goal of designing fostering policies that account for the needs of potential EV adopters, it is crucial to describe their predisposition towards changes in their mobility habits with tangible features, that can be inferred and quantitatively determined from data. To this end, in this section we discuss a possible approach to extract quantitative indexes describing the individual adaptability for a transition towards EVs, which we will consider as a proxy of their inclination towards this green mobility solution. These indicators are constructed according to the location of the base position and the features on the trips and stops characterizing the activity of each of the 582 ICE vehicles. This information is here embedded into an *EV-adoptability DNA*, which is completely defined based on the mobility habits of each agent and it is inspired by the EV-adoptability DNA introduced in Fugiglando et al. (2017). With respect to an initial proposal of characterizing drivers' DNA made in Fugiglando et al. (2017), our approach enriches it by manipulating mobility information with insights on known socio-economic and technological barriers preventing the mass adoption of EVs. This allows us to combine important socio-economic/technological factors driving EV adoption to purely motion-based indicators, which are crucial to capture the full complexity of the adoption mechanism (Coffman et al., 2017). Subsequently, we introduce the main features of the proposed DNA, which encompass several aspects that can shape the individual inclination towards the adoption of an electric vehicle (Singh et al., 2020; White and Sintov, 2017). Note that all the elements composing the *EV-adoptability DNA* are defined so as to lay within the interval $[0, 1]$, for them to be easily compared and merged.



(a) Distribution of EPs over the network (b) Distribution of EPs over the drivers

Fig. 5. EP index distributions over the network and the agents. Overall, EPs have values very close to 1 independently from the location of the base stops.

Electrification predisposition (EP). transitioning to an alternative mobility solution generally implies a change in individual mobility habits. This is a shift one might be resistant to perform. The EP index is thus introduced as a measure of "EV-switch" suitability, *i.e.,* a proxy to indicate how much individual mobility habits have to be changed to accommodate an immediate shift to an EV. Accordingly, EP is constructed by combining the characteristics of individual mobility habits, namely the cumulative distance covered on active days by the ICEs and the duration of stops in those days, and relevant technological features of an electric vehicle. Specifically, based on the *daily kilometers traveled* (DKT), active days are distinguished into *critical* and *non-critical* ones, with the first characterized by DKT> 300 [km]. We stress that this classification of active days is performed by considering a rather conservative bound on the kilometers that can be covered with an EV without recharge. Critical days are further divided into two sub-groups, namely the sets of *eligible* and *non-eligible* days. While the first class is characterized by stops longer than 30 min, which allow one to gain back some travel range with a recharge, the second group of critical days does not feature such stops. Therefore, the mobility requirements of days that are critical and non-eligible cannot be generally fulfilled with an EV. Based on this classification, we define the *critical ratio* CR_v of an agent $v \in \mathcal{V}$ as follows:

$$\mathrm{CR}_v = \frac{|\text{Critical days } v| - |\text{Eligible days } v|}{|\text{Active days } v|}, \quad \mathrm{CR}_v \in [0,1], \tag{1a}$$

where $|\cdot|$ indicates the cardinality of a set. These indexes are then normalized to better discriminate between the agents, leading to the construction of a new quantity given by

$$\mathrm{CR}_v^n = \frac{\mathrm{CR}_v - \min_{w\in\mathcal{V}}(\mathrm{CR}_w)}{\max_{w\in\mathcal{V}}(CR_w) - \min_{w\in\mathcal{V}}(\mathrm{CR}_w)}, \quad \mathrm{CR}_v^n \in [0,1]. \tag{1b}$$

Since CR_v^n is closer to one whenever an agent is characterized by more critical and non-eligible days, we define the EV-suitability index EP as follows:

$$\mathrm{EP}_v = 1 - \mathrm{CR}_v^n, \quad \mathrm{EP}_v \in [0,1]. \tag{2}$$

so that the closer EP is to 1, the more an agent is suited for a shift switch to an EV. As shown in Fig. 5, the obtained EPs suggest that the considered agents do not have to excessively modify their mobility habits to cope with the limitations imposed by the EVs technology.

Purchase power (PP). A factor that is known to prevent a transition from a traditional ICE vehicle to an EV is the (still) considerable difference in price of these two mobility solutions. It is thus crucial to consider this aspect in defining the EV-suitability DNA. Meanwhile, the available dataset does not allow us to directly access information on the purchase power of the ICE owners. To overcome the limitations imposed by our anonymized data, we here indirectly evaluate it by constructing a proximal index, that combines the location of base stops with the average price [€/mq] of houses sold in the associated area (see Fig. 6 for the resulting distribution of price ranges). Indeed, provided that the investment required to buy an EV is more consistent that the one needed to buy an ICE car, the higher the price of houses in the location of the base stop is, the less an agent is likely to be prevented from buying an EV from an economic standpoint. The distribution shown in Fig. 6 allows us to categorize the agents into 19 classes, ultimately leading to the construction of the PP index as follows:

$$\mathrm{PP}_v = \frac{\mathrm{CPP}_v}{\max_{w\in\mathcal{V}}(\mathrm{CPP}_w)}, \quad \mathrm{PP}_v \in [0,1]. \tag{3}$$

where $\mathrm{CPP}_v \in [0,18] \subseteq \mathbb{N}$ indicates the price range of houses associated with the vth agent base position. As shown in Fig. 7(a), agents with base stops located closer to the city of Parma generally have a higher purchase power index with respect to the ones located further away from the city. In particular, the PP indexes follow quite a skewed distribution centered at rather high values, as shown in Fig. 7(b).

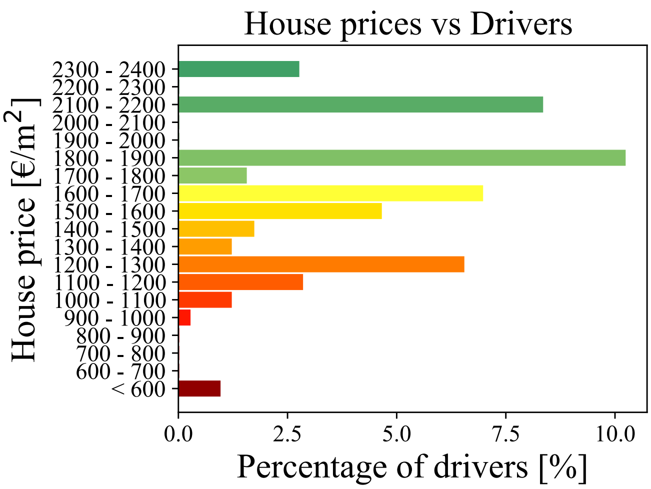
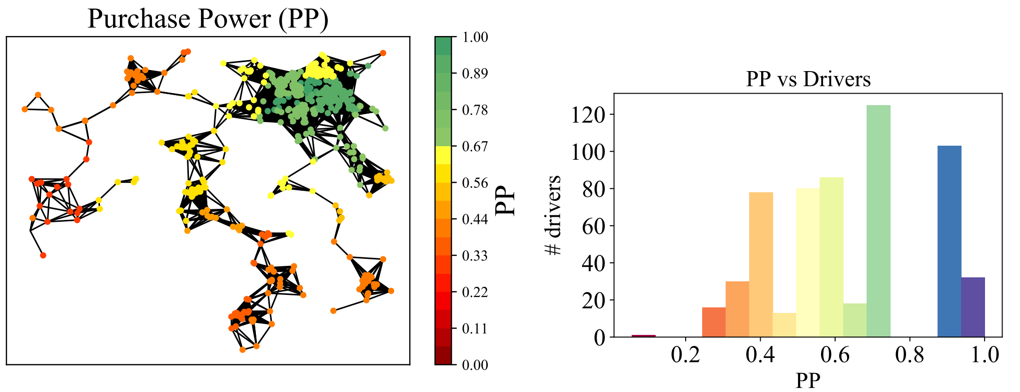


Fig. 6. Distribution of price ranges over the agents.



(a) Distribution of PPs over the network. (b) Distribution of PPs over the agents.

Fig. 7. PP index distributions over the network and the agents.

Range trust (RT). One of the main factors precluding the mass diffusion of EVs is the so-called *range anxiety* (Bonges and Lusk, 2016), *i.e.,* the concern or even fear of being stranded with a discharged battery away from the electric infrastructure. We include a quantitative indicator for this feature by considering that range anxiety is more likely to be experienced when the mobility patterns of an ICE owner are characterized by long trips with relatively short stops on average. According to this inkling, the RT index is computed by combining information on the average trip length ATL_v of each agent $v \in \mathcal{V}$ (the distribution of which over the drivers is shown in Fig. 8(a)), so as to account for the feeling of anxiety (or lack thereof) that can be related to the vehicle range, and the average stops' duration ASD_v (whose distribution is depicted in Fig. 8(b)). This last quantity is computed by neglecting overnight and base stops, so as to consider only those stops that can contribute to increasing the range anxiety over daily trips due to the EVs charging constraints. Both the average trip length and stop duration are normalized as follows:

$$\mathrm{ATL}_v^n = \frac{\mathrm{ATL}_v - \min_{w\in\mathcal{V}}(\mathrm{ATL}_w)}{\max_{w\in\mathcal{V}}(\mathrm{ATL}_w) - \min_{w\in\mathcal{V}}(\mathrm{ATL}_w)}, \quad \mathrm{ATL}_v^n \in [0,1], \tag{4a}$$

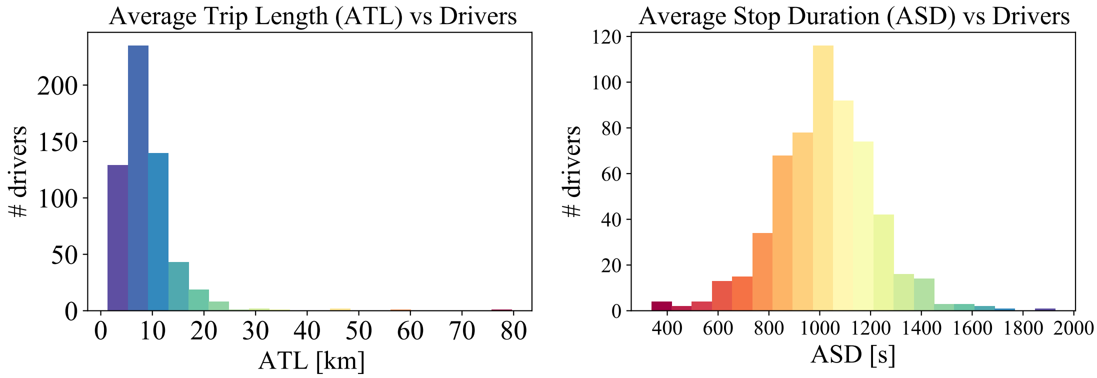
$$\mathrm{ASD}_v^n = \frac{\mathrm{ASD}_v - \min_{w\in\mathcal{V}}(\mathrm{ASD}_w)}{\max_{w\in\mathcal{V}}(\mathrm{ASD}_w) - \min_{w\in\mathcal{V}}(\mathrm{ASD}_w)}, \quad \mathrm{ASD}_v^n \in [0,1], \tag{4b}$$

This normalization allows us to combine these two information into a *range anxiety* index RA_v, defined as

$$\mathrm{RA}_v = \frac{ATL_v + (1 - ASD_v)}{2}, \quad \rho_v \in [0,1], \tag{5a}$$

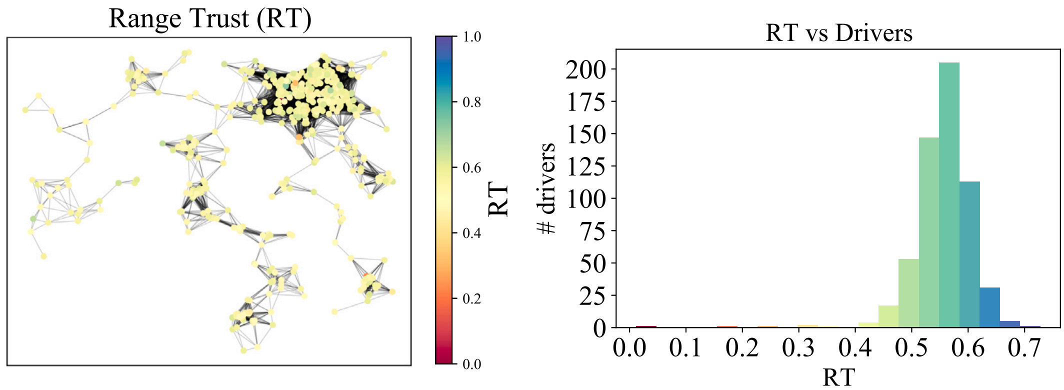
that accounts for the fact that the longer the trips and the shorter the stops, the higher the range anxiety is. It is worth pointing out that this index is computed under the assumption that the average trip length and the average stop duration have an equal impact on the individual feeling of anxiety. Based on this definition of RA_v, the range trust index is then computed as follows:

$$\mathrm{RT}_v = 1 - \mathrm{RA}_v, \quad \mathrm{RT}_v \in [0,1], \tag{5b}$$



(a) Distribution of ATLs over the drivers. (b) Distribution of ASDs over the drivers.

Fig. 8. Distributions of the average trip length (ATL) and the average stop duration (ASD) over the drivers. Clearly, most agents are characterized by a relatively low ATL, thus being less likely to experience anxiety due to the vehicle range. Meanwhile, most of them is characterized by stops that last about 17 min on average, thus generally not being able to fully recharge the vehicle at a public charging station.



(a) Distribution of RTs over the network. (b) Distribution of RTs over the drivers.

Fig. 9. RT index distributions over the network and the agents.

thus being as higher as the individual is less likely to experience range anxiety according to its mobility habits. As it can be seen from Fig. 9(a), the RT indexes associated to the agents do not depend on the position of their base stop, with most drivers characterized by similar values of this index (see the distribution in Fig. 9(b)). This result can be linked to the concentration of the average trip lengths and stop duration of most agents around the same values, as it can be noticed from Figs. 8(a)–8(b).

Public charging potential (PuCP). The availability of public charging stations in proximity of sufficiently long stops (so as to allow for, at least, a partial recharge of an EV) is another factor that must be taken into account when characterizing the EV-suitability of each ICE owner. Indeed, one might be more inclined to a switch to an EV if individual mobility habits already accommodate the recharging needs of this class of vehicles. To introduce this additional element in the individual DNA, we construct an index that merges information on the location of the stops and their duration with the position of public charging stations already available in the province of Parma.[5] Driven by the intuition that the longer and closer stops are to charging stations, the more one would be able to recharge the EV without significant changes in daily habits, we evaluate the geodesic distance between stops that last at least 30 min and the position of the closest charging station. In this computation, we neglect base and overnight stops, under the assumption that EVs are charged at home during the night. Meanwhile, we do not consider stops shorter than 30 min, since they would not allow for a sufficient gain of driving range in case of recharge. For all agents $v \in \mathcal{V}$, we then retrieve the average minimum distance from the charging stations ACD_v, resulting in the distribution shown in Fig. 10. Clearly, in many cases the stops are not excessively distant from existing charging stations, thus indicating that several agents would eventually be able to recharge an EV during their stops. The final PuCP index is then defined based on the normalized ACD_v as follows:

$$\mathrm{PuCP}_v = 1 - \frac{\mathrm{ACD}_v - \min_{w\in\mathcal{V}}(\mathrm{ACD}_w)}{\max_{w\in\mathcal{V}}(\mathrm{ACD}_w) - \min_{w\in\mathcal{V}}(\mathrm{ACD}_w)}, \quad \mathrm{PuCP}_v \in [0,1], \tag{6}$$

[5] https://www.colonnineelettriche.it/index.php?z=PR

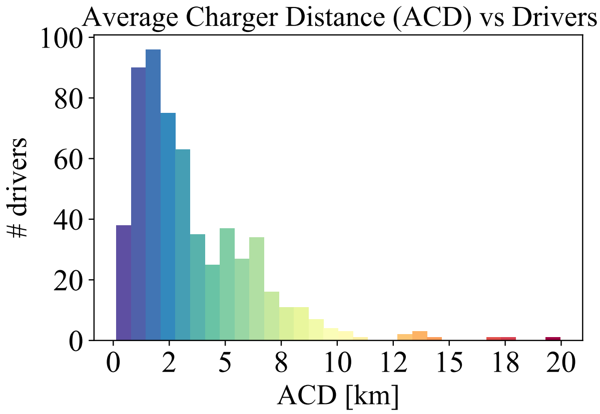
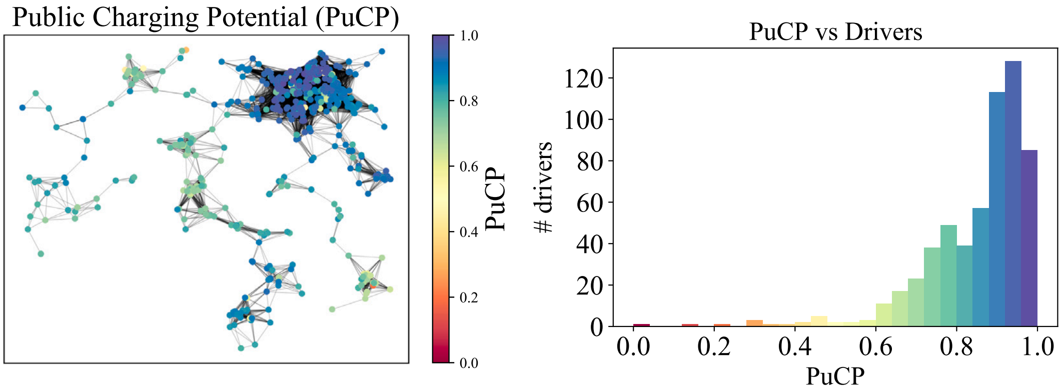


Fig. 10. Distribution of the average minimum distance from a charging station ACD_v over the agents.



(a) Distribution of PuCPs over the network. (b) Distribution of PuCPs over the agents.

Fig. 11. PuCP index distributions over the network and the agents.

and it is obtained by considering that the higher ACD_v, the less suited one potentially is for a transition to an EV based on its recharging needs. As it can be seen from the distributions of the PuCP reported in Figs. 11(a)–11(a), the value of this indicator is generally close to the maximum, with higher values mainly characterizing agents with base stops in proximity of the city of Parma.

Private charging potential (PrCP). The availability of an EV home charging station would favor a transition to an EV, since public charging is usually more expensive than private one. Nonetheless, domestic recharge requires the availability of either a fully private parking space or one shared with few others. Based on the idea that in more populated areas one is less likely to own a private garage or parking spot where to recharge an EV over night, we construct the PrCP index by combining the information on the location of the base position and the population density in the associated area. As shown in the distribution in Fig. 12, about 57% of drivers would be able to charge an EV in a private facility consistently with the fact that their base position is either far away from the center of Parma or it is located in its surrounding belt. This result is translated into the defined PrCP_v index, for $v \in \mathcal{V}$, as:

$$\mathrm{PrCP}_v = 1 - \frac{\mathrm{PD}_v - \min_{w\in\mathcal{V}}(\mathrm{PD}_w)}{\max_{w\in\mathcal{V}}(\mathrm{PD}_w) - \min_{w\in\mathcal{V}}(\mathrm{PD}_w)}, \quad \mathrm{PrCP}_v \in [0,1], \tag{7}$$

which is retrieved from the normalized population density at the base stop PD_v. As it can be seen in Fig. 13, the previous consideration on the distribution of the population density is reflected on that of the PrCP index over the network.

Break even feasibility (BEF). Since EVs are generally more expensive than traditional ICE vehicles, their cost might prevent one to buy them, especially if the initial investment is not repaid (Dumortier et al., 2015). Let alone fixed expenses (*e.g.,* circulation taxes, insurance), EVs become more cost efficient than traditional ICE vehicles when the driving activity is high, due to the significantly lower costs of recharging with respect to refueling. As such, the chance of a break even can be linked to the need of refuel (which depends on the kilometers covered by each vehicle) and the difference in costs between traditional fuels and electricity. Along this line, we construct an index based on the kilometers traveled yearly by each ICE vehicle. Specifically, we consider the *yearly kilometers*

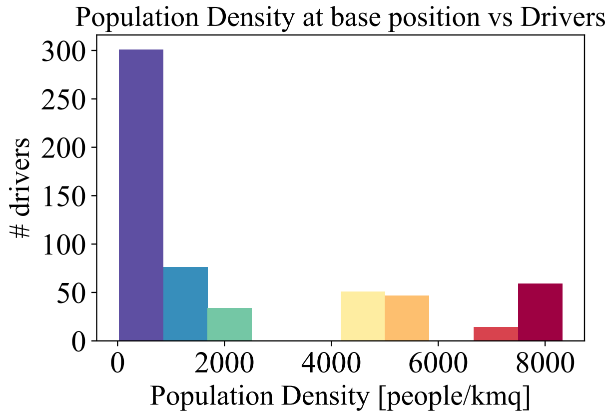


Fig. 12. Distribution of the population density at base stops over the agents.

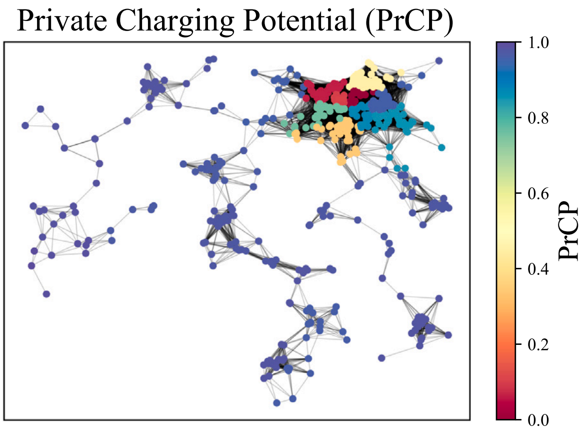


Fig. 13. PrCP distribution over the network.

traveled (YKT) by each agent, the distribution of which is reported in Fig. 14. Clearly, most of the agents cover less than 20000 km per year, thus being less close to pay back the initial investment. The final index exploited in the definition of the EV-suitability DNA is defined by normalizing the value of YKT_v, for all $v \in \mathcal{V}$, thus being given by

$$\text{BEF}_v = \frac{\text{YKT}_v - \min_{w\in\mathcal{V}}(\text{YKT}_w)}{\max_{w\in\mathcal{V}}(\text{YKT}_w) - \min_{w\in\mathcal{V}}(\text{YKT}_w)}, \quad \text{BEF}_v \in [0,1]. \tag{8}$$

Given the YKTs of the considered drivers, it is not surprising that the BEF index is rather low all over the network, independently from the position of their base stops, as shown in Fig. 15.

EV-adoptability DNA. Based on the considered features, each individual v will be fully characterized by a signature

$$\pi_v = (\text{EP}_v, \text{PP}_v, \text{PrCP}_v, \text{PuCP}_v, \text{BEF}_v), \tag{9}$$

that we call *EV-adoptability DNA. This indicator is envisioned to* compactly describe and distinguish each individual from the others (see Fig. 16 for a pictorial representation).

3.3. Combining the DNA features into a single indicator of EV-suitability

Provided the detailed insights on the individual EV-suitability resulting from the constructed DNA, it is important to define a compact indicator summarizing all the information contained in the latter. In this work, we construct such an index by considering the weighted average of individual DNA features, namely

$$\mu_v = \sum_{i=1}^{6} w_v^{[i]} \pi_v^{[i]}, \quad \mu_v \in [0,1], \ \forall v \in \mathcal{V}, \tag{10a}$$

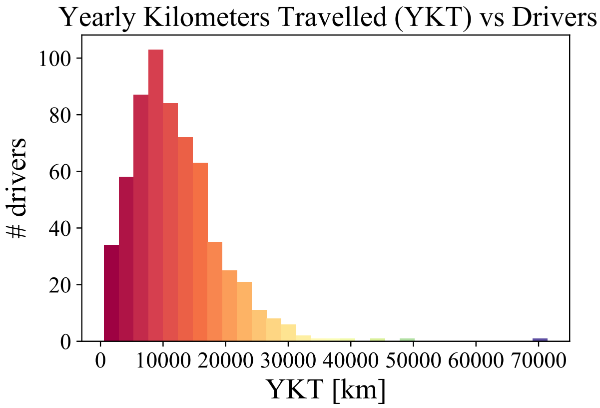


Fig. 14. Distribution of the yearly kilometers traveled (YKT) over the agents.

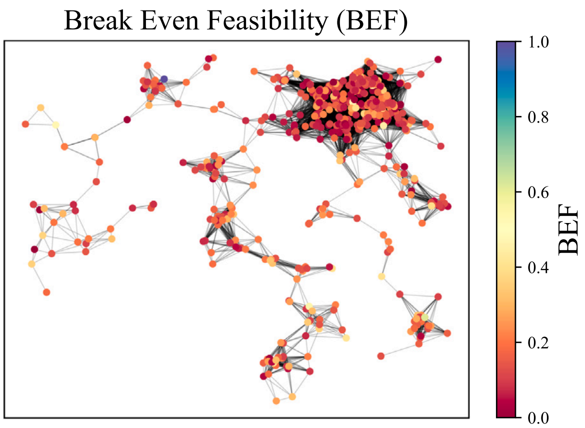


Fig. 15. BEF distribution over the network.

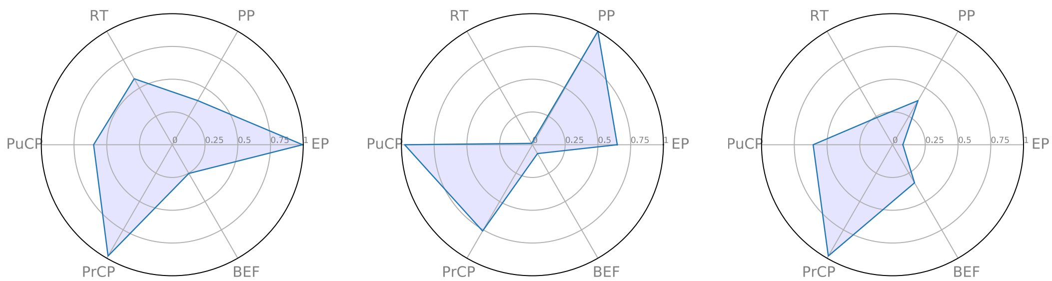


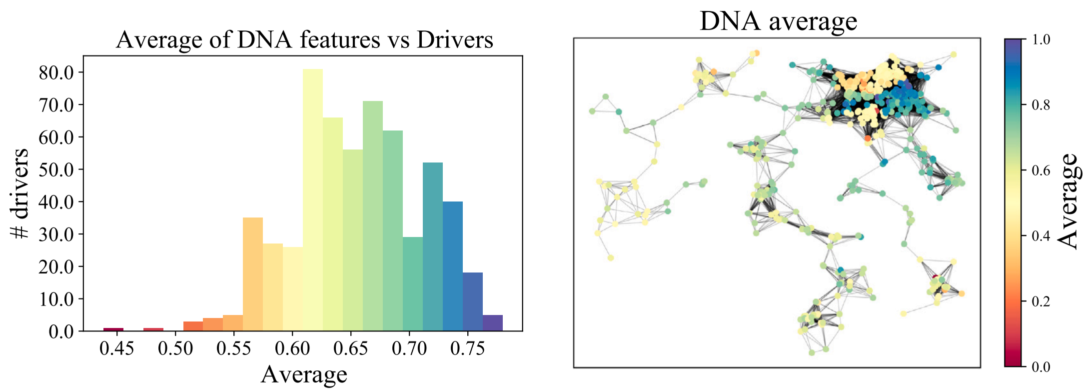
Fig. 16. EV-adoptability DNA of three different users, inferred from their real mobility patterns.

where the weights satisfy the following relationship:

$$\sum_{i=1}^{6} w_v^{[i]} = 1, \quad \text{with} \quad w_v^{[i]} \in [0,1], \quad i = 1, \dots, 6. \tag{10b}$$

Since we have no specific insights other than mobility traces, a possible choice for the weights is to set them all equal, *i.e.*, $w_v^{[i]} = 1/6$ for $i = 1, \dots, 6$. This definition allows us not to prioritize any feature with respect to the others, while preserving differences in individual predisposition. Nonetheless, the definition in (10a) is flexible enough to embed information on the relative importance of the different DNA features in dictating the resistance of each individual to EV adoption.

By considering equal weights, the distribution of μ_v over the agents is shown in Fig. 17(a). Note that, few agents are characterized by values of the DNA average below 0.5, and this compact indicator is never above 0.8. This concentration around relatively high values of the average reflects the distributions of the DNAs' features shown previously, even if the considered compact indicator does



(a) DNAs averages over the agents. (b) DNAs averages over the network.

Fig. 17. DNAs average distribution over the network and the drivers.

not explicitly preserve insights on the variance of the DNA features. Moreover, our choice allows us to account for the geographical distribution of the single features. Indeed, as shown in Fig. 17(b), ICE owners generally result to be less ready for an immediate shift to an EV if their base stop is far from Parma.

4. Adoption dynamics

Provided a model describing the mutual influence between individuals and a quantitative description of their predisposition to an EV transition, it is now crucial to characterize how changes in people's beliefs are triggered.

As shown in several surveys (Coffman et al., 2017; Taalbi and Nielsen, 2021; Wei et al., 2021; Hardman et al., 2017; De Gennaro et al., 2014; Krishna, 2021; Rezvani et al., 2015; Sierzchula et al., 2014; Singh et al., 2020; White and Sintov, 2017), many potential buyers are unfamiliar with new technologies or hesitant to adopt them because of the difficulty in accurately estimating the financial and/or environmental costs and benefits of electric vehicles compared to other vehicles. Therefore, consumer choices are not necessarily based on objective and accurate assessments of the suitability of switching to EVs, and preferences over a finite set of options are often influenced by the media and social networks.

Starting from this consideration, we adopt a simple model of EV adoption, able to account for the intertwining of (i) an individual-dependent utility function resulting from EV adoption, and (ii) social imitation, a psychological factor that is observed when the market share of a given type of vehicle increases. We remark that a large amount of scientific literature has adopted agent-based cascade models (see Hesselink and Chappin, 2019a; Zhang and Vorobeychik, 2019; McCoy and Lyons, 2014 and references therein) since the latter allow to specifically account for changes in consumer behavior in response to the technology diffusion, compared to traditional discrete-choice models that consider a static distribution of decision-making strategies. In this body of literature, adoption is modeled as a binary choice and agents have a threshold beyond which the benefits of adoption outweigh the costs. The agents' utility is a function of their socio-economic characteristics, behaviors, and environmental attitudes. Hence, utility from adoption increases with that by their peers and as the popularity of the innovation increases within the population.

In summary, we rely on two main intuitions (already leveraged in McCoy and Lyons (2014)):

1. the relative popularity of EVs among neighbors can drive a shift of individual opinions on their adoption;
2. an agent would not go back to an ICE vehicle after the adoption of an EV.

Based on these assumptions, we describe the EV-adoption process of interest through an *irreversible deterministic* cascade model on $\mathcal{G}$ (Granovetter, 1978). We thus endow each node in $\mathcal{V}$ with:

- a static threshold $\alpha_v \in [0,1]$ condensing the information encrypted in the EV-adoptability DNA and compactly representing the personal resistance to EV adoption. Accordingly, here we consider the compact indicator summarizing the EV-adoptability DNA in (10a), and we define the individual thresholds as

$$\alpha_v = 1 - \mu_v, \quad \forall v \in \mathcal{V}. \tag{11}$$

  This choice relies on the rationale that the higher is the average μ_v, the lower is the number of neighbor adopters needed to switch to an EV thanks to the high adaptability of the vth agent to the EV transition.
- A binary and *dynamical* state $z_v(t) \in \{0,1\}$, with $v \in \mathcal{V}$, indicating whether the agent has shifted to an EV ($z_v(t)=1$) or not ($z_v(t)=0$) at time $t \in \mathbb{N}$. Based on the idea that EV diffusion is driven by the relative popularity of EV adoption, this state switches according to the following logic:

$$z_v(t+1) = \begin{cases} 1, & \text{if } \frac{|\mathcal{N}_v^\star(t)|}{|\mathcal{N}_v|} \geq \alpha_v \text{ or } z_v(t)=1, \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

so that a change in the binary state of the vth agent happens when the ratio between the number of EV-adopters neighbors $|\mathcal{N}_v^\star(t)|$ at time t and the number of neighbors $|\mathcal{N}_v|$ is above the prefixed acceptance threshold α_v. It is thus worth pointing out once again that, according to this model, EV-adoption stems from the relative popularity of EVs among neighbors.

Given a *seed set* S_0 of early adopters (*i.e.,* $S_0 = \{v \in \mathcal{V} : z_v(0) = 1\}$), the set of new users S_t at each time instant $t \in \mathbb{N}$ thus evolves according to the following EV diffusion model:

$$S_t = \left\{ v \in \mathcal{V} \setminus (\cup_{\tau=0}^{t-1} S_\tau) : \frac{|S_t^\star \cap \mathcal{N}_v|}{|\mathcal{N}_v|} \geq \alpha_v \right\} \tag{13}$$

where $S_t^\star := \cup_{\tau=0}^{t} S_\tau$ represents the total amount of EV-adopters in the network up to time t. Therefore, $S_t^\star$ is monotonically increasing in time. We remark that the choice of this class of contagion models might realistically describe EV adoption over a community within relatively short time horizons only. Indeed, in this case individuals are likely not to drastically change their socio-economic status and their "social" connections, while substantial advancement in the EV technology are likely not to have reached production yet. Meanwhile, in the long run, all the aforementioned features can drastically change, thus limiting the validity of the model. As such, although modeling the adoption dynamics as in (13) guarantees that $S_t^\star$ is monotonically increasing in time and that the dynamics converge to a final adopters set $\overline{S}^\star$ (Acemoglu et al., 2011).

Remark 1 (*Asynchronous Cascade Model with Random Activation*)**.** It is worth remarking that the available dataset does not allow us to retrieve any information on the average length of car ownership. Therefore, we cannot consider the length of car ownership in our simulations without introducing additional assumptions. However, the general framework proposed in this work can be extended to account for additional uncertainty about an individual's choice to reconsider his or her mobility. As an example, a simple approach would be to consider individual asynchronous cascade models, where the state of each agent is updated at random activation times governed by a Poisson clock with an individual rate. In Ravazzi et al. (2023) asynchronous semi-anonymous dynamics (including the cascade model with Poisson clocks activation) are considered with random noisy response to the state of neighbors. In particular, it can be shown that the two dynamical systems exhibit the same features and share the same set of equilibrium points.

5. Simulation results

In this section, we present the results of a set of extensive simulation with the objective of showing the effectiveness of the proposed framework as a tool for the analysis of EV adoption over a community of individuals and the design of policies to boost such a phenomenon. To this end, we initially simulate the free evolution of the cascade model, later comparing it with the one obtained by applying a set of sample static policies. All these steps allow us to show all the operations a policy maker can perform with the proposed framework.

5.1. Simulation setting

The simulation setting considered when studying both the free diffusion of a positive inclination towards EVs over the network and the effects of human-centered policies is characterized by the following features.

- **Time frame.** We examine the spread of EVs over the network for a time span of about 5 years. This choice allows us to account for a (conservative) estimate of the time currently required for relevant changes in the EV technology to be put in production and, thus, for them to be available to the masses. Instead, longer time horizons might be characterized by significant improvements in the technology, which are likely to reshape the individual inclination to an EV and, thus, the agents' DNA and the irreversible cascade model. All simulations are carried out over this time frame by considering steps of 6 months each, bearing in mind that people are not likely to reconsider their mobility choice often, especially when this entails investing money to buy a new vehicle. Meanwhile, since no information is available on individual car ownership, the latter is not accounted for in our simulations. Nonetheless, we would like to stress that the proposed framework is flexible enough to allow for alternative horizons and time spans, without relevant changes in its mathematical formulation, while easily allowing to introduce insights on the individual length of car ownership (see, *e.g.,* Remark 1).
- **Seed set construction.** To evaluate the spread of EVs over the network, we have to select a set of early adopters from which the diffusion of EVs can originate (Campbell et al., 2012). As the available data are anonymous, our only insight on individual inclinations is given by the DNA extrapolated from the data, that we use to construct the seed set S_0. We refer the readers to McCoy and Lyons (2014), Campbell et al. (2012), Saarenpää et al. (2013) for alternative techniques to determine the early adopters. Specifically, in Campbell et al. (2012) a clustering algorithm on Census data is used to determine regions with high density of early adopters, and in Saarenpää et al. (2013) this method is enriched by exploring the correlation between demographic and socio-economic features and early EV adoption. Our work takes a different and more sophisticated perspective. As suggested in McCoy and Lyons (2014), Campbell et al. (2012), Saarenpää et al. (2013), the early adopters are individuals with high openness to the EV technology. Low range anxiety, high purchase power and a social environment which is perceived as EV-friendly are found to be the strongest drivers of EV adoption likelihood. All these features are embedded

Table 2
Calibrated parameters to mimic the diffusion of EVs in Italy from 2019 to 2021.

δ	$w_v^{[1]}$	$w_v^{[2]}$	$w_v^{[3]}$	$w_v^{[4]}$	$w_v^{[5]}$	$w_v^{[6]}$
0.01	0.65	0.075	0.025	0.2	0.025	0.025

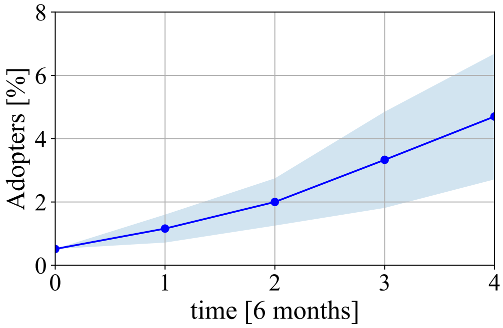


Fig. 18. Free evolution over 78 realizations of the seed set: average percentage of adopters over time (blue line) and its standard deviation (shaded blue area).

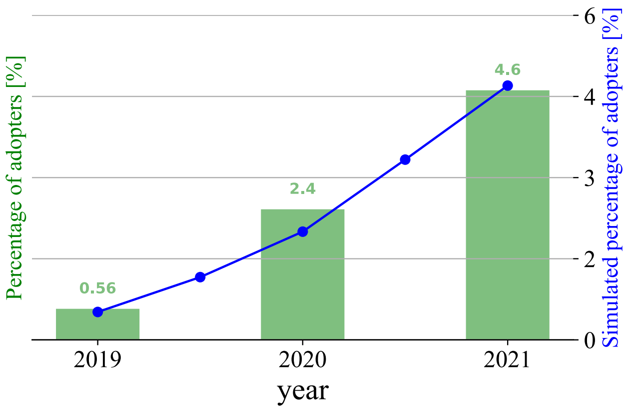


Fig. 19. Free evolution over 78 realizations of the seed set: average percentage of adopters over time (blue line) *vs* percentage of registered EVs in Italy between 2019 and 2021.

in the individual threshold parameter. These considerations lead us to consider the following rule. Given the averages of the DNA features of all the agents $\{\mu_v\}_{v\in\mathcal{V}}$, the seeds are randomly extracted according to a Bernoulli distribution with mean

$$\mu = \frac{\delta}{|\mathcal{V}|}\sum_{v\in\mathcal{V}} \mu_v, \tag{14}$$

where $\delta \in [0,1]$ is a scaling factor, used to modify the size of S_0 and, thus, control the expected dimension of the seed set. Not to bond the analysis to a specific seed set, simulations of the proposed framework can be carried out by considering several realizations of S_0. We stress that this randomization can be avoided if information on actual EV adopters is available. Nonetheless, in situations where no priors on "early adopters" and/or the actual inclination towards EVs, the proposed approach represents a possible strategy to perform a robust analysis of the spread of individual's inclination with respect to EVs over a community.

5.1.1. Calibration of the cascade model with respect to EV diffusion in Italy

To employ the proposed model for policy design and evaluation, it is important to demonstrate that the proposed framework can accommodate a calibration phase, so as to be able of tuning the model parameters to match historical data. In this case, we aim at showing that we can replicate the evolution of the actual diffusion of EVs. Nonetheless, since statistical information on the percentage of electric vehicle registered in the province of Parma is not available or easily accessible, calibration is here performed for the free evolution of the cascade model to result in a realistic behavior with respect to EV adoption at a national (*a.k.a.*, Italian) level. To this end, we have tuned the degrees of freedom of the model, namely the thresholds $\{\alpha_v\}_{v\in\mathcal{V}}$ in (11), for its free evolution to match the percentage of EVs registered in Italy starting from 2019 up to 2021,[6] *i.e.,* over 4 steps in our time frame. To do this, a simple optimization problem has been solved, which calibrates the free parameters of the model so as to minimize the error in the reconstruction of the overall diffusion dynamics. We remark that this approach is fully general, and can be used within our framework as an additional automatic step to be performed after the construction of the adoption network before using it for policy evaluation.

Since each threshold α_v is driven by μ_v in (10a), our degrees of freedom for calibration are represented by the weights $\{w_v^{[i]}\}_{i=1}^{6}$ in (10a) . Changes in these weights have also an impact on the construction of the seed set, along with the parameter δ, according to (14). By properly tuning δ, such a dependence on $w_v^{[i]}$ allows us to also calibrate the seed set, which is (in our setting) unknown. As we have no insights on the "true seeds" within the population under observation, the weights and δ are thus tuning knobs that we select to reproduce the percentage of adopters in Italy both at the beginning and throughout the considered time frame. To simplify the calibration process, we suppose that the importance weights w_v are equal for all agents, *i.e.,* $w_v = w_j$, for all $v, j \in \mathcal{V}$ with $v \neq j$. Nonetheless, it is worth to point out that this assumption can be easily removed, if additional information on the factors driving the individual resistance to EV adoption are available.

The values of the tuning knobs resulting in the least error between the simulated behavior of the cascade model and the actual diffusion of EVs at the Italian level are reported in Table 2. The calibrated weights thus indicate that the features that impact the most on the individual resistance are the *electrification predisposition* (EP) and the *public charging potential* (PuCP), signaling the importance that the adaptability of personal mobility habits and the existing recharging infrastructure have on EV adoption. The resulting evolution over 154 random extractions[7] of the seed set is reported in Fig. 18. Clearly, the dispersion of the percentage of adopters with respect to its mean value tends to increase over time, as it is largely dependent on the positions of the seed within the adoption network. Nonetheless, on average, the calibrated model allows us to mimic the diffusion of EVs at the national level, as proven by the comparison in Fig. 19.

These results show that the proposed framework allows for the cascade model to fit different scenarios, by properly calibrating its tuning knobs once the individual DNA and the network are constructed. As such, the flexibility of the proposed modeling framework makes it a general tool to the description of the spread new mobility solutions by social contagion, allowing one to analyze and test the expected outcome of possible incentive policies within a model that fits the historical evolution of the adoption process under study.

5.2. Free evolution of the cascade model

Within the calibrated setting, we now comment upon the results obtained by simulating the free evolution of the cascade model. Fig. 20 shows the average opinion of each individual with respect to a possible adoption of an EV over the 154 realizations of the seeds at beginning and the end of the considered temporal horizon. Quantitatively, these results translate into an average of 21.3% individuals within our population that become favorably predisposed to EVs. As such, a positive inclination towards EVs tends to spread over the network, even if no policy is enacted to boost the diffusion of this green mobility solution. In addition, many of those agents that are favorable to EV adoption are located in peripheral regions of the graph, while the diffusion within the biggest cluster of agents in the network is instead rather slow. These (eventually *optimistic*) "unincentivized " spread of EVs can be linked to the scarcity of insights on early adopters,[8] which might lead to an over-approximation of the final percentage of positively inclined individuals. In our simulations, we will keep the calibrated δ and weights in (11) reported in Table 2 for the differences between the unincentivized behavior and the policy-induced one to be appreciable.

5.3. Sample DNA-based policies to boost people's acceptance of EVs

The mathematical model of the adoption process, the individual predisposition and the network of potential users allow one to design strategies promoting EV adoption by directly taking into account people's predisposition and mutual influences. As a test-bench for this idea, here we we consider the initial setting resulting from the calibration parameters in Table 2, and we restrict our analysis to a set of sample policies directly enacting changes in *one feature* of the individual EV-adoptability DNA, *i.e.,*

$$\left(\pi_v^{[i]}\right)^+ = \min\left\{\pi_v^{[i]} + \Delta\pi_v^{[i]}, 1\right\}, \tag{15}$$

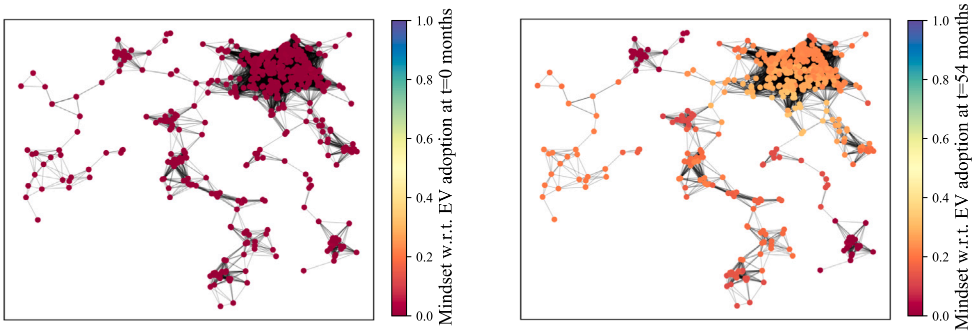
with $\Delta\pi_v^{[i]}$ being the change impressed by the considered policy on the ith DNA attribute. Accordingly, the effect of each policy is epitomized by the quantity $\Delta\pi_v^{[i]}$, which can be freely designed by the policy maker. In our simulations, we restrict our preliminary analysis to policies that are enacted statically, *i.e.,* $\pi_v^{[i]}$ is modified according to (15) *only once* (at $t = 0$)and then it is not further changed throughout the evolution of the cascade model. Since infinite budgets are unlikely to be available in practice, we further assume that the following holds

$$\sum_{v\in\mathcal{V}} \Delta\pi_v^{[i]} < \bar{\pi}, \tag{16a}$$

[6] https://www.unrae.it/pubblicazioni/book-statistiche-annuali

[7] We have performed 200 extractions of the seed set and removed those that did not led to the activation of the cascading phenomenon.

[8] Namely, the absence of priors on the actual individual predisposition with respect to EVs and on the position of early adopters within the network.



(a) Beginning (b) After about 5 years

Fig. 20. Average free diffusion of a positive attitude towards EVs over the network, when 0.51% of the agents are comprised into the seed set. The closer to red is the color of a node, the less the associated agent is inclined to change its attitude towards EVs over the Monte Carlo seeds sets. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

where $\bar{\pi}$ is a maximum budget fixed beforehand by the policy maker, in turn derived by a tailored projection of a resource budget into the considered numerical domain. In this study, we determine $\bar{\pi}$ as:

$$\bar{\pi} = \beta|\mathcal{V}|, \tag{16b}$$

where $\beta \in (0,1)$ scales the "wort-case scenario budget" $|\mathcal{V}|$, *i.e.,* the cost of augmenting the features of all agents of 1. According to this constraint, here the overall budget is allocated to each potential adopter according to the following logic:

$$\Delta\pi_v^{[i]} = \frac{\kappa_v}{\sum_{v\in\mathcal{V}\setminus\{S_0\}}\kappa_v}\bar{\pi}, \tag{17}$$

where $\kappa_v \in [0,1]$ can be equal for all individuals or it can be dictated, among others, by:

- the features of the agent's EV-adoptability DNA;
- its centrality in the diffusion process based on each nodes degree d_v, $v \in \mathcal{V}$;
- the interplay between centrality and personal resistance, here evaluated according to the Balanced Index (BI) (Karampourniotis et al., 2019):

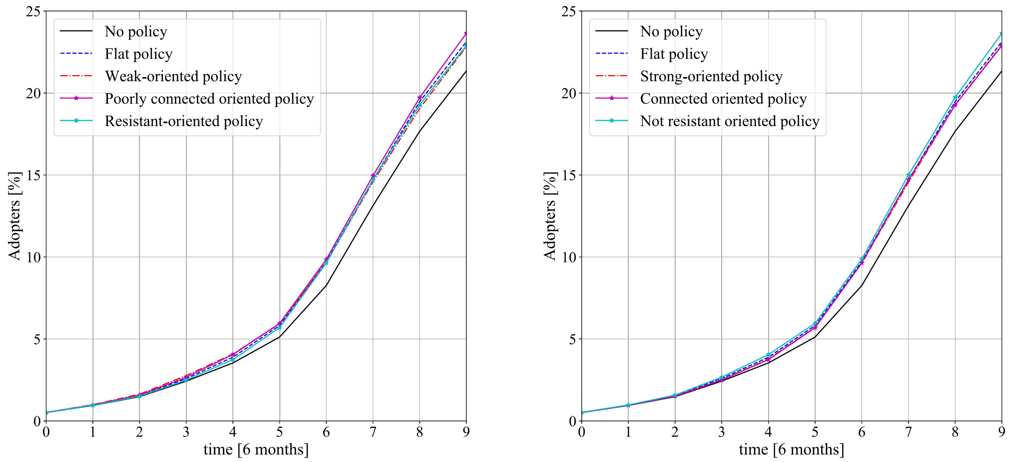
$$BI_v = \frac{1}{3}\left[\alpha_v|\mathcal{N}_v| + k_v^{\text{out}} + \sum_{\substack{h\in\mathcal{N}_j \\ \alpha_j|\mathcal{N}_j|=1}} (k_h^{\text{out}} - 1)\right], \tag{18}$$

where k_v^{out} is the subset of non-adopters in $\mathcal{N}_v$.

Although conceptually simple, this policy design approach allows us to simulate how different boosting strategies can foster EV adoption, by leveraging quantitative information on the individual propensity to EVs and the features of the network where the agents are immersed.

According to the rationale in (17), we test the following set of human-centered policies.

- By regarding individuals as *weak* if they have *low* $\pi_v^{[i]}$ (*i.e.,* $\pi_v^{[i]}$ is close to zero), and *strong* when they are characterized by $\pi_v^{[i]}$ close to 1, we test a set of *feature-centered* policies. Specifically, we consider:
  - *weak* (W) oriented policies, for which $\kappa_v = 1 - \pi_v^{[i]}$, $v \in \mathcal{V}$;
  - *strong* (S) oriented policies, *i.e.,* $\kappa_v = \pi_v^{[i]}$, $v \in \mathcal{V}$.
- By looking at individuals as *influencers* when they have a higher (normalized) degree $\tilde{d}_v \in [0,1]$, we consider the following pair of *homophily-oriented* policies:
  - *connected* (C) oriented policies, *i.e.,* $\kappa_v = \tilde{d}_v$, $v \in \mathcal{V}$;
  - *poorly connected* (PC) oriented policies, for which $\kappa_v = 1 - \tilde{d}_v$, $v \in \mathcal{V}$.
- Combining insights on the individual predisposition towards EV and towards a change in mindset induced by others, we exploit the Balanced Index in (18) to construct a set of *resistance-based* policies. Specifically, we consider



(a) Policies directed towards "weak" agents (b) Policies directed towards "strong" agents

Fig. 21. Incentive policies based on the Purchase Power (PP): average percentage of adopters over time for a seed set comprising 0.51% of the agents and a fixed budget $\bar{\pi} = 58.2$.

- *resistant* (R) oriented policies. promoting EV adoption towards people whose habits are not suited for a swift switch to EVs and that are less likely to be influenced by others via[9] $\kappa_v = \tilde{\text{BI}}_v$, $v \in \mathcal{V}$;
- *resistant* (R) oriented policies, namely $\kappa_v = 1 - \tilde{\text{BI}}_v$, $v \in \mathcal{V}$.

All these human-tailored policies are compared with the Flat (F) one, *i.e.,*

$$\kappa_v = 1, \quad \forall v \in \mathcal{V} \backslash S_0, \tag{19}$$

namely a policy where resources are equally distributed among the agents, independently of their predisposition along the considered DNA direction. Note that this is a juxtaposition that can be performed by the final user of the framework (*a.k.a.,* the policy maker), to understand the advantages/pitfalls of policies promoting EV adoption by exploiting insights on personal and interpersonal traits of each potential adopter over myopic ones.

In the subsequent analysis, we focus on policies that act on the individual purchase power PP_v, thus mimicking the use of a monetary incentive to foster EV adoption, and strategies that influence the public charging potential PuCP_v (as through the installation of new charging stations Hardman, 2019). Note that, a maximum monetary budget for either direct incentives or installations can be easily translated into (16b) by making a simple proportion and viceversa. As an example, let us assume that a policy maker has 1M€ as the worst-case budget to promote EV adoption. Moreover, assume that $\beta = 0.2$ (*i.e.,* the policy maker aims at using only 20% of the worst-case budget). Then, $\bar{\pi} = 0.2|\mathcal{V}|$ can be translated into a monetary constraint of the policy design problem as:

$$\frac{1\text{M€}}{|\mathcal{V}|} \cdot \bar{\pi} = 200000\ \text{€}.$$

5.3.1. Analyzing DNA-based policies' effect on the agents inclination

Given the benchmark represented by the average unforced change in individual of EVs over our network, we now want to investigate how the quantitative description of individual inclinations towards electric vehicles can be exploited to design impactful, yet "cheap", policies. To this end, we test all the strategies previously introduced, to highlight their effect on the diffusion of a positive attitude towards EVs over the network. To understand which policy might be more advantageous, we implement our policies by:

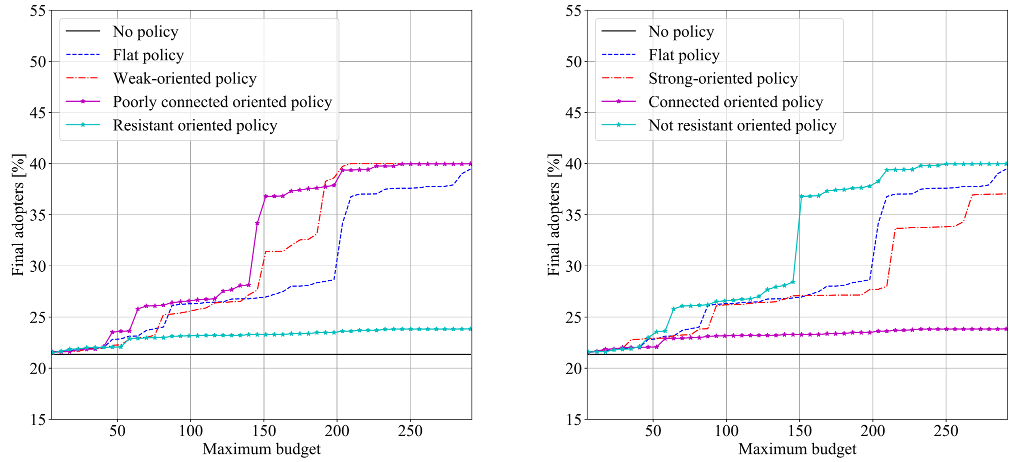
- arbitrarily *fixing* the budget to $\bar{\pi} = 58.2$;
- *varying* the budget $\bar{\pi}$ from a minimum around 5.82 up to a maximum of about 291.

Note that, even if alternative choices can be made with respect to the fixed budget $\bar{\pi} = 58.2$, the second analysis allows to understand the impact that different choices of the latter have on the final attitude (and, thus, the ultimate outcome) of the considered population towards EVs. With an abuse of notation, in the following we will refer to individuals who have changed their attitude towards EVs (according to the model in (12)) as *adopters*.

[9] $\tilde{\text{BI}}_v \in [0, 1]$ is the normalized Balanced Index for the vth agent.

Table 3
Incentive policies based on the Purchase Power (PP): average number of agents that have changed their attitude towards EVs. Unforced *vs* flat and DNA-based strategies.

	Unforced	Flat	W	PC	R	S	C	NR
Avg. number of "adopters"	124	135	133	138	133	134	133	138



(a) Policies directed towards "weak" agents (b) Policies directed towards "strong" agents

Fig. 22. Incentive policies based on the Purchase Power (PP): average percentage of final adopters for increasing budgets and seeds fixed to the 0.51% of the agents.

Table 4
Installation policies based on the Public Charging Potential (PuCP): average number of final adopters. Unforced *vs* flat and DNA-based strategies.

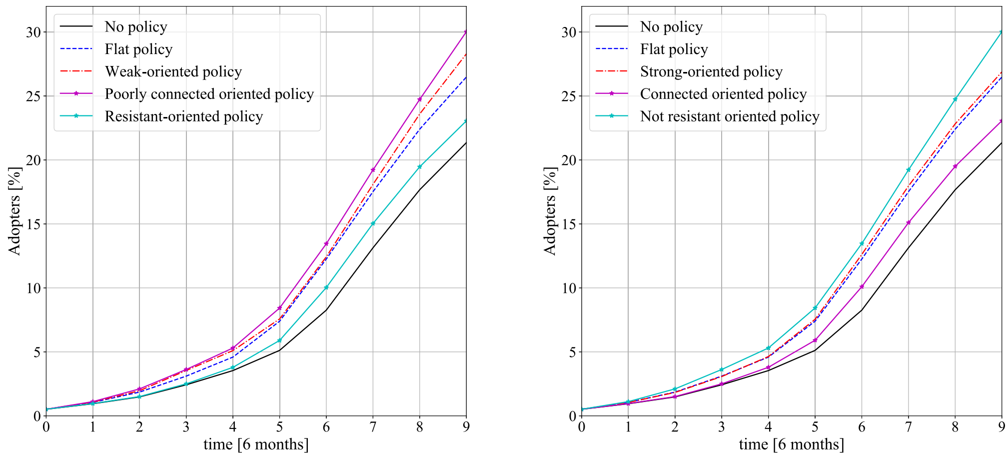
	Unforced	Flat	W	PC	R	S	C	NR
Avg. number of "adopters"	124	154	165	175	134	156	134	175

Policies based on the purchase power. When fixing the budget, we analyze the effect that the different policies have on the attitude towards EVs of the population over time. Despite the relatively low importance that the purchase power has on defining the individual barrier to adoption (see Table 2), a differences between policies based on the purchase power can still be appreciated by looking at Fig. 21. Although a *myopic* flat strategy may be more advantageous than policies oriented towards agents at intermediate points in time (*e.g.,* see the behavior around the 5th and 6th steps of our simulation in Figs. 21(a)–21(b) most human-centered policies tends to pay-off comparably to the flat one on the long run. This result is further highlighted by the average percentages of final adopters reported in Table 3. By combining these outcomes, it results that incentivizing *poorly connected* or *not resistant* agents allows for a vaster change in attitude within the considered network. As such, in our scenario, it is best to invest on convincing people that are not influenced by the rest of the population or in fostering the transition towards EVs over central and not resistant agents, *i.e.,* "good influencers". By looking at Figs. 4(a) and 7(a), it is clear that investing on poorly connected agents indirectly implies that investments are mainly directed towards people with a low PPs.

The results in Fig. 22 indicate that the trends shown in Fig. 21 are generally preserved, even when considering budgets other than $\bar{\pi} = 58.2$. Specifically, when *weaker* agents are targeted by a policy, it is preferable to look at their connection, rather than their predisposition or their resistance to a switch to an EV. It is indeed clear that incentivizing agents in isolated (and potentially peripheral) regions of the network leads to tangible advantages over a *myopic* flat policy. Meanwhile, when the budget becomes sufficiently high, also targeting weak agents based on their predisposition only is more advantageous than a *myopic* flat policy and, eventually, preferable to a policy looking at the agents' connections (see Fig. 22(a) when the budget is around 200). Instead, accounting for the individual resistance (or better the lack thereof) seems beneficial for policies directed towards *stronger* agents, as soon as the available resources become sufficient.

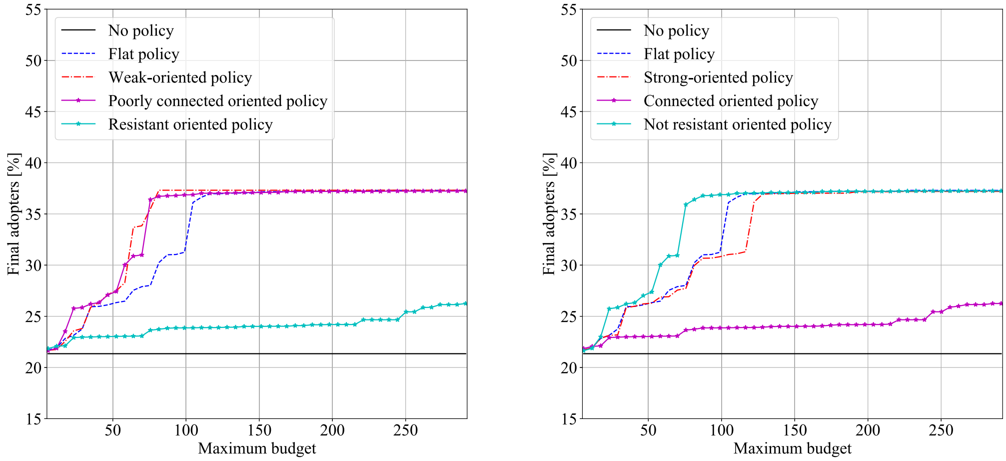
Policies based on the public charging potential. The same analysis performed for PP-based policies is now carried out for strategies based on the individual Public Charging Potential. For a fixed budget, once again policies promoting EV adoption within poorly connected nodes tends to outperform the other strategies directed towards *weaker* agents, as shown in Fig. 23. Nonetheless, even the weak-oriented policy outperforms the *flat* strategy in the long run. Meanwhile, non resistant agents seems to be the one to be targeted by policies directed towards *stronger* individuals. These results are further summarized by the average number of final "adopters" shown in Table 4.

When the amount of resources is varied , policies based on the individual PuCP lead to the change in the percentage of final adopters depicted in Fig. 24. From this results, it can thus be deduced that installation campaigns directed to improve the public



(a) Policies directed towards “weak” agents (b) Policies directed towards “strong” agents

Fig. 23. Installation policies based on the Public Charging Potential (PuCP): average percentage of adopters over time for a seed set comprising 0.51% of the agents and a fixed budget $\bar{\pi} = 58.2$.



(a) Policies directed towards “weak” agents (b) Policies directed towards “strong” agents

Fig. 24. Installation policies based on the Public Charging Potential (PuCP): average percentage of final adopters for increasing budgets and seeds fixed to the 0.51% of the agents.

recharging potential of poorly connected or not resistant agents are beneficial for EVs to become widespread, when the available resources are rather limited. When the budget increases, all policies but those directed towards resistant and connected agents tend to ultimately lead to a more generalized positive attitude towards EVs over the network. By comparing Figs. 22 and 24, it is clear that policies acting on the infrastructure are preferable when the budget is limited, meanwhile initiatives directed towards increasing the individual purchase power have more impact when the budget is high. This result can be related to the relative importance of the public charging potential and purchase power indicated in Table 2, in turn, suggesting that moderate investments on the infrastructure can already impact on the individual predisposition to adoption, while only consistent investments in reducing cost-related barriers can make PP-directed policies effective.

6. Analysis of the impact of human-centered policies

The outcome of the considered policies must be analyzed according to a human-centered paradigm, to have a *measure* of the related sustainability, environmental impact and social inclusiveness (among others). To this end, we introduce a set of self-contained Key Performance Indicators (KPIs) that enable the quantification of these (apparently subjective) features. These indexes allow us to score the policies by taking into account different perspectives (*e.g.,* efficiency, effectiveness, sustainability), ultimately enabling a quantitative comparison that extends beyond the sole quantification of changes in individual inclinations towards EVs.

Table 5
Impact indicators: policies on the purchase power for a fixed budget $\bar{\pi} = 58.2$.

Policy	OD	OT [%]	R-CO_2 [%]	C-F
F	594.30	31.02	28.61	60.16
W	592.49	30.91	29.54	60.81
PC	591.93	30.80	29.57	61.03
R	593.72	30.86	28.59	60.29
S	594.32	30.98	28.60	60.18
C	593.72	30.86	28.59	60.29
NR	591.93	30.80	29.57	61.03

Table 6
Impact indicators: policies on the public charging potential for a fixed budget $\bar{\pi} = 58.2$.

Policy	OD	OT [%]	R-CO_2 [%]	C-F
F	587.3	30.44	33.93	63.24
W	583.98	29.94	36.79	63.80
PC	579.06	30.01	36.15	65.23
R	594.71	30.80	28.88	60.34
S	587.25	30.50	33.87	63.20
C	594.72	30.81	28.89	60.33
NR	579.06	30.01	36.15	65.23

6.1. Impact on the infrastructure

Obviously, a large penetration of EVs into the existing infrastructure may have a negative impact on the distribution grid, including severe voltage variation and overloading of the network. Based on the available mobility patterns, we assume that overloads of the network might occur if all new adopters have base positions in highly populated areas. Indeed, in such configurations, several people might need to recharge at the same time, in the same area and for rather long time intervals, potentially overloading the network. To quantitatively evaluate this situation, we introduce the Overload-Density (OD) indicator, obtained as the mean of population densities in the areas where adopters' base positions are located, normalized with respect to the minimum value of population density within the province of Parma (*i.e.,* around 11 people/km^2). Independently from the DNA feature the policy is enacted on, our tests with fixed budget highlight that strategies directed towards poorly connected or not resistant agents lead to new adopters that will challenge less the existing power grid (see Table 5–6). Nonetheless, by fostering adoption through changes in the purchase power, one ends up with sets of final adopters that generally stress the network more than the ones obtained when public charging potential based strategies are employed.

Another important aspect that must be considered is the effect that a spread of EVs has on public recharging facilities. To account for this additional element, we rely on the intuition that overloads of the network/public charging stations might occur if all new adopters need to recharge the vehicle during the day at the same time. We thus introduce an additional indicator, the Overload-Time (OT) index. To compute it, we check the cardinality of the largest set of final adopters having stops longer than 15 min at the same time throughout the day, normalized with respect to the average number of EV adopters at the end of the horizon. In this case, those strategies that are to be favored according to the OD index tends to result in the minimum OTs (see Table 5). On the contrary, as shown in Table 6, initiatives directed towards weak agent that are based on their predisposition only lead to the smallest OT, while not resulting in the smallest OD. Moreover, even in the worst cases, PuCP-based strategies seems to be the slightly more convenient. These results thus highlight the need to trade-off between increasing the number of adopters and selecting policies impacting the infrastructure less, further compromising between the effect that private and public recharges have on the network load.

When evaluating policies based on the purchase power, we further check whether the existing infrastructure for public recharge is sufficient to cope with the potential charging requests. To this end, we evaluate the weighted mean of the public charging potential of final adopters, introducing the so-called infrastructure Adequacy (I-A) index. Once again each weight is chosen as the number of instances within which the corresponding node is an adopter at the end of the considered time span. Independently on the feature they are focused on, all policies generally lead to an I-A indicator around 0.85, entailing that the charging needs of most of new adopters are likely to be accommodated.

6.2. Environmental impact

The potential of electric vehicles to reduce greenhouse gas emissions highly depends on vehicle usage (Plötz et al., 2018). To assess the impact of the policies on the environment, we evaluate the percentage reduction of CO_2 emissions (R-CO_2) triggered by the adoption process as

$$\text{R-CO}_2 = 100\frac{|\text{CO}_2^T - \text{CO}_2^0|}{\text{CO}_2^0}, \quad [\%] \tag{20}$$

where $\text{CO}_2^t = \frac{1}{50}\sum_{i=1}^{50}\sum_{v\notin S_t^i} T_v^d c_1 c_2$, with S_t^i indicating the set of adopters at time t when considering the ith realization of the seed set, T_v^d [km] being the distance traveled yearly by the vth driver, $c_1 = 8$ [L/100 km] being the fuel consumption of a mid-sized vehicle and $c_2 = 2.29$ [kg of CO_2/L] being the CO_2 emissions due to the consumption of 1 liter of gasoline (Natural Resources Canada, 2014, 2019). In this regard, the policies favoring poorly connected drivers seem to favor a cutback of emissions, independently from the considered policy . According to the final number of adopters, the obtained results further indicate that strategies looking at the public charging potential generally leads to a greater reduction of CO_2 emissions. A consistent set of human-centered strategies (see Table 5–6) lead to a drop in emissions higher or close to the flat one, showing that human-centered policies can have a positive impact on the environment.

6.3. Social impact and inclusiveness

To analyze the effect that the considered policies can have at a societal level, we first check if the policies are inclusive with respect to the individual purchase power. We thus define the Income Fairness (I-F) index as the range prices of houses [€] associated to the area in which the base position of a new adopter is mainly located. In general, all policies favor the class of individuals characterized by the I-F index $1600 - 1700$ [€] . Surprisingly, we thus obtain that policies ultimately lead to favor a change in mindset over groups of individuals with relatively higher income, even when they are targeting agents that have *lower* PP.

Another aspect that can be looked at is the capability of the policies to actually include people that are not initially inclined towards the adoption of an electric vehicle. We evaluate this additional feature of the policies by computing the average value of the DNA of the final adopters (over the 153 random realizations of the seed set). Overall, we obtain a mean value of 0.66, independently from the adopted policy. This indicates that the tested strategies might not be too fair with respect to very skeptical individuals, but they are not solely directed to those people fully convinced to buy an EV already.

Due to the clear influence that the position within the network has on a change of mindset with respect to EVs, we finally compare the different strategies in terms of inclusiveness of individuals that are not central in the network. To this end, we compute the (weighted) average number of neighbors of the final adopters, introducing the Centrality Fairness (C-F) index. Surprisingly, the flat strategy results to be the most inclusive among the ones acting on the purchase power, meanwhile initiatives directed towards resistant and connected individuals are more inclusive in this sense when PuCP-based policies are enacted.

7. Discussion

The study of opinion formation over networks is well-recognized as a promising approach for the analysis of innovation diffusion in general (Valente, 1995; Deffuant et al., 2000; Jackson, 2008; Schelling, 1978), and environmental innovations spread in particular, *e.g.,* the adoption of alternative fuel vehicles (see Higgins et al., 2012; Shafiei et al., 2012; Tran et al., 2012 to mention just a few). Indeed, through this paradigm, one can model the formation of beliefs at the societal level as emerging from individual behaviors and local interactions. Additionally, it is possible to follow the dynamic evolution of these beliefs in a hyper-connected society with a quantitative and rigorous approach (Granovetter, 1978; Acemoglu et al., 2011; Montanari and Saberi, 2010). However, classical models of contagion and innovation diffusion are not fully adequate to describe opinion formation for mobility related decisions, and, thus, to characterize a massive shift to EVs. Indeed, these models are mostly univariate, *i.e.,* they deal with opinions on one specific topic/issue only (Hegselmann and Krause, 2002). Moreover, they mainly account for rational factors, such as costs and driving range (Schuitema et al., 2013; Ajzen and Albarracin, 2007), neglecting essential psychological aspects influencing the individual intention to adopt EVs, *e.g.,* range anxiety, public charging potential, brake even feasibility, and so on.

First attempts to embrace the multifaceted factors driving individual opinions on EVs under a unique framework is made in the recent works (Wolf et al., 2015; Breschi et al., 2020), where an influence network and individual rational and psychological factors extracted by data are combined into a unique model. Here, we extend the approach of Breschi et al. (2020) by introducing a human-centered framework, envisioned to allow policy makers to account for individual traits and mutual influences in the policy-making process. The key elements of the proposed architecture are:

- a *set of data*, needed to characterize individuals and their mutual connections;
- the *EV-adoptability DNA* and the *agents' network*, introduced in Section 3, respectively providing a compact (quantitative) representation of several traits shaping personal inclinations towards EVs, and a formal description of influences among individuals;
- the *model* formalized in Section 4, which allows us to characterize the evolution of the agents' inclination over time;
- the *policies* (see Section 5.3), here enacted "statically" by modifying one of the traits of the individuals' DNA only once in time.

The combination of these elements allows us to provide a general framework for the design of human-centered policies to foster a massive EV adoption, while setting the ground for the analysis of the EV adoption process and of existing EV-promoting policies.

7.1. Assets and limits of the data, the EV-adoptability DNA and the network

At the core of the proposed framework lays the availability of an informative dataset, which is used to directly construct two of its main building blocks (*i.e.,* the EV-adoptability DNA and the network), and that is indirectly leveraged to model the adoption process. In this work, we show how to extract information on the individual predisposition by relying on anonymize mobility traces. This allows us to show that the proposed framework can be build even when no direct access of socio-economic information is available. Moreover, having a direct access to individual mobility traces makes the EV-adoptability DNA encoding the information needed to assess the suitability of individual habits to an immediate transition to EVs. At the same time, it is clear that the anonymity of the available data has its shortcomings. Indeed, this prevents us to encode in the DNA explicit information on the socio-economic status of each individual and on its actual predisposition towards EVs. As such, the adherence of the EV-adoptability DNA extracted in this paper to the actual inclination of each agent cannot be validated. At the same time, the available data does not guarantee access to explicit insights on the social bond between individuals, here extracted by solely looking at their mobility habits. As a consequence, we can only characterize the network via an undirected and unweighted graph, thus not being able to consider the actual direction and strength of inter-personal influences. Finally, the available data do not provide any insight on the individual length of car ownership, thus not enabling us to consider this additional feature without making further assumptions. Nonetheless, the generality of the proposed framework would allow to include information on the length of car ownership and consider different responses to the states of the neighbors, *e.g.,* as discussed in Remark 1.

7.2. Assets and limits of the cascade model

Differently from existing works in the literature (see, *e.g.,* McCoy and Lyons, 2014), the model introduced in Section 4 explicitly leverages the information embedded into the EV-adoptability DNA and the data-driven network to characterize the evolution of individual inclinations. As such, it directly and fully exploits the insights we get from data to characterize the dynamics of mindset changes over time. At the same time, the proposed model has three main limitations. First, it is *irreversible*, thus not allowing for bidirectional changes in individual inclinations. However, people's opinion on technological innovations might change several time, based on advances of the technology and users' experiences, among others. Therefore, the proposed model is clearly suited when relatively short time spans are considered. Second, the model is *binary*, thus envisioning only two possible situations (adoption or not). As a consequence, the model does not account for the intermediate levels that the acceptance of a new technology might entail. Third, the model in (13) depicts the spread of a positive attitude towards EVs over a community as a cascade phenomenon over a *fixed network*. This implies that changes in individual bonds are not accounted for by the current model. Nonetheless, despite its simplicity and its limitations (and those of the available dataset), the introduced cascade model has shown its ability to effectively represent the adoption phenomenon when properly calibrated (see the results in Section 5.1.1).

7.3. Assets and limits of the sample policies

The results obtained with the proposed framework using a set of arbitrarily designed sample policies to promote EV adoption lay the foundation for studying the effectiveness of several interventions in different market segments, and for designing appropriate policies tailored to the heterogeneous needs of different individuals. At the same time, the strategies we have tested are fairly limited for two main reasons. On the one hand, the policies are only *enacted once*, at the beginning of the time horizon, and then we analyze their impact on the free-evolution of the cascade model. Consequently, at the moment we do not account for their effect over time and we do not modify the policies based on their impact over time. On the other hand, policies are directed towards changing only *one feature* of the DNA. Therefore, our analysis does not assess the effect of policies targeting at improving the adaptability of several aspects of individual mobility habits to a transition to EVs.

8. Concluding remarks and future work

In this work, we introduce a human-centered, diversity-aware design framework, which we believe could become trademark of control-enabled systems of the future (Wang et al., 2020). Humans are indeed put at the center of our architecture by introducing the so-called *EV-adoptability DNA*, that characterizes the traits shaping individual readiness to EV adoption. The introduction of this crucial building block allows policy makers to exploit the proposed framework to envision the implications of sustainable policies at an *individual* level, consequently having a better understanding on how to design strategies to promote EV adoption. Meanwhile, we provide well-grounded tools to quantify (and control) the expected impact of specific actions performed by the policy maker on the dynamic evolution of the opinions' spread, intended to maximize the adoption of EVs in large urban settings.

Our results show that the proposed framework can be of help in supporting the design of effective policies to foster the adoption of greener mobility habits, thus embodying an actionable weapon for the fight of climate change. Specifically, the DNA-based description of the agents allows for a quantitative analysis of the socio-economic factors that are most relevant in preventing adoption of the considered technologies. Such a contextualization offers a new way for communicating them to the general public, allowing to overcome cultural barriers and initiate a change of perspective corroborated by the support of quantitative data. The cost/benefit analysis of the incentive policies further allows for the optimization of public spending decisions for driving the considered adoption processes, thus having a tangible economic and social impact on the ultimate choices made by the policy maker. By working with anonymized data, we additionally show how to benefit from limited information to characterize both individual features and mutual influences, towards the design of effective policies.

In the future, our aim is to overcome the main limitations of this work. In particular, thanks to the generality of the proposed DNA-based representation, we aim at exploiting different datasets to enriching the individual DNA with socio-economic features and validating it. Moreover, we plan to enhance the generality of the considered model for EV adoption, by shifting towards a continuous dynamics and by considering more complex changes in the individual predisposition, *e.g.,* including the effect of the length of individual car ownership, and in the interactions between individuals.

CRediT authorship contribution statement

Valentina Breschi: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Visualization. **Chiara Ravazzi:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Silvia Strada:** Resources, Writing – review & editing. **Fabrizio Dabbene:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Mara Tanelli:** Conceptualization, Methodology, Resources, Writing – original draft, Writing – review & editing, Supervision.

Data availability

The authors do not have permission to share data.

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References

Acemoglu, D., Ozdaglar, A., Yildiz, E., 2011. Diffusion of innovations in social networks. In: 2011 50th IEEE Conference on Decision and Control and European Control Conference. pp. 2329–2334.
Ajzen, I., Albarracin, D., 2007. Predicting and changing behavior: A reasoned action approach. pp. 3–21.
Alraddadi, E.E., Allen, S.M., Whitaker, R.M., 2019. Homophily, mobility and opinion formation. In: Nguyen, N.T., Chbeir, R., Exposito, E., Aniorté, P., Trawiński, B. (Eds.), Computational Collective Intelligence. Springer International Publishing, Cham, pp. 130–141.
Bonges, H.A., Lusk, A.C., 2016. Addressing electric vehicle (EV) sales and range anxiety through parking layout, policy and regulation. Transp. Res. A 83, 63–73.
Breschi, V., Ravazzi, C., Strada, S., Dabbene, F., Tanelli, M., 2022. Fostering the mass adoption of electric vehicles: a network-based approach. IEEE Trans. Control Netw. Syst. 1.
Breschi, V., Tanelli, M., Ravazzi, C., Strada, S., Dabbene, F., 2020. Social network analysis of electric vehicles adoption: a data-based approach. In: 2020 IEEE International Conference on Human-Machine Systems. ICHMS, pp. 1–4.
Campbell, A.R., Ryley, T., Thring, R., 2012. Identifying the early adopters of alternative fuel vehicles: A case study of Birmingham, United Kingdom. Transp. Res. A 46 (8), 1318–1327.
Coffman, M., Bernstein, P., Wee, S., 2017. Electric vehicles revisited: a review of factors that affect adoption. Transp. Rev. 37 (1), 79–93.
De Gennaro, M., Paffumi, E., Martini, G., Scholz, H., 2014. A pilot study to address the travel behaviour and the usability of electric vehicles in two Italian provinces. Case Stud. Transp. Policy 2 (3), 116–141.
Deffuant, G., Neau, D., Amblard, F., Weisbuch, G., 2000. Mixing beliefs among interacting agents. Adv. Complex Syst. 3 (1–4), 87–98.
Delre, S.A., Jager, W., Bijmolt, T.H.A., Janssen, M.A., 2010. Will it spread or not? The effects of social influences and network topology on innovation diffusion. J. Prod. Innov. Manage. 27 (2), 267–282.
Docherty, I., Marsden, G., Anable, J., 2017. The governance of smart mobility. Transp. Res. A 115.
Dumortier, J., Siddiki, S., Carley, S., Cisney, J., Krause, R.M., Lane, B.W., Rupp, J.A., Graham, J.D., 2015. Effects of providing total cost of ownership information on consumers' intent to purchase a hybrid or plug-in electric vehicle. Transp. Res. A 72, 71–86.
Fugiglando, U., Santi, P., Milardo, S., Abida, K., Ratti, C., 2017. Characterizing the "driver DNA" through CAN bus data analysis. In: CarSys '17. Association for Computing Machinery, New York, NY, USA, pp. 37–41.
Granovetter, M., 1978. Threshold models of collective behavior. Am. J. Sociol. 83 (6), 1420–1443.
Hagberg, A.A., Schult, D.A., Swart, P.J., 2008. Exploring network structure, dynamics, and function using NetworkX. In: Varoquaux, G., Vaught, T., Millman, J. (Eds.), Proceedings of the 7th Python in Science Conference. Pasadena, CA USA, pp. 11–15.
Han, B., Kim, J., Rasouli, S., Timmermans, H., 2019. On the relative importance of social influence in transport-related choice behaviour: empirical evidence from three stated-choice experiments. In: Plaut, P., Shach-Pinsly, D. (Eds.), Digital Social Networks and Travel Behaviour in Urban Environments. Routledge Taylor & Francis Group, United Kingdom, pp. 94–107.
Hardman, S., 2019. Understanding the impact of reoccurring and non-financial incentives on plug-in electric vehicle adoption – A review. Transp. Res. A 119, 1–14.
Hardman, S., Shiu, E., Steinberger-Wilckens, R., Turrentine, T., 2017. Barriers to the adoption of fuel cell vehicles: A qualitative investigation into early adopters attitudes. Transp. Res. A 95, 166–182.
Hegselmann, R., Krause, U., 2002. Opinion dynamics and bounded confidence, models, analysis and simulation. J. Artif. Soc. Soc. Simul. 5 (3), 2.
Helmus, J.R., Lees, M.H., van den Hoed, R., 2022. A validated agent-based model for stress testing charging infrastructure utilization. Transp. Res. A 159, 237–262.
Hesselink, L.X., Chappin, E.J., 2019a. Adoption of energy efficient technologies by households – Barriers, policies and agent-based modelling studies. Renew. Sustain. Energy Rev. 99, 29–41.
Higgins, A., Paevere, P., Gardner, J., Quezada, G., 2012. Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles. Technol. Forecast. Soc. Change 79 (8), 1399–1412.
Huang, Q., Wong, D.W.S., 2016. Activity patterns, socioeconomic status and urban spatial structure: what can social media data tell us? Int. J. Geogr. Inf. Sci. 30 (9), 1873–1898.
Jackson, M.O., 2008. Social and Economic Networks. Princeton University Press, USA.
Karampourniotis, P., Szymanski, B., Korniss, G., 2019. Influence maximization for fixed heterogeneous thresholds. Sci. Rep. 9.
Krishna, G., 2021. Understanding and identifying barriers to electric vehicle adoption through thematic analysis. Transp. Res. Interdiscip. Perspect. 10.
Leng, N., Corman, F., 2020. The role of information availability to passengers in public transport disruptions: An agent-based simulation approach. Transp. Res. A 133, 214–236.
Lucas, Jr., H.C., Spitler, V., 1999. Technology use and performance: A field study of broker workstations*. Decis. Sci. 30 (2), 291–311.
Manser, P., Becker, H., Hörl, S., Axhausen, K.W., 2020. Designing a large-scale public transport network using agent-based microsimulation. Transp. Res. A 137, 1–15.
McCoy, D., Lyons, S., 2014. Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland. Energy Res. Soc. Sci. 3, 89–101.

McCullen, N.J., Rucklidge, A.M., Bale, C.S.E., Foxon, T.J., Gale, W.F., 2013. Multiparameter models of innovation diffusion on complex networks. SIAM J. Appl. Dyn. Syst. 12 (1), 515–532.

Montanari, A., Saberi, A., 2010. The spread of innovations in social networks. Proc. Natl. Acad. Sci. 107 (47), 20196–20201.

Natural Resources Canada, 2014. Learn the facts: fuel consumption and CO_2. https://www.nrcan.gc.ca/sites/www.nrcan.gc.ca/files/oee/pdf/transportation/fuel-efficient-technologies/autosmart_factsheet_6_e.pdf.

Natural Resources Canada, 2019. 2019 fuel consumption guide. https://www.nrcan.gc.ca/sites/www.nrcan.gc.ca/files/oee/pdf/transportation/tools/fuelratings/2019%20Fuel%20Consumption%20Guide.pdf.

Plötz, P., Funke, S.Á., Jochem, P., 2018. The impact of daily and annual driving on fuel economy and CO2 emissions of plug-in hybrid electric vehicles. Transp. Res. A 118, 331–340.

Popovich, N., Rajagopal, D., Tasar, E., Phadke, A., 2021. Economic, environmental and grid-resilience benefits of converting diesel trains to battery-electric. Nat. Energy 6, 1017–1025.

Pritchard, J.P., Moura, F., de Abreu e Silva, J., 2016. Incorporating social network data in mobility studies: Benefits and takeaways from an applied survey methodology. Case Stud. Transp. Policy 4 (4), 279–293.

Ravazzi, C., Como, G., Garetto, M., Leonardi, E., Tarable, A., 2023. Asynchronous semi-anonymous dynamics over large-scale networks. SIAM J. Appl. Dyn. Syst. (in press), availbale at https://arxiv.org/abs/2102.03840.

Ravazzi, C., Dabbene, F., Lagoa, C., Proskurnikov, A.V., 2021. Learning hidden influences in large-scale dynamical social networks: A data-driven sparsity-based approach. IEEE Control Syst. Mag. 41 (5), 61–103.

Rezvani, Z., Jansson, J., Bodin, J., 2015. Advances in consumer electric vehicle adoption research: A review and research agenda. Transp. Res. D 34, 122–136.

Saarenpää, J., Kolehmainen, M., Niska, H., 2013. Geodemographic analysis and estimation of early plug-in hybrid electric vehicle adoption. Appl. Energy 107, 456–464.

Schelling, T.C., 1978. Micromotives and Macrobehavior. W. W. Norton & Company.

Schepers, J., Wetzels, M., 2007. A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. Inf. Manag. 44 (1), 90–103.

Schuitema, G., Anable, J., Skippon, S., Kinnear, N., 2013. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. Transp. Res. A 48, 39–49.

Shafiei, E., Thorkelsson, H., Ásgeirsson, E.I., Davidsdottir, B., Raberto, M., Stefansson, H., 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. Technol. Forecast. Soc. Change 79 (9), 1638–1653.

Sierzchula, W., Bakker, S., Maat, K., van Wee, B., 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. Energy Policy 68, 183–194.

Singh, V., Singh, V., Vaibhav, S., 2020. A review and simple meta-analysis of factors influencing adoption of electric vehicles. Transp. Res. D 86, 102436.

Taalbi, J., Nielsen, H., 2021. The role of energy infrastructure in shaping early adoption of electric and gasoline cars. Nat. Energy 6, 970–976.

Tran, M., Banister, D., Bishop, J., Mcculloch, M., 2012. Realizing the electric-vehicle revolution. Nat. Clim. Change 2, 328–333.

Valente, T., 1995. Network models of the diffusion of innovations. Comput. Math. Org. Theory 2, 163–164.

Wang, H., Zhao, D., Meng, Q., Ong, G.P., Lee, D.-H., 2020. Network-level energy consumption estimation for electric vehicles considering vehicle and user heterogeneity. Transp. Res. A 132, 30–46.

Wei, W., Ramakrishnan, S., Needell, Z., Trancik, J., 2021. Personal vehicle electrification and charging solutions for high-energy days. Nat. Energy 6, 105–114.

White, L., Sintov, N., 2017. You are what you drive: Environmentalist and social innovator symbolism drives electric vehicle adoption intentions. Transp. Res. A 99, 94–113.

Wolf, I., Schröder, T., Neumann, J., de Haan, G., 2015. Changing minds about electric cars: An empirically grounded agent-based modeling approach. Technol. Forecast. Soc. Change 94 (C), 269–285.

Zhang, H., Vorobeychik, Y., 2019. Empirically grounded agent-based models of innovation diffusion: A critical review. Artif. Intell. Rev. 52 (1), 707–741.