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Falling short in 2030: Simulating battery-electric vehicle adoption behaviour in the Netherlands

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ABSTRACT

The widespread adoption of battery electric vehicles (BEVs) is a crucial element in climate policy for the transport sector. To design effective policies to stimulate the uptake of BEVs, it is essential to understand the barriers and drivers that influence consumers' choices for a BEV. To this aim, we present a computational model named CODEC, a hybrid choice model that estimates the future market share of different vehicle types. The model gives insight into the different effects of technical, financial and other behavioural factors that influence the adoption decision. We included social factors and routine behaviour, which are rarely analysed in other research. We assessed the share in sales of BEVs and gasoline vehicles in the Netherlands between 2020 and 2030 for privately owned new cars. To initialize the model we used data from a survey on the perceptions of prospective car buyers ($n = 1522$). Our analysis shows that the BEV market share in new car sales will be between 26 and 40 % in 2030, well below the government target of 100 %. The analysis also shows that current barriers for BEV adoption: higher purchase price and lower driving range, will become less important over time. In 2030 routine purchasing behaviour and social factors are the main barriers for widespread BEV adoption. New policy measures are needed to lower these barriers. Factors that affect BEV adoption positively have a relatively small effect, so also measures to reduce the attractiveness of gasoline vehicles should be considered.

1. Introduction

Electric vehicles are seen as one of the major options to reduce CO_2 emissions in the transport sector [1]. The Netherlands has adopted the goal of 100 % of new cars sold to be emissions-free by 2030 [2] and stimulating policies have been implemented. These policies are mainly based on tax exemptions. BEVs are exempt from vehicle registration tax (which ranges from €1000 to more than €15,000 depending on the CO2-emission of the car) and road tax (€500–€1500 per year for gasoline cars), but not from Value Added Tax [3]. In addition, an information, communication, and innovation programme has been initiated by the government [4] and public charging facilities were installed. The Netherlands is leading in slow charging and one of the front runners in fast charging in Europe [1]. As part of the European Union, the EU CO_2 emission targets for fleets of newly registered passenger cars also affects car sales in the Netherlands [1]. There is dedicated policy in place for company lease cars. In the Netherlands between 50 and 60 % of the new car sales are fleet or company cars [6], which is comparable to the UK [7]. Users of a company car have to add a percentage of the purchase price to their income to account for private use of the car, and subsequently pay income tax. For BEVs this percentage was 0 % before 2014, and was gradually increased from 4 % between 2014 and 2019 to 12 % in 2021. Users of ICE (internal combustion engine) company cars have to add 22 % of the purchase price to their income [3].

The share of BEVs in total new car sales in the Netherlands increased strongly: from 5.4 % in 2018 to 13.7 % in 2019 and 20.3 % in 2020 [5], which made the Netherlands one of the front runners in Europe in EV sales [1]. These numbers are however mostly driven by fleet/company car sales: the policies mentioned above led to high sales of new electric vehicles in the company car market (8 % in 2018, 20 % in 2019 and 28 % in 2020) [6]. For new registrations of privately owned cars, BEV sales were lower: the percentages for 2018, 2019 and 2020 are 2 %, 7 % and 10 %, respectively [6].

Electric Vehicle Choice Modelling is essential because we do not yet fully understand which factors determine the shares of BEVs in the total sales of new passenger cars. The uptake of BEV differs widely between countries [1]. It appears that there are higher BEV penetration levels in countries with registration, ownership and/or value added tax

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reductions or exemptions for BEVs [8,9]. Based on 2012 car sale data across 30 countries Sierzchula et al. [10] find that the share of electric vehicles (EVs: plugin hybrid electric vehicles and battery electric vehicles) is positively correlated with the presence of financial incentives in a country as well as with the number of charging stations.

However, although financial stimulation and tax exemptions do evidently promote BEV sales, it is also true that even in cases where EVs are cheaper than comparable ICEs - like in Norway and for company lease customers in the Netherlands - a share of consumers still do not buy (or lease) a BEV [1]. Hence, policy makers may benefit from insights in a range of factors influencing BEV adoption.

To this aim, we present in this paper a computational model, CODEC (Consumer Decisions Comprehended), that simulates the future uptake of BEVs. In essence, CODEC is a choice model that includes technical, financial and behavioural or psychological factors, and is used for predicting market penetration rates of new energy technologies. The model has been used to estimate the effect of policy measures that promote the uptake of home-based Photo Voltaic (PV) systems [11,12]. For the current study, CODEC was improved and adapted to model the adoption of electric vehicles in the Netherlands.

In this paper we use CODEC to study purchase intentions of buyers of new privately-owned cars in the Netherlands, which represent 22 % of new car sales [13]. We focused on this specific group of private car buyers, because in the Netherlands, BEV purchases by private car buyers is still relatively low. To reach the 2030 target of 100 % zero-emission vehicle sales, also this group should shift to BEVs. We collected consumer preference data on four drive trains (gasoline, BEV, dieseland plug-in Hybrid electric vehicles (PHEVs)). For the modelling study, we decided to consider only gasoline and BEV, as PHEV and diesel are essentially non-existent in the privately-owned new car market in the Netherlands [6]. Diesel used to have a larger share in this market but has virtually disappeared and is likely not to be relevant in the future. New sales of PHEVs are essentially limited to the company lease market [6].

This paper is structured as follows. In Section 2 we present a literature review and a description of the model structure and calculations. In Section 3 we describe the survey results and market data we used as model input values. In Section 4 we describe the model results: the estimated uptake of BEVs for 2030 for the new car market in the Netherlands, compare these to the historic uptake of BEVs, and the impact of different model factors on the uptake of BEV. In Section 5 we discuss the results, provide suggestions on how barriers could be lowered, describe limitations and provide suggestions for future research. In the final Section 6 we draw conclusions.

2. Literature review and CODEC model description

In this section we summarize existing literature and explore the research gap that the CODEC model aims to fill (2.1), and describe the literature the model structure is based on (2.2).

2.1. Literature review EV choice modelling

In literature, several reviews of modelling EV uptake have been published (see, for example [9,14–19]). Jochem et al. [18] differentiate EV uptake models into three broad categories: 1) bottom-up models that make use of disaggregated data and subsequently aggregate the choices of heterogenous agents to produce realistic model outcomes; 2) top-down models that make use of aggregated regional or sector level data (such as prices, income, and consumption patterns) and subsequently use optimization or econometric estimation techniques to estimate optimal EV uptake shares; and 3) hybrid models that combine different modelling approaches, such as macro and micro models. Jochem et al. [18] point out that hybrid models are still underrepresented in literature while they show the promise of creating more realistic estimations.

The CODEC model builds on these hybrid model examples and combines and integrates insights from market data, technical data and from different empirical models: the Consumer Decision Model [20] the Integrative Model (IM) of behavioural prediction [21], and Rogers' theory on the Diffusion of Innovation [22]. CODEC is a choice model that includes latent psychological factors, following on work of Train et al. [23] on Integrated Choice and Latent Variable models, that have shown to have benefits over choice models in which only observable variables, such as product attributes, are modelled [24]. In CODEC a deliberation score is calculated (Γ, see Eq. (2)) by a type of discrete choice model which uses a utility function to calculate the score on factors determining the attractiveness (the Intention phase). This score is combined with factors which enabling factors that are treated as barriers for the adoption of a certain vehicle type.

There are several applications of hybrid models for studying the car market which we summarize here to show how they compare to CODEC. Glerum et al. [25] combine a latent variable model with a logistic model with multiple alternatives to estimate market uptake of EV in Switzerland. They found that the attitudes or perceptions towards electric vehicles play a significant role in predicting the uptake. Kangur et al. [26] created a hybrid model and looked at the entire Dutch car fleet (including both privately-owned as well as company lease cars) using an agent-based social simulation model (STECCAR). Similar to CODEC, STECCAR uses factors such as willingness and ability to pay for an EV, the functionality of the car (which includes the driving range) and social factors, which encompasses belonging and status. Subsequently, they modelled 1750 agents based on all the respondents to a survey asking about their transport, social and economic characteristics.

Greene et al. [27] use LAVE-TRANS, a hybrid model to study the uptake of BEV, PHEV and Fuel Cell Vehicles (FCV) in the U.S. car market. Next to costs, range, familiarity with the technologies, and refuelling infrastructure, they also used factors related to different groups of consumers: the majority's aversion to risk of new technology and the willingness to pay for novel technologies by innovators. The authors acknowledge that there is a lack of understanding about these factors in relation to the uptake of electric vehicles, among other because when this study was published in 2014 the penetration of electric vehicles was still very low. In the current paper we study differences in innovation groups by distinguishing between individuals who want to be different from others, and individuals who want to fit in, based on e.g. a survey taken in 2019, when BEVs were becoming visible in Dutch car sales.

The REPAC model [28] studies the uptake of EVs in the Canadian car market and uses a latent class discrete choice model estimated from data collected via a survey. The model incorporates some of the factors used in CODEC, such as home charging access, purchase price, and familiarity with electric vehicles. Social factors were not included. In a recent paper [29], the same group uses a new model (AUM) that pays more attention to the supply side and the availability of a sufficient choice of EV models than CODEC: a consumer choice model is combined with an automaker model. Brand et al. [7] use a similar approach to CODEC, a multinominal logit model to calculate market shares of different powertrains. Next to vehicle attributes, such as costs and range, they also include preferences and social factors, based on survey results. The approach to include the improvement in knowledge on EVs by consumers and to the neighbour or 'look like others' effect are similar to CODEC. Yang and Chen [30] used a model to study BEV uptake in two Chinese cities using a model with a strong emphasis on social-psychological factors. Like in CODEC, knowledge of BEVs, social factors such as the neighbourhood effect as well as personality factors such as innovativeness and environmental concern, were used in the model.

CODEC has some similarities to other models, and some innovative elements. In all models purchase price, running costs, range and ease of refuelling are included as factors to estimate the BEV uptake in the consumer market. Several models also use one or more so-called behavioural factors like knowledge of BEVs and the neighbour effect. CODEC uses multiple psychological and social factors and explores the effect on BEV uptake of each of them. Only in the recent paper of Yang and Chen [30] a similar comprehensive set of factors was used.

Moreover, CODEC uses a different approach to most models in the sense that it first divides the car buyers in a group that makes a routine purchase and a group the considers alternatives. The vehicle purchases of the remaining group of 'deliberate purchase makers' is modelled using a choice model using factors similar to other studies [28,30,31].

2.2. General model structure and theory

The CODEC model is based on a number of psychological theories, which we will describe below.

2.2.1. Three decision phases

The calculations in CODEC are structured into three phases (see Fig. 1) based on the Consumer Decision Model [20]. While buying a product, a consumer (unconsciously) goes through several steps: 1) noticing a need (car needs replacement), 2) collecting information about product options, 3) evaluation of the alternatives, 4) choice, 5) evaluation of choice. Based on the first four steps, CODEC distinguishes between three 'phases' that influence the innovation adoption rate: attention to a need (Attention, step 1), qualification of each option as practically feasible (Enable, step 2), and the weighing of the pros and cons of each option (Intention, based on step 3) leading to a choice to adopt or reject the option (step 4). CODEC does not include the evaluation step. Each of the three phases is split into a number of factors (i.e., variables that influence the decision to buy a certain type of car) with a score between 0 and 1 (0 %–100 %).

The *Attention* phase determines how many people face a decision moment. People are not maximisers [32]: they are not constantly looking for the best option. Instead, most people only go looking for a new car when there is a reason to do so. In addition, when people start looking they may make a routine decision, without weighing the pros and cons (again), but choosing the car type the currently own [32]. In the *Attention phase* we calculate the percentages of consumers that make a more deliberate choice and advances to the Enable and Intention phase (see Fig. 1).

The *Enable* phase determines how many people are practically able to buy and use each of the car types. This phase includes factors about whether the use and purchase of a vehicle type is possible for people. The availability of charging infrastructure is one of those factors, see for example Yao et al. [33]. Another factor is the share of people having sufficient knowledge about the alternative choices, which was found to be an important factor in the uptake of electric vehicles [31].

The *Intention* phase determines the attractiveness of the different product options. The intention to engage in a certain behaviour is determined by a person's attitude towards the behaviour and the social norm concerning the behaviour, according to the Integrative Model (IM) of behavioural prediction [21]. CODEC takes into account attitude in the form of financial attractiveness, other characteristics that differ between the product options (such as sustainability), and social norms (see Fig. 1). Note that investment costs are both factors in the enable phase and in the intention phase. The difference is that in the enable phase it is determined which share of consumers is able to buy a certain vehicle type, while in the intention phase investment costs are used to determine the relative attractiveness between car options.

Concerning financial attractiveness, CODEC uses discounted utility [34]: the model takes into account that the investment costs will have more weight in the decision to buy a product option than the running costs (fuel or electricity, maintenance, taxes). CODEC also takes into account the prospect theory [35]: when a product option is more expensive than purchasing the product option consumers own at the moment again and thus exceeds the mental budget they want to spend on a car (mental accounting, [36]), this is considered as a loss and will therefore be more unattractive to them [37].

Social influences are an important determinant of behavioural intention (e.g., Rogers' theory on the Diffusion of Innovation [22]). Mau et al. [38] showed the importance of social comparison or neighbour effect in the adoption of alternative fuel vehicles. Surveys also show the importance of knowing someone who already owns an EV [39,40]. Like Yang and Chen [30], CODEC distinguishes between social status (wanting to distinguish from others) and social comparison (wanting to look like others).

3. Model input values and calculations

3.1. Survey

3.1.1. Survey topics

We developed a survey to substantiate several of the model assumptions. The first set of questions provided insight into the current situation of respondents, such as which car type they currently drive. The subsequent questions focused on comparing four different vehicle types (diesel, gasoline, BEV, PHEV). In the current study, only survey data on gasoline and BEV were used. The data for diesel and PHEVs is relevant for later use of CODEC for other market sections such as user/choosers of company cars [6,7].

Respondents rated each of the car types for different characteristics: "How do the different types of cars score on these characteristics according to you: purchase costs, running costs, resale value, effects on the

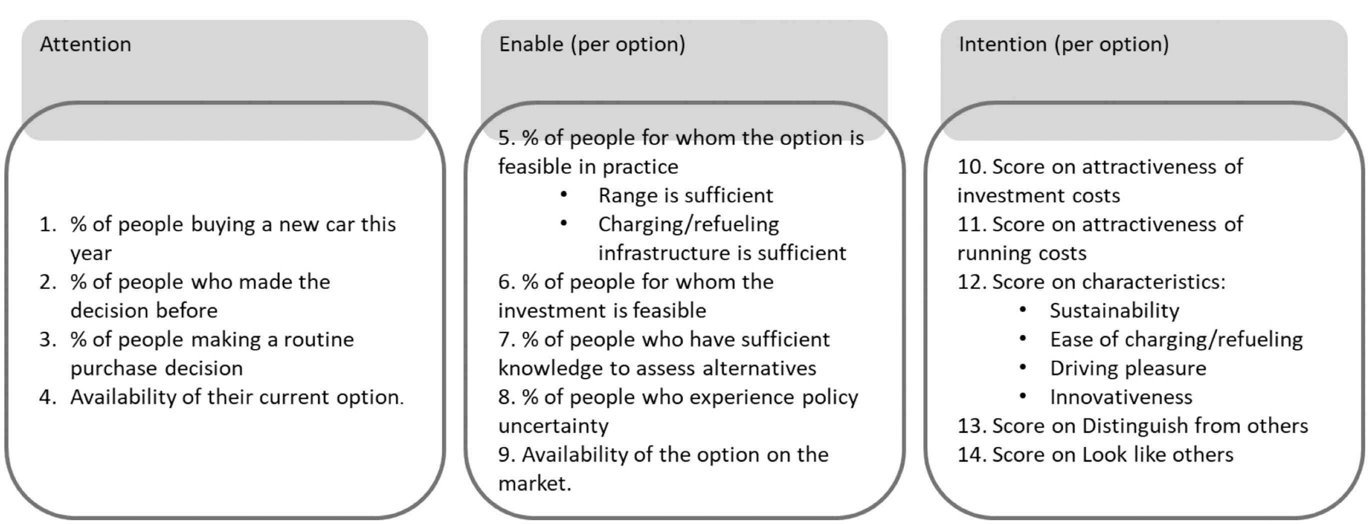

Fig. 1. Schematic overview of the three phases of factors in CODEC.

environment, access to environmental zones (in cities), ease of refuelling / charging, driving comfort (sound, changing gear), reliability, and driving pleasure (acceleration, power). We selected these characteristics based on Dutch monitoring research [42] into the barriers and drivers of the uptake of EV. The participants also rated the four vehicle types on social factors: innovativeness, status, distinctiveness, and whether it is a car you would want to be seen in.

In addition, we asked questions about the purchase and running costs people are willing to pay, the driving range a fully charged (or fuelled) car should have, and the ability to charge their car near their house. Finally, we asked three questions to measure purchase intention (similar to Bockarjova & Steg [43]): whether someone would take each car type into consideration, whether someone would be interested, and whether someone would actually buy a specific car type. For the exact questions and more information about the survey see Appendix 1.

3.1.2. Survey sample

The survey was sent by I&O research to the members of their panel by e-mail in November 2019, in total 1522 participants responded. See Table 1 for demographic information. To make our sample representative of the Dutch population, we applied a weighing factor based on these demographic variables to all further analyses. For more information about the sample and the weighing factor see Appendix 1.

3.1.3. Survey results

Survey results can be found in Addendum 1. We describe the relevant results for the factors in the Attention and Enable phase (the input values) in Tables 3 and 4. In this section we describe the survey results relevant for the Intention phase.

To determine the relative importance of the factors in the Intention phase, we performed a fixed effects regression on behavioural intention regression analysis and determined the weight (β_i) of the different factors, as well as the score ($\overline{X}$) of four car types (see Addendum 1) for different characteristics. Table 2 shows the survey results for the participants with a privately-owned car, for the two car types of interest: gasoline and BEV. We performed a multinominal fixed effects regression because we wanted to distinguish between vehicle types and we expected a certain degree of variance related to vehicle type that would not be explained by the included factors. This unexplained variance is reflected in the constants in the first row of the table. For example, Table 2 shows that gasoline has an advantage (c = 2.25) over BEV, which is not explained by the included factors. The resulting purchase intention γ, for example for BEV, is calculated like in Eq. (1).

$$\gamma_{BEV} = c_{BEV} + \beta_{\text{Purchase costs}} {}^{*}X_{\text{Purchase costs}} + \beta_{\text{Running costs}} {}^{*}X_{\text{Running costs}} + \text{etc.} \quad (1)$$

The analysis shows that purchase costs, running costs, environmental effects, ease of refuelling, driving pleasure, innovativeness and 'this is a vehicle you want to be seen in' were found to be significant. All factors were measured on the same scale: very negative (1) to very positive (7), therefore the positive regression weights (Table 1) mean that the more positive respondents are about the characteristic, the higher their intention to buy a car type. Only significant factors were included in the model.

Table 1
Demographics of the survey sample and the subgroups of car owners and owners of new cars.

		Entire sample	Car owners	Owners of new cars	Dutch population
Participants		1522	1027	273	–
Gender	Male	833 (55 %)	562 (55 %)	147 (54 %)	50 %
	Female	689 (45 %)	465 (45 %)	126 (46 %)	50 %
Age	18–39	352 (23 %)	299 (29)	33 (12 %)	34 %
	40–64	744 (49 %)	501 (49 %)	145 (53 %)	42 %
	65+	426 (28 %)	227 (22 %)	95 (35 %)	24 %

Table 2
Results of the multinominal fixed effects analysis of survey results for private car owners for gasoline and BEV.

		All car types	Gasoline	BEV
	Constant (c)		*2.25*	*1.37*
	Variable	β	$\overline{X}$	$\overline{X}$
Purchase costs	Purchase costs	0.13	4.88	3.19
Running costs	Maintenance, tax and fuel	0.09	4.29	4.79
Characteristics	Environmental effects	0.13	3.31	5.10
	Access to environmental zone	0*	4.14	5.79
	Ease of refuelling/ charging	0.07	5.91	3.47
	Driving comfort	0*	5.21	5.24
	Reliability	0*	5.43	4.57
	Driving pleasure	0.07	5.49	4.98
Social factors	Status	0*	4.46	5.19
	Innovativeness/ special	0.14	4.17	5.33
	Being seen in this vehicle	0.31	4.64	4.95

Note. This table presents regression coefficients (β) and means (X). The dependent variable is the intention to purchase a specific car type. The explained variance of the model is $R^2 = 0.54$. Number of respondents (n) included in this analysis is 1318. Each of the private car owners answered questions for the vehicles types, resulting in 5272 observations. Outliers (predicted values further away than 3 times standard deviation) were deleted from the analyses, resulting in 5251 observations. When a factor does not significantly explain variation ($p \geq 0.05$), this is reflected in the table by a * and the weight is set to zero. Note that while the regression coefficients are the same for the car types, the factor means differ.

3.1.4. Weights of the Intention factors

We normalized the β values from Table 2, so that their sum is one, to get the Intention weights. Fig. 2 shows the resulting weights for each factor. To determine the weights of the two social factors we calculated the total social factor (including both look like others and distinguish from others) by looking at the regression weight of 'this is a car you want to be seen in' and dividing this by the sum of all significant regression coefficients, resulting in a combined weight of 33 %. This effect size is consistent with other studies: from different disciplines (smoking [44] and solar panels [45,46]) as well as the overall effect sizes found in a meta-analysis of studies regarding the adoption of electric vehicles [47].

The statement 'this is a car you want to be seen in' can be interpreted in two ways: either as pressure to conform (wanting to look like others) or as a reward for being different (wanting to distinguish from others). Therefore we determined the social factor weight should be split between these two components. Since we are looking at the population as a whole, we assume that the weight should be proportional to the size of the groups on Roger's theory of innovation diffusion [22] it affects. This means that the two weights should have a ratio of 16 %/50 % = 1/3 (see Fig. 4 for these groups). As a consequence, we assign 25 % of the social factor weight to wanting to distinguish from others and 75 % to wanting to look like others, resulting in respective weights of 8 % and 25 %.

3.2. Input values and calculations

In this section we describe the general CODEC model calculations, see Fig. 3 for an illustration of the general calculation structure. Subsequently, we list the model input values for the various factors and the equations used to calculate the factor scores.

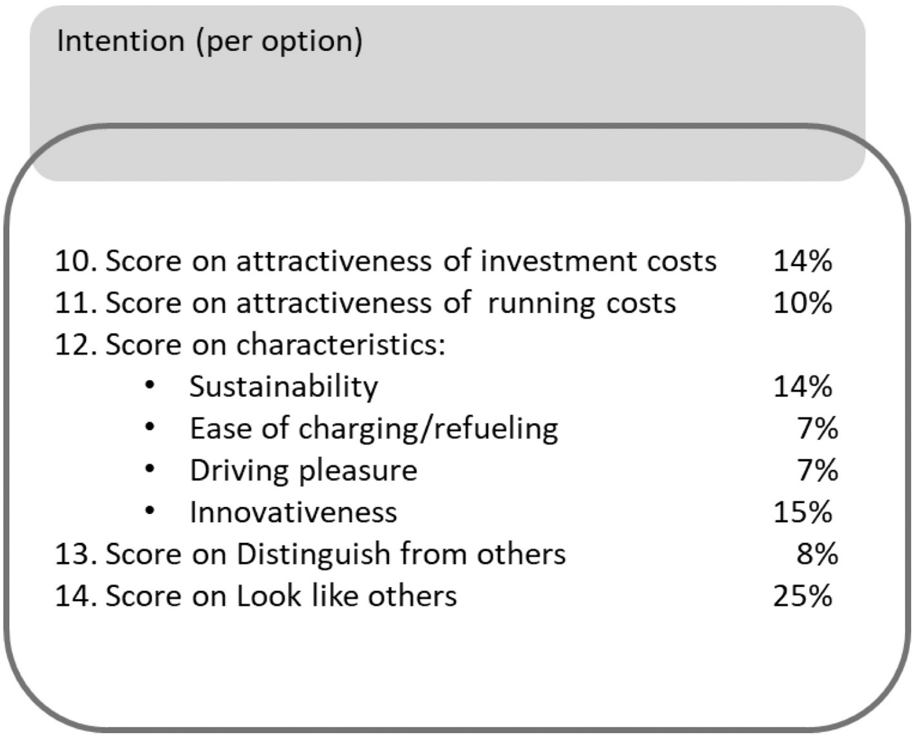

Fig. 2. Weights of the different factors of the intention phase.

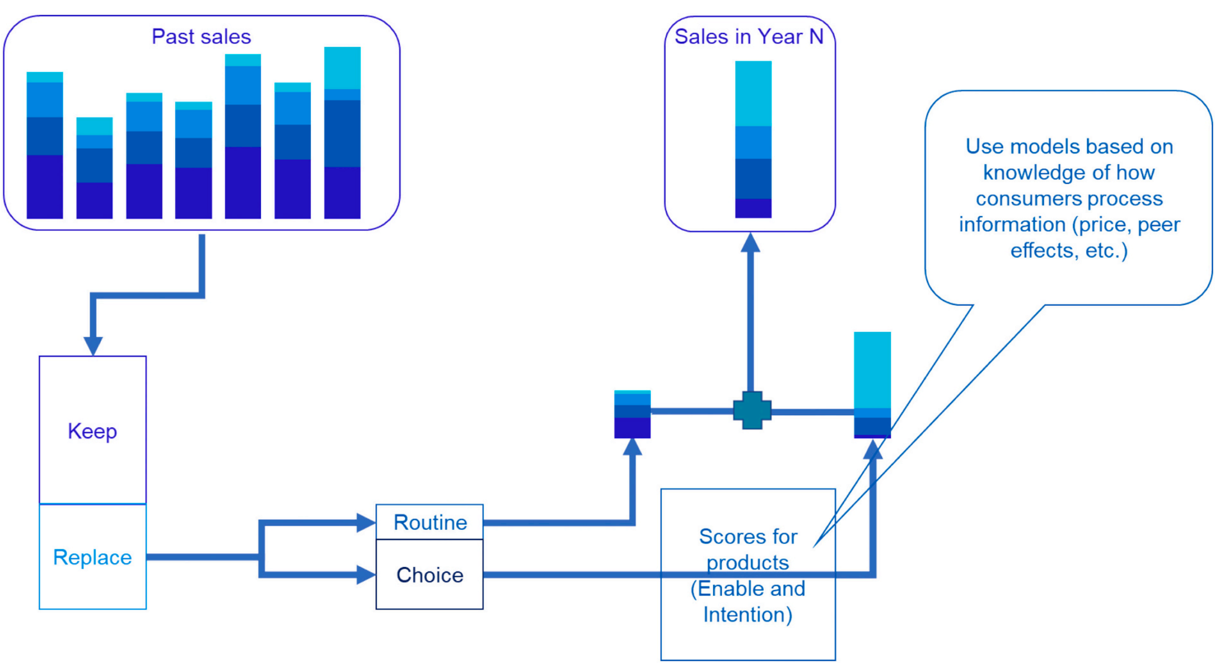

Fig. 3. General Calculation Structure of CODEC. The blue bars represent the different car types.

3.2.1. *Attention: determining how many consumers make a deliberate choice*

The current car fleet in the Netherlands is used as a starting point for the *Attention* phase [41]. The number of consumers that will replace their car is taken from car sales data (see Table 3). Subsequently, we determine which percentage are routine replacements. The resulting number of consumers going through a deliberate choice process is input for the combined Enable and Intention phase.

3.2.2. *Enable and intention: comparing car types*

To calculate how many people choose each car type, we compute a deliberation score for each car type, which combines the scores in the Enable and the Intention phases. We assume that the sales are proportional to this deliberation score. In other words, if a gasoline car has a deliberation score twice as high as a battery-electric car, then the deliberate purchases of gasoline cars in that year will be twice the sales of battery-electric cars.

First, we compute the Enable score by multiplying the scores of all

Table 3
Input values for the factors in the attention phase.

Nr.	CODEC factor	Input values	Explanation
1	% of people buying a new car this year	The ownership time is given by a log-normal probability distribution with an average of 6.6 years, and a standard deviation of 4.4 years. This is assumed to be stable over time.	This is based on a fit of the Dutch car fleet data [41] to a log-normal distribution.
2	% of people who made the decision before	100 %: all consumers. This is assumed to be stable over time.	All consumers are assumed to have bought a car before and are thus able to buy a similar car in a routine manner.
3	% of people making a routine purchase	34 % of consumers make a routine purchase. This is assumed to be stable over time.	The survey results show that the percentage of car owners that will not look at cars with a different kind of engine than their current car is 34 %.
4	Availability of their current option	100 % for all car types. This is assumed to be stable over time.	We assume that all types of car remain available.

Enable factors (see Fig. 1). This reflects the fact that Enable factors are barriers in the purchasing process. Each factor has a score between 0 and 1, and by multiplying these scores the Enable score becomes lower. However, a low score does not necessarily mean that this car type will not be purchased. It also depends on the Deliberation score of the other car type.

Secondly, we compute the Intention score by making a weighted sum of the Intention factors, since in this phase we are not dealing with barriers, but the different car options differ in their attractiveness. We normalize each of the Intention factors: for the owners of a given car type the sum of all vehicle types for each Intention factor is one. This reflects the fact that these factors are related to a preference comparison of vehicle properties. We then multiply these two scores and normalize the answers to produce the deliberation score $\Gamma(\nu)$ of vehicle type ν, see Eq. (2):

$$\Gamma(\nu) = \Theta\prod_{i=1}^{N}\Xi_i(\nu)\sum_{j=1}^{M}\omega_j\Psi_j(\nu) \tag{2}$$

where $\Xi_i(\nu)$ is the Enable score of vehicle type ν for the i-th Enable factor, N the amount of enable factors, ω_j is the weight of the j-th Intention factor, and the factor score $\Psi_j(\nu)$, is the Intention score of vehicle type ν for the j-th Intention factor, and M the amount of intention factors. The normalization factor Θ is chosen such that the sum of the scores of all possible vehicles is one, in this case: $\Gamma(gasoline) + \Gamma(BEV) = 1$. We assume that all consumers either buy a BEV or a gasoline vehicle, so the deliberation score of one vehicle is relative to the other. So, hypothetically, If a BEV has a $\Gamma$of 0.1 before normalization and a gasoline vehicle 0.2, this means that one-third of the consumers that make a deliberate purchase will buy a BEV and two thirds a gasoline vehicle.

Finally, we multiply the deliberation score with the number of deliberate purchases to determine the number of purchases for each car type. The total purchases in a given year are the sum of the routine purchases and deliberate purchases (see Fig. 1).

3.2.2.1. Attention. This phase determines how many people will replace their cars in a given year and how many make a deliberate choice. The Attention phase has four factors, shown in Table 3.

3.2.2.2. Enable. Table 4 provides an overview of the assumptions for each of the five Enable factors and a more detailed discussion of the factors concerning practicality and affordability.

The practicality score consists of two sub scores: a range score and an infrastructure score, which we multiply. For each vehicle type we determine which percentage of people would be satisfied with this vehicle's range, using range data as described in Table 5. The score is 50 % if the range of the vehicle is equal to the mean, goes to 100 % if the range is several standard deviations above the mean and to 0 % if the range is several standard deviations below the mean. Note that while people might not actually need this kind of range for their mobility needs, we are interested in the range they feel they need: their perceived needs determine their purchase. For the actual computations of the score in Eq. (2) we use the cumulative normal distribution function:

$$\Xi(\nu) = \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{R_\nu} exp\left(-\frac{(r-\mu)^2}{2\sigma^2}\right)dr, \tag{3}$$

where $\Xi(\nu)$ is the Enable score for Range, R_ν is the range of vehicle ν, μ is

Table 4
Input values for the factors in the enable phase.

Nr.	CODEC factor	Input values	Explanation
5.1	Practical feasibility: range	461 km is the desired range (standard deviation: 186 km). This is assumed to be stable over time.	From survey results among car owners. We used a threshold function in the form of a cumulative normal distribution with a mean and standard deviation for the desired range.
5.2	Practical feasibility: refuelling infrastructure	BEV charging infrastructure coverage starting value = 59 %. It is assumed it takes 10 years to reach 100 %. For gasoline the value is 100 %.	The starting value was determined from the survey. It is the percentage of respondents answering: “I believe so” to the question: “Is it practically feasible for you to charge an electric car near your home?”.
6	Investment feasible	The average price people want to pay for a car is €27,203 (standard deviation: €14,511). This is assumed to be stable over time.	We found in the survey that owners of new cars (n = 273) say that they on average are willing to spend on average €27,203 Euro (SD = €14,511) on a new car.
7	Knowledge	Consumers 2019 knowledge level: Gasoline: 77 % BEV: 70 % (annual growth: 5 %)	Survey answers to the question to what extent participants believed they could acquire sufficient knowledge to decide whether a specific engine type would be suitable for them. We assume this will improve over time for BEV with 5 % each year.
8	Policy uncertainty	0 % for all car types. This is assumed to be stable over time.	We assumed that policy uncertainty was no obstacle.
9	Availability	100 % for all car types. This is assumed to be stable over time.	We assumed that there were enough models of each vehicle type on the market for a consumer to be able to buy the desired type.

Table 5
Input assumptions about purchase costs, running costs and range.

	Purchase costs (€)		Running costs (€/month)		Range (km)	
	2020	2030	2020	2030	2020	2030
Gasoline	30,850.-	30,850.-	268.-	268.-	750	750
BEV	36,607.-	33,000.-	145.-	190.-	381	562

the mean desired range (461 km), and σ is its standard deviation (186 km). This is also the way we computed the social factors, with the only changes being the values of the mean and standard deviation and the value we evaluate/integrate up to.

3.2.2.2.1. Input assumptions costs and range per vehicle type. In Table 5 we summarize the assumptions on vehicle properties that we used, namely the purchase costs, the running costs, and the range. The purchase costs include the purchase costs plus VAT (21 %) and a vehicle registration tax that depends on CO_2 emission per km of the car. A number of changes in the taxation policy are foreseen due to the Climate Agreement [2], which have been included in the model. BEVs are exempt from both the registration and vehicle use taxes (in Dutch: motorrijtuigenbelasting) up to 2024, after which the vehicle registration tax increases to €360 .The vehicle use tax for BEV's increases to 25 % of the tax for other car types in 2025 and to 100 % from 2026 onwards.

We determined the average purchase price, by combining prices from BOVAG (the Dutch organization of car dealers) for cars in segments A to E by drivetrain [48] with sales data of the privately owned car market [13].

For gasoline cars, the costs and range have been assumed to remain the same from 2020 up to 2030. For BEVs, we assumed that the decline in battery costs (from 120 €/kWh in 2020 to 50 €/kWh in 2030 [49]), combined with an increase in the average size of battery packs increases from 57 kWh (which corresponds to a range of about 380 km) in 2020 to 85 kWh (about 562 km) in 2030 brings the purchase price closer to the one of gasoline cars (about €2000 higher).

The running costs are the sum of the yearly vehicle use tax (which depends on the vehicle type and the province the vehicle is registered in [50]), the energy costs, which are the yearly kilometrage (13,000 km [51]), the fuel consumption of a typical vehicle (0.15 kWh/km for BEV and 6 l/100 km for gasoline), and fuel prices ([52] for gasoline and [53] or electricity), as well as insurance costs [54] and repair/maintenance costs [54].

3.2.3. Intention

Table 6 summarises how we obtained the input data for the Intention score (see Eq. (2)). We also describe the calculation of the cost factors (purchase costs and running costs) and the social factors (wanting to look like others and wanting to distinguish from others) in more detail below.

Table 6
Input values for the factors in the intention phase.

Nr.	CODEC factor	Input values	Explanation
10	Attractiveness of investment costs	The maximum people want to spend on a car is on average €27,203 (standard deviation: €14,511) This is assumed to be stable over time. This data is compared to the purchase costs of the different car types, see Table 5.	Survey results for owners of new cars ($n = 273$)
11	Attractiveness of Running costs	Input data from Table 5 with the following additional data: €207 standard deviation, plus value function parameters given below.	The standard deviation was derived from the survey question how much running costs people are prepared to pay each month.
12	Characteristics	Combined scores for Environmental effects, Ease of refuelling/charging, Driving comfort, and Driving pleasure per car type.	Weights are determined using a fixed effects regression, see Section 3.1. Each of the scores S from Table 2 are converted to Ψ with the following formula $\Psi = \frac{(S-1\}}{6}$
13	Wanting to look like others	Market shares for each vehicle type for each computation year (we take the previous year, as this is what the consumers will be aware of). We assumed a threshold value of 50 % (=Late Majority and Laggards) with a standard deviation of 12.5 %.	Market shares are the outcome of the model computations. The threshold is based on Rogers' innovation theory [22]. See below for the sub-model explanation.
14	Wanting to distinguish from others	Market shares for each computation year (we take the previous year, as this is what the consumers will be aware of). We assumed a threshold value of 16 % (with 4 % standard deviation) for BEV and 0 % for gasoline	Market shares are the outcome of the model computations. The threshold is based on Rogers' innovation theory [22]. See below for the sub-model explanation.

3.2.3.1.1. Intention: attractiveness of investment costs and loss aversion. Next to determining the willingness to pay in the Enable phase, we included a score for the attractiveness of the price of the different vehicle types. This is essential since it is not sufficient to just know what a consumer is willing to pay for a certain type of car, it is also important how the price of a car compares to what people are used to.

We base this score on insights from Tversky and Kahneman [37], which show that consumers feel that the pain of losing a given amount of money is worse than the pleasure of gaining that same amount of money, also known as loss aversion. Consumers compare the car prices to the cheapest car type and in addition to their current car type, and this determines how they feel about the investment costs of a given car type. We implement this principle with the following formula for the score $\Psi(\nu_X)$of a given vehicle (noted as ν_X):

$$\Psi(\nu_X) = \frac{\phi(\nu_C)}{\phi(\nu_X)} \frac{N(\mu(\nu_X, \nu_O))}{N(\mu(\nu_C, \nu_O))} \tag{4}$$

ν_C is the cheapest available car type (as mentioned, car types in this research are: BEV, and gasoline). The price function Φ is simply the price of a given car (either the cheapest or the one under consideration). N denotes a cumulative normal distribution that uses the value of the car type under consideration (for example a BEV), compared to the type of car the user currently owns, noted with ν_O (for example a gasoline car, note that this comparison is for the prices in the evaluation year). The mean is for the case where the user buys the car again (where the value is zero), and the standard deviation is given by a reference standard deviation on price given by the survey. The value function μ is based on a difference Δ between the car type at hand (either under the one under consideration or the cheapest one) and the car type the user currently owns. The value function is given by Δ^α if $\Delta > 0$, and $-\lambda(-\Delta)^{\beta}$ if $\Delta < 0$, with $\alpha = \beta = 0.88$ and loss aversion coefficient $\lambda = 2.25$ [37]. We do the same for running costs, with the same parameters, but with running costs instead of purchase costs.

3.2.3.1.2. Intention: social factors. For the two social factor scores (wanting to look like others and wanting to distinguish from others), we use threshold functions: one that grows with the market share of the car type we are looking at (wanting to look like others), and one that decreases with the market share of the car type we are looking at (wanting to distinguish from others). Fig. 4 shows these threshold functions, including their thresholds, and how they related to Rogers' groups [22]. Essentially, we assumed that innovators and early adopters are sensitive to the 'wanting to distinguish from others' aspect of BEVs. We assumed that the scores for gasoline is always zero. As for wanting to look like others, we assumed that the late majority and laggards were sensitive to that aspect, leading to a threshold of 50 % (sum of these two groups, with the function being one minus a cumulative normal distribution, as shown in Fig. 4) after which this effects strongly grows. Finally, we

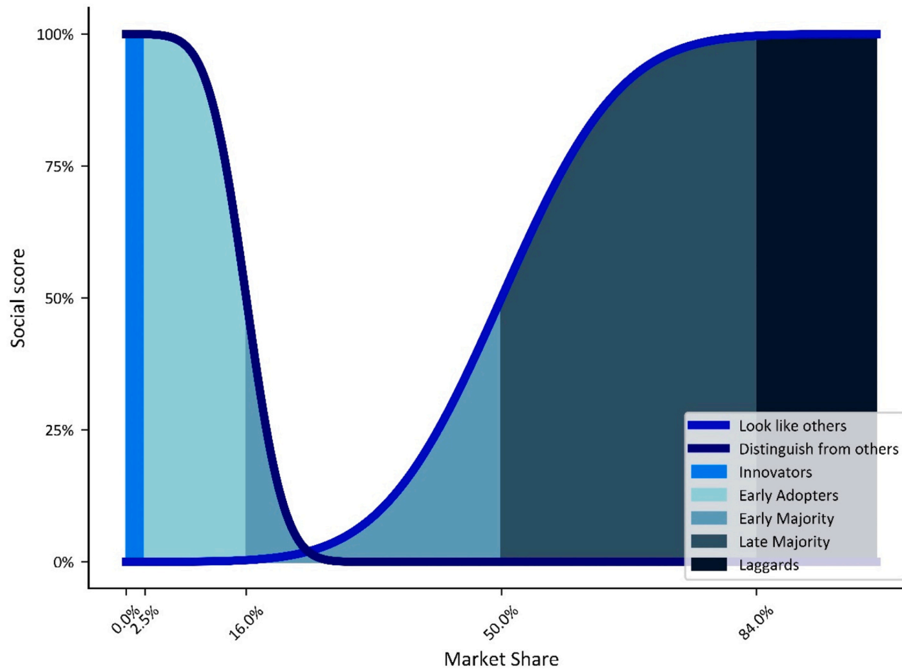

Fig. 4. Visualisation of the factors wanting to look like others and wanting to distinguish from others.

assumed a standard deviation that was proportional to the threshold value with a factor of 0.25. The score Ψ in Eq. (1). is calculated in a similar manner as for the range (see Eq. (3)), by using the corresponding means and standard deviations and using one minus the function in Eq. (3) for Distinguish form others.

4. Model results

In this section we describe the results of modelling the uptake of battery electric vehicles in the privately-owned market. We begin by showing the estimated market shares for our computation years (2019–2030). We then explore the factors contributing to these results by looking at routine choices and the impact of individual factors. Finally, we show in a sensitivity analysis what happens if we disable the most important factors differentiating the uptake of gasoline and battery-electric cars.

4.1. The uptake of battery electric vehicles

Fig. 5 shows the results of our computations for the market shares for gasoline and BEV. The estimated share of BEVs increases from 5 % in 2019 and 6 % in 2020 up to approximately 26 % in 2030. The computed

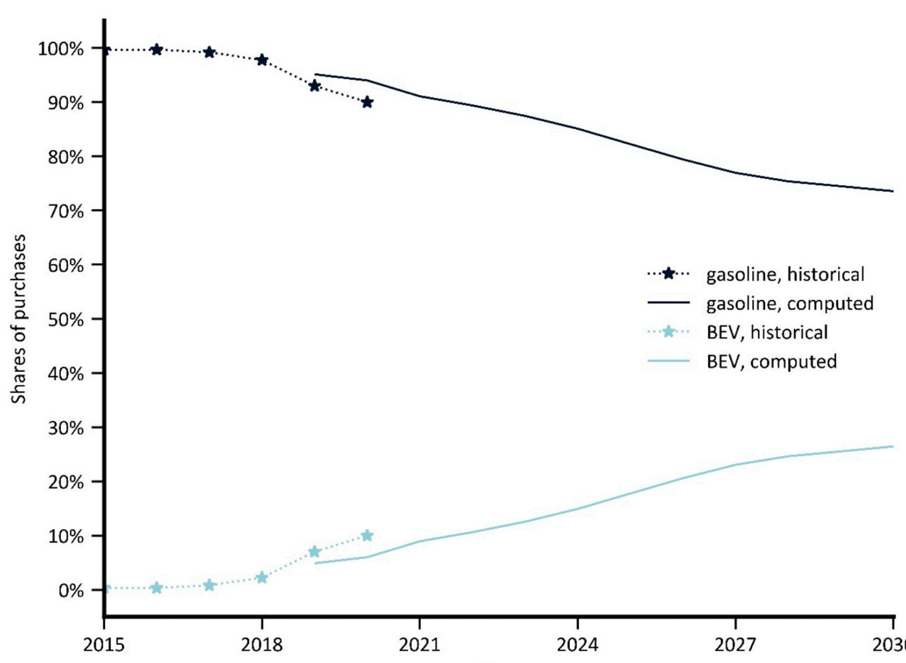

Fig. 5. Market shares of new vehicle purchases for gasoline and BEV. The dashed line with stars for 2015–2021 represents historical sales data [6], solid data are modelling results. The solid lines are CODEC projections.

value is somewhat lower than the actual sales 7 % and 10 %, respectively [6]. The next step is to understand how the various decision steps have an impact on the purchase decisions and therefore on the market shares.

4.2. Attention: routine versus deliberate choice

Fig. 6 shows the sales of BEVs and gasoline cars for people making a deliberate choice. Fig. 7 shows sales for the group of people that make routine purchases. Our survey shows that routine purchases are about a third of all sales. The figure shows that these routine purchases are overwhelmingly gasoline cars, because gasoline cars make up for the overwhelming majority of past purchases. Fig. 6, the deliberate choice, shows a steeper decline in choice for gasoline. This means that routine behaviour is a barrier in the uptake of BEV.

4.3. Enable and intention: impact of individual factors

To get a better idea of the impact of each factor in the Enable and Intention phase, we look at what the distribution of deliberate purchases would be between gasoline and BEV, if they were only different in one of the factors (see Fig. 8). We ran the CODEC model multiple times, in which we used the input values from Section 3.2 for BEV and gasoline for only one factor and assumed all other factors to be the same for both car types. We focus on people who currently own a gasoline car. Each bar corresponds to a decision factor of the Enable and Intention phase, and shows which percentage of people making a deliberate purchase would buy a BEV in a given year, if only this factor would determine the decision. If a factor causes the uptake of BEV to decline the corresponding bar goes to the left (dark blue shading). If the factor causes the uptake of BEV to increase the bar goes to the right (light blue shading). Fig. 8 shows that the limited range and the limited willingness to pay (investment is feasible) are the main obstacles to growth of the uptake of BEV in the first years and that these barriers become significantly lower in the later years. The negative impact of wanting to look like others remains relatively high throughout, because the market share of BEVs is still relatively small. The impact of the driving range decreases over the years, but remains relatively high.

4.4. Sensitivity analyses

We performed sensitivity analyses to determine what the uptake of BEV would look like under different assumptions. We do this for routine purchases and social factors since these are factors that not all BEV uptake models take into account. We also studied the impact a lower purchase price on BEV sales, to study the effect of a higher price reduction of BEVs than in our baseline assumption (see Table 5).

Based on the survey results, 34 % of all car buyers buy a car with the same drivetrain as their current vehicle. When we remove this effect of routine (i.e., all car buyers make a deliberate decision), the uptake of BEVs is 15 to 25 % higher compared to the baseline (see Fig. 9).

CODEC includes two social factors: wanting to look like others and wanting to distinguish from others. In the baseline case, the gasoline option benefits from people wanting to look like others as the market leader and BEVs benefit from people wanting to distinguish from others as a new innovation on the market. We excluded these factors to show their impact on the market share projections (see Fig. 9). The effect of wanting to look like others is larger than wanting to distinguish from others. When both social factors and routine purchases are disables, BEV uptake is approximately 40 % higher than in the baseline. This means that these factors have a significant impact on BEV sales.

Finally, we studied the impact of a lower purchase price of BEVs. In the base case we assumed BEVs still to be €2000 more expensive than gasoline cars in 2030 (see Table 5). We studied the impact of a lower purchase price of BEVs: €29,000 in 2030, which makes them about €2000 cheaper than gasoline cars. The results are shown in Fig. 10: a lower purchase price of BEVs than gasoline cars increases sales, but the effect is smaller than the impact of routine purchases and social factors.

5. Discussion

In this section, we compare our results with recent literature on the uptake of BEVs. We first compare our overall modelling results of the uptake of BEVs with actual sales modelling studies on the car market in the Netherlands. Subsequently, we compare the dominant factors predicting the uptake of BEVs towards 2030 we found to those in the literature. This leads us to identify several opportunities for policy intervention to leverage an increase in BEV uptake. Finally, we discuss

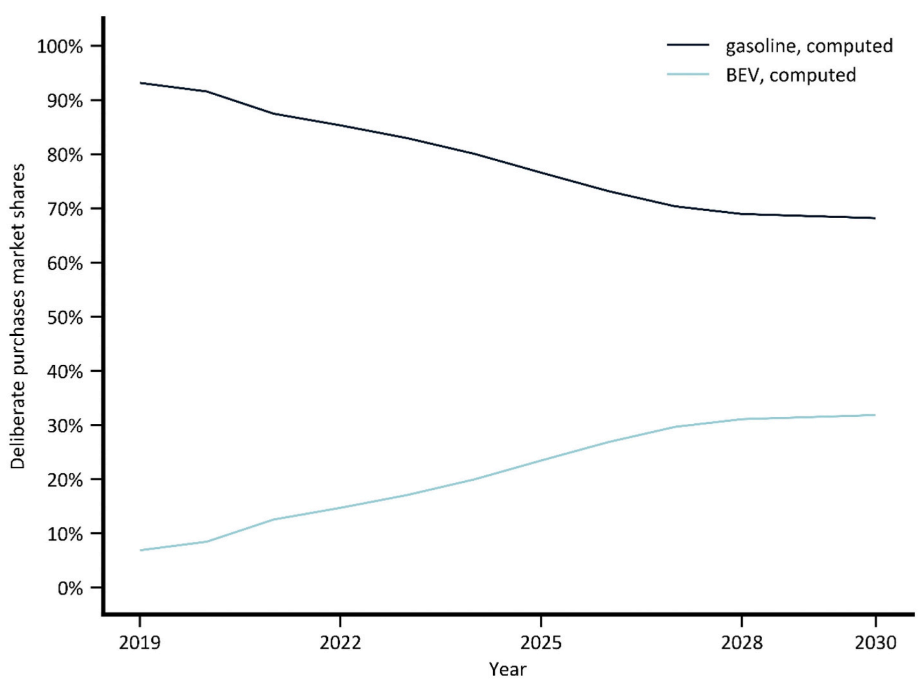

Fig. 6. Estimated markets shares for the deliberate purchases.

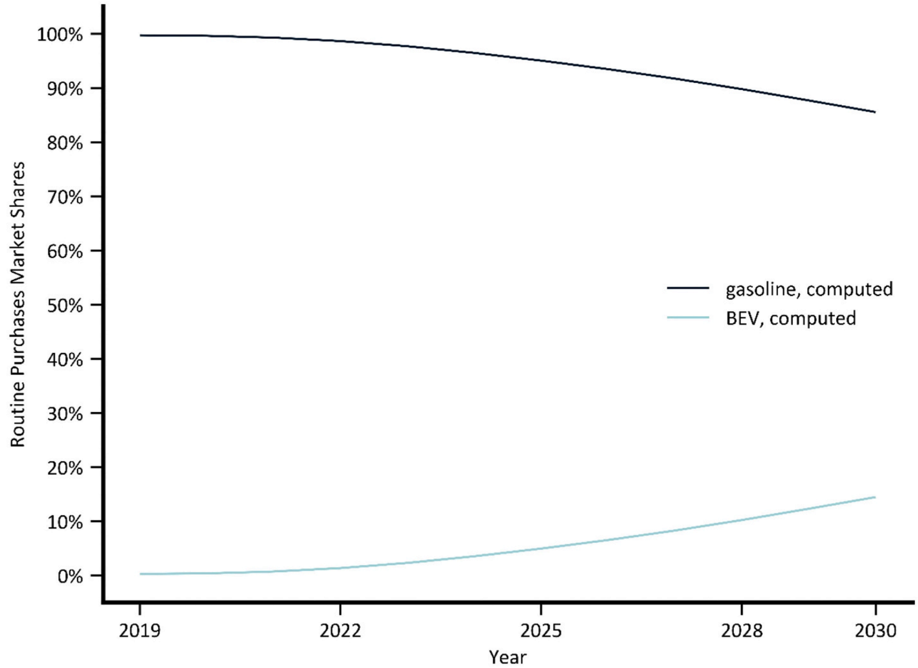

Fig. 7. Estimated markets shares for the routine purchases.

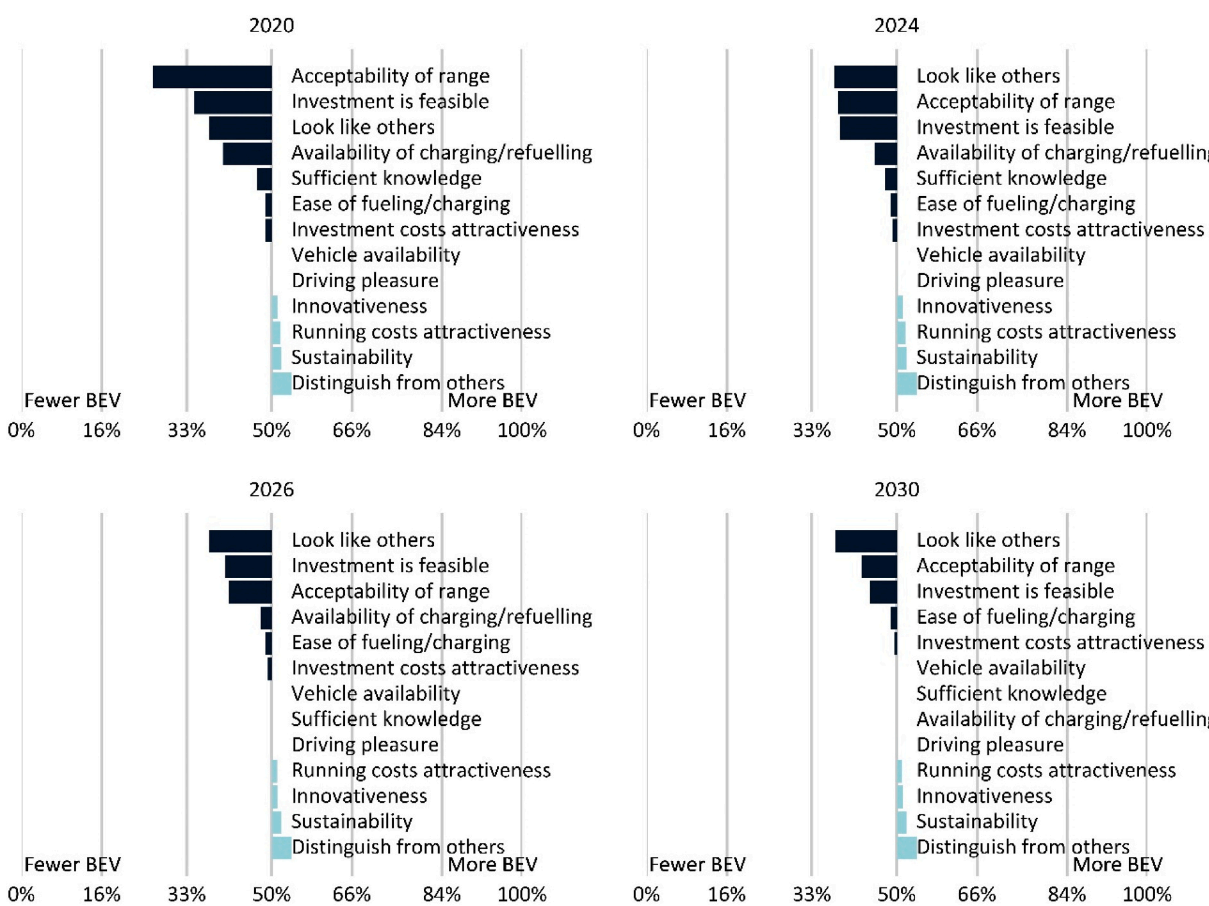

Fig. 8. Impact of enable and intention factors on the market shares of BEV for deliberate purchases for the years 2020, 2024, 2026 and 2030.

the limitations of our findings and suggestions for further research. While we only included the Dutch car market in our study, we do believe that countries with similar goals concerning BEVs will benefit from these insights, since similar factors of influence will play a role.

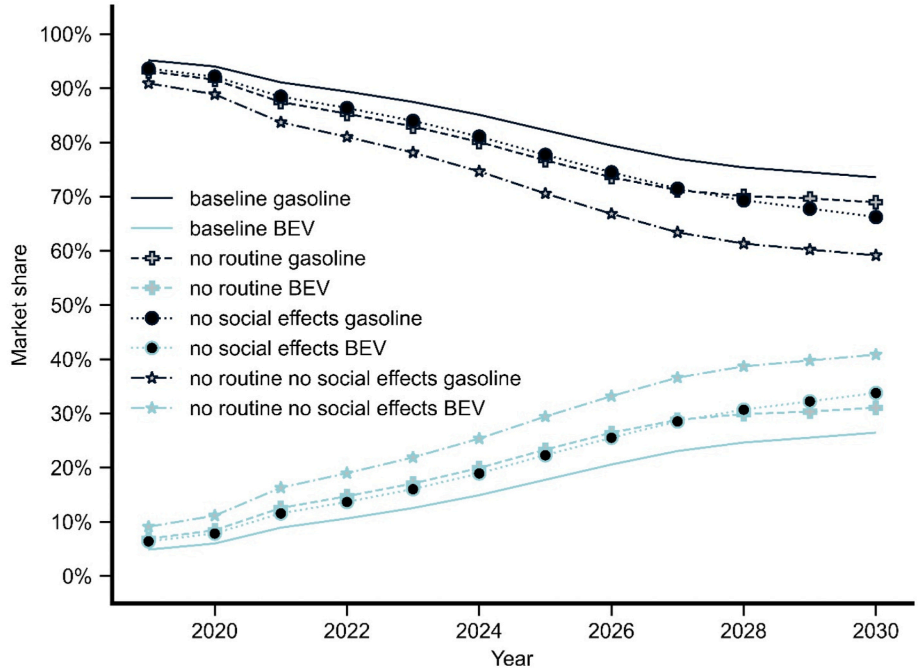

Fig. 9. Shares of new vehicle purchases for gasoline and BEV with and without routine purchases and social factors.

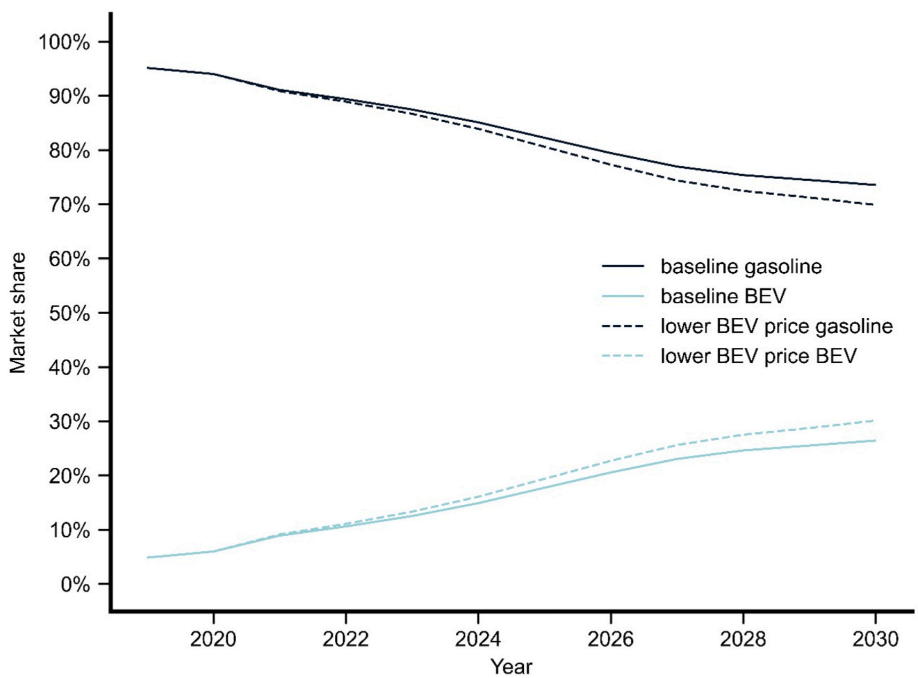

Fig. 10. Shares of new vehicle purchases for gasoline and BEV, for baseline and reduced BEV prices.

5.1. The uptake of battery electric vehicles

Our results show that in the market for new privately-owned passenger cars, the share of BEVs as a percentage of annual car sales in the Netherlands is estimated to increase from about 5 % in 2019 to 26 % in 2030. Even in an optimistic case, where we have ignored the impact of some of the factors that we expect to slow down BEV uptake (routine purchases and social factors), our model results show that not >41 % of new, privately-owned car purchases in 2030 will be a BEV. These numbers are far removed from the Netherlands policy target of 100 % zero-emission vehicles sales in 2030.

Comparing the modelling results for 2019 and 2020 (5 % and 6 % share of BEVs) with the actual sales data (7 % share of BEVs in the privately-owned car sales for 2019 and 10 % for 2020), shows that CODEC somewhat underestimates the actual sales. The input for the model was based on a survey held in 2019, just before BEV sales were taking off in the privately-owned market in the Netherlands. It may be assumed that awareness and perception of BEVs improve rapidly in a growing market [55], see also Section 5.3 (Limitations). Actual sales in 2019 and 2020 were boosted by several new, more affordable BEV models becoming available such as Tesla model 3 and Volkswagen ID3 [6].

A thorough literature review did not uncover research focusing specifically on the privately-owned cars in the Netherlands. Van Gijlswijk et al. [19] compare total costs of ownership (TCO) and find a maximum share of BEVs in 2030 for the privately-owned car market of approximately 40 % in 2030. In our results, the 2030 shares of BEV in car sales were lower (26 %), which could be explained by the fact that we have taken into account other factors next to TCO and purchase price, such as routine, social factors and the effect of the range of BEVs.

5.2. Factors influencing the uptake of BEV

Our study of the uptake of BEVs in the Dutch car market using the CODEC model made it possible to discriminate between different technical, financial and social factors that influence the car purchase decision. The main factors or barriers that negatively affect the uptake of BEVs towards 2030 in the market for privately-owned cars were:

1. Purchase costs: this factor becomes less important over time, because the price of BEVs was assumed to decrease between 2020 and 2030;
2. Range: the driving range of BEVs was assumed to increase over time, but does remain an important factor;
3. Routine purchases: a certain share of car buyers always buy the same type of car when it is available; and
4. Social factors (wanting to distinguish from others, or wanting to look like others): the relatively low share of BEVs in the car population in the period 2020–2030 (and high gasoline share) make the desire to look like others favour the purchase of gasoline cars over BEVs.

Purchase price and range have been identified in many studies as barriers that are currently important in several different countries [7,27,28,30]. The effect of social factors on BEV uptake has been found before [38] and studied in detail a recent paper by Yang and Chen [30]. The effect of routine purchases on BEV uptake has, as far as we know, not been studied before. We compare these four factors compared to other research on BEV uptake. Finally, we discuss the barriers and the drivers that have been found to be important by others, but have a smaller effect on BEV uptake in our current study. In each section, we discuss how current and future policies interact with the factors.

5.2.1. Purchase price

Purchase price is still a major barrier in 2020, but less so in 2030. In our baseline, we assumed the purchase price of a BEV to be 20 % higher than an equivalent gasoline car in 2020 and to decline to a 7 % higher price in 2030. In the CODEC model, the purchase price is used in two separate factors. In the enable phase we determine the fraction of the car buyers for whom the purchase of a BEV is feasible. We hereby assume that the consumer either buys a gasoline car or a BEV. As the BEV purchase prices becomes closer to gasoline cars, this factor becomes much less important over time. The other factor in which purchase price plays a role is the relative attractiveness of the purchase price compared to the alternative. We found that this a relatively small factor (see Fig. 8). Since prices of BEVs are dropping quickly, which might continue, we studied the impact of purchase price by running the model using a 7 % lower price for a BEV compared to gasoline. This only leads to a somewhat higher share of BEVs in car purchases (30 % in 2030, vs. 26 % in the base case).

Kangur et al. [26] model the uptake of BEVs in the Netherlands using an agent-based model, showing the evolution of the average satisfaction with BEVs of the agents in the period from 2012 to 2025. They found that the influence of cost perception (including purchase costs, running costs, taxes and subsidies) was stable over time, while the social factors (belonging and status) and the perception of functionality (to be able to travel desired distances) became slightly more influential over time, which is partly in line with our results.

The tax exemptions for BEVs are being reduced in the Netherlands in the coming years, because price parity between BEV and ICE cars is expected to be reached [2]. This is in line with our findings that other factors than purchase price will become dominant in determining BEV uptake. To stimulate BEV sales in the period when purchase prices are still higher, subsidies can have a significant effect [26]. As part of the Climate Agreement [2], the Dutch government established a subsidy scheme in 2020 (after this research was performed) which ends in 2025 directed at the privately-owned market. It might be considered to continue the tax exemptions and/or subsidy schemes beyond 2025, because we find that lowering the price of BEVs below gasoline cars does help to increase sales. However, this effect is relatively small and policy measures aimed at the other barriers for BEV uptake might be more effective. In addition, in a recent survey among electric vehicle drivers respondents indicated that the subsidy scheme had functioned more as a cue to action than that it removed a financial barrier for them [56]. This shows that also people who do not need a subsidy to be able to afford a BEV car make use of them.

5.2.2. Driving range

Concerning the driving range, we find that although it improves over time, it is still a barrier for the uptake of BEVs in 2030. In our modelling we used an average desired range (461 km) with a relatively large standard deviation, representing the fact that there is large variety in the driving range that people desire. While we assume that the range of BEVs will surpass the average desired range before 2030 (for 2030 we assume an average range of 560 km for BEVs), there will still be a considerable portion of car buyers who desire a larger range. The driving range has been found to be an important factor determining BEV uptake in several studies [28,30,57]. Bockarjova et al. (2015) [58] studied range and charging as barriers for the Dutch uptake of BEVs in more detail. They found that the minimum range (the range under unfavourable circumstances) is the most important determining factor. In our study, when determining the range per vehicle type (BEV, gasoline) we only used a maximum range under favourable circumstances.

The removal of the driving range as a barrier for BEV uptake is not only a technical issue. The perception of what a suitable range for a BEV is, may change over time when people see that for example their BEV-driving neighbours get by easily with a lower range for most of their trips. On average, in 2020 Dutch inhabitants lived on average 22 km from their workplace [59]. This is <10 % of the battery capacity we assumed for BEVs in 2020. Policy interventions could aim at letting people experience how the range of a BEV matches with their driving profile through offering test drives of several days, since Dutch research among new BEV drivers shows the limiting effect of the range is less than they expected beforehand [60].

5.2.3. Routine purchases

Concerning routine purchases, we found in our survey that about one third of car buyers makes a routine purchase: they do not consider other types of drive train than their current one. Since at present, almost all privately owned cars are gasoline cars, this routine purchases effect considerably slows down the uptake of BEVs. This is in line with survey research from the Netherlands showing that not all people are considering an electric car when replacing their car: 25 % of the respondents do not consider the option to buy a BEV in the next five years, 25 % do consider it, and 50 % are undecided [40]. The model results show that if consumers would make a deliberate choice a higher percentage would choose for BEV (see Fig. 9).

This implies that policy interventions should be directed at decreasing the number of people making a routine decision. For example by trying to convert routine behaviour into a more deliberate choice process through mass media campaigns that include an implementation intention [61]. Implementation intentions are a psychological behaviour change technique that can be used to couple the moment people need a new car to automatic behaviour to check a specific website for the comparison of different vehicle types for one's specific situation. Another way to reduce routine purchases is the implementation of zero-emission zones in major cities, a policy that is being discussed in the Netherlands for implementation in 2025 [1]. Making certain cities not accessible anymore for gasoline and diesel cars, will at least make consumers consider the zero-emission alternatives and break the routine choice for what one already know suits one's needs.

5.2.4. Social factors

Social factors were found to be a major determining factor that limit the market share of BEVs compared to ICEs between 2020 and 2030. We modelled two social factors: wanting to distinguish from others and wanting to look like others. The former factor benefits BEV sales when BEVs are not common yet, the latter when the market penetration reaches a certain level [22]. Wanting to look like others affects a much larger group and is the effect that consumers have a preference for the most abundant technology. In 2030 this is the second most important factor that reduces the market share of BEVs. Our findings are in line with a recent study on the BEV uptake in China, which finds the social factors to be more important than other psychological factors [30].

Our results also correspond to the finding in a Dutch survey, which shows that when people know more people who have a BEV, they are more interested in buying a BEV themselves [40]. In addition, in the review study conducted by Liao, Molin, and van Wee (2017) [9], several choice experiments show that there are significant effects of what other people buy on the uptake of BEV. Based on survey data, Habich-Sobiegalla et al. [39] found that if consumers have a wide social network and if they know someone who already owns an EV, their intention to purchase an EV is high.

Currently there are no policies directed at the social factors in the Netherlands. Policy instruments aimed at influencing the social factors on EV adoption could be targeted at making electric mobility more visible, for example by a different design of the license plate or a remarkable design of charging facilities. Next to increasing visibility, social factors can be mimicked by making electric vehicles look like the norm. This can be done for example by showing role models (such as celebrities) driving a BEV [62] featuring electric vehicles in popular TV shows, films [63] and series, and by rearranging parking lots in such a manner that all drivers will have to pass the charging stations and see the they are close to the destination, such as stores.

5.2.5. Other barriers

The limited availability of charging infrastructure has a negative effect on BEV uptake in 2020, but quickly becomes a less important barrier. The charging infrastructure in the Netherlands is expanding quickly, and public charging density is the highest in Europe [64]. Indeed, 59 % of our survey respondents believe to be able to charge an electric car close to home. We assumed that the charging network will be expanded in the coming years, which leads to this factor becoming less significant towards 2030. Of course, this means that current policies to expand the charging network and reinforce the electricity grid should be maintained or expanded. Another policy intervention could focus on fast-charging facilities so BEV drivers can easily extend their range. Fast charging has not been included as a factor in the current study. Yao et al. (2020) [33] studied the effect of a number of policy measures on EV uptake in 13 different countries, including the Netherlands, for the period 2015–2018. They conclude that the charging infrastructure, and especially the amount of fast chargers per vehicle in a country correlates strongly positively with the sales and subsequent market shares of BEVs. On the other hand, Bhardwaj et al. [65] find that the effectiveness of charging deployment incentives have not been sufficiently studied.

In several studies, the lower knowledge on BEVs was found to be a barrier [28,31]. However, in our study this factor has a relatively low impact. The initial knowledge on BEVs is already rather high according to our survey: 70 % of the respondents indicated to have access to sufficient knowledge to decide whether to buy a BEV. The level of knowledge seems to be a less significant factor currently – at least in the Netherlands – than it was in earlier studies, as described in Greene & Ji [31]. This is also in line with a recent paper on the BEV uptake in China [30].

Finally, we assume that the availability of BEV models is not a significant barrier, which is not in line with several other studies [27,28]. This is partly because in our study the availability of affordable models with sufficient range is already captured in other factors in the Enable phase: ‘investment is feasible’ and ‘acceptability of range’. We assumed that if people wanted to buy a BEV, they could choose from a sufficient number of models. This assumption is in line with survey results from 2019: only 6 % of car drivers answered that they will not buy a BEV because there are no models available that suit their needs [40]. To check this assumption, we modelled a restricted BEV availability: set at 50 % lower than availability of gasoline models in 2019 and growing linearly to 100 % in 2030. This leads to a slightly lower market share of BEV until 2025, but has only a minor effect towards 2030. This is in line with observation that the availability of BEV models to choose from is increasing rapidly [6].

5.2.6. Drivers for BEV

Next to barriers there are also factors which make BEV more attractive than gasoline cars: drivers. Some factors that were included in the model, such as the sustainability of a car, the innovativeness and driving pleasure were found to have a positive, albeit very small, effect on the uptake of BEVs (Fig. 8). This limited effect of these factors is in line with Yang and Chen [30], who studied the role of several psychological factors on BEV uptake in China.

Also the running costs (which includes the fuel price), on which BEVs score better than gasoline, only have a limited effect on BEV purchase intention. It must be noted that the survey was held long before the steep rise in fuel prices that occurred in 2022. The running costs advantage can be utilized by promoting private lease which removes the high purchase costs from the equation, especially when also differences in fuel costs are presented when showing this comparison. The low effect of running costs, could have been caused by survey correspondents being unaware of the advantage of BEVs in this respect. This lack of knowledge could be remediated by including what the equivalent cost for registration etc. for a BEV would be on the invoices sent to ICE car drivers each year.

Given that the factors that positively affect BEV uptake have a relatively small effect, it should be noted that even when all barriers for BEVs are removed, this does not yet make them *more* attractive: there is no relative advantage [22]. Therefore, it does not necessarily mean that gasoline cars will not be purchased anymore without appropriate policy interventions. For gasoline cars to become the less popular option, its characteristics should become less favourable compared to BEVs. This can for example be done by changes in the pricing of cars or fuel and limiting the number of gas stations. Yao et al. [33] found that policy measures directed at making the ICE a less attractive option like zero-emission mandates and ICE sales restrictions (that exist in China) have a positive correlation with BEV sales. Bhardwaj et al. [65] found that a zero-emission vehicle mandate can be effective in reducing CO2 emissions from light-duty vehicles. Several countries, including the UK, have announced ICE bans for 2030 [1,29]. Recently, the European Commission and parliament and the member states have reached an agreement that all new cars and vans registered in Europe have to be zero-emission by 2035 [66]. This removes gasoline vehicles from the choice set for consumers that want to buy a new (not second hand) car.

5.3. Limitations and suggestions for future research

Our research has several limitations that we will address here, which could have caused over- or underestimation of the share of BEV in the sales of privately-owned cars. We also provide suggestions for future research based on these limitations.

A simplification of the model is that we treat the factors in the enable phase as independent of each other. In the Enable phase the scores of the factors are multiplied with each other. This might lead to an underestimation of the uptake of BEV: the group of consumers that in the enable phase are estimated not to have sufficient funds could overlap with the percentage of consumers which requires a larger range. In future research the model could make use of survey or choice experiment data on how these factors are correlated, and test whether treating the Enable score in a similar way as the Intention score, similar to for example Yang & Chen [30], creates an even better fit to the historic data.

We used a survey to measure the preferences of car buyers on the cars available in 2019 and assumed these preferences to remain stable in the future, while preferences of car buyers might change over time. Recent advances in modelling applied on the Portuguese car market focus on this variability in preferences [55]. Not only do the factor values (such as purchase price, or range) change over time, but also the consumer preferences for each factor might change. Future research could study the effect of changing consumer preferences over time on the uptake of BEVs. In addition, we made the simplification of using the same weight of preferences for all consumers. Future research could distinguish between different target groups to better reflect reality, as for example was done in a study into generational target groups [67].

We have modelled the private passenger car market completely separate from the company lease market. Some of the factors, however – especially the social factors such as wanting to look like others – are affected by the entire car base in the Netherlands: there is no visible distinction between leased cars and the privately-owned cars.

A limitation of CODEC is that the supply side is not modelled, while this does have an effect on the uptake of BEVs [31]. As mentioned, in the current research we assumed that if consumers wanted to buy a BEV, they could. Future research could include the changes in the supply of different car types on the market. An approach could be to combine the choice model CODEC, with a car manufacturers model and study the interaction between the two [29].

We used an exogeneous growth of the knowledge or awareness of BEVs among consumers, while in reality the awareness of BEVs and charging infrastructure will depend on the market share of BEVs. Other models use awareness as an endogenous parameter [68]. Future research could include this in the CODEC model. We also did not include all possible factors of influence, such as the possibility of using the car for long-distance travel a few times per year or the ability to tow a caravan, and charging time, which other research found to be relevant [58].

Finally, we created the CODEC model to model the effects of different policies on BEV uptake. After creating this base line scenario different policy scenarios, based on suggestions we mentioned, will be created to support policy making.

6. Conclusions

In 2019, the Netherlands adopted a policy goal of a 100 % share of zero-emission vehicles (ZEV) in new car sales in 2030 [2]. In recent years, the sales of BEVs has increased in the Netherlands, especially in the company lease market. In the sales of privately-owned new cars (22 % of all car sales), BEVs are still a relatively small fraction (10 % in 2020). We have modelled the future market shares in the Netherlands of gasoline and BEV for new privately-owned passenger vehicles by modelling and analysing the influence of technical and behavioural factors. We used the CODEC model to calculate estimated market shares of the different vehicle options and used input parameters and factor weights derived from a survey among prospective car buyers. This study contributes to the existing literature by providing insight into the effects of the different factors that influence the adoption decision, including psychological factors. In addition, the model accounts for routine behaviour: according to our survey, about one third of car buyers does not seriously consider a vehicle another drivetrain than they currently own.

Our results (in which no additional policy interventions were included other than the policies currently in place) show that the share of BEVs will increase from close to 5 % in 2019 to approximately 26 % in 2030, which is still far removed from the targeted 100 %. Between 2021 and 2025, the relatively high purchase price and low driving range of BEVs compared to the incumbent ICE technology, are the most important factors that influence consumers to choose gasoline cars. After 2025, however, the assumed price reductions of EVs means that the price difference becomes less of an issue. Also the range becomes a lower, albeit still significant, barrier, due to anticipated growing average battery size. After 2025, the social factors (wanting to look like others) and routine purchases become the main factors that cause the BEV market share to be considerably lower than ICEs. Factors that affect BEV adoption positively, such as environmental friendliness and lower running costs, have a relatively small effect, so also measures to reduce the attractiveness of gasoline vehicles should be considered.

To reach the goal of 100 % zero-emission vehicle sales in 2030, policy interventions should target these social factors and break routine purchase behaviour. So, next to policies that are currently in place, such as tax incentives, subsidies and investments in public charging, policies such as the use of role models, zero-emission zones, a zero-emission vehicle mandate or an ICE ban could be considered.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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