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Consumer preferences for public EV charging tariffs and infrastructure reliability: A choice experiment

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A B S T R A C T

Public charging infrastructure (CIS) and its corresponding tariffs are becoming increasingly important for growing the market share of electric vehicles. To investigate the optimal design of such tariffs by gaining a better understanding of how consumers value the different attributes and the reliability of CIS, a choice-based conjoint analysis was conducted with 516 participants in Germany. Results suggest that the energy price is the most important attribute. However, unlimited tariffs are not perceived as being the most beneficial: A medium energy price combined with a moderate monthly fee is considered the most attractive option across the sample. Increased reliability provides high utility compared to the current status quo of about 80 % successful charging sessions. Additional services, such as a towing service or a mobility guarantee, are not regarded as beneficial by most participants. Policies should focus on ensuring competition for attractive charging prices and for sufficient and reliable CIS.

1. Introduction

The European Union aims to reduce its greenhouse gas emissions by 55 % by 2030 compared to 1990 (EC 2019). In the transportation sector, the goal is to reduce emissions from passenger cars and to achieve zero emissions from new cars by 2035 (EC 2023). In Germany, transport sector emissions have barely decreased since 1990 and accounted for about 18.77 % of total greenhouse gas emissions in 2021 (EEA 2023).

In 2023, EVs accounted for only 4.0 % of the German vehicle stock (IEA 2023). With a growing variety of models and government subsidies for electric vehicles (EVs), consisting of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), consumers are increasingly switching from conventional internal combustion engine vehicles (ICEVs) to more climate-friendly vehicles. However, inadequate charging infrastructure (CIS), particularly in the public sector, remains a key factor for the low adoption rate of EVs. Although EV registration figures are rising – between 2019, when about 108,000 EVs were newly registered in total, and 2022, new registrations of BEVs and PHEVs increased by 643.60 % and 698.48 % respectively (KBA 2023) – the development of the public CIS is not keeping pace with this growth.

In Germany, a total of 85,072 public standard charging stations (alternating current, AC) and 20,507 public fast charging stations (direct current, DC) were publicly available in September 2023 (BNetzA 2023). Given the expected increase in EVs and limited access to private CIS, the question is whether these numbers and their development are sufficient. The International Energy Agency (IEA) estimates that only about 50 %–60 % of BEV drivers in Europe have access to charging stations at home (IEA 2022). Consequently, in addition to those charging for longer trips, a large proportion of EV users also rely on public CIS in everyday life, which underlines its importance.

Early adopters of EVs were mainly consumers with their own private parking space and CIS at home (Jia et al., 2023; Guerra and Daziano, 2020; Wolbertus and Gerzon, 2018; Trommer et al., 2015). As a result, most cars were mainly charged at home in earlier years (Anderson et al., 2022; Hardman et al., 2018), and consumers had not to worry about public EV charging. Therefore, public CIS was used only occasionally, and rarely for daily charging (Trommer et al., 2015). Thus, the charging behavior of early adopters of EVs cannot be seen as representative when assessing current and future business models for public CIS (Wolbertus and Gerzon, 2018).

A large fraction of the existing literature focuses on EV adoption, mainly on vehicle attributes and their prices, e.g. Jia et al. (2023) and Beak et al. (2020), as well as on range anxiety, e.g. Pevec et al. (2020) and Melliger et al. (2018). Range anxiety describes a phenomenon in which people perceive that the battery capacity and the associated range of their EVs do not match their driving needs. Often, this perception turns out to be unjustified, as most of the trips can be completed within

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Abbreviations

AC	Alternating current
BEV	Battery electric vehicle
CBC	Choice-based conjoint analysis
CIS	Charging infrastructure
CPO	Charge point operator
DC	Direct current
EMP	E-mobility provider
EV	Electric vehicle
HB	Hierarchical Bayes
ICEV	Internal combustion engine vehicle
MCMC	Monte Carlo Markov Chain
PHEV	Plug-in hybrid electric vehicle
RLH	Root likelihood
SoC	State of charge
WTP	Willingness to pay

Symbols

d	Parameter d of the vector β_n
D	Number of parameters in the vector β_n, i.e. the length of the vector β_n
I_D	Identity matrix of order D
Imp_{nk}	Importance of the attribute k for individual n
$IW(\nu, \Psi)$	Inverse Wishart distribution with degrees of freedom ν and scale matrix Ψ
j	Alternative j
J	Number of alternatives
k	Attribute k
K	Number of attributes
$L(\cdot)$	Likelihood function
l_k	Level l_k of the attribute k
L_k	Number of levels of the attribute k
n	Individual n
N	Number of individuals
$N(\mu, \Sigma)$	Multivariate normal distribution with mean vector μ and covariance matrix Σ
p_{njt}	Probability that individual n chooses alternative j in choice task t
t	Choice task t
T	Number of choice tasks
U_{nj}	Individual total utility of alternative j for individual n
x_j	Design vector (indicates whether an attribute level is part of alternative j)
Y	Collected data
y_n	Vector of choice data for individual n
Y_{njt}	Choice data for individual n and alternative j in choice task t
α	Part-worth utility vector at population level
β_n	Part-worth utilities for individual n
β_{nkl}	Part-worth utility of level l of attribute k for individual n
ε_{nj}	Error term
Θ	Model parameters
$\phi(\beta \mid \mu, \Sigma)$	Density function for parameter vector β of the multivariate normal distribution with mean vector μ and covariance matrix Σ
Ω	Covariance matrix

the range of the EV, even more so if public CIS has been adequately expanded (Melliger et al., 2018). Many publications that investigate EV adoption have concluded that access to CIS is one of, if not the most important factor influencing EV adoption and willingness to pay (WTP) a higher purchasing price for EVs (Azarova et al., 2020; Guerra and Daziano, 2020; Abotalebi et al., 2019; Patt et al., 2019; Lieven, 2015).

Several studies have identified problems related to missing or insufficient CIS that can prevent people from switching from ICEVs to EVs. Sun et al. (2017) found in their study, conducted in China, that the existing CIS network is not sufficient, especially for traveling longer distances. Anderson et al. (2022) discovered that public CIS does not meet the everyday needs of EV drivers in Germany. Similar findings are described for the South Korean market by Jang and Choi (2021), who call for more government support for CIS. These findings are backed up by Kim et al. (2022). As a temporary solution, they suggest the implementation of mobile charging services that facilitate charging in locations without CIS if EVs run out of battery. Kühl et al. (2019) found that Twitter (now: X) users in Germany perceive the current CIS situation to be insufficient. According to Hardman and Tal (2021), some EV owners switched back from EVs to ICEVs due to the inconvenience of charging or the lack of sufficient access to CIS.

As EVs now represent a significant share of new car sales in many countries, there is an additional need for public CIS and other charging solutions for people without a private CIS at home. In Germany, EVs

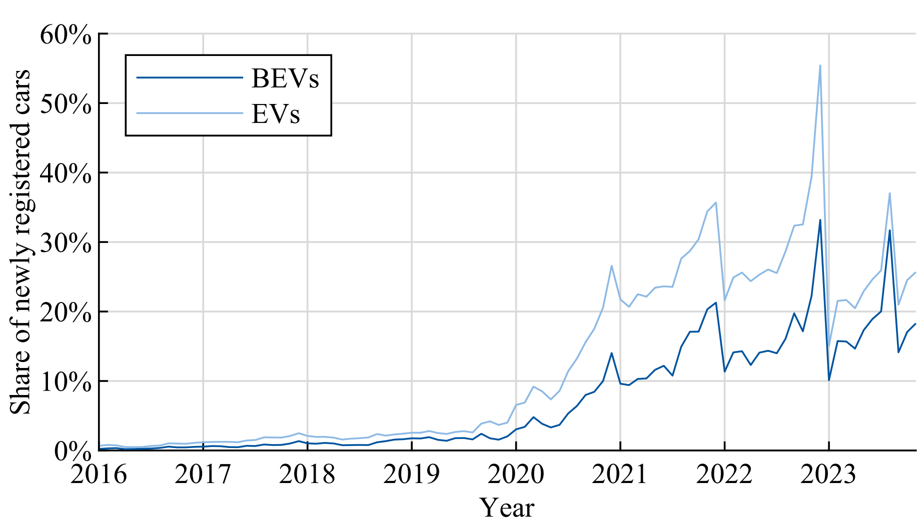

Fig. 1. Share of EVs and BEVs in newly registered passenger cars in Germany since 2016, adapted from KBA (2023).

accounted for 25.67 % (BEVs 18.29 %) of the total number of newly registered vehicles in November 2023, shown in Fig. 1 (KBA 2023). Azarova et al. (2020) point to the large proportion of Europeans who do not live in single-family homes and therefore have problems installing private CIS. This growing customer segment has to rely on public CIS (Guerra and Daziano, 2020; Globisch et al., 2019; Hardman et al., 2018).

Trommer et al. (2015) have pointed out in their work that even though it was not in great demand by early adopters, later customer segments would definitely have a need for public CIS. In its "Charging Infrastructure Masterplan II", the German federal government has set the goal of installing one million public charging stations by 2030 (BMDV 2022). Efforts are also being made at the European level to significantly expand the public charging network as part of the "Fit for 55" program (Soone, 2023). As of September 2023, 105,579 public charging stations had been installed in Germany (BNetzA 2023). However, the numbers shown in Fig. 2, still leave much room for improvement regarding the country's above-mentioned expansion target.

As the demand for public CIS increases, the price of charging an EV becomes more important, as some customer segments charge their EVs primarily or even exclusively via public CIS. The studies performed by Will et al. (2022) in Germany and Yan et al. (2021) in China support this hypothesis, although the aforementioned works did not investigate a realistic price structure for public charging. Sun et al. (2017) and Yan et al. (2021) even argue for a government limit or regulation of the electricity price at public charging stations.

Providing a dense network of charging stations is not sufficient. CIS must also be available and reliable (Yan et al., 2021; Kühl et al., 2019). Fabianek and Madlener (2023) found that EV consumers in Germany prioritize CIS availability and functionality over price. In a study by Anderson et al. (2022), availability of public CIS was ranked first by participants, i.e. as being even more important than the energy price. Hardman et al. (2018) point out the current difficulties of compatibility between EVs and CIS for charging at all locations due to a lack of interoperability. Hence, improving the interoperability of all systems involved in the charging process is an important aspect to increase consumer satisfaction. Sun et al. (2017) suggest creating a real-time information system that displays CIS availability and other charging-related information in order to further improve the customer experience.

There are a few recent studies that include some aspects related to the pricing of public charging. Anderson et al. (2022) found a significant positive correlation between an acceptable charging price and drivers' annual mileage in their stated choice experiment conducted in Germany. Dorcec et al. (2019) observed that WTP for charging increases with higher household electricity prices and decreases with higher state of charge (SoC). Users used to high energy prices at home are also willing to pay more for charging at public CIS. Also, users who need the service of a public CIS due to a low SoC are willing to pay more than people whose SoC is perceived as sufficient. Charging power and time of the day were found to have no significant effect on the WTP for charging. Guerra and Daziano (2020) surveyed US consumers and showed that a monthly fee, the charging speed, and the charging network density have the greatest impact on consumer satisfaction with CIS. However, most of the participants in their sample did not own an EV. Therefore, the validity of their findings regarding the preferences of EV drivers is limited. Potoglou et al. (2023) emphasize the need for further research in charging tariff models. Table 1 summarizes the literature overview highlighting relevant factors influencing people's public charging choices. Overall, little to no current research has been undertaken specifically on public charging pricing, particularly in relation to the reliability of public CIS. Given the large number of theoretically possible tariff structures, some of which are already available in the market, it is particularly important to be able to adapt tariff structures to customer requirements and to price them appropriately, thus increasing the utilization of the CIS and at the same time improving customer satisfaction.

Summarizing the insights from the literature despite growing consumer interest in public CIS and increasing manufacturer experience in handling and implementing CIS in the existing power grid, several problems persist: Not all contracts with e-mobility providers (EMPs) grant access to the charging network of every charge point operator (CPO), authentication methods are inconsistent or do not work, pricing structures lack transparency, and billing methods can be inconvenient. More convenient access methods, such as plug-and-charge, are currently supported by only a few vehicles and charging stations (Hubject GmbH, 2023).

Against this background, it is crucial to understand end-user preferences and willingness to pay for different tariff attributes for public charging. Gaining knowledge in this field and thus closing the described research gaps can help to develop charging services that are both attractive and user-friendly, thereby promoting the uptake of EVs. The aim of the study at hand is therefore to investigate which charging tariff attributes of public EV charging are particularly attractive and convenient for end users and which attributes are seen as less beneficial. A choice-based conjoint analysis is used to analyze customer preferences and willingness to pay for public charging tariffs and the reliability of the public charging infrastructure. In particular, the following two research questions are addressed.

1) Which tariff models for charging electric vehicles at public charging stations are attractive to private consumers?

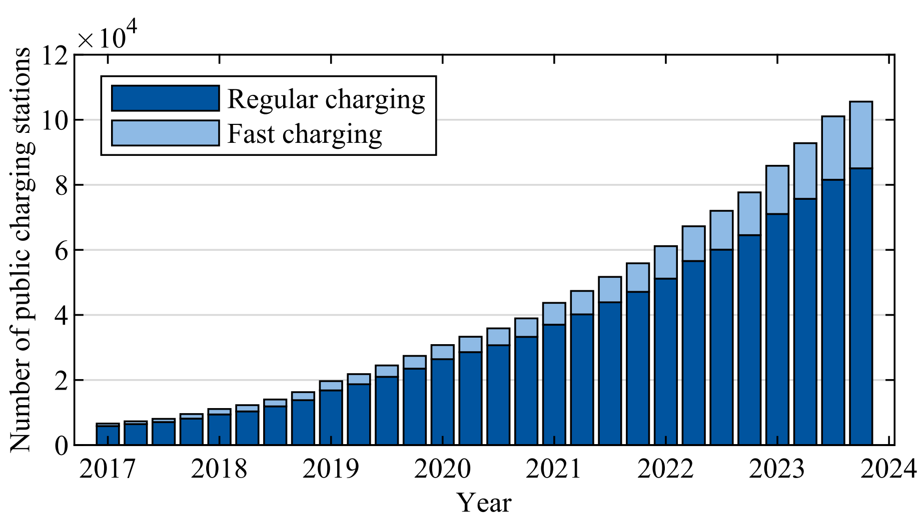

Fig. 2. Development of installed public charging stations in Germany since 2017, adapted from BNetzA (2023).

Table 1
Literature overview of factors influencing people's public charging choices (own table).

No.	Reference	Factors influencing people's public charging choices				
		Price	Network density	Availability	Functionality/reliability	Duration
1	Fabianek and Madlener (2023)	x	–	x	x	–
2	Potoglou et al. (2023)	x	x	x	x	x
3	Anderson et al. (2022)	x	x	x	–	–
4	Will et al. (2022)	x	–	–	–	–
5	Jang and Choi (2021)	–	x	–	–	x
6	Yan et al. (2021)	x	–	–	–	–
7	Guerra and Daziano (2020)	x	x	–	–	x
8	Dorcec et al. (2019)	x	–	–	–	–
9	Globisch et al. (2019)	x	x	–	–	x
10	Kühl et al. (2019)	–	x	x	x	x
11	Hardman et al. (2018)	x	–	–	x	–
12	Sun et al. (2017)	x	x	–	–	–
Sum		10	7	4	4	5

2) What value is attributed to the reliability of public charging stations for electric vehicles and how does this translate into willingness to pay?

The remainder of this article is structured as follows: In Section 2, the survey design and the statistical model are introduced. Following a description of the sample, the results are presented and discussed in Section 3. Finally, conclusions and possible future research topics are provided in Section 4.

2. Methods and data

Charging tariffs incorporate multiple attributes that vary in importance to consumers, and their subordinate levels vary in perceived utility. There are two main research streams in this context. The first one investigates behavior based on unobservable psychological variables, e. g. the Theory of Planned Behavior by Ajzen (1991). The other stream focuses on the economic preferences of consumers and tries to quantify them. Here, conjoint analyses are used to investigate the economic consumer preferences for product or service attributes in public CIS (Backhaus et al., 2021). Potential consumers have to make trade-off decisions according to their preferences and then sort the different products presented or select a product option (Auspurg and Liebe, 2011; Street and Burgess, 2007).

Choice-based conjoint analysis (CBC) can simulate a purchase decision across a wide range of created product designs (Sawtooth Software, 2017), including products in development or pre-market (Danne et al., 2021). The decision situation can be reproduced multiple times with little effort for all parties involved (Layer et al., 2017; Dütschke and Paetz, 2013; Gensler et al., 2012). This makes it possible to determine the participants' preferences under largely real conditions (Pinnel, 2005; Orme, 2000; Johnson and Orme, 1996; Huber et al., 1992). However, CBC cannot determine why consumers prefer certain attributes over others (Hansla et al., 2008). The deriving of results from a CBC is based on Lancaster's New Approach to Consumer Theory (Lancaster, 1966) and McFadden's Conditional Logit Analysis of Qualitative Choice Behavior (McFadden, 1974). Both state that a product's attributes define its utility and that consumers will choose the product with the highest perceived utility.

The present CBC experiment was set up in Lighthouse Studio, provided by Sawtooth Software (Sawtooth Software, 2024). This software was subsequently used to compute utility and WTP estimates. The participants had to answer 15 CBC questions with different levels within the attributes, followed by sociodemographic questions. This approach meets the amount of CBC tasks recommended by Johnson and Orme (1996). Each CBC question presented a choice set consisting of two choice cards, each of which represented a charging tariff. The choice cards were generated automatically; there were no restrictions or forced cards.

Following Wolff and Madlener (2020, 2019) and Dhar (1997), participants were not allowed to opt out. Since it is projected that BEVs will have a significant market share by 2030 (Bundesregierung Deutschland, 2022), individuals will eventually have to choose a tariff for public charging. By prohibiting any opting out, participants were compelled to make precisely this decision in the present study.

2.1. Charging tariff choice experiment and survey

The survey was divided into two parts. The first part contained the choice experiment in the form of a CBC with four attributes per alternative (see Fig. 3). In the second part (see Appendix A), participants were asked questions to capture their sociodemographic characteristics, such as gender, age, annual income, and whether they had an EV and/or a CIS at home.

The market for public charging in Germany was investigated and summarized (see Appendix B). The tariffs were available throughout Germany and did not depend on any further contractual obligations. From this investigation, four attributes, namely *energy price*, *walking distance to the nearest CIS*, *reliability*, and *monthly fee* (see Table 2) were developed into a set of different attributes and levels for the CBC. The attributes were chosen because, based on the literature review, they are important decision factors for customers in the context of public charging. According to Sawtooth Software (2017) and Johnson and Orme (1996), no more than six attributes should be selected so that a decision can reasonably be made. However, the pre-test of the survey showed that these six attributes were too many in this case, which is why their number was reduced to four. Except for *reliability*, the selected attributes are relevant attributes of typical tariff structures found on the German market (see Appendix B). The *energy price* attribute represents the cost in Euro per kWh charged. *Walking distance* indicates the time it takes to walk to the nearest charging station. The *monthly fee* is associated with varying conditional prices. The *reliability* attribute was specifically included in the survey in accordance with the data obtained from the EMoT project, which was funded by the German Federal Ministry for Economic Affairs and Climate Action (BMWK) under the funding code 01MV21009B. The scope of this project is to improve public CIS in the long run. At the start of the project, the overall benchmark was at 80 % successful charging sessions without occurring errors. Thus, reliability in our case represents the percentage of successfully conducted charging sessions at available CIS compared to all attempted ones. Occupied or blocked CIS is not included in this calculation.

The investigation of tariffs showed that in many cases the energy price was decreasing as the monthly fee increased. Thus, this dynamic was applied to the energy price attribute and the respective conditional price: the higher the monthly fee, the lower the price per kWh. The

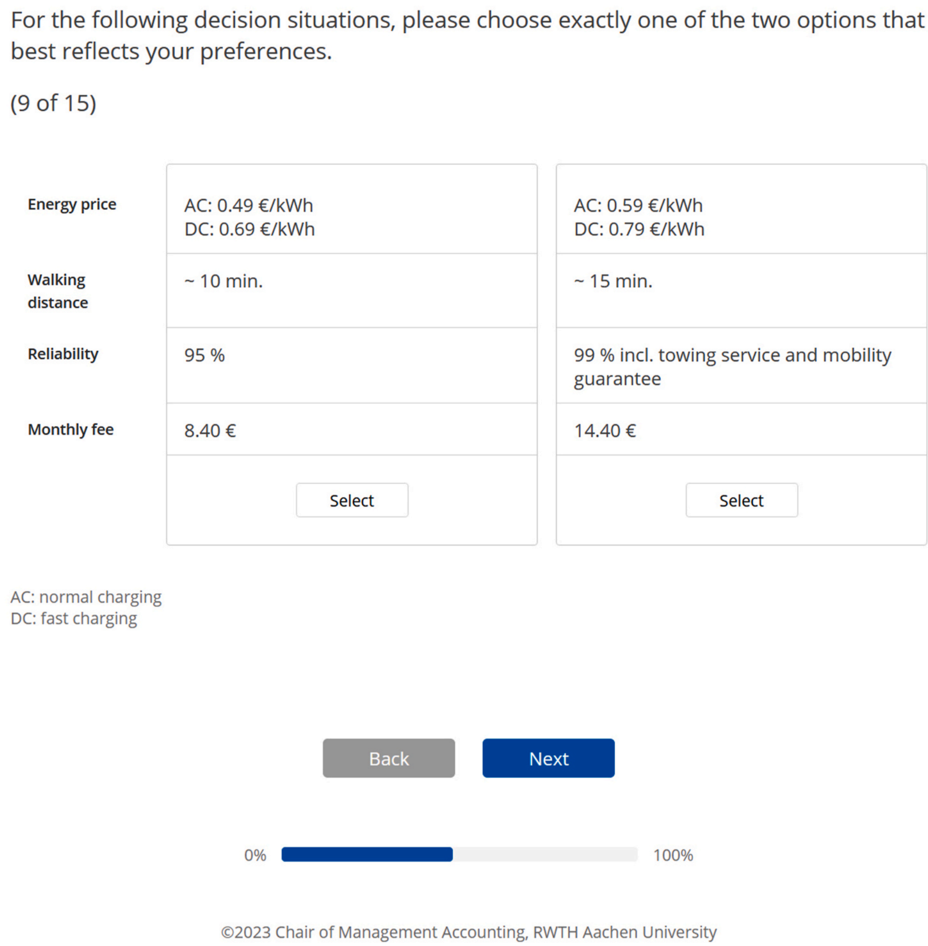

Fig. 3. Example for a CBC task (own figure).

Table 2
Attributes provided with corresponding levels of the charging tariffs (own table).

Attributes	Levels	Conditional price (if applicable) in €/month
Energy price in €/kWh	AC: 0.00, DC: 0.00	120 €
	AC: 0.39, DC: 0.59	12 €
	AC: 0.49, DC: 0.69	6 €
	AC: 0.59, DC: 0.79	2 €
	AC: 0.69, DC: 0.89	0 €
Walking distance in minutes	~5	
	~10	
	~15	
	~20	
Reliability	80 %	0 €
	95 %	1 €
	99 %, incl. towing service	6 €
	99 %, incl. towing service and mobility guarantee	10 €
Monthly fee	−20 %	
	0 %	
	+20 %	

increments between the levels are always 0.10 €, and the difference between AC and DC costs is always 0.20 €. An exception is the flat rate tariff, where no cost occurs for the charged energy, but which has the highest conditional price (see Appendix B).

The number of accessible charging stations is independent from both energy price and monthly fee but instead depends on the CPO (see Appendix B). Also, the investigation gave a fixed number of accessible charging stations in Europe, ranging from 200,000 to 310,000 (elvah 2022; Maingau 2022). As it might be difficult to understand the practical impact of this number, the attribute *walking distance* was adapted from this number. It represents a hypothetical assumption of how long it would take to walk from home, work, or destination to the nearest available charging station. Hence, *walking distance* reflects the degree of inconvenience associated with public CIS if users do not have access to a private charging station at home for regular charging. A 5-min increment was chosen.

Although none of the companies studied disclosed the *reliability* of their CIS, it was still considered a relevant attribute based on the literature review and on the data from the EMoT project, indicating that the current market base case is 80 %, while 95 % was deemed a suitable standard for the near future. One company offered insurance in the case of non-working CIS; therefore, levels with different types of insurance were included and assigned a certain conditional price. Covered services provide assistance in situations where an electric vehicle cannot be charged due to an inoperable charging station. These services include a towing service that transports the stranded vehicle to the nearest operational charging station, ensuring that drivers can continue their journey without significant delay. In addition, a mobility guarantee often provides a replacement vehicle, allowing drivers to seamlessly continue their journey. Both services are designed to minimize inconvenience in the event drivers encounter an inoperable charging station.

In the choice task, the conditional prices of the displayed levels were accumulated and varied in the attribute *monthly fee* ranging from −20 % to +20 % to determine how price sensitive consumers are.

The conditional price of a choice card consists of the conditional prices of the levels included in that choice card. For example, a choice card with an energy price of 0.49 €/kWh (AC) and 0.69 €/kWh (DC), a reliability of 95 % and a monthly fee variation of +20 % would have a conditional price of $(6\ € + 1\ €)(1 + 0.2) = 8.4\ €$.

Other attributes were excluded from the CBC either because there was little to no difference between competitors or because the attributes were very complicated to understand. The authentication method at CIS is almost always the same: all the tariffs offer access via app, a charging card, or chip. Blocking or idle fees, which accrue after a certain period of charging, were excluded for the same reasons.

2.2. Data collection and sample characteristics

The survey was conducted in Germany in 2023. The sample was expanded and balanced by paid participants from the "clickworker" survey service (clickworker GmbH, 2024). Of the original 536 respondents to the survey, three were excluded due to a very short completion time combined with their always selecting the same option in the CBC section, and four were excluded due to invalid data entry. The survey was available in German and English and was aimed at European citizens. However, only 13 participants resided in countries other than Germany. As this group is too small to serve as a comparison sample, all responses from outside Germany were also excluded. This resulted in a final sample of 516 complete and valid responses. As described in Section 1, Germany has a growing EV market and ambitious goals regarding public CIS. In addition, relevant cost factors, such as fuel price (EC 2024), are at least partially comparable across European countries, making the results of this study also applicable outside of Germany. The sociodemographic description of this sample is shown in Table 3.

In the present sample, the respondents are predominantly male (72.87 %). The mean age is 41.8 years (median: 39.0 years, std. dev.: 14.0 years). Compared to the general German population, the average age of those surveyed is slightly lower (BiB 2023). Both aspects can be attributed to the group of people who are particularly interested in EVs, which tends to be younger and male (Robinson, 2025; Bratzel et al., 2022; Statista, 2022; Sovacool et al. 2018, 2019). The online format of the survey may also explain the younger age distribution. Respondents have a mean annual net household income of 56,283 € (median: 48,000 €, std. dev.: 51,035 €). The sample shows relatively equal shares of EV owners (55.04 %) and non-EV owners. Since the topic will soon become relevant for all user groups through the foreseeable decarbonization of private transport, the inclusion of non-EV owners is important for obtaining a broad as possible picture of both groups' preferences. The same applies to people in rural versus urban areas, and with and without private CIS. The sample is not necessarily representative of the German population. However, since all participants are interested in EVs, relevant information regarding the research questions can still be derived from their responses.

Table 3
Sociodemographic characteristics of the sample (own table) and of Germany, adapted from Destatis (2024), BiB (2023), Destatis (2023), and The World Bank (2022).

	Germany	Sample (n = 516)
Gender	a 18 years or older	
Female	51.17 %	26.74 %
Male	48.83 %	72.87 %
Diverse		0.39 %
Age	a	
18–19	2.30 %	2.71 %
20–29	13.62 %	17.83 %
30–39	15.82 %	30.81 %
40–49	14.54 %	17.83 %
50–59	18.27 %	18.02 %
60–69	16.09 %	9.50 %
70–79	10.65 %	2.91 %
≥ 80	8.72 %	0.39 %
Education	b 25 years or older	
No qualification	21.58 %	0.19 %
Middle School or similar		0.97 %
Junior high school or similar		4.26 %
Senior high school or similar		13.95 %
Apprenticeship/traineeship or similar	56.73 %	17.83 %
Academic degree (bachelor/master) or similar	19.92 %	45.93 %
PhD or similar	1.77 %	16.86 %
Rural/urban	c	
Rural location	22.35 %	35.27 %
Urban location	77.65 %	64.73 %
Own EV		
Yes	No data	55.04 %
No	No data	44.96 %
Private CIS		
Yes	No data	36.43 %
No	No data	63.57 %
Annual household income (net) in EUR	d	
≤ 5999	0.94 %	15.70 %
6000–11,999	3.72 %	3.29 %
12,000–14,999	3.32 %	1.16 %
15,000–17,999	3.67 %	1.94 %
18,000–23,999	9.59 %	2.71 %
24,000–29,999	11.01 %	4.46 %
30,000–35,999	10.13 %	6.20 %
36,000–41,999	10.08 %	6.20 %
42,000–47,999	9.10 %	3.68 %
48,000–59,999	14.43 %	10.47 %
≥ 60,000	23.98 %	36.43 %
Not specified	0.02 %	7.75 %

[a] BiB (2023)
[b] Destatis (2023)
[c] The World Bank (2022)
[d] Destatis (2024)

2.3. Statistical model

Data from the CBC survey were processed using a hierarchical Bayes (HB) approach. Averaging the sample data by calculating the population mean utility values of the attribute levels would reflect the preferences of a persona that most likely does not exist (Baumgartner and Steiner, 2021). It is more probable that the population's preferences are fragmented into at least several segments, possibly consisting of one individual each at the extreme end. Therefore, it is reasonable to estimate individual preferences rather than only measuring the presence of what is often referred to as "heterogeneity in the customer's part-worths" in the literature, e.g. by Lenk et al. (1996). Achieving this objective through traditional estimation methods usually requires complete information about each respondent for calculating all individual part-worth utilities (Lenk et al., 1996). A traditional conjoint analysis, where each respondent orders all possible alternatives, can provide such information. For studies with a substantial amount of alternatives, this approach leads to extensive surveys resulting in reduced response rates and increased response biases (Lenk et al., 1996). To avoid this issue, CBCs provide a beneficial alternative to conventional conjoint analyses. In this method, a limited number of alternatives are presented to the respondents in a set of choice tasks, constituting a reduced design. This poses a new problem, as the raw data of CBCs are sparse, which does not allow direct computation of individual preferences (Howell, 2009). Hierarchical Bayes estimation enables individual estimations despite the scarcity of data (Baumgartner and Steiner, 2021; Kurz and Binner, 2011; Lenk et al., 1996; Allenby and Ginter, 1995). Other approaches, such as latent class analysis or segmentation algorithms, are compromises between aggregated and individual estimations (Baumgartner and Steiner, 2021). However, these approaches are not considered further, as the actual range of individual utility values is considered, which can best be assessed by using the HB approach.

The HB approach belongs to the class of Bayesian methods (Ben-Akiva et al., 2019). These calculate the probability distribution of the model parameters Θ[1] by considering the collected data Y, in contrast to conventional methods, where an assumed parameter model is evaluated by how much the collected data align with certain hypotheses (Orme, 2016; Gelman et al., 2014). The Bayes theorem leads to the expression indicated in Eq. (1), which represents the fundamental concept of Bayesian methods. Posterior probability draws result in a probability distribution of the part-worth utilities (Gelman et al., 2014; Allenby et al., 1995; Allenby and Ginter, 1995):

$$p(\Theta|Y) \propto p(Y|\Theta)p(\Theta) \tag{1}$$

HB estimation of individual part-worth utilities was first introduced by Allenby et al. (1995), Allenby and Ginter (1995), and Lenk et al. (1996). However, at that time, computational power was a limiting factor when applying HB estimation to more complex studies (Orme, 2016). Today, the combination of CBC analysis and HB estimation is a widely utilized and popular state-of-the-art approach for assessing choice data and deriving individual preferences (Goeken et al., 2021; Ben-Akiva et al., 2019; Sawtooth Software, 2017; Howell, 2009).

Its two-level structure, consisting of a lower level or individual level and an upper level or population level, gives the HB algorithm its name (Train, 2009). At the upper level, the part-worth utilities of the population are assumed to be multivariate and normally distributed, whereas at the individual level, a multinomial logit model is supposed to describe the individual choice behavior (Orme, 2016; Johnson, 2000). Individuals are assumed to behave in a utility-maximizing manner (Goeken et al., 2021; Train, 2009). The estimation of reasonable part-worth utilities β_n for all individuals $n \in \{1, \ldots, N\}$ is accomplished through an iterative Monte Carlo Markov Chain (MCMC) (Ben-Akiva et al., 2019; Orme, 2016; Gelman et al., 2014). Using MCMC, the parameters are drawn from a distribution that increasingly approximates the actual posterior distribution, which eliminates the need to calculate the parameters directly (Ben-Akiva et al., 2019; Gelman et al., 2014). Each vector β_n consists of the parameters $d \in \{1, \ldots, D\}$ to be estimated, where D can be derived from the sum of all levels $l_k \in \{1, \ldots, L_k\}$ over the attributes $k \in \{1, \ldots, K\}$. The individual total utility U_{nj} of a given alternative $j \in \{1, \ldots, J\}$ can be calculated from the individual part-worth utilities according to Eq. (2), where the design vector x_j indicates whether an attribute level is part of alternative j:

$$U_{nj} = x_j' \beta_n + \varepsilon_{nj} \tag{2}$$

The steps of the "Gibbs sampler", a specific MCMC method used in HB estimation, are described in various studies, such as Baumgartner and Steiner (2021), Ben-Akiva et al. (2019), Orme (2016), and Train (2009), and are shown in Eqs. (3)–(5):

$$\alpha \sim N\left(\overline{\beta}, \frac{\Omega}{N}\right) \text{ with } \overline{\beta} = \frac{1}{N}\sum_{n=1}^{N}\beta_n \tag{3}$$

$$\Omega \sim IW\left(D+N, \frac{DI_D + N\overline{S}}{D+N}\right) \text{ with } \overline{S} = \frac{1}{N}\sum_{n=1}^{N}(\beta_n - \alpha)(\beta_n - \alpha)' \tag{4}$$

$$\beta_n \propto L(y_n|\beta_n)\phi(\beta_n|\alpha,\Omega) = \prod_{t=1}^{T} p_{njt}{}^{Y_{njt}}\phi(\beta_n|\alpha,\Omega) \;\; \forall n \tag{5}$$

In the first step, Eq. (3), the population level part-worth utility vector α is drawn from a multivariate normal distribution with the covariance matrix Ω. Second, in Eq. (4), a new Ω is drawn from an inverse Wishart distribution, which is the conjugate prior for the covariance matrix of a multivariate normal distribution (Gelman et al., 2014). In the final step, a new β_n is drawn by using a Metropolis-Hastings algorithm. Here, ϕ represents the density of the normal distribution, while p_{njt} denotes the probability of respondent n choosing alternative j in choice task $t \in \{1, \ldots, T\}$, and $Y_{njt} \in \{0, 1\}$ indicates the actual choice data collected from the survey for this situation.

Initially, all elements of β_n are set to zero (Orme, 2016). From there, the process is divided into two phases: the burn-in phase and the actual recording of the estimates. The first iterations are conducted in the burn-in phase, during which the β_n draws converge and must be discarded (Gelman et al., 2014). The recommended range for iterations required during the burn-in phase is from 10,000 to 20,000 (Ben-Akiva et al., 2019; Johnson, 2000). In the current study, 20,000 iterations were used. During subsequent iterations, the actual estimates are generated and consolidated into distributions for each individual (Ben-Akiva et al., 2019; Allenby et al., 2005). Due to the iterative character of the estimation process, successive draws may be subject to serial correlation (Ben-Akiva et al., 2019; Gelman et al., 2014). Ben-Akiva et al. (2019) suggest using only every tenth draw to reduce serial correlation, while Gelman et al. (2014) argue that serial correlation is not critical, since draws are identically distributed after convergence and the order of the draws is of no further interest. In the study at hand, 100,000 iterations were used during the estimation phase without skipping any draws.

The structure of the HB model presented so far leads to some shrinkage of the individual parameter vectors towards the population mean (Kurz and Binner, 2011). However, with a sufficient number of respondents, the effect remains small (Kurz and Binner, 2011). It is possible to include covariates representing individual characteristics of the respondents in the HB model (Rossi et al., 2005; Lenk et al., 1996). The idea behind the inclusion of covariates is to explain some of the heterogeneity in individuals' part-worths, so that the shrinkage of an individual's part-worths should no longer tend towards the population mean but rather towards the mean of a subgroup or segment of the population that shares the same characteristics (Orme, 2016; Kurz and Binner, 2011). However, compared to well-chosen exogenous variables, common sociodemographic variables, such as gender, age, income, etc., do not appear to provide sufficient additional information for estimating choices (Kurz and Binner, 2011; Orme and Howell, 2009). After analyzing ten studies, Kurz and Binner (2011) could not validate the use of covariates for enhancing estimation outcomes. Therefore, they concluded that additional covariates are not necessary in CBC studies with an adequate sample size. This finding is supported by Sentis and Geller (2011). Consequently, covariates were not included in the analysis of the study at hand.

To gain a more comprehensive understanding of the preferences, the attribute's importance as well as a ranking of all possible alternatives can be calculated from the individual part-worth utilities. The importance of an attribute Imp_{nk} among the surveyed attributes for a given individual results from Eq. (6) by setting the range of individual part-worth utilities across all levels for that attribute in relation to the range of individual part-worth utilities across all levels for all attributes. A distribution of the results for all individuals in the sample provides an overview of which attribute should be given special attention in the design of actual product offerings:

$$Imp_{nk} = \frac{\max\limits_{l \in \{1,\ldots,L_k\}}(\beta_{nkl}) - \min\limits_{l \in \{1,\ldots,L_k\}}(\beta_{nkl})}{\sum\limits_{k=1}^{K}\left(\max\limits_{l \in \{1,\ldots,L_k\}}(\beta_{nkl}) - \min\limits_{l \in \{1,\ldots,L_k\}}(\beta_{nkl})\right)}. \tag{6}$$

The overall preferred alternatives can be determined by calculating the average total utility of each alternative and then ranking them according to these values.

2.4. Estimating the willingness to pay

The WTP was derived from the utilities. There are several ways to estimate the WTP in general, e.g. by asking respondents how much they

[1] Variables are explained when they are first used in the text. For an overview of all variables, please refer to the list of symbols.

would be willing to pay for a service (Breidert et al., 2006) or by calculating the price value for a gain in utility (Mengelkamp et al., 2019; Salm et al., 2016). These approaches typically underestimate the influence of competition and market reactions, and thus overestimate the WTP (Orme, 2021). To address this issue, the built-in WTP estimation in Lighthouse Studio was used (Sawtooth Software, 2024). The simulation approach can incorporate market behavior, such as choosing a competitor if they offer the same utility but at a lower price. The bootstrap sampling approach was used here with the 1000 sets of participants recommended in the literature (Orme, 2021), consisting of 516 participants in each set. The sets were compiled from the original set, but some of the participants do not appear in each set, while others appear two or more times in certain sets (Orme, 2021). Using the built-in scenario sampling method, these generated participant sets with their specific preferences were then matched with hundreds of randomly generated offers with displayed conditional prices from 20 competitors (Orme, 2007, 2021). The fictitious participants are assumed to choose the alternative that gives them the highest overall utility (Sawtooth Software, 2023b). Considering competition and using bootstrap sampling, a market share is calculated for each of these scenarios by averaging the choice probabilities across all respondents. Now, one offered alternative is improved by changing one level within one attribute in the simulation. Consequently, the average choice probability (market share) of the improved alternatives increases with each scenario. The price that returns the market share to its original value is taken as the WTP. The WTP is then derived from the median of the bootstrap samples, also calculating the confidence interval (Sawtooth Software, 2023a). Each competitor is allowed to potentially offer all levels of the attributes, thus considering the necessary assumptions for a successful simulation (Orme, 2001). Therefore, this approach focuses more on the overall market than on individual WTP. For further explanation, see Orme (2021). People with actual utility gains therefore contribute more to the average choice probability because they are actually "willing to pay" more for the service, as opposed to people who would accept or reject it for a given price. People who have an unusually high or low probability of choice for that level do not contribute much to the average probability of choice, but people who are "on the cusp of choice" do.

3. Results and discussion

3.1. Utilities

The results for the individual utilities are shown in box plots in Fig. 4. High utilities indicate that this level is perceived as attractive. In contrast, low or even negative utilities do not necessarily indicate unattractiveness (Sawtooth Software, 2023c). Utilities should be compared only within an attribute because the scale is not fixed across attributes.

Regarding the attribute *energy price*, the spreads of the individual utility of levels with a high or low energy price and a corresponding low or high conditional price (see Table 2) are large, indicating that these tariffs are controversial among users. They meet the needs of some users, which is reflected in a high utility value while not meeting the needs of other users, resulting in a low utility value. When both the energy price and the conditional price are medium, this spread becomes smaller. This means that the respective level roughly satisfies the needs of all participants and is less controversial across the sample. The utilities of the flat rate tariff are different from those of the other levels. It shows by far the highest maximum and the lowest minimum, the largest quartile spread, and the lowest median and mean. This could be due to, first, the high conditional price of 120 € per month or, second, the discontinuous gap to the next level. Overall, there is no significant difference in individual utility between EV owners and non-EV owners. Considering the conditional prices for the attribute *energy price*, moderate energy prices seem to be more attractive than an all-inclusive charging flat rate or a monthly free option. In this study, the highest individual utility among all respondents was in the third level with 0.49 €/kWh (AC) and 0.69 €/kWh (DC) for 6 € per month.

A similar effect appears for the attribute *reliability*. Both levels, the one with relatively low reliability and a low conditional price and the one with high reliability including a towing service and a mobility guarantee and a high conditional price, are controversial and thus show a larger spread from the maximum to the minimum utility and from the lower quartile to the upper quartile, compared to the other two attributes. In this study, the level representing a reliability of 95 % for a conditional price of 1 € per month shows the smallest spread from maximum to minimum, the narrowest gap between the lower quartile

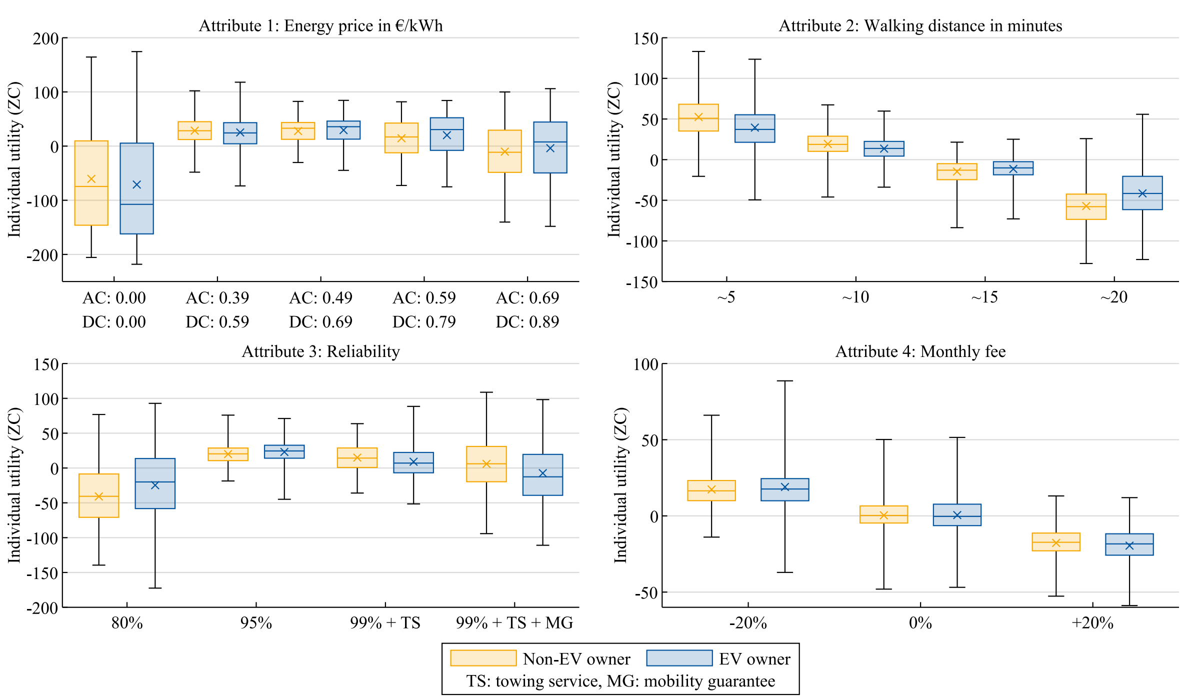

Fig. 4. Part-worth utilities of levels within attributes (own figure).

and the upper quartile, and the maximum average individual utility. This indicates that a relatively small amount of money can provide a large increase in utility. It can also be supported that availability and compatibility are important as a part of reliability (Kühl et al., 2019; Hardman et al., 2018). The 99 % reliability level including an additional towing service or a mobility guarantee add utility compared to the base case of 80 % reliability. However, both levels do not add utility to the best case of 95 % reliability. Yet, these two services are more controversial in terms of their utility distribution across the sample. Individual utility of the first level is on average 10.3 points higher ($p < 0.05$) and for the last two levels lower (3.8 points, $p < 0.1$, and 8.1 points, $p < 0.05$) for EV owners than for non-EV owners, ceteris paribus. For the second level, there is no respective significant difference. Thus, non-EV owners tend to have a higher need for safety, while for EV owners the increase in individual utility from the 80 % to the 95 % level is lower and the drop in utility from level three to four is steeper. Considering the conditional prices for *reliability*, the best value at a reasonable price is achieved at the 95 % level in the current study.

As expected, the slope of the variation in *walking distance* and *monthly fee* is inversely proportional to the level. The lower the *walking distance* or *monthly fee,* the higher the average utility. Of course, a walk of only 5 min is convenient, while a walk of up to 20 min is not practical in everyday life. For EV owners, the slope of the drop in individual utility over the levels of the attribute *walking distance* is flatter than for non-EV owners ($p < 0.01$ for ~5 min and ~20 min, $p < 0.05$ for ~10 min, and not significant for ~15 min). Regarding the attribute *monthly fee,* there is no significant difference between EV owners and non-EV owners in the average individual utility, except for the 20 % discount, where the individual utility for EV owners is on average 2.5 points higher, ceteris paribus ($p < 0.1$). Concerning the discount on the monthly fee, not surprisingly, a 20 % discount is in general always better than a regular or an increased price. For further information on the regression results, see Appendix C.

The utilities derived from the choice tasks have a high average root likelihood (RLH) of 0.781 (std. dev.: 0.093, max.: 0.944, min.: 0.454). The RLH is a measure of how well the solution fits the data, with a theoretical maximum of 1 (Sawtooth Software, 2017). Only two participants out of 516 have a RLH of less than 0.5, which makes the estimation not a good fit for these two, but for all the other 514 participants. This measure, as well as the expected results for the *monthly fee* and *walking distance* attributes, leads to the conclusion that the results are reliable for the examined sample. The mean utility of each level and the standard deviations are shown in Table 4.

3.2. Importances

The attribute importances across the sample are shown in Fig. 5 and the respective mean is displayed in Table 4.

By far the most important attribute is *energy price* for all participants. For EV owners, the importance of the attribute *energy price* is on average 4.5 percentage points higher than for non-EV owners, ceteris paribus ($p < 0.01$). On the one hand, it seems that the energy price is perceived as the decisive price factor and not the monthly fee. This could be due to the high contribution of the attribute energy price to the displayed monthly fee through the associated conditional price, which might lead to an anchoring effect (Tversky and Kahneman, 1974). Usually, EMPs offer lower energy prices in exchange for a higher monthly fee (see Appendix B). On the other hand, the *monthly fee* reflects the price variation of ±20 %, not the sum of all conditional prices constituting the actual fee, and this is perceived as less important. Typically, attributes of low importance receive only little attention (Hensher, 2014), as in this case the ±20 % variation. The attribute contributing most to the sum, in this case the *energy price*, is highly valued by consumers. It might be that consumers prefer the price displayed as a price per kWh over a price displayed as a monthly fee, or that the price structure is too complex (Layer et al., 2017) and could lead to confusion. All attributes have a minimum close to zero, which means that each attribute is not important for some consumers. *Energy price* has an outstanding maximum individual importance of over 75 % for EV owners (81 % for non-EV owners), while *walking distance* has a maximum of 65 % (62 %), *reliability* 62 % (67 %), and *monthly fee* 29 % (34 %). The importance of the attribute *walking distance* is on average 4.3 percentage points lower for EV owners than for non-EV owners, ceteris paribus ($p < 0.01$), while there is no significant difference between the two groups in the importance of the attribute *reliability*. Both attributes provide a certain degree of convenience, either to avoid long walks or to be covered in case problems with the CIS occur. Overall, the attributes could be grouped into three segments according to their perceived importance: price, convenience, and price variation.

3.3. Best and worst charging tariffs

From the mean utility of each level shown in Table 4, the most attractive and the least attractive combinations were calculated and ranked. The different alternatives were assigned the sums calculated from the utilities of the levels included. The most attractive tariff consists of an *energy price* of 0.49 €/kWh for AC and 0.69 €/kWh for DC charging, a *walking distance* of only 5 min, a *reliability* of 95 %, and a discount of −20 % on the *monthly fee,* which results in a total of 5.60 €

Table 4
Importances of attributes, mean utilities, and standard deviations of levels for EV owners and non-EV owners (own table).

Attributes	Importance EV (non-EV)	Levels	Conditional price in €/month	Mean utility EV	Mean utility non-EV	Std. dev. EV	Std. dev. non-EV
Energy price in €/kWh	46.16 %	AC: 0.00, DC: 0.00	120 €	−71.017	−60.531	106.602	94.691
	(39.48 %)	AC: 0.39, DC: 0.59	12 €	25.196	28.492	32.128	27.390
		AC: 0.49, DC: 0.69	6 €	29.529	27.760	23.997	21.985
		AC: 0.59, DC: 0.79	2 €	20.141	14.507	40.222	33.072
		AC: 0.69, DC: 0.89	0 €	−3.848	−10.228	62.049	51.009
Walking distance in minutes	21.95 %	~5		39.418	52.472	27.976	26.836
	(28.13 %)	~10		13.573	19.294	15.334	15.09
		~15		−11.466	−14.686	15.916	15.695
		~20		−41.525	−57.081	30.175	30.047
Reliability	21.44 %	80 %	0 €	−24.693	−40.845	45.063	44.610
	(22.84 %)	95 %	1 €	23.065	19.966	16.801	14.998
		99 %, incl. towing service	6 €	9.007	14.946	20.576	19.465
		99 %, incl. towing service and mobility guarantee	10 €	−7.379	5.933	38.036	37.553
Monthly fee	10.44 %	−20 %		18.99	17.353	14.945	12.063
	(9.54 %)	0 %		0.545	0.377	11.632	11.037
		+20 %		−19.535	−17.730	12.001	10.710

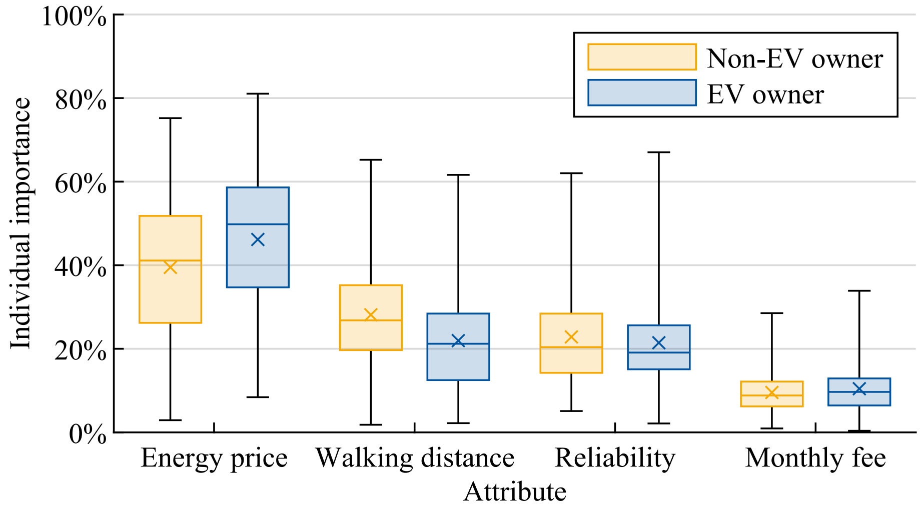

Fig. 5. Attribute importances (own figure).

per month. In contrast, the flat rate tariff with no additional energy costs, a 20-min walking distance, a lower functionality of only 80 %, and a surcharge of +20 % on the conditional price, summed up to 144 € per month, is the least attractive. The distribution of the tariffs ranked by the average total utility are shown in Fig. 6. Table 5 provides an overview of the top and bottom five alternatives. When analyzing EV owners and non-EV owners separately leads to the same result, with the smallest deviations, and therefore the same implications.

While the tariffs with a high overall utility have a smaller spread in the standard deviation, the spread widens as the tariffs become less attractive. This effect is statistically significant and suggests that attractive tariffs are perceived as equally good within the sample, and that the advantages and disadvantages of the unattractive tariffs are perceived very differently by the participants. Attractive tariffs meet the needs of most, while unattractive tariffs meet the specific needs of only a few participants. This might be explained by individual price sensitivity and risk awareness. Regarding the feasibility of offering these tariffs, both the energy price and the monthly fee of the best tariffs are in the range of the real-world tariffs offered shown in Appendix B. Therefore, they should allow to run a profitable business in reality.

3.4. *Willingness to pay*

WTP can be derived as described in Section 2.4. The resulting values and their standard errors are shown in Fig. 7. The reference level of each attribute as well as the price attribute (*monthly fee*) have no WTP value and are not shown. All WTP values are relative to their corresponding reference level (0.69 €/kWh AC/0.89 €/kWh DC; 20 min; 80 %) and are not additive.

A high value is attributed to *energy price*. In particular, the flat rate tariff has the absolute highest WTP with 121.03 €/month for EV owners and 111.10 €/month for non-EV owners. It should be noted that the flat rate only makes sense for people with monthly charging energy costs above this value. Based on the average annual mileage of 12,320 km in Germany (KBA 2024), this value is not reached by an average BEV. The WTP for other levels within this attribute is comparably low. The simulation approach allows the identification of a threshold for respondents in this sample who are hesitant about whether the flat rate tariff is appropriate for them. In this way, the focus is on people who are inclined to buy or to refuse, rather than those who will buy anyway or who will not buy at all. The large gap in WTP from the flat rate tariff to the next level could again be due to the discontinuous design in this attribute or to the high conditional price.

Regarding *reliability*, EV owners are willing to pay up to 9.20 €/month for the “all-inclusive” mobility guarantee service (non-EV owners 8.00 €/month). To answer the second research question, a high additional utility from the reference level of 80 %–95 % was found, but only moderate utility gains for a towing service (EV owners 6.30 €/month and non-EV owners 4.80 €/month) or a mobility guarantee. Nevertheless, this high utility gain can be achieved by a WTP in the market of only 1.56 €/month (non-EV owners 1.16 €/month).

For *walking distance*, the results are as expected. The shorter the walking distance in minutes, the higher the WTP. At most, EV owners would pay 10.54 €/month (non-EV owners 12.00 €/month) for a parking space with CIS nearby. Saving time and having everyday convenience has a comparatively high WTP. This could be compared to a private parking space that some people rent from their landlord or near to their workplace. In Germany, it is common to pay up to 30 € per month for a

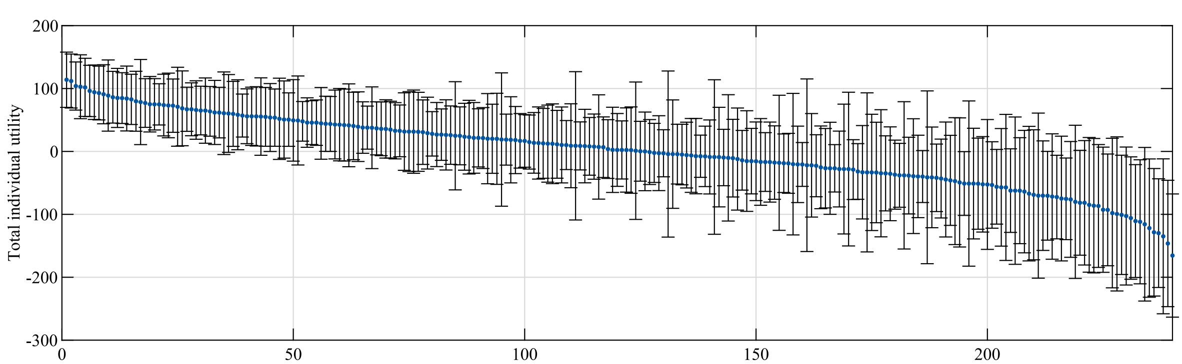

Fig. 6. Tariffs ranked by their perceived utilities (own figure).

Table 5
Top and bottom tariff alternatives (own table).

Rank	Energy price in €/kWh	Walking distance	Reliability	Monthly fee	Conditional price	Average total individual utility
1	AC: 0.49, DC: 0.69	~5 min	95 %	−20 %	5.60 €	113.947
2	AC: 0.39, DC: 0.59	~5 min	95 %	−20 %	10.40 €	111.892
3	AC: 0.49, DC: 0.69	~5 min	99 % + TS	−20 %	9.60 €	103.953
4	AC: 0.59, DC: 0.79	~5 min	95 %	−20 %	2.40 €	102.822
5	AC: 0.39, DC: 0.59	~5 min	99 % + TS	−20 %	14.40 €	101.897
…	…	…	…	…	…	…
236	AC: 0.00, DC: 0.00	~20 min	80 %	−20 %	96.00 €	−128.523
237	AC: 0.00, DC: 0.00	~15 min	80 %	+20 %	144.00 €	−129.896
238	AC: 0.00, DC: 0.00	~20 min	99 % + TS + MG	+20 %	156.00 €	−134.939
239	AC: 0.00, DC: 0.00	~20 min	80 %	0 %	120.00 €	−146.308
240	AC: 0.00, DC: 0.00	~20 min	80 %	+20 %	144.00 €	−165.501

TS: towing service, MG: mobility guarantee.

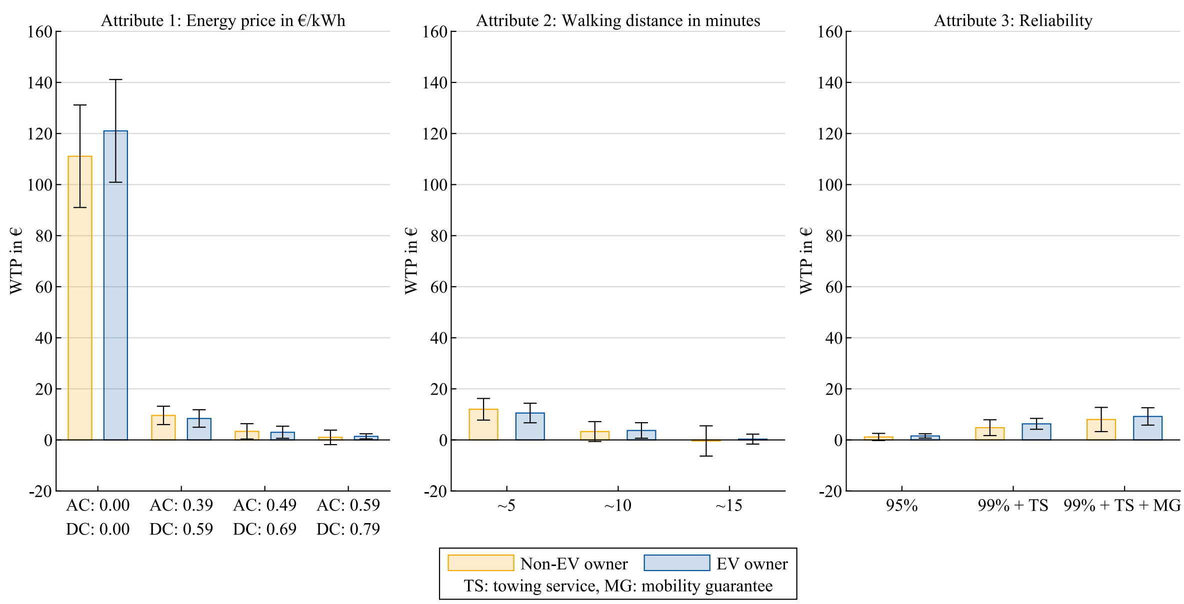

Fig. 7. WTP for levels (own figure).

city parking ticket (Gieße, 2024). For all attributes, values below zero, especially towards the lower bound of the standard error, can be seen as a necessary compensation (Bass et al., 2021).

All differences in the WTP results between EV owners and non-EV owners are not statistically significant. Therefore, the WTP can be considered aggregated and both consumer groups can be summarized. Both *reliability* and *walking distance* reflect a certain value of time that consumers are willing to pay for. In the case of the walking time to a nearby available charging station, consumers are likely to want a convenient long-term solution to meet their recurring needs as easily as possible. Unreliability does not lead to a regular loss of time, but it does result in tighter time constraints as soon as the charging station does not work as desired. Consumers are likely to value the relatively small but real daily time loss due to walking over the potential sporadic but then significant and unforeseeable time loss.

4. Conclusions and outlook

Using a CBC analysis, this paper provides insights into consumer preferences for public charging tariffs. The choice of methodology makes it possible to make statements about the broad market, but also to take individual cases into account. Consumers have different needs, which may be very different from the preferences of the general public; therefore, there is no single best tariff for all consumers. One research question addressed the attractiveness of certain attributes for private consumers. To answer this research question: on a theoretical level, it can be concluded that pricing is the most important factor when accepting or rejecting a charging tariff. A medium energy price and a medium monthly payment are perceived to be better than extreme values in either direction. Consumers calculate the most suitable tariff by weighing a monthly fee against a lower energy price. In a practical context, both consumers and CPOs can find the best tariff to choose or to offer, respectively. Consumers with a high demand for public charging can choose tariffs with a lower energy price to break even on the monthly fee, while the market can offer tariffs with a high energy price to consumers who use public CIS less frequently. In the current study, a flat rate tariff was not perceived as an attractive solution compared to the other options, probably because currently most charging sessions still take place at home (Anderson et al., 2022) or at work. As pointed out, this is forecasted to change in the future as the share of consumers publicly charging increases. It can also be concluded that convenience is important, at least in terms of a nearby charging opportunity and a reliable charging session. The closer the parking lot with available CIS, the more convenient it is perceived to be. When it comes to the reliability of charging stations, a high level of functionality is sufficient without any additional services such as a towing service or a mobility guarantee. The results show that the preferences of EV owners and non-EV owners are broadly similar. Both groups show no significant difference in individual utility in terms of energy price and monthly fee. EV owners are slightly more concerned about the price of energy, but less concerned about walking distance. Non-EV owners have a higher need for safety in terms of reliability, but the overall importance of reliability is similar in both groups. For real-life application, the findings indicate that the primary need that CIS must meet is the provision of energy at a reasonable price. If prices are too high, people may be reluctant to switch to BEVs, and CPO income will be lost. Second, this energy should be provided nearby as a reliable source. The results also point to convenience as being an increasingly important business case in the future, where public CIS will need to be increasingly convenient to use. For this purpose, future policies should focus on ensuring a high level of competition in the CIS sector, leading to lower prices and more available and reliable charging stations for consumers.

The second research question tackled the issue of unreliable CIS. Consumers need a reliable infrastructure for them to fully accept BEVs, e.g. Azarova et al. (2020). Looking at the corresponding utilities in the theoretical results given by the levels of *reliability,* there is no need for an "all-inclusive" solution, but for a significantly improved reliability standard throughout the market. The lowest form – the current state – of 80 % is the least attractive. In contrast, the 95 % (WTP 1.56 €/month for EV owners) solution gives on average the highest utility, better than the levels with an included towing service or a mobility guarantee. Utility increases rapidly from 80 % to 95 %, but only marginally towards a towing service or a mobility guarantee. These do not seem to be mandatory for the acceptance of a public charging tariff, so CPOs should affirm, improve, and promote their reliable CIS with a low price at the same time. The combination of a reasonable price and high reliability was perceived as the best tariff in the survey. In reality, CPOs could use the revenue from a reliability fee to improve the system if it does not already reach 95 % or higher. Consumers have a high demand for convenience. Both short walking distances and reliable CIS result in lost time when minor problems occur on a daily or probabilistic basis. One pronounced result of this study is that consumers are demanding a denser but above all more reliable network of public CIS but are also prepared to pay a premium for it. Policymakers should incentivize CPOs to implement more charging stations but also improve their reliability so that both problems can be addressed: on the one hand, consumers would have closer access to CIS, and on the other hand, consumers would also have a backup solution in case one charging station was not working. The results suggest that consumers are willing to pay for this kind of convenience.

Despite the theoretical and practical implications of the present work, there are still some limitations. The attributes selected for the choice tasks were only a fraction of all potentially available attributes of charging tariffs on the market. In a pre-test for this survey, participants did not want to handle too many attributes at the same time. This limits the survey to a certain degree, makes tariffs difficult to transfer into practice (see Appendix B), and can lead to a WTP that is often overestimated. By prohibiting opting out in the choice task, a decision in favor of one choice set was enforced. Nevertheless, the results show that the WTP estimates are comparable to the current market offers (ADAC 2024; elvah, 2022). The results are not necessarily representative of Europe as a whole, but since the relevant cost factors are comparable across European countries, the transferability of the results is reasonable. Offered tariffs undergo changes constantly, for example due to energy price increases. Nevertheless, the results are still applicable to tariffs in the market for public charging. Although certain socio-demographic variables are already included in our study, other variables not included in our study may be of interest for more specific questions in the future. These include, for example, the location from which a charging station is accessed (work, home, etc.) or the exact composition of the household surveyed.

Further research could investigate to what extent the lack of reliability of CIS impeding the market entry of BEVs. Perhaps this effect depends on the investigated market, e.g. China, Europe, and USA. Sun et al. (2017) call for a government-regulated price or a customer experience tracking system. However, based on the work presented here, a more coordinated improvement of CIS, implemented by an independent entity in the market, is suggested to incorporate these customer experiences and the entire knowledge obtained from all the market participants into a reliable and standard-compliant CIS for a good customer journey.

CRediT authorship contribution statement

Peter Letmathe: Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Dustin Sperling:** Writing – original draft, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Richard Woeste:** Writing – original draft, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interests

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.

Appendix

A Questionnaire (without CBC tasks)

1) Please indicate your gender. (Female, Male, Other).
2) Please indicate your age.
3) Please indicate the country where you live.
4) Please indicate your postal code.
5) Please indicate whether you live in a rural or urban location. (Rural location, Urban location).
6) Please indicate your highest educational level. (No qualification, Middle School (or similar), Junior high school (or similar), Senior high school (or similar), Apprenticeship (or similar), Academic degree (bachelor/master/diploma) (or similar), PhD (or similar)).
7) Please indicate your annual household income (net) in Euro.
8) Please indicate the number of vehicles in your household.
9) Please indicate the number of electric vehicles (BEV) in your household.
10) Please indicate if you have a private charging point (e.g., a wall charger) where you can charge your battery electric vehicle (BEV). (Yes, No).
11) Please specify your vehicle no. # in more detail. Please, start with electric vehicles first if applicable: Annual mileage (in km). Average energy consumption (liter or kWh per 100 km). Vehicle type (Combustion engine vehicle, Electric vehicle).

12) Please indicate the proportions in which you use the charging options shown for charging your battery electric vehicle (BEV) no. #: (Private charging at home, Public charging point (AC), Public charging point (DC), Charging point at work).
13) Please estimate the share of charging processes of your electric car that run incorrectly, abort or do not start at all for any reason (in %).
14) Please specify the occurring errors and their reasons in more detail if you can (optional).
15) If you'd like to give us feedback (optional):

B Overview of the tariffs investigated for attributes and levels

Table 6
Overview of the tariffs investigated, based on elvah (2022), EnBW (2022), Maingau (2022), Shell (2022).

Attribute		Tariff					
		Maingau	EnBW standard	EnBW heavy user	Shell	elvah M	elvah L
Monthly fee in €/month		0.00	0.00	5.99	0.00	50.00	100.00
Energy price in €/kWh	AC	0.49	0.45	EnBW: 0.36 Other: 0.39	Shell: 0.46 Some: +0.02 ct/min	0.54 (90 kWh free)	0.54 (180 kWh free)
	DC	0.59	0.55	EnBW: 0.46 Other: 0.49	Shell: 0.59 Other: 0.64	0.69 (90 kWh free)	0.69 (180 kWh free)
	Ionity	0.75	0.79	0.79	0.81	0.69	0.69
Charging network in Europe		310,000	300,000	300,000	275,000	200,000	200,000
Authentication		RFID card or app	RFID card or app	RFID card or app	RFID card or app	App only	App only
Idle fee in €/min		0.10 (after 4 h AC or 1 h DC, max. 12 €)	0.10 (after 4 h AC or 1 h DC, max. 12 €)	0.10 (after 4 h AC or 1 h DC, max. 12 €)	None	None	None
Security		None	None	None	None	Towing service	Towing service, mobility guarantee
Session fee in €/session		None	None	None	0.35 (max. 7.00 €/month)	None	None

C Statistical tables

Table 7
Part-worth utilities of levels within *Energy price* (own table).

	(1)	(2)	(3)	(4)	(5)
	AC: 0.00, DC: 0.00	AC: 0.39, DC: 0.59	AC: 0.49, DC: 0.69	AC: 0.59, DC: 0.79	AC: 0.69, DC: 0.89
BEV	0.388	−1.682	0.714	1.840	−1.259
Male	15.230	−2.408	−3.211	−4.390	−5.221
Other	160.739**	−19.055	−38.581**	−45.055*	−58.048
Age	−1.104***	0.017	0.194**	0.376***	0.518***
Education	−0.866	3.448***	2.483**	−1.283	−3.782
Income (in kEUR)	0.190**	0.009	−0.028	−0.081**	−0.089*
Rural	−4.879	1.512	2.542	1.505	−0.680
Private CIS available	−14.253	−2.485	1.294	4.887	10.556
_cons	−30.249	9.531	9.089	13.287	−1.659
Obs.	516	516	516	516	516
adj. R–sq.	0.032	0.006	0.034	0.030	0.020

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 8
Part-worth utilities of levels within *Walking distance* (own table).

	(1)	(2)	(3)	(4)
	~5 min.	~10 min.	~15 min.	~20 min.
BEV	−8.966***	−3.370**	1.105	11.231***
Male	−2.781	−1.050	−1.449	5.280*
Other	−20.407	−13.189	5.301	28.295
Age	−0.089	−0.045	0.040	0.094
Education	3.245***	1.492**	−0.688	−4.049***
Income (in kEUR)	0.051**	0.027**	−0.023	−0.055**
Rural	−6.186**	−3.693***	2.001	7.879***
Private CIS available	−6.300**	−3.773**	3.805**	6.268*
_cons	39.917***	13.692***	−11.218***	−42.390***

(continued on next page)

Table 8 (*continued*)

	(1)	(2)	(3)	(4)
	~5 min.	~10 min.	~15 min.	~20 min.
Obs.	516	516	516	516
adj. R-sq.	0.094	0.073	0.022	0.114

*p < 0.10, **p < 0.05, ***p < 0.01.

Table 9
Part-worth utilities of levels within *Reliability* (own table).

	(1)	(2)	(3)	(4)
	80 %	95 %	99 %, incl. TS	99 %, incl. TS and MG
BEV	10.346**	1.504	−3.750*	−8.101**
Male	0.848	0.797	−1.502	−0.143
Other	−24.174	−11.279	0.557	34.896
Age	0.639***	0.038	−0.190***	−0.487***
Education	−0.453	0.726	−0.078	−0.195
Income (in kEUR)	−0.025	−0.019	0.005	0.039
Rural	9.520**	1.420	−3.831**	−7.109**
Private CIS available	4.313	3.093*	−2.031	−5.374
_cons	−65.997***	14.067***	25.052***	26.878***
Obs.	516	516	516	516
adj. R-sq.	0.072	0.013	0.040	0.068

*p < 0.10, **p < 0.05, ***p < 0.01.

Table 10
Part-worth utilities of levels within *Monthly fee* (own table).

	(1)	(2)	(3)
	−20 %	0 %	+20 %
BEV	2.511*	−0.881	−1.630
Male	1.374	−0.226	−1.147
Other	−10.180	6.932	3.248
Age	0.010	0.000	−0.010
Education	−0.143	−0.451	0.594
Income (in kEUR)	−0.003	0.015	−0.013
Rural	1.219	−1.346	0.127
Private CIS available	−1.964	1.735	0.229
_cons	16.717***	2.633	−19.351***
Obs.	516	516	516
adj. R-sq.	−0.004	−0.004	−0.002

*p < 0.10, **p < 0.05, ***p < 0.01.

Table 11
Attribute importances (own table).

	(1)	(2)	(3)	(4)
	Energy price	Walking distance	Reliability	Monthly fee
BEV	4.509***	−4.330***	−1.137	0.957*
Male	−0.127	−0.984	0.498	0.613
Other	−6.556	−9.354	19.446***	−3.536
Age	0.179***	−0.071*	−0.104***	−0.004
Education	−0.028	1.102**	−0.539	−0.535**
Income (in kEUR)	−0.029**	0.024**	0.002	0.003
Rural	3.794***	−2.885**	−1.275	0.367
Private CIS available	2.621	−2.699**	0.429	−0.351
_cons	32.703***	25.474***	29.747***	12.076***
Obs.	516	516	516	516
adj. R-sq.	0.081	0.096	0.028	0.010

*p < 0.10, **p < 0.05, ***p < 0.01.

Data availability

Data will be made available on request.

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