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# The role of norms and collective efficacy for the importance of techno-economic vehicle attributes in Germany

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## Abstract

The shift to electric mobility lags pursued goals. In this article we analyze the consumer's perspective and examine, which technology attributes and person-related factors influence electric vehicle (EV) adoption, and whether differences in person-related factors affect vehicle attribute importance. A total of 1922 participants took part in a Germany-wide, representative study comprising a questionnaire measuring person-related factors and a discrete choice experiment determining the importance of technology-specific attributes. Results from the choice experiment for all vehicles classes reveal that purchase price was the most important vehicle attribute. Less important for the choice of a small-sized vehicle were in descending order: range, fuel costs, fuel type, refueling infrastructure, CO<sub>2</sub>-emissions and CO<sub>2</sub>-tax. Regression analyses further indicate that subjective norms, collective efficacy, technological risk attitude and perceived information were the strongest predictors for purchase intention in the questionnaire. Participants showing high values on these factors also weighted attribute importance in the choice experiment differently, but throughout favoring EVs, than participants with low values on these factors. Factors that are disadvantageous for EV, such as range and price, were de-emphasized by these respondents. In addition, preference shares for battery electric vehicles were more than twice as high as for conventional vehicles in three out of four groups with high values. Socio-psychological factors, therefore, seem to relativize the impact of mere techno-economic factors on electric vehicle adoption. Hence, we recommend that these factors receive greater attention in the discourse on policy measures.

## 1 | INTRODUCTION

Considering the climate catastrophe already taking place, the transformation of the energy sector presents one of the most urgent challenges of humankind (IPCC, 2018). Still, the transformation of the energy system presents a political, economic and societal challenge to fulfill the time-bound commitments for international climate protection. For reaching national, European or within the Paris Agreement decided climate targets, the electrification of the transportation sector

is crucial (Federal Ministry for Economic Affairs and Energy BMWi, 2011; IPCC, 2014). With the National Development Plan for Electric Mobility, the German Federal Government has promoted electric mobility and set the interim goal of having at least one million electric vehicles registered until 2020 (Federal Ministry for Economic Affairs and Energy BMWi, 2019). Considering that in 2019 only 83.175 battery-electric vehicles (BEV) were actually registered (0.18% of the 2019 car stock; Kraftfahrt-Bundesamt [KBA], 2019) and only 7% of the new registrations were BEV in 2020 (ICCT, 2020), it

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appears very unlikely that the intended numbers can be reached within the set timeframe.

Having this in mind, the questions arise, why these numbers are that low and what factors can influence the battery electric vehicle (BEV) and fuel cell electric vehicle (FCEV) adoption. The primary focus of this article lies on consumer perceptions. Yet, we do not intend to neglect or undermine the role of the car industry as supply side and the (EU) policy framework in shaping market availability and consumer perception and, hence, the diffusion of electric vehicles. This is especially important as fleet-average CO<sub>2</sub>-emission levels have increased instead of decreased since 2015 (Tietge et al., 2020). Latter development counteracts collective efforts for keeping global warming well below 1.5°C as declared in the Paris Agreement (IPCC, 2018). Further it must be noted that official figures for emission levels do not align with real-world emissions and, in 2018, had an approximate gap of 14%–39%, depending on the type of measurement applied (Dornoff et al., 2020). Moreover, the number of EVs available on the market has remained quite low and instead, larger and heavier cars keep being developed. EU regulation has potentially indirectly supported this development as it concedes higher CO<sub>2</sub>-emission levels to heavier car fleets. However, higher requirements for CO<sub>2</sub>-emission standards beginning to apply in 2021 (95 g/100 km) will likely lead to rising efforts to lowering car fleet emissions by manufacturers. So far, most manufacturers drastically fail to reach these targets with the current manufacturer pooling, on average by 21% (Tietge et al., 2020).

Further, next to electrifying car fleets, modal shifts in transport are necessary for reducing greenhouse gas emissions (Pastori et al., 2018). However, Mattioli et al. (2020) point out that a number of (political-economic) decisions made in past decades and subsequent reinforcing factors have led to a state of car dependence. The authors argue that the car industry not only influences the products available on the market and their respective advertising but also, how (public) financial resources are distributed especially concerning the role of public transport and the supposed necessity of expanding and maintaining road networks as state basic supply. These infrastructural effects and the way cities and road constructions have been designed in turn influence the role cars play in our daily lives. Moreover, they shape the narratives and wider social context of the desirability of travel and car use (Mattioli et al., 2020). Mattioli et al. (2020) introduce the term “car culture” to address the complexity of elements influencing and reinforcing the centrality of private car ownership. Alternatives which have a lower climate (and environmental) impact are pushed to the margin by the dominance of individual car mobility, which needs to be addressed through an open and aware political program. Creutzig et al. (2020), for example, argue that local and global environmental damages like congestion and air pollution and, concurrently, opportunities of modal shift should be considered in policymaking to overcome the dilemma of public accepted climate policy (e.g., yellow vest protest in France as a consequence of rising fuel prices).

The lock-in effects caused by car dependence and political framework conditions should not be ignored when examining the development of the vehicle stock as they play an important role in consumers'

choices. Yet, in addition to challenging framework factors, also individual perceptions of and preferences for certain vehicle types and respective attributes have influenced electric vehicle diffusion. In this article we focus on underlying (socio-) psychological factors of the consumer decision and how these factors are related to the importance of vehicle attributes (e.g., range or price).

So far, the public discourse has primarily been on financial and convenience issues that prevent people from buying electric vehicles (EV). However, next to techno-economic and infrastructural barriers, the acceptance of the technology seems to also be lacking in other regards (Taylor, 2019). Person-related factors and the social context have mostly been neglected in the political discourse about strategies how to increase electric vehicle adoption. Also, in previous research, the focus of most studies concerning EV adoption has primarily been on the techno-economic aspects of electric mobility and less on psychological and social parameters. The existing studies that primarily address individual-specific psychological factors work with theories, such as the Theory of Planned Behavior (Ajzen, 1991) or Rational Choice Theory (Becker, 1976), to predict purchase intentions of EV and to identify influential factors in the decision-making process (Rezvani et al., 2015). To the authors' knowledge there is only one study by Goetz et al. (2012) in which market shares were calculated including sociodemographic variables and environmental awareness.

Further, to our knowledge, no study has addressed both, the actual choice between vehicles (conventional and electric) and individual-specific psychological factors. In previous studies it does not become clear whether sociodemographic and socio-psychological factors solely affect EV purchase intention, in case of applying the TPB, for example, primarily through attitude towards EVs, or whether differences in socio-psychological factors are also related to the actual vehicle choice participants take in choice experiments. So far, it is not clear how the preference structure for certain vehicle attributes (e.g., range) is related to person-related variables. However, literature on consumer behavior suggests that the way, product attributes are perceived, for example, in terms of attribute importance, depends on individual characteristics, such as salient personal motives or feelings and the perceived match between product and self (Hahnel et al., 2014).

Therefore, in the present article we attempted to combine rather psychological approaches by examining socio-psychological factors that predict EV adoption with the primarily economic approach of applying a discrete choice experiment through varying EV attributes and vehicle options. The aim of this study is to examine, which technology attributes and person-related factors influence EV adoption, and whether differences in person-related factors affect the preference for EV (attributes). The work seems highly relevant to provide insights into the investment decision process of individuals, as it influences technology diffusion. Identifying differences in the utility of certain EV attributes depending on socio-psychological factors could help in developing more consumer-oriented promotion of EVs. Moreover, it might contribute to developing policies that go beyond mere financial incentives and technological progress but in addition address rather individual, societal and cultural attitudes, values and beliefs.

## 2 | THEORETICAL BACKGROUND

Various studies have focused on the impact of specific technology attributes and framework conditions on EV adoption and distribution. Many of these studies applied discrete choice experiments to examine the preference for certain technology attributes by individuals (e.g., price, infrastructure, CO<sub>2</sub>-emissions, etc.). By technology-specific factors, we refer to the technical, financial, infrastructural and policy parameters that influence the purchase decision for an EV (see Section 2.1) in contrast to person-related psychological and socio-economic factors (see Section 2.2).

### 2.1 | Technology-specific factors influencing EV adoption

The technology related factors that have mostly been found significant in previous experimental studies are *purchase price*, *operation cost*, *driving range*, *charging time*, *engine power*, *acceleration time*, *maximum speed*, *CO<sub>2</sub>-emissions*, *brand*, *range*, *warranty*, *charging availability* as well as *pricing* and *land-use policies* (Liao et al., 2017). For a review of choice studies regarding EV adoption, see Liao et al. (2017). Also, Hoen and Koetse (2014) provide a detailed overview on attributes that were included in many peer-reviewed choice studies. The attributes we eventually identified as most relevant for our choice experiment are depicted in Table 1 with respective literature references.

A higher *purchase price* has a negative effect on intended EV adoption and has been found critically important in many studies (see Table 1). People who prefer buying a used or small car are more price-sensitive than people preferring new cars (Jensen et al., 2017), whereas adopters from the luxury segment tend to be less price-sensitive (Higgins et al., 2017). Also, higher *fuel costs/operation costs* have a negative effect on purchase intention. As the fuel and maintenance costs of BEVs are lower than of conventional vehicles, this is favoring BEV adoption. An increase in *driving range* has a positive

**TABLE 1** Selected technology attributes influencing EV adoption

Attributes	Source
Purchase price	Barth et al., 2016; Hackbarth & Madlener, 2016; Hoen & Koetse, 2014; Valeri & Danielis, 2015; Ziegler, 2012, and so on
Fuel costs/operation costs	Achtnicht et al., 2012; Daziano & Achtnicht, 2014; Hackbarth & Madlener, 2016
Infrastructure for refueling	Byun et al., 2018; Ziegler, 2012
Driving range	Barth et al., 2016; Hackbarth & Madlener, 2016; Hidrue et al., 2011; Valeri & Danielis, 2015
Fuel type	Byun et al., 2018; Valeri & Danielis, 2015
Policy incentives	Chorus et al., 2013; Hoen & Koetse, 2014
CO <sub>2</sub> -emissions	Byun et al., 2018; Hackbarth & Madlener, 2016

Note: This is a non-exhaustive overview over important technology-specific factors influencing EV adoption.

effect in most studies on intended EV adoption. Further, a good *infrastructure for refueling*, namely the number of charging stations and refilling time, has a positive effect on EV adoption. In previous studies, *policy incentives* had an ambiguous impact. Among these, pricing policies seemed to be most effective (Liao et al., 2017). *CO<sub>2</sub>-emissions* have a negative impact on the car choice as in cars with higher emissions are less preferred. In some studies the impact varies depending on the consumer group (Hackbarth & Madlener, 2016). Regarding the *fuel type* (conventional gasoline vehicle vs. hybrid EV vs. BEV, etc.), gasoline still seems to have the highest utility in some studies (Valeri & Danielis, 2015). In other studies, FCEV and BEV have a higher utility and are therefore, the preferred fuel type (Byun et al., 2018).

### 2.2 | Person-related factors influencing EV adoption

There is a variety of person-related factors that affect the adoption of electric vehicles. Among those factors are variables that can be classified as socio-economic, psychological or mobility related. Liao et al. (2017) and Li et al. (2017) provide an overview of studies concerning person-related factors. In Table 2 the person-related factors influencing EV adoption that we selected for the survey are presented with literature references.

Regarding EV adoption and car choice in general, socio-economic variables tend to have an inconsistent influence which, if existent, is rather small. Mobility-related variables are, among others, *driving experience* with BEV and FCEV or *mobility habits*, such as commuting or the frequency of long trips. Experience with EV and knowledge about EV are linked with a higher technology acceptance and the intention to use an EV. Next to socio-economic and mobility related variables, there are also psychological factors that have been shown to contribute to the preferences for vehicles. Previous studies, for example, have examined the role of environmental concern, symbols, attitudes and values (see Liao et al., 2017 for overview). Further, as Barth et al. (2016) point out, achieving nationwide (or rather global) mobility

**TABLE 2** Selected person-related factors influencing EV adoption

Factors	Source
Sociodemographics	See Liao et al., 2017
Experience and mobility habits	Barth et al., 2016; Franke & Krems, 2013, Hoen & Koetse, 2014
Norms	Barth et al., 2016; Petschnig et al., 2014
Collective efficacy	Barth et al., 2016
Innovative self-concept and technological risk attitude	Barth et al., 2016; Hackbarth & Madlener, 2016; Hidrue et al., 2011; Valeri & Danielis, 2015; following Rogers, 1983

Note: This is a non-exhaustive overview over important (or hypothesized to be important) person-related factors influencing EV adoption.

that is based on renewable energies with zero emissions is, next to individual contributions, the work of collectives. To contribute to the collective goal, people need to believe that with shared effort the group's goals can be achieved. In literature, this concept is considered as *collective* or *group efficacy* (Mummendey et al., 1999; van Zomeren et al., 2008). One recent example for collective efficacy is the Fridays for Future movement. Thousands of young people have taken the faith of humankind's future in their hands and started striking for climate action—demanding to stay within 1.5°C global warming. Among other aspects they have one thing in common: the belief that collective action can change public policy (Wahlström et al., 2019). In the context of adoption of electric vehicles this implies that the personal conviction of being able to transform the mobility sector, if people act together, should increase the individual adoption intention. Barth et al. (2016) found that collective efficacy was an at least equally strong predictor of the acceptance and the buying or sharing intention of EVs as personal cost–benefit variables. Also, in most countries, the diffusion of EV is still at an early stage. This circumstance might also impact who is at the forefront of buying an EV. Following Rogers' Diffusion of Innovation theory (Rogers, 1983), the process of technology diffusion follows an S-shaped diffusion curve. During this process, different adopter groups become relevant. The most important ones to spark diffusion in this theory are innovators and early adopters. One characteristic of these two groups is that they consider themselves as rather innovative and have a comparatively higher readiness to take risk. As the distribution of EVs in Germany is still in the starting phase, we assumed that a more innovative self-concept and a higher technological risk attitude also predict adoption intentions of EV.

All in all, previous studies have demonstrated that various factors influence EV purchase intentions, both from technological and socio-psychological nature. However, studies addressing person-related factors often solely rely on regression models examining factors that predict adoption intention or interest in electric vehicles. In contrast, research applying choice experiments mostly comprises only technological attributes. Thus, the effect of socio-psychological factors on vehicle attribute importance and actual purchase probability remains unclear. This applies especially to settings in which one can decide whether to buy a conventional gasoline vehicle or an EV. Even though to the authors' knowledge no (published) study has been conducted on the effects of individual and groups variables on attribute importance of electric vehicles, insights from literature on consumer behavior give reason to assume so. For example, multi-attribute models postulate that consumers have individual preferences, but also perceive attribute importance differently. Attitude formation is thus seen as a consequence of the cognitive evaluation of product attributes with aspects of the self (Fishbein, 1963). Building on these models, research on self-image congruence has identified that consumers' purchase intentions are influenced by the perceived matching of product attributes with consumers' self-image and domain-specific motives, such as ecology, hedonism, finance, and so on (Hahnel et al., 2014).

Furthermore, King and Slovic (2014) found evidence that not only cognitive processes, for example, gathering and evaluating

information, but also a person's feeling about the product influences product attribute perception. Their findings specifically relate to product evaluations of innovations and thus, also to EV, which are characterized by uncertainty in both, risk and benefits.

Therefore, the aim of this study is to examine, which technology attributes and person-related factors influence EV adoption, and, in particular, whether differences in person-related factors also affect the preference for EV and vehicle attributes identified through a choice experiment.

The following research questions served as guidance for this study: Which person-related factors from a sociodemographic and socio-psychological domain predict purchase intention assessed via questionnaire?, what are the technology-specific attributes of (electric) vehicles that determine vehicle choices in the DCE?, and, do the person-related predictors of purchase intention in the survey also influence vehicle choice and attribute importance in the discrete choice experiment?

Concerning research question one we hypothesize that norms, collective efficacy, technological risk attitude and an innovative self-concept are significant predictors of EV purchase intention, independently of socio-economic variables (Hypothesis 1). Further, as emphasized in previous research, we expect that purchase price is the attribute with the highest importance rating in the DCE (Hypothesis 2). Research question three is based on multi-attribute models and on perceived matching of product attributes with the self. We anticipate that the predictors with the biggest impact on purchase intention also influence the importance of the different vehicle attributes and general purchase probabilities of EV in the DCE. Thus, we hypothesize that people reporting higher normative influence regarding EV, a stronger sense of collective efficacy, a higher technological risk attitude or a higher innovativeness compared to people with lower values on these variables, show differences in the attribute importance ratings in favor of electric vehicles (Hypothesis 3). Moreover, we hypothesize that these individual characteristics lead to higher preference shares for EV (Hypothesis 4).

### 3 | METHOD

A Germany-wide (representative for gender, age, income, education, federal states) survey was conducted in August and September 2018 which included a questionnaire to assess person-related variables (see Section 3.1) and a discrete choice experiment for determining vehicle attribute importance (see Section 3.2). We chose this two-step approach since we prioritized applying a conjoint-based discrete choice experiment using Hierarchical Bayes for calculating individual utility values over aggregated models not considering individual utilities (e.g., mixed or multinomial logit models). Choice based conjoint methodology originates from consumer research. It is a method for predicting product choices of individuals by examining the product attributes that are favorable to individuals in contrast to a stated preference approach. In choice experiments, participants are exposed to hypothetical products with different characteristics (Liao et al., 2017). Respondents select the product which matches best with their

preferences. Since trade-offs between different product-attributes need to be made, it is possible to calculate individual utilities for the varying attribute levels and, therefore, assess individual preferences. The underlying notion is that individuals aim for utility maximization and that this utility is characterized by the different product attributes and not the product per se (Sammer, 2007). Yet, only a limited number of attributes can be included. DCEs thus serve well to operationalize a limited amount of technology attributes of EV, whereas collecting empirical questionnaire data and applying regression analysis is a standard method for evaluating the influence and relevance of attitudinal and other person-related factors. To assess the relevance of technology attributes as well as person-related factors, we therefore combined DCE and questionnaire in one study.

Participants were recruited via an online panel by a market research institute. The study was pretested with a small sample and adjusted multiple times. The final version of the web-based study included three parts: (1) sociodemographic and mobility-related questions, (2) person-related factors regarding attitudes, norms, perceptions of EV and (3) the DCE for gasoline vehicles, BEV and FCEV. Before the DCE started, respondents were instructed about how choice experiments work and to select the vehicle that they like most. Additionally we asked them to state, whether they would realistically buy the vehicle (total of 10 choice cards). An exemplary choice card is depicted in Figure 1. At the end of the survey, the purpose of the study was clarified. Also, respondents had the possibility to give feedback or contact us for questions.

A total of 2311 respondents completed the web-based survey and the discrete choice experiment, of which a total of  $N = 1922$  ( $M_{Age} = 45.03$ ,  $SD_{Age} = 14.25$ , female identified = 49.8%, one other identified) were eventually used for the analysis of the questionnaire

and  $N = 2011$  for the choice experiment after excluding participants who took less than 480 s to complete the survey. The difference in participant numbers is due to missing data in the questionnaire results. Minimal required sample size for the questionnaire was computed a priori with G\*Power ( $N_{required} = 127$ ). The data set is openly available [dataset] (Berneiser & Senkpiel, 2020).

In the following, the design of the survey and the subsequent choice experiment are explained in more detail.

### 3.1 | Survey design

Participants were asked for demographic data (age, gender, household net income, education, federal state, number of cars in the household). They also indicated whether they intended to buy a car in the next 5 years and whether they had already driven with an EV (BEV and/or FCEV).

After a short introduction in BEVs and FCEVs, participants were asked to give answers to the following topics. If not indicated otherwise, all items were measured with Likert scales ranging from 1 to 6 (with 6 being absolute agreement with the statement). The questionnaire was designed in German and translated by the authors.

#### 3.1.1 | Information

As information is a predictor of purchase intention in the literature, the following question was included in the study: "How well have you informed yourself about alternative vehicles so far?" (with 6 meaning *very well informed*).

	offer 1	offer 2	offer 3	offer 4
vehicle type	battery-electric vehicle	gasoline vehicle	fuel-cell electric vehicle	battery-electric vehicle
purchase Price	36.400€	15.600€	52.000€	26.000€
fuel cost [€/100 km]	2,00€	4,00€	7,20€	2,00€
range [km]	320 km	560 km	160 km	320 km
refuelling infrastructure	with strong limitations		with limitations	without limitations
W2W CO <sub>2</sub> emissions [g/km]	no emissions	low	medium	low
additional CO <sub>2</sub> tax for CV		yes		
	<input type="button" value="select"/>	<input type="button" value="select"/>	<input type="button" value="select"/>	<input type="button" value="select"/>

**FIGURE 1** Exemplary choice card in the DCE for minis and small cars (vehicle class 1)

Would you actually buy this vehicle or not?	
<input type="button" value="I would buy this vehicle"/>	<input type="button" value="I would NOT buy this vehicle"/>



### 3.1.2 | Purchase intention

The purchase intention was asked for both, BEVs and FCEVs separately, with the two items: "I've decided to invest in an alternative drive car over the next few years" and "An investment in a car with alternative drive is a possible option for me." However, for reasons of brevity we chose to focus on BEV in the following regression analysis as they, on the one side have a greater market potential than FCEV in the private passenger vehicle segment (Sterchele et al., 2020) and also because FVEV were no viable option regarding refueling infrastructure at the time of the study. (BEV:  $r = .68, p < .01$ ; rf. Ajzen, 1991; Korcaj et al., 2015).

### 3.1.3 | Social norms

Different norms were included in the survey. Subjective norms were measured with three items, for example, "Many people who are important to me would find it great if I invested in an alternative vehicle" (Cronbach's  $\alpha = .87$ ; rf. Korcaj et al., 2015). Moral norms were included with two items ( $r = .68, p < .01$ ; Abrahamse & Steg, 2009), for example, "I feel morally obliged to make my mobility environmentally friendly regardless of what others do."

### 3.1.4 | Self-concept innovation

Three items were measured for a self-concept innovation, for example, "I consider myself as someone who likes technical innovations" (Cronbach's  $\alpha = .83$ ; Krömker & Dehmel, 2000).

### 3.1.5 | Collective efficacy

Collective efficacy was included with three items, for example, "We, as inhabitants of this region, we can create the mobility turnaround together" (Cronbach's  $\alpha = .58$ ; Barth et al., 2016).

### 3.1.6 | Technological risk attitude

According to the DOI (Rogers, 1983), the early adopters of a technology are among others characterized by a willingness to take financial risks. As we could not find a scale that adequately addressed this topic, we created one item on our own: "How willing are you to take financial risks for technical innovations?" (1 = *not willing at all*; 6 = *very willing*).

### 3.1.7 | Environmental benefit

The perceived environmental benefit of an electric vehicle was measured with two items: "With an electric vehicle I can save natural resources" and "With an electric vehicle I can protect the

environment" ( $r = .73, p < .001$ ; rf. Korcaj et al., 2015). Further, we asked people whether they were members of an environmental organization, such as Greenpeace.

Confirmatory factor analysis was conducted for the factors purchase intention, social norms, moral norms, self-concept innovation, technological risk attitude and environmental benefit to check for model fit. The test statistics indicate a sufficiently good fit for conducting further analyses (SRMR = 0.045, RMSEA = 0.068 [90% CI = 0.063, 0.073], CFI = 0.961).

## 3.2 | Discrete choice experiment

The stated-preference DCE included battery-electric vehicles (BEVs), fuel-cell electric vehicles (FCEVs) and conventional fuel vehicles (CFVs). Further, the DCE was split up in three vehicle classes to optimize the vehicle choice tasks (see also Goetz et al., 2012; Higgins et al., 2017). As future electric vehicles will have attributes that are not available yet, we made predictions on the development of these attributes (e.g., price or range) until 2050. To do so, we analyzed various research papers and databases, and calculated potential pathways. Generally, we calculated the initial values of the specified attributes by averaging vehicle models existing in 2018. Next, we identified lower and upper bounds of attribute developments and conducted own calculations for the years 2020, 2030, 2040 and 2050. For reasons of brevity, these assumptions on the future development of the attribute levels are described in more detail in (Senkpiel et al., n.d.). The participants were distributed to the different categories depending on which class they stated to be interested in for a future car purchase. The selected attributes and their identified current and future levels for small cars are depicted in Table 3 in the group of small cars.

Each respondent had to complete 10 separate choice tasks. On every choice card, all attributes were represented with one level each. In theory (and for statistical reasons) levels from the different attributes are assigned randomly to each other so that preferences for all possible level combinations can be tested. Yet, for realism, some combinations were excluded from the choice sets. For example, the range of conventional vehicles did not vary as much as for AVs since a range of only 160 km for conventional cars would probably be irritating to participants. The combinations of attribute levels in the choice tasks were chosen randomly by the software. Thus, participants saw randomly generated choice cards that were not set constant across vehicle classes or participants, in general. We did not offer a choice card specifically referring to the status quo as an alternative, since the subjective perceptions probably differ tremendously. However, the current conditions are indirectly represented in the levels that were chosen and also used for simulating the bottom-up diffusion of electric vehicles in Senkpiel et al. (n.d.).

We further included a none-option as a dual response approach. Firstly, participants were asked to select their preferred alternative and in a second step, to decide, whether they would realistically buy the product. With this approach, both, the attribute preference and more accurate individual level utilities regarding a purchase decision

can be generated (Brazell et al., 2006). A market research institute set up the DCE using Sawtooth Software (Johnson, 1983). Sawtooth applies Hierarchical Bayes method (here: CBC/HB package) to calculate the individual partial utilities per attribute level. This method is based on Bayes theorem which can be described as following. Firstly, the joint probability of  $y$  and  $\Theta$  can be described as the product of the prior distribution  $P(\Theta)$  and the sampling distribution  $P(y|\Theta)$ .

$$P(\Theta, y) = P(\Theta)P(y|\Theta)$$

With the basic property of conditional probability, the posterior distribution is then:

$$P(\Theta|y) = \frac{P(\Theta, y)}{P(y)} = \frac{P(y|\Theta)P(\Theta)}{P(y)}$$

with  $P(y) = \sum_{\Theta} P(\Theta)P(y|\Theta)$  being the sum over all possible values of  $\Theta$  when it is not continuous. The prior distribution  $P(\Theta)$  describes the distribution of  $\Theta$  before incorporating the data from the actual study, if new data is available, the calculated posterior distribution becomes the prior distribution in the new calculation, therefore sequential analyses are a key aspect of Bayesian method. Hierarchical models are used when data on different levels of observational units is available, in our case on the individual level and on the level of the whole sample (Gelman et al., 2014).

HB has been shown to be more effective than multiple regression or multinomial logit models (Wellman & Vidican, 2008) as utilities are calculated on an individual level and, therefore, take the heterogeneity of the population into consideration (Gelman et al., 2014). For this study, it was particularly important to obtain values on the individual level since, in a second step, we developed a diffusion model to simulate electric vehicle diffusion based on individual utilities (see Senkpiel et al., n.d.). A total of 5000 draws were used for each respondent and 20,000 iterations were performed to estimate the parameters.

## 4 | RESULTS

The result section is structured accordingly with the order of the research questions. At first, the person-related factors predicting purchase intention are examined. Secondly, the results solely from the DCE are displayed. Lastly, the attribute importance and preference shares for EV and CV of participants showing high values on the predictor variables are illustrated.

### 4.1 | Which person-related factors predict purchase intention?

#### 4.1.1 | Demographic variables and mobility behavior

On average,  $M = 2.50$  ( $SD = 1.14$ ) persons live in one household. 32.8% stated to have a household net income of less than €2000/

month, 28.3% have €2000–€3000, 20.1% €3000–€4000 and 18.8% reported to have more than €4000 available as net income. 13.1% of the participants reported to not own a car at all in the entire household, 50.1% have one car, 30.6% possess two cars, 5% have three and 1.4% own more than three cars. 90% of the participants drive less than 25,000 km/year with a median of 12,000 km/year. Further, only 0.8% reported to drive more than 100 km each day and 29.7% drive more than 100 km once a month (every day, several times/week, once a week, several times/month and once a month). We found a significant effect of gender on purchase intention, with male-identified participants showing higher intentions ( $N = 963$ ,  $M = 2.90$ ,  $SD = 1.45$ ) than female-identified ( $N = 958$ ;  $M = 2.65$ ,  $SD = 1.39$ ),  $F(1, 1919) = 15.17$ ,  $p < .001$ ,  $\eta^2 = .01$ . Also, there was a weak negative correlation between age and purchase intention ( $r = -.09$ ,  $p < .001$ ).

For the following three variables, a multifactorial ANOVA was calculated. No interaction effects were significant.

#### 4.1.2 | Personal experience, membership in environmental organization, number of cars and purchase intention

Participants who have already driven with a BEV showed a higher purchase intention ( $M = 3.39$ ,  $SD = 1.52$ ) than participants who have not ( $M = 2.63$ ,  $SD = 1.36$ ),  $F(1, 1913) = 16.67$ ;  $p < .001$ ,  $\eta^2 = .01$ ). Also, participants who are members of an environmental organization had a higher BEV adoption intention ( $M = 3.47$ ,  $SD = 1.50$ ) than participants who are not ( $M = 2.73$ ,  $SD = 1.41$ ),  $F(1, 1913) = 14.43$ ;  $p < .001$ ,  $\eta^2 = .01$ . However, there was no significant effect on purchase intention of BEV between people who reported owning one car as a household or no car at all ( $M = 3.29$ ,  $SD = 1.43$ ) and people who owned more than one car in the household ( $M = 3.24$ ,  $SD = 1.43$ ).

#### 4.1.3 | Predictors of purchase intention

The intercorrelations, means and standard deviations for the predictors are depicted in Table 4. Hierarchical regression analysis was performed for demographic variables and the measures depicted in Table 4 for predicting purchase intention of BEV. The variables with the highest correlations with purchase intention were entered first into the model. Altogether, three steps were undertaken to reach a final model which accounted for 47% of the variance. In the first step, subjective norm and moral norm were entered. Secondly, collective efficacy, technological risk attitude and self-concept innovation were added to the model. In a next step, environmental benefit, personal experience and perceived information were entered. Finally, the demographic variables net income, education, age and gender were included in the model. Significant increases in  $R^2$  for each step were found. Two variables did not predict purchase intention of BEV: education and gender. Both were excluded for the final model. Supporting Hypothesis 1, norms (subjective and moral), collective efficacy, technological risk attitude and self-concept innovation all predicted



Attribute	BEV	FCEV	CV
Purchase price	15,600	15,600	15,600
	26,000	26,000	26,000
	36,400	36,400	36,400
	–	52,000	–
Fuel cost [€/100 km]	2.00	2.00	–
	4.00	4.00	4.00
	7.20	7.20	7.20
	10.00	10.00	10.00
Range [km]	160	160	–
	320	320	–
	560	560	560
	–	800	800
W2W CO <sub>2</sub> emissions [g/km]	None	None	–
	Low	Low	Low
	Medium	Medium	Medium
	–	High	High
Refueling infrastructure	With strong restrictions	With strong restrictions	–
	With restrictions	With restrictions	–
	Without restrictions	Without restrictions	–
Additional CO <sub>2</sub> tax for CV			Yes
			No

**TABLE 3** Attribute levels for BEV, FCEV and CV in vehicle class 1 (minis and small cars)

Note: No future restrictions for the existing gasoline refueling infrastructure were assumed.

**TABLE 4** Intercorrelations, means and standard deviations (SD) of predictors

Predictor	1	2	3	4	5	6	7	8
1 Purchase intention	–	.61*	.52*	.43*	.45*	.47*	.51*	.38*
2 Subjective norm		–	.61*	.44*	.49*	.48*	.54*	.37*
3 Moral norm			–	.53*	.46*	.55*	.48*	.29*
4 Environmental benefit				–	.39*	.64*	.32*	.18*
5 Selfconcept innovation					–	.35*	.43*	.47*
6 Collective efficacy						–	.38*	.16*
7 Technol. risk attitude							–	.35*
8 Information								–
M (SD)	2.77 (1.43)	2.54 (1.29)	3.06 (1.38)	4.03 (1.38)	3.54 (1.30)	3.56 (1.09)	2.45 (1.36)	2.92 (1.51)

\* $p < .001$ .

purchase intention significantly. In Table 5, the final regression model is illustrated.

## 4.2 | Which technology attributes determine vehicle choice?

The relative importance of the vehicle attributes was calculated using Hierarchical Bayes with Sawtooth Software. The relative importance differed for some attributes between the chosen vehicle

classes. In class 1 (minis, small and compact class) the most important attribute for vehicle choice was purchase price (28.3%), followed by range (17.8%), fuel costs (14.3%), fuel type (13.1%), refueling infrastructure (11.9%), CO<sub>2</sub>-emissions (10.5%) and the introduction of a CO<sub>2</sub>-tax on gasoline (4%). In class 2 (mid-sized cars), also the purchase price had the highest importance to the participants (27.5%), then range (17.9%), fuel type (14.9%), fuel costs (14.6%), refueling infrastructure (11.9%), CO<sub>2</sub>-emissions (8.8%) and lastly, the CO<sub>2</sub>-tax (4.3%). Again, in class 3 (upper mid-sized cars and luxury cars), purchase price (22.1%) was the most relevant attribute

**TABLE 5** Hierarchical regression on purchase intention, final model

Predictor	B	$\beta$	t
Subjective norm	.33	.30	12.72***
Moral norm	.08	.08	3.25***
Collective efficacy	.16	.12	5.22***
Technol. risk attitude	.16	.15	7.23***
Self-concept innovation	.06	.06	2.59*
Information	.11	.11	5.49***
Experience	-.20	-.05	-3.01**
Environmental benefit	.11	.10	4.50**
Age	-.004	-.04	-2.40**
Net income	.06	.05	2.65**

Note: Experience was coded 1 = driving experience with EV and 2 = no driving experience.  $R^2 = .48$  for step 1.  $\Delta R^2 = .06$  for Step 2 ( $p < .001$ ).  $\Delta R^2 = .02$  for Step 3 ( $p < .001$ ).  $\Delta R^2 < .01$  for Step 4 ( $p < .05$ ).

\* $p < .05$ ;

\*\* $p < .01$ ;

\*\*\* $p < .001$ .

for selecting the preferred car, followed by range (18%), fuel type (17.4%), fuel costs (16.5%), refueling infrastructure (12.4%), CO<sub>2</sub>-emissions (9.5%) and CO<sub>2</sub>-tax (4.3%). Hypothesis 2 that purchase price is the most important vehicle attribute can, therefore, be confirmed for all three vehicle classes.

More details on the utilities of the different levels to the respective attributes can be found in Berneiser and Senkpiel (2020). The only attribute that differs in its level utilities between classes 1, 2 and 3 is fuel type. Participants choosing class 1 attributed the highest utility to BEV followed by combustion engine and showed the least utility values for FCEV. Class 2 and 3 in contrast, preferred combustion engines much over BEV and FCEV.

### 4.3 | Do person-related predictors affect vehicle attribute importance?

In a next step, the effects of selected person-related factors on the relative importance of the vehicle attributes were tested. We, therefore, chose factors with regression weights  $\beta > .10$  on purchase intention for BEV to check whether differences in person-related variables also influenced attribute importance and vehicle choice in the DCE. As illustrated in Table 4, the predictors explaining (additional) variance  $\beta > .10$  were subjective norm, collective efficacy, technological risk attitude and perceived information. We divided participants artificially into two groups (plus and minus one standard deviation) for each variable and calculated the relative importance per subgroup. ANOVAs were calculated for the different attribute importance as dependent variables, with the artificial groups ( $\pm 1$  SD) being the independent variable to test for significance. As most people chose class 1 for a future car (67.8%), in the following only results concerning that category will be reported.

#### 4.3.1 | Low and high collective efficacy on attribute importance

Participants with low and high values on collective efficacy differed significantly in their attributed importance to fuel costs,  $F(1, 423) = 20.49, p < .001, \eta^2 = .05$ , range,  $F(1, 423) = 70.90, p < .001, \eta^2 = .14$  and CO<sub>2</sub> emissions,  $F(1, 423) = 68.94, p < .001, \eta^2 = .14$ . The two groups did not show differing values on CAPEX, vehicle type, CO<sub>2</sub> tax or infrastructure. Participants with a high collective efficacy attributed more importance to fuel costs and CO<sub>2</sub> emissions, and less importance to range.

#### 4.3.2 | Low and high subjective norm on attribute importance

Participants with a low subjective norm for BEV revealed a higher importance for purchase price ( $F(1, 568) = 4.07, p < .05, \eta^2 = .01$  and range  $F(1, 568) = 59.88, p < .001, \eta^2 = .10$ , and less importance for fuel costs  $F(1, 568) = 16.45, p < .001, \eta^2 = .03$ , vehicle type,  $F(1, 568) = 11.17, p < .01, \eta^2 = .02$ , and CO<sub>2</sub> emissions,  $F(1, 568) = 54.68, p < .001, \eta^2 = .09$  than participants having high degrees of subjective norm for BEV. The attribute importance did not differ between CO<sub>2</sub> tax and infrastructure.

#### 4.3.3 | Low and high technological risk attitude on attribute importance

Participants with a high technological risk attitude had a higher importance for fuel costs  $F(1, 286) = 5.65, p < .05, \eta^2 = .01$  and CO<sub>2</sub> emissions  $F(1, 286) = 34.33, p < .001, \eta^2 = .01$ , and lower importance for range  $F(1, 286) = 19.78, p < .001, \eta^2 = .01$ . No difference was found for vehicle type, purchase price, refueling infrastructure and CO<sub>2</sub> tax.

#### 4.3.4 | Low and high information on attribute importance

Participants who reported to be well informed about BEV revealed a higher importance for vehicle type  $F(1, 517) = 57.39, p < .01, \eta^2 = .02$  and CO<sub>2</sub> emissions  $F(1, 517) = 10.70, p < .01, \eta^2 = .01$ , and less importance for range  $F(1, 517) = 15.08, p < .001, \eta^2 = .03$  than participants that have barely informed themselves. There was no difference for purchase price, refueling infrastructure and CO<sub>2</sub> tax.

The average importance of the different groups and attributes are depicted in Table 6.

Hypothesis 3 is, therefore, partially confirmed. We replaced self-concept innovation and moral norms with information as the standardized regression weight for information was higher (above  $R^2 = .1$ ). For subjective norm, collective efficacy and technological risk attitude the hypothesis is confirmed.

**TABLE 6** Average importance of attributes in vehicle class 1 (minis and small cars) according to sub groups of personal-related variables

Person-related variable	Group $\pm$ 1SD	Purchase price	CO <sub>2</sub> tax	Fuel costs	Infra-structure	Range	Vehicle type	CO <sub>2</sub> emissions
Collective efficacy	High	27.80	4.09	15.48***	11.36	14.40***	13.96	12.91***
	Low	29.94	4.03	12.48	12.04	20.10	13.27	8.14
Being informed	Well	27.53	4.00	14.48	11.37	16.28***	14.72**	11.63**
	Poorly	28.30	4.00	14.00	12.10	19.06	12.69	9.84
Subjective norm	High	26.53*	3.76	15.56***	11.15	14.85***	15.46	12.69***
	Low	28.81	3.98	13.23	11.94	19.83	13.24	8.97
Technological risk attitude	High	24.62	4.20	15.12*	12.23	15.55***	14.76	13.52***
	Low	27.11	4.24	13.30	12.09	19.59	14.27	9.40

\* $p < .05$ ;\*\* $p < .01$ ;\*\*\* $p < .001$ .

Car type	BEV	FCEV	CV
Purchase price [€]	25,370	44,934	18,335
Fuel cost [€/100 km]	3.63	5.41	6.41
Refueling infrastructure	With restrictions	With strong restrictions	No restrictions
Range [km]	240	452	791
CO <sub>2</sub> -emissions	Low	Medium	Medium
CO <sub>2</sub> -tax	No tax	No tax	No tax

**TABLE 7** Assumptions for car attributes for small and mini cars in 2020

#### 4.4 | Do person-related factors also influence preference shares for EV and CV?

In addition to calculating the effect of socio-psychological variables on attribute importance, we examined how these differences also affect preference shares for EVs and CVs. The preference shares were calculated using logit choice probabilities (Train, 2016). The calculations are based on the following assumptions displayed in Table 7 regarding average vehicle characteristics in a moderate scenario for the year 2020 (Senkpiel et al., n.d.).

In Table 8, the calculated market shares for simulated purchase decisions in 2020 are displayed considering the groups with low and high values on the person-related variables. Considering the forecasted technology attribute development for 2020, clear differences in preference shares between BEV, CV and FCEV are demonstrated. Altogether, also Hypothesis 4 can be partially confirmed except for the exchange of innovative self-concept with information as explained before. As can be seen in Table 7, participants with high values on collective efficacy and subjective norm revealed a minimal likelihood of 50% to choose a BEV when the other attribute levels were kept constant. In contrast, participants with low values on collective efficacy and subjective norm for alternative vehicles had preference shares for BEV below and around 20%. Moreover, for the better informed participants and the ones with a high technological risk attitude the BEV preference shares were comparatively high. FCEV overall had a small preference share with less than 10% in all groups.

## 5 | DISCUSSION

The aim of this paper was to examine, which technology attributes and person-related factors influence EV adoption, and in particular whether differences in person-related factors affect the preference for EV and vehicle attribute importance. We hypothesized that price was the most important attribute for vehicle choice. Furthermore, we suggested that norms, collective efficacy, technological risk attitude and an innovative self-concept were significant predictors of EV purchase intention, independently of socio-economic variables. In addition, we expected that these predictors of purchase intention also influenced the importance for the different vehicle attributes and the vehicle preference shares in the discrete choice experiment.

### 5.1 | Predictors of EV purchase intention

Among person-related factors, as expected from previous studies (Barth et al., 2016; Goetz et al., 2012), the socio-economic variables only had a small influence on EV adoption intention, if at all. Age was negatively related to purchase intention, implying that older people showed a lower willingness to buy than younger people. From a habitual point of view it could be that older people are more used to conventional vehicles which makes them potentially less flexible or feel less secure to adapt to a new technology with

**TABLE 8** Preference shares of EV and CV for simulated purchase decisions in 2020

Person-related variable	Group $\pm 1$ SD		BEV	CV	FCEV
Collective efficacy	High		0.54	0.43	0.03
	Low		0.16	0.81	0.02
Information	Well informed		0.41	0.54	0.05
	Poorly informed		0.28	0.69	0.03
Subjective norm	High		0.51	0.43	0.07
	Low		0.22	0.74	0.03
Technological risk attitude	High		0.47	0.46	0.07
	Low		0.24	0.71	0.05
Vehicle type	Offer 1 Battery-electric vehicle	Offer 2 Gasoline vehicle	Offer 3 Fuel-cell electric vehicle	Offer 4 Battery-electric vehicle	
Purchase price	36.400€	15.600€	52.000€	26.000€	
Fuel cost [€/100 km]	2,00€	4,00€	7,20€	2,00€	
Range [km]	320 km	560 km	160 km	320 km	
Refueling infrastructure	With strong limitations		With limitations		Without limitations
W2W CO <sub>2</sub> emissions [g/km]	No emissions	Low	Medium	Low	
Additional CO <sub>2</sub> tax for CV	Yes				

different driving characteristics. Further, in line with previous research (Liao et al., 2017), net income had a small effect, in the way that the higher the net income, the higher the EV purchase intention. As BEV still tend to be more expensive than comparable CV on the market this might implicate that people favoring BEV with a medium to high net income will switch to BEV before people with low incomes. Also, it must be noted that a large extent of vehicle demand is for used-cars which were not addressed in our study. However, this further implies that EV must be available on the used-car market which takes additional time for the diffusion of EV. The environmental benefits of an EV influenced the adoption intention positively, but played a minor role compared to other factors. This might be the case, since especially BEVs have been questioned for their environment-friendliness in the public discourse due to the current electricity mix (still containing coal), the use of lithium, human rights violations and the lack of recycling facilities up to now. Yet, people that reported to be members of an environmental protection organization showed a higher purchase intention than people who are not engaged which potentially exemplifies the complexity of the aspects related to e-mobility. Also Hackbarth and Madlener (2011) found that people with a high environmental awareness preferred BEV over other fuel types. Further findings are in line with evidence from previous studies and confirm our Hypothesis 1 that social, subjective and moral norms (Liao et al., 2017; Petschnig et al., 2014) as well as collective efficacy predict purchase intention (Barth et al., 2016; Liao et al., 2017). Moreover, as hypothesized, the identification as an innovative person and technological risk attitude predicted purchase intention significantly. The higher the willingness to take financial risks and the higher the innovative self-concept, the higher was the purchase intention.

## 5.2 | Attribute impact on vehicle choice

Regarding technology-specific attributes, previous research was confirmed in this study that technology-related disadvantages negatively impact the EV purchase intention (Krupa et al., 2014). In all vehicle classes, price was the most dominant attribute for vehicle choice and thus, in line with Hypothesis 2. Since BEV and FCEV are more expensive than conventional vehicles, this probably remains a barrier for EV diffusion if lower maintenance and fueling costs aren't integrated into price calculations. In addition, to date the prices for FCEV heavily outweigh those of CV as well as BEV and very few models are available on the market which probably explains the low preference shares in all vehicle classes for FCEV. As expected, the purchase price was less relevant for the participants that selected class 3, as this segment represented high class, and therefore, more expensive cars, anyway. This result is in line with previous studies (Higgins et al., 2017; Liao et al., 2017). In accordance with nearly all other literature (Liao et al., 2017) the second most relevant attribute for vehicle adoption was range which clearly constitutes a relevant (subjective) disadvantage for many people. Even though the mobility behavior of most people indicates that from an objective point of view range is a negligible issue if charging stations are available, since less than 1% of the participants reported to drive more than 100 km/day. Yet it remains an additional (subjective) disadvantage to conventional vehicles. CO<sub>2</sub>-emissions played a comparatively minor role for vehicle choice which corresponds partially with previous research (Hackbarth & Madlener, 2016). This is also rather unsurprising considering that the actual demand for carbon-intensive SUV and larger vehicles keeps rising (IEA, 2019). Rather interestingly is the finding that vehicle type was even more important than refueling

infrastructure, with BEV having the highest utility for the participants in class 1 (minis and small cars) in contrast to classes 2 and 3. It appears that many people preferring small cars would favor BEV over conventional vehicles independently of the other attributes. However, this finding does not align with the supply on the electric vehicle market so far as most offered EV are midsize or large vehicles (Gersdorf et al., 2020).

### 5.3 | Influence of predictors on attribute importance

Participants showing higher values in subjective norm, collective efficacy, technological risk attitude, and perceived information weighted attribute importance differently in the choice experiment. Participants with a high collective efficacy attributed more importance to fuel costs and CO<sub>2</sub>-emissions, and less importance to range. The same pattern was revealed for participants with a high technological risk attitude. Similarly, participants with a high subjective norm had lower importance for range and price and a higher importance for fuel costs. Participants that reported to be well-informed also revealed higher importance for vehicle type, and thus BEVs, and CO<sub>2</sub>-emissions whereas less importance for range. Interestingly, these attributes are all favorable to electric vehicles, as fuel costs and CO<sub>2</sub> emissions are lower and the purchase price higher for EVs than conventional vehicles. Range, which is usually perceived as one of the major disadvantages of EVs (Liao et al., 2017) appears to be de-emphasized by participants showing higher values on these predictor variables. It could be that people who hold the collective welfare above pure personal utility maximization accept additional behavioral expenses in the realm of individual mobility (e.g., limited range). Yet, this would not explain the shift from the emphasis on purchase price to fuel costs. Potentially, people endorsing EV specifically search for information that is consistent with their prior belief which speaks for a confirmation bias. Explanations for the confirmation bias are a biased search for information that is consistent with the underlying goal (Kunda, 2002) or the limited human capacity to process information (Doherty & Mynatt, 1990). Since choice experiments represent a situation which requires cognitive effort, having the tendency to confirm existing attitudes/beliefs by choosing information that is in favor of BEVs, could be a potential explanation. However, from this study it cannot be inferred, whether this is a causal effect and if yes, which way it works. Do people with higher perceived collective efficacy and subjective norm like electric vehicles better and, subsequently, deemphasize disadvantageous aspects of e-mobility? Or do they intrinsically care less about range and price but instead about fuel costs and CO<sub>2</sub>-emissions and therefore, prefer electric vehicles? Generally, it must be regarded, that there was a medium- to high-sized correlation between the predictor variables, meaning that the same participants could be represented in more than one group. Participants having high values on subjective norm could also have high values on collective efficacy.

### 5.4 | Influence of predictors on preference shares of EV in 2020

Considering forecasted technology attributes of BEV, CV and FCEV for the year 2020, the preference shares of the respective vehicle type differed considerably between the groups having high or low values on the predictor variables. Participants with high values showed far higher preference shares for BEV than participants scoring lower on these variables. This finding is interesting and important in this regard that differences in the salience of socio-psychological factors might have a higher impact on the development of the electric vehicle share than the pure financial and technical features of e-mobility that tend to be discussed primarily for promoting vehicle diffusion.

### 5.5 | General discussion and outlook

One major result of this study is that person-related, namely socio-psychological factors, predict purchase intention more than socio-economic factors. Further, the predictive socio-psychological variables were related to the importance ratings of attributes that are disadvantageous for BEV, such as range and price. Favorable aspects of BEV, such as fuel costs and CO<sub>2</sub>-emissions, were of increased importance to participants who scored higher on these predictor variables. Interestingly, this does not only comprise different social norms which have been quite established as influential for technology adoption, but also technological risk attitude or collective efficacy, the personal conviction or belief that, together, we can make a difference.

Considering these findings, the following questions arise: Do people who intrinsically like BEVs pay more attention to the aspects of cars that are advantageous for BEV and devalue aspects that speak against them? Or is it the other way around, that people truly care for these vehicle attributes and thus prefer AVs? This research contributes to existing literature on individual and group variables influencing consumer evaluations (Solomon, 2004) by demonstrating that normative as well as social identity variables, namely collective efficacy in this study, impact consumers' perceptions of attribute importance. Next to personal feelings as a reflection of the consumer as individual (King & Slovic, 2014), also group-based variables appear to be relevant not only setting purchase intentions but also in the way how important product attributes are perceived. Further, our results speak for the relevance of self-image congruence models that the consumer's self-image and perceived product attributes are matched mentally. The emphasis on attributes favorable for EV might imply that during the matching process certain product attributes attain more value if the product itself fits to the consumer's self-image.

Another finding of this study was that person-related differences in the chosen predictor variables also led to different outcomes in the calculated electric vehicle share. In further studies it could be tested whether an experimentally evoked collective efficacy and social norm for e-mobility indeed leads to a significant increase in purchase

(intention), electric vehicle choice and a decrease in attribute importance for attributes that are unfavorable for EV choice.

We acknowledge that this was a rather experimental approach of integrating socio-psychological factors into discrete choice models and preference share calculations that has some limitations. However, the strength of this paper is the two-step procedure, namely the combination of a choice experiment using hierarchical Bayes method with a questionnaire to assess person-related variables for calculating attribute importance and market shares. This approach revealed the impact differences in socio-psychological factors can have on the diffusion of electric vehicles. Further, the large sample size and the representativeness of the sample according to age, gender, income and education ensure robust effects. One other approach to combine questionnaire with DCE data is by developing hybrid choice models. However, we decided against using a multinomial logit model but instead focused on individual utilities calculated with hierarchical Bayes. Yet, with our data it is possible to develop a hybrid choice model, and we welcome additional research that applies our data.

For this study, it must be considered that all regression analyses are of correlational and not causal nature. Therefore, from the results of this study, it cannot be inferred that if we achieve to increase norms for clean mobility or strengthen the sense of collective efficacy, that people will actually rather buy EVs than CVs. Yet, other experimental studies addressing different research questions concerning social identity variables such as collective efficacy suggest so (Jugert et al., 2016). Future research could address this weakness of our study and test the effects of socio-psychological variables on EV adoption experimentally. Further, regression analyses did not contain all possible variables that are predictors for adoption intention. In specific, technical attributes were left out as they were operationalized in the DCE. However, the aim was not to calculate a regression model explaining the highest variance possible but to use socio-psychological variables that predict adoption intention well to calculate attribute importance and preference shares. Moreover, we created the item for measuring technological risk attitude without testing for validity. We, thus, advice against using our item but instead pledge for developing a scale for measuring this complex construct. Another limitation regarding external validity is the German sample since our findings cannot be generalized. Automobility seems to play an exceptional role in Germany as a country with a long automotive history (e.g., VW, BMW, Daimler). Yet, we believe that also in other countries with similar characteristics (income, role of individual mobility, historical distribution of conventional vehicles, awareness of global warming impact of conventional vehicles, etc.), social and psychological factors affect EV adoption similarly. Regarding results for FCEV it must also be noted that FCEV barely exist on the market and until now, are not really viable options for a private person. The results for FCEV must therefore be considered with caution.

## 5.6 | Discrete choice experiment

As the results from the DCE are hypothetical and not combined with a real transaction, the preference shares from the experiment

probably only reflect preferences and not future purchases. No measures for external validity of our results are provided in this study, which reflects overall scarcity of indicators of external validity in different disciplines (Lancsar & Swait, 2014). However, we carefully designed the DCE in a way that elicits authentic choices and ensures valid results through limiting the number of attributes and levels to an acceptable number (Que et al., 2017), provided realistic values and combinations of the levels and checked for logic and consistency (Johnson et al., 2019). Further we accounted for the imposed cognitive load through limiting the experiment to 10 choice tasks per participant (Que et al., 2017). Considering the amount of choice experiments conducted in different disciplines but also regarding transport choices, future research should focus on the evaluation of external validity.

Altogether, we identified leverages that are usually not focused on to promote EV diffusion. Even though EVs are a technology, the adoption process is not and cannot be reduced to being merely of technological nature. This study extends previous research as we demonstrated that person-related variables, such as subjective norms, technological risk attitude and collective efficacy are not only related to EV purchase intention but also to the importance of vehicle attributes. If social identity variables such as collective efficacy not only influence our purchase intentions but, also, our preference structure for technology attributes, this finding has implications for environment-friendly adoption behavior. Promoting technological progress, more variety in market supply and decreasing costs of EVs are necessary for stimulating EV adoption. However, our findings show that there might be different strategies to make the allegedly disadvantageous aspects of e-mobility less relevant to people. Political and scientific discourse on the diffusion of electric vehicles should in our opinion, therefore, put psychological and social parameters into focus and broaden policy approaches. With this paper, we want to stress that next to technological developments it might also be a relevant strategy to work on societal characteristics. The latter includes the degree to which people feel they can influence and change the environment they live in (collective efficacy) and spark public discussion about what values and norms bind us, and which we aspire as a society.

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## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in <http://dx.doi.org/10.24406/fordatis/11>

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