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Consumer preferences for the design of a demand response quota scheme – Results of a choice experiment in Germany

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A B S T R A C T

Demand response (DR) programs are increasingly discussed as policy options to facilitate an efficient energy transition. More recently, quota schemes, a novel type of incentive-based DR program that aims to restrict electricity consumption of some household appliances at certain times, have received considerable attention as a tool for preventing local grid congestion. However, little is known about the preferences of household consumers regarding the design of DR programs in general and quota schemes in particular. We examined the preferences of 1034 German consumers using data from a choice experiment. Our model results show that respondents' choices for quota scheme designs are mainly driven by the time period during which consumption is constrained, followed by the financial compensation. That said, the order of importance reverses if consumers are free to choose whether to participate or not, while the frequency and duration of DR measures remain unimportant. This shift in preferences suggests that preferences for certain DR programs may not necessarily translate into willingness to participate. Sociodemographic characteristics explain these preferences only to a limited extent, with female and older persons and persons currently purchasing green electricity showing a slightly higher willingness to participate. We discuss policy implications arising from these findings.

1. Introduction

The ongoing climate change and its consequences incentivizes many countries around the world to make their energy systems more sustainable. This transformation process involves both the generation side, for example, by expanding photovoltaic, wind, and biomass generation, but also the consumption side with new appliances such as heat pumps or electric vehicles. However, today's grid infrastructure is not designed for such increases in (fluctuating) generation and demand, which results in a need for grid expansion. Grid expansion, on the other hand, besides often falling behind schedule, comes with limited acceptance (see IEA, 2020, p. 13) and considerable costs (for Germany, see, e.g., netztentwicklungsplan.de, 2021). To keep these costs under control and within socially acceptable limits, grid expansion should be economically efficient (see Federal Ministry for Economic Affairs and Energy, 2021), i.e., the marginal utility of grid expansion should be balanced against its marginal costs. In order to enhance economic efficiency, it is essential to include both the generation and the consumption of electricity in the provision of flexibility (e.g., Agora Energiewende, 2019, p. 37). Given these considerations, demand response (DR) programs are becoming increasingly important. DR is defined as a change in the usual consumption behavior in time or quantity in response to an incentive signal or when required by system reliability (Albadi and El-Saadany, 2008). DR programs can be designed for both the commercial and household sector, although recent political discussions have put a higher focus towards the latter (see, e.g., S&P Global Platts, 2020).

A comprehensive body of literature has investigated the effects of DR programs, for example, by modelling their potentials (e.g., Gils, 2014) or by examining how much load is shifted by participating households (e.g., Faruqui et al., 2014; Nilsson et al., 2018). There is, however, a lack of research on why households may choose to participate in DR programs in the first place (see Parrish et al., 2019; Parrish et al., 2020; Sloot et al., 2022). In addition, the focus of these studies is mostly on consumer characteristics, for example, by examining what underlying consumer motivations, such as financial or environmental ones, can explain participation. In contrast, less research has focused on how different design aspects of DR programs determine participation. As DR programs can be designed with a variety of attributes, such as how often or how long households need to provide flexibility, this leads to the question of what type of DR programs consumers prefer. For example, research from

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various fields has shown that consumers are willing to accept less comfortable or more expensive, yet sustainable services or products (e.g., Lehmann et al., 2021; Feldmann and Hamm, 2015), which could also apply to DR programs. The only recent studies that we are aware of by Srivastava et al. (2020) and Yilmaz et al. (2021) examine household preferences for design attributes of DR programs in Belgium and Switzerland, respectively. Both studies, however, focus on Direct Load Control (DLC), a specific type of DR, and have limited and non-representative samples. For more robust and generalizable insights, further results are needed, especially from other countries.

We investigate the preferences of household consumers for participating in quotas schemes, an incentive-based DR program. In quota schemes, if a quota is issued, pre-determined appliances are allowed to obtain only a predefined share (e.g., 50%) of their baseline electrical power during a specific time period (e.g., from 2 to 5 p.m.) (see Sloot et al., 2022). In addition to the time period, quota schemes can vary in other design attributes that should be considered before implementation, such as the number and duration of constraints in electricity consumption and the financial incentives offered. To this end, we conducted a representative online survey with 1034 respondents from Germany in fall of 2020, which included, among others, a choice experiment, where respondents had to repeatedly choose between several DR programs. We also assessed behavioral non-attendance and respondents' sociodemographic characteristics. Since DR is a concept most consumers are unfamiliar with and the stated preferences are hypothetical, we use a novel method to control for consumers' non-attendance to certain design attributes and to identify the underlying reasons explaining why certain attributes do not receive attention.

The remainder of this paper is structured as follows: Section 2 reviews the related literature, presents the research questions and derives hypotheses. Section 3 details the methodology, followed by the results in Section 4. Section 5 concludes with a discussion of the results and outlines future research needs.

2. Theoretical background, research questions and hypotheses

There is a plethora of DR programs that can be broadly divided into the two categories of price-based and incentive-based programs. Price-based programs include, for example, time of use, critical peak pricing, and critical peak rebate programs, while incentive-based programs include, for example, direct load control and interruptible load programs (see Albadi and El-Saadany, 2008). More recently, quota schemes, a special type of interruptible load program, have also been discussed in practice and academia, especially for the household sector (e.g., Sloot et al., 2022). In quota schemes, once a quota is issued, pre-determined appliances (e.g., electric vehicles) are allowed to only consume a certain share (e.g., 50%) of their electrical power during specified time periods (e.g., from 2 to 5 p.m.). Quota schemes come with two key strengths: First, once the number of participants with appropriate appliances is sufficient, the entity that uses the flexibility (e.g., grid operator) can be certain that a quota is met and flexibility is provided. Second, quota schemes give flexibility providers (e.g., households) the opportunity to bilaterally trade the quotas (i.e., the obligations for flexibility provision, see Exner et al., 2020). Although quota schemes can be established by various entities, such as energy suppliers or aggregators, they are currently being discussed mainly as a tool for grid operators to prevent local grid congestion. To this end, grid operators perform ex-ante grid simulations using temporal and spatial generation and consumption data. Based on these simulations, constraints on electricity consumption (i.e., quotas) are communicated to participants with a predefined lead time (e.g., day-ahead).

DR programs must be technically feasible and economically viable, but consumers' willingness to participate is also a key factor. Preliminary evidence suggests that different DR types affect consumers' preferences for participation but research comparing preferences for different programs is scarce. Notably, even within a program type, there can be wide variations in designs, such as which appliances participate in the program, the level of financial compensation, and the extent to which flexibility is required (e.g., Dütschke and Paetz, 2013; Annala et al., 2014; Layer et al., 2017; Yilmaz et al., 2020; Srivastava et al., 2020; Yilmaz et al., 2021). These design attributes are likely to differ in their importance to potentially participating consumers. Yet, little is known about how specific DR programs should be designed to facilitate voluntary participation. This leads to the first research question:

RQ1. *What design attributes of DR programs (i.e., quota schemes) determine the willingness of household consumers to participate?*

Although DR programs offer many design attributes, it is essential to focus on only a few aspects that are believed to be most relevant to potential participants. In our case, these design attributes of quota schemes are the *frequency*, *duration*, and *time period* of quota events, as well as the *financial compensation* offered for participation. These design attributes were selected based on the scientific literature, but also on discussions with experts of the research project *flexQgrid* (Netze BW GmbH, 2021), which focuses on the design, implementation, and piloting of quota schemes in the distribution grid. In the following, the four design attributes are briefly discussed.

Frequency: Whereas static time of use programs typically have the same tariff structure on all (week)days, other programs like critical peak pricing and critical peak rebate programs have irregular variations in their tariff structure or the number of days during which flexibility is required in a given period, for example, on twelve pre-selected days per year (see Faruqui and Sergici, 2011). To date, there is little research that has directly examined the importance of the frequency of flexibility retrieval in DR programs. In general, findings on the importance of convenience loss as a barrier to the diffusion of DR programs suggest that less frequent quotas should be preferred (e.g., Parrish et al., 2020; Paetz et al., 2012). These considerations are in line with the results of Srivastava et al. (2020), who conducted a choice experiment between DR programs in Belgium and varied the number of days per week from two to seven. They find that increasing the number of days is the strongest barrier to acceptance, meaning that consumers prefer programs that require flexibility on fewer weekdays. In the study by Yilmaz et al. (2021), the frequency of interventions is also relevant, but of lesser importance and, in particular, preferences are more heterogeneous. Taking these considerations and findings into account, we arrive at the first hypothesis:

H1. *Consumers prefer DR programs (i.e., quota schemes) with less frequent flexibility retrieval (i.e., fewer quotas per year)*.

Duration: Similar to frequency, a longer duration of a quota event means that consumers need to adjust their habitual behavior and the greater the loss of comfort. So far, research has not paid much attention to the duration of flexibility retrieval as a determinant of program participation. In one study, Aryandoust and Lilliestam (2017) find that acceptance for load shifting of washing machines is high for a duration of 1 h but decreases substantially for longer time periods. In line with this, Radenković et al. (2020) find a high acceptance for load shifting of air conditioners of up to 1 h, but did not examine longer durations. We apply these findings to quota schemes and hypothesize the following:

H2. *Consumers prefer DR programs (i.e., quota schemes) with a shorter duration of flexibility retrieval (i.e., shorter quotas)*.

Time period: Energy behavior tends to be highly habitual (Verplanken and Whitmarsh, 2021) and the use of appliances, such as the use of the washing machine, often follows established routines, which could pose a barrier to available flexibility potential (see D'hulst et al., 2015) or to acceptance (see Parrish et al., 2020) of DR programs. For example, dynamic tariffs with freely varying prices throughout the day have been found to be less attractive to consumers than static tariffs without variation (Nicolson et al., 2018). In line with this, Sundt et al. (2020) find differences in the acceptance of DR programs depending on the time of day, indicating that people require a higher financial compensation for being flexible in the afternoon compared to mornings and evenings. In the study by Yilmaz et al. (2021), the time of day when flexibility is required is also a key factor, at least for some respondents. These results suggest that the time period may be a relevant aspect for consumers. Accordingly, the third hypothesis is as follows:

H3. *Consumers prefer DR programs (i.e., quota schemes) that retrieve flexibility at night and noon (as opposed to mornings, afternoons, and evenings), as they are more likely to be able to adapt their energy behavior during these time periods.*

Compensation: In addition to the impact of DR on daily life behaviors and the associated comfort restrictions, financial incentives are often cited as the most important design attribute of DR programs (see Parrish et al., 2020). Empirical data suggests that study participants are more likely to respond to higher discounts on electricity prices (Faruqui et al., 2014) or to higher one-time payments for participation (Yilmaz et al., 2021), thus leading to the notion that financial incentives may play an important role a-priori in the decision of whether or not to participate. On the other hand, although financial incentives may motivate participation in DR for the majority of consumers, it is questionable whether monetary incentives always drive participation, as some consumers are likely to be insensitive to monetary incentives and may (not) participate for other reasons (see Kim and Shcherbakova, 2011; Gyamfi et al., 2013). Hence, we conclude with the last hypothesis:

H4. *Consumers prefer DR programs (i.e., quota schemes) with a higher financial compensation, yet for some consumers, financial incentives play a subordinate role.*

Whether or not households participate in a DR program and which program they prefer can depend on the individuals, program design, or both (see Section 1). However, the information processing strategies leading to individual decisions are not easily observable. In consequence, if there are several DR programs to choose from, only the design attributes of the programs and their levels, the choices, and perhaps individuals' characteristics are known. In the context of discrete choices, information processing strategies frequently mentioned in the literature include attribute non-attendance (ANA), lexicographic choice behavior, elimination-by-aspects, selection-by-aspects, and heuristics (see Mariel et al., 2021, pp. 87–89). Among these, ANA has received considerable attention in the scientific community and is particularly relevant in the context of DR. ANA is defined as non-compensatory choice behavior where certain attributes of alternatives are ignored in the evaluation of alternatives (Mariel et al., 2021, p. 91).

The reasons for ANA are manifold and can, again, be attributed to the individuals making choices (e.g., their cognitive capabilities (see Hensher et al., 2005)), to the alternatives available (e.g., a high number of alternatives, attributes, and attribute levels (see Hensher, 2014)), or to the context (e.g., complex or unfamiliar choice situations (Mariel et al., 2021, p. 93)). However, compared to what attributes of DR programs consumer prefer, even less is known about why individuals tend to ignore certain attributes. This leads to the second research question:

RQ2. What attributes of DR programs (i.e., quota schemes) are more likely to be ignored and why?

While individuals may ignore an attribute as it is actually irrelevant for their decisions, there is reason to believe that other factors may be at play. Given the unfamiliarity of DR programs to consumers, ANA may also be driven by the complexity of an attribute. According to Hensher et al. (2005), the complexity of an attribute can either be caused by being too difficult to evaluate (for example, individuals may struggle to assess its upsides and downsides) or by making a trade-off against the effort required for processing (for example, individuals may feel that assessing an attribute is not worth the time required). Consequently, we will examine if the three reasons for ANA proposed in the literature (i.e., complexity, not being worth the effort, or irrelevance) can be empirically distinguished and whether they influence individuals' preferences regarding the four attributes of quota schemes.

3. Methodology

To answer the research questions and to test the hypotheses from Section 2, we conducted an online survey with 1034 German household consumers in fall of 2020 that is representative in terms of age, gender, and education (see Section 3.3).[1] The survey included the three following parts, among others[2]: a choice experiment where respondents had to choose between different quota schemes (see Section 3.1), questions regarding ANA (see Section 3.2), and questions regarding respondents' sociodemographic characteristics (see Section 3.3). The survey was implemented and conducted using the software *Lighthouse Studio* (Sawtooth Software Inc, 2021a).

3.1. Choice experiment

Numerous approaches exist for measuring individual preferences (see Breidert et al., 2006). In choice experiments, individuals have to repeatedly choose from different alternatives, which are composed of multiple attributes (e.g., quality and price) and attribute levels (e.g., low and high). By observing and examining individuals' choices, their preferences can be derived. In contrast to other approaches, the main advantage of choice experiments is their high degree of realism, as choosing between several alternatives is an everyday situation (see, e.g., Johnson and Orme, 1996; Desarbo et al., 1995).[3] Choice experiments are mostly based on the theory of consumer behavior by Lancaster (1966) and the random utility theory (see, e.g., Horowitz et al., 1994). The theory of consumer behavior posits that the utility of an alternative results from its attributes, while the random utility theory states that a person usually chooses the alternative that gives him or her the highest utility.[4] Based on the findings in Section 2, *frequency*, *duration*, and *time period* of quota events, as well as the financial *compensation* for participation were chosen as attributes of quota schemes in our choice experiment. Each attribute comprises different levels (see Table 1), which are briefly explained below.

Frequency: Future technical restrictions on the grid infrastructure (e.

Table 1
Attributes and levels in the choice experiment.

Attributes	Levels				
Frequency	5	15	25	35	–
Duration	0.5 h	1 h	2 h	3 h	–
Time period	Morning[a]	Noon	Afternoon	Evening	Night
Compensation	30€	60€	90€	120€	150€

[a] Reference level.

[1] Even though we use the term households in this paper, our analysis is based on individual consumer preferences that are not necessarily representative for their household. This is a common problem of empirical studies (see, e.g., Seebauer et al., 2017), as the households' willingness to participate can be the product of multiple household members' preferences and social influences processes within the household.

[2] The remaining, but irrelevant parts of the survey for this study, can be found in Sloot et al. (2022).

[3] Other advantages of choice experiments include the low propensity of individuals to give strategic answers (see Mariel et al., 2021, p. 27), to give socially desirable answers (see Donche et al., 2015, p. 87), and their suitability for low-involvement products (see Huber et al., 1992).

[4] Other behavioral models also exist, such as random regret minimization (Chorus et al., 2008). Depending on the context, these models may explain choices better than random utility models (see, e.g., Boeri and Longo, 2017).

g., maximum power of a transformer in a local grid) in combination with electricity demand (e.g., number and timing of electric vehicles charging) will determine the frequency of local quota events. However, neither can be predicted with certainty today. Hence, it is not surprising that the number of interventions in DR programs in comparable studies varies significantly from multiple interventions per week (e.g., Srivastava et al., 2020) to only a few interventions per year (e.g., Yilmaz et al., 2021). As we faced the same problem, we consulted representatives of a distribution system operator and set the annual number of quota events at *5*, *15*, *25*, and *35*. The minimum number of quota events can be considered the technically necessary lower limit for quota schemes to be effective.

Duration: Very short-term reductions in electric power consumption pose the risk that grid congestion will reoccur after a quota event expires, as constrained appliances are likely to make up for their electricity demands (see also Hu et al., 2016). Accordingly, depending on local and temporal conditions, there is a minimum duration that a quota event should last (see also Yilmaz et al., 2021). On the other hand, it is reasonable to believe that there is a maximum duration of DR measures that households are willing to accept (see, e.g., Aryandoust and Lilliestam, 2017). With this in mind, and again in consultation with representatives of a distribution system operator, we set the levels of this attribute to 0*.5h*, *1h*, *2h*, and *3h*.

Time period: The five levels *morning* (6–9 a.m.), *noon* (11 a.m.–2 p. m.), *afternoon* (2–5 p.m.), *evening* (7–10 p.m.), and *night* (1–4 a.m.) of this attribute were defined considering the standard load profile H0 for German household consumers (BDEW, 2017). During these time periods, the H0 load profile shows certain patterns, such as a strong increase in electricity consumption in the morning starting at 6 a.m. or a high absolute level in the evening hours.

Compensation: It is important to consider a realistic range of financial incentives for participation based on technical and economic constraints. For example, the opportunity costs of grid, generation, and/or storage expansion should be the upper limit in DR programs (see also Kim and Shcherbakova, 2011). Assuming that the flexibility of quota schemes serves to stabilize the local grid, current regulation may also place an upper limit on financial incentives for participation in quota schemes. In Germany, grid fees currently account for around 25% of the end-consumer price (see BDEW, 2021). With an electricity consumption of 2000 kWh for an electricity-intensive appliance (e.g., electric vehicle[5]) and a price of about 30 cents per kilowatt hour (see BDEW, 2021), the maximum discount on grid fees amounts to 2000 × 0.30 x 0.25 = 150 euros per year. For enough variation in the choice sets (see, e.g., Rose and Bliemer, 2014; Holmes et al., 2017), the levels were set to *30€*, *60€*, *90€*, *120€*, and *150€*.

Willingness to participate: In choice experiments, respondents are often asked to choose one of the alternatives displayed (so-called forced choices), followed by the question whether they would actually choose the alternative they had chosen before (so-called free choices). This dual response approach (see, e.g., Diener et al., 2006) provides information on both respondents' preferences for the attributes and for (not) choosing an alternative, that is, the none-option.[6] We also used this approach in our choice experiment, but replaced the discrete choice with a 7-point Likert scale ranging from 1 ("certainly not") to 7 ("certainly yes") in the free choice part.[7] This allowed our respondents to provide more accurate feedback on whether they would actually participate in the respective quota scheme.

A short introduction video at the beginning of the survey introduced quota schemes to our survey participants and explained the attributes (see Supplementary Material). Electric car, heat pump, air conditioner, washing machine, and dishwasher were stated as appliances of a household affected by a quota scheme. Respondents were told that these appliances cannot be charged or used during a quota event. Although dishwashers and washing machines have low electrical powers and are therefore unlikely to have a relevant impact on local grid congestion when part of a DR program (see also D'hulst et al., 2015; Yamaguchi et al., 2020), these appliances are well known to the German population (unlike, for example, electric vehicles, which are not yet widespread), so that constraints on their use and behavioral impacts are more readily understood.

It should be kept in mind that in a survey, financial incentives may initially seem attractive, with consumers having trouble to grasp the consequences of their choices in a real-world scenario. To address hypothetical bias, we included a cheap talk script (Cummings and Taylor, 1999), which reminded half of respondents of the hypothetical nature of the survey. The other half did not get to see the cheap talk script, which allows us to check whether the script worked.[8]

3.2. Latent variables and sociodemographic variables

We asked respondents to indicate the extent to which they ignored an attribute in six questions (items) for each attribute on a 7-point Likert scale. These questions addressed the three reasons for ANA described in Section 2, namely the *cognitive complexity* of an attribute (e.g., "*This attribute was too difficult to evaluate.*"), the *cognitive costs* necessary to process its information (e.g., "*I ignored this attribute to make my decision easier.*"), and the actual *irrelevance* of an attribute (e.g., "*This attribute was completely irrelevant for my decision.*"). The responses to these items entered our second model as latent variables (LV) (see Section 3.4) and are described in more detail in the Supplementary Material.

Finally, and in addition to questions on ANA, we asked questions about respondents' sociodemographic characteristics (i.e., gender, age, education, and net household income) and current living conditions (i. e., whether they purchase green electricity, are homeowners, and own at least one appliance with high electrical power demand[9]). For a description of the LV and sociodemographic characteristics, see Tables 8 and 9 in the Appendix, respectively.

3.3. Data collection and sample description

Data on a representative quota sample with regard to age, gender, and education (based on gik, 2020) was collected with the help of a professional online panel provider. The initial sample of 1102 respondents was screened for extreme response behavior in the choice tasks (see Schlereth and Skiera, 2017), straightlining of the item questions (see Schonlau and Toepoel, 2015), and attention check items (see Abbey and Meloy, 2017) already during the survey. Post data collection, the sample was further screened for very short response times on item

[5] The average energy consumption of an electric car is about 15 kWh per 100 km (Verivox, 2021). With an annual charging capacity of 2000 kW h, this results in an annual mileage of 13,333 km, which is approximately equivalent to the average annual mileage of German passenger cars 2020 (KBA, 2021).

[6] The dual response approach is particularly useful if a high proportion of respondents choose the none-option, as it increases statistical efficiency and power (Diener et al., 2006). For the downsides of DR, see, for example, Schlereth and Skiera (2017).

[7] Likert scales are often used for certainty questions that (are intended to) measure uncertainty in respondents' choices (see, e.g., Ready et al., 2010; Fifer et al., 2014; Beck et al., 2016).

[8] For an overview of ex-ante methods to reduce hypothetical bias, see Mariel et al. (2021, pp. 19–23).

[9] In this work, appliances with high electric power demand include electric car, heat pump, and air conditioner.

questions (<2 s[10]) as well as randomized choices in combination with speeding (see Orme, 2019), with the latter defined as being faster/slower than 95% of respondents, resulting in the final sample with 1034 respondents. This sample is largely representative even if compared with data from the German Federal Statistical Office, though minor deviations, mainly in home ownership and household size, are apparent (see Table 2).

3.4. Models

We estimated a Joint Model (JM) to capture individuals' preferences in the first (the forced choice) and second (the free choice) stage of each choice task (RQ1). The JM contains a Mixed Multinomial Logistic (MIXL) model component for the forced choice data and a Mixed Ordered Logit (OL) model component for the free choice data. Second, to examine the reasons of ANA (RQ2), we estimated a Hybrid Choice Model (HCM) that uses the forced choice data only. This model includes a MIXL model component and a structural equation model (SEM) component. As the names of their model components suggest, both models include continuous parameters with inter-individual mixing (i.e., heterogeneity across respondents) for the attributes described in Section 3.1. By doing so, we are able to account for unobservable preference heterogeneity and get further insights into respondents' choice behavior. Using continuous parameters places high demands on data quantity and quality (see Hess and Train, 2011). Yet, in our case, there are sufficient observations both at the sample and respondent level.[11] For model estimations, we relied on the R package 'Apollo' (Hess and Palma, 2021) and its implementation of Hierarchical Bayes (HB) estimation using the Metropolis Hastings algorithm. Both models, the JM and the HCM, are briefly described in the subsequent sections.

Table 2
Sample characterization (N = 1034).

	Sample (%)	German average (%)
Gender		
Male	49.0	49.5
Female	51.0	50.5
Age		
18–24 years	8.4	11.9
25–29 years	8.3	7.2
30–39 years	16.1	14.8
40–49 years	16.8	15.0
50–59 years	21.5	19.0
60 years or older	28.9	32.1
Education		
No degree	0.6	4.2
Secondary school graduate	36.8	30.8
General certificate of secondary education	26.2	31.1
General higher education qualification	36.5	33.9
Household income (monthly net)		
Less than 900€	10.2	8.2
900–1500€	17.8	17.5
1500–2000€	13.7	15.4
2000–2600€	15.5	15.7
2600–3200€	15.6	11.7
3200–4500€	16.0	16.6
More than 4500€	11.2	14.9
Home ownership		
Ownership	37.6	46.5
Rental	62.4	53.5
Household size		
1 person	32.7	41.9
2 persons	48.8	33.8
3 persons	10.7	11.9
4 persons	5.9	9.0
5 persons and more	1.8	3.4

[a] Own calculations based on data for 2018 of the Federal Statistical Office (Federal Statistical Office, 2020a, 2020b, 2020c, 2020a).

3.4.1. Joint Model

The JM (see Fig. 1) comprises a MIXL model (see Hensher and Greene, 2003) and an OL model (see Hess and Palma, 2021, pp. 52–54) component. As is common in choice modeling, we used an additive utility function, so that deterministic utility V of respondent n for alternative j in choice situation t is given by:

$$V_{n,j,t} = c + \beta_n' X_{n,j,t} \tag{1}$$

where c denotes a constant, β the vector of part-worth utilities, and X the design matrix. We chose a normal prior distribution for the non-monetary attributes *frequency*, *duration*, and *time period*, so that $\beta_{A,n} = \mu_A + \sigma_A \xi_{A,n}$, with μ_A and σ_A being the means and standard deviations, respectively, and $\xi_{A,n}$ denoting standard normal variates. To avoid negative parameter estimates for increases in the monetary attribute *compensation*, we chose a lognormal prior distribution, yet augmented with the Fosgerau and Mabit (2013) polynomial to control for its heavy tail property (see also Hensher and Greene, 2011).[12] Hence, the coefficient for *compensation* can be expressed as:

$$\beta_{C,n} = \exp\left(\mu_{C,log} + \sigma_{C,log}\xi_{C,n,log} + \sigma_{C,log,2}\xi^2_{C,n,log}\right) \tag{2}$$

In eq. (2), $\mu_{C,log}$ denotes the mean for the log of the positive *compensation* coefficient and $\sigma_{C,log}$ and $\sigma_{C,log,2}$ account for inter-individual heterogeneity. With regard to attribute coding, it is worth noting that for reducing model complexity, only the *time period* was modeled as discrete (i.e., one parameter per attribute level), but the other attributes as continuous (i.e., one parameter per attribute).[13]

To check for effects of sociodemographic characteristics (e.g., gender) and current living conditions (e.g., whether there is at least one appliance with high electrical power demand in the respective household) on respondents' behavior in the forced choices, we integrated covariates z into the part-worth utility coefficients β.[14] In the case of the non-monetary attributes, covariates entered additively, so that $\widetilde{\beta}_{A,n} = \beta_{A,n} + \delta_A z_{A,n}$, whereas for *compensation*, covariates entered the exponential directly, so that $\widetilde{\beta}_{C,n} = \beta_{C,n} \cdot \exp(\delta_{C,log} z_{C,n})$. Both, δ_A and $\delta_{C,log}$, measure the effects of the covariates on the part-worth utilities.

It remains to explain constant c in eq. (1): in the case of the forced choices, c was defined as an alternative-specific constant c_j capturing left-right effects (see Daly et al., 2016). For the free choices, however, c captures the fixed effects of the covariates on utility in the OL model component, i.e., $\widetilde{c}_n = \delta_c z_{c,n}$, allowing us to measure the effects of respondents' characteristics on their rating on general willingness to

[10] For faster responses, it is assumed that respondents were unable to read and cognitively process an item.

[11] In total, we have 1034 × 12 = 12,408 observations for the free and forced choices, respectively.

[12] Note that, strictly speaking, *frequency* and *duration* are negative attributes, which is why a distribution limited to negative values may seem appropriate. However, besides being more complex and thus leading to problems in model estimation, using a lognormal distribution (with and without the Fosgerau and Mabit (2013) polynomial) also resulted in a reduced model fit.

[13] In our case, a test between two MNL models, the first with one continuous parameter for each of the attributes *frequency* and *duration* and the second with one parameter for each attribute level, resulted in only moderate differences in model fit.

[14] Between all covariates used, the maximum bivariate correlation found was 0.33 (between income and house ownership), indicating no strong multicollinearity (see Dormann et al., 2013).

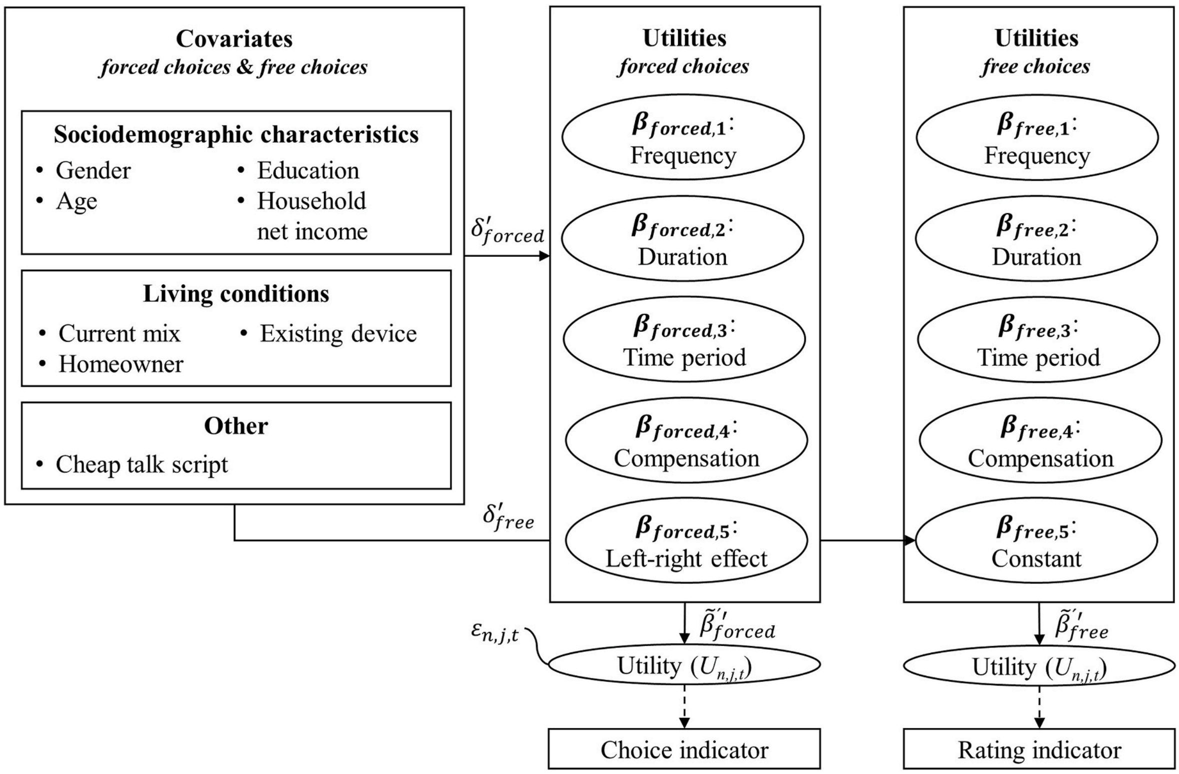

Fig. 1. Structure of the joint model.

participate in quota schemes.

In the OL model component, the probability of observing rating p in choice situation t, with $p = 1, \ldots, 7$ corresponding to the responses in the Likert scale questions, is given by (see Hess and Palma, 2021, p. 52):

$$P_{Y_{n,t}=p} = \frac{e^{\tau_p - V_{n,t}}}{1 + e^{\tau_p - V_{n,t}}} - \frac{e^{\tau_{p-1} - V_{n,t}}}{1 + e^{\tau_{p-1} - V_{n,t}}} \tag{3}$$

whereas τ_p denotes the threshold parameters to be estimated and $V_{n,t}$ is the determisitic utility of the alternative that a respondent had preferred in the forced choices plus the constant. Please note that the OL model component uses the same prior distributions for its part-worth utilities as the MIXL model component, but without attribute-specific covariates to reduce model complexity.[15] For a detailed description of the covariates and their effects on the respective model coefficients, see Tables 9 and 10 in the Appendix, respectively.

3.4.2. Hybrid Choice Model

There is no clear answer on how to include ANA in choice modeling (Hensher et al., 2005). While basic approaches simply set the utility coefficients of (allegedly) ignored attributes (close) to zero, more sophisticated approaches use, for example, differing scale parameters or utility coefficients for subsets of respondents (Mariel et al., 2021, pp. 91–92). Recent approaches use Hybrid Choice Models (HCM) that treat respondents' answers to behavioral ANA questions as dependent variables (e.g., Hess and Hensher, 2013), thus circumventing the endogeneity problem when including the answers as exogenous covariates. HCMs can further account for different sensitivities in the effects of ANA on utility coefficients, which is essential, as respondents' answers and behaviors do not necessarily have to coincide (see Hess and Hensher, 2010; Hensher, 2014).

Building upon these findings and recent approaches, we specified our HCM inspired by Hess and Hensher (2013), but extended and adapted for the purpose of this study. Specifically, our HCM differs in one major aspect: Respondents were asked not only if they ignored a certain attribute, but also to what extent and why (see Section 3.2), allowing us to incorporate more detailed information on ANA into our model.

The HCM (see Fig. 2) is similar in structure to the JM, but is restricted to the forced choice data. Therefore, it has no OL model component. Further, we no longer use covariates z to explain differences in the sensitivities of the part-worth utilities β, but to explain the LV α_l in the structural equation model, with two LV per attribute k, $k = 1, \ldots, 4$ and thus $l = 1, \ldots, 8$. An error component $\sigma_l \xi_{n,l}$ accounts for random heterogeneity, with $\xi_{n,l}$ being a standard normal variate,[16] so that LV l for respondent n is given by:

$$\alpha_{n,l} = \gamma_l' z_{n,l} + \sigma_l \xi_{n,l} \tag{4}$$

with γ_l measuring the effects of the covariates on α_l. It is important to note than even though it was our initial intention to separate between the three reasons for ANA given by Hensher et al. (2005), principal component analysis (see Supplementary Material) did not allow for separation, but led us to merge the LV *cognitive complexity* and *cognitive costs*.

The responses to the 24 behavioral ANA questions $I_{k,s}$, $s = 1, \ldots, 6$, were measured on a 7-point Likert scale. We used linear regression to explain the responses (see Hess and Palma, 2021, pp. 55–56).

The effects of the LV on the parameters of the MIXL model component were established using shrinkage factors λ explaining the scaling of

[15] In general, it is also possible to use the same part-worth utilities in multiple model components, but with differing scale parameters (see Hensher and Bradley, 1993). In the study at hand, however, not only the scales but also the marginal rates of substitution between the forced and free choices differ, making this an inadequate approach (see Bradley and Daly, 1997).

[16] For normalization of the LV, we set their scale to be equal to one of their indicators, as described in Ben-Akiva et al. (2002), rather than fixing their variances (see Bolduc et al., 2005).

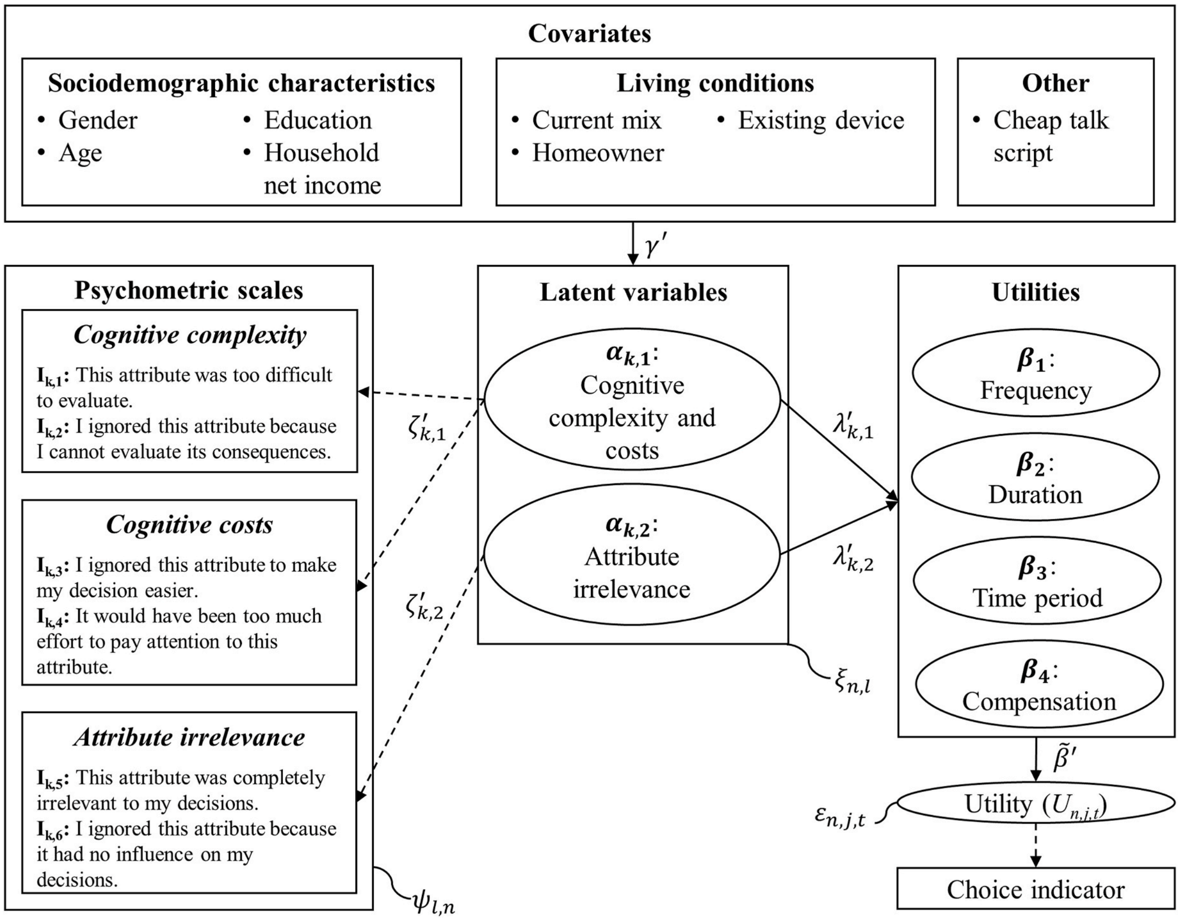

Fig. 2. Structure of the Hybrid Choice Model with two latent variables per attribute.

part-worth utilities (see Hess and Hensher, 2013), so that part-worth utility $\widetilde{\beta}_{k,n}$ after incorporating the LV on ANA can be expressed as:

$$\widetilde{\beta}_{k,n} = \frac{1}{e^{\lambda_{k,1}\alpha_{k,1}+\lambda_{k,2}\alpha_{k,2}}}\beta_{k,n} \tag{5}$$

From eq. (5), it follows that if the exponent in the denominator is positive, a respondent's part-worth utility decreases and vice versa.

4. Results

The comprehensive analyses using two separate models allow only excerpts of the results to be presented.[17] Model results not included in this section can be found in the Appendix and Supplementary Material, respectively. To check internal validity, we calculated the HIT rate, both for the JM and HCM. The HIT rate measures the percentage of correct predictions in a given data set (see Louviere et al., 2000, p. 56). In the JM, the HIT rates are 80.15% (MIXL model component) and 50.27% (OL model component), whereas in the HCM, the HIT rate is 82.18%. These values indicate a good model fit.[18]

4.1. Joint Model

4.1.1. Attributes

Starting with the JM, all continuous parameters have the expected signs (see Table 3), i.e., an increase in the *frequency* and *duration* of quotas events leads to a decrease in utility, whereas utility increases with *compensation*. This result supports H1 and H2 (i.e., that DR programs with less frequent and shorter quota events are preferred) and also in part H4 (i.e., that consumers prefer higher financial compensations). With regard to the latter, it should be noted that parameter $\sigma_{C,log,2}$ is not significant in the MIXL model component, meaning that the non-parametric distribution for *compensation* collapses to a (parametric) lognormal distribution. The heavy tail property of the lognormal distribution indicates some respondents having extreme utilities for *compensation*, but we will come to this again in the next paragraph. The picture is more diverse concerning the *time period*: with *morning* being the reference, a change from this level to *noon, afternoon, or evening* leads, on average, to disutility. While rejection for the latter two time periods was to be expected, the preference for quota events in the *morning* rather than at *noon* is surprising, as people are usually more likely to be at home and thus to consume electricity in the early hours (see, e.g., Sundt et al., 2020). Therefore, H3 is only partially supported. This, however, may be a temporary result of the Corona situation, which causes people to spend more time at home, especially for work (see Demmelhuber et al., 2020). In contrast, the on average strongest preference for quota events at *night* is in line with expectations, meaning that respondents prefer *time periods* for DR measures that do not result in restrictions in comfort or behavior (see, e.g., Vanthournout et al., 2015; D'hulst et al., 2015). Yet, the potential effectiveness of quotas at *night* to avoid grid congestion is likely to be limited, since households – at least

[17] Tests for interaction effects between attributes (see Sawtooth Software Inc., 2021b) resulted in only marginal gains in the log-likelihood function, but deterioration in the information criteria.

[18] The HIT rates with the naïve models are 33.33% for the MIXL and 14.29% for the OL model components, respectively.

Table 3
Results for the parameters of the Joint Model.

				μ		σ		σ2	
Model component	Attribute	Level	Importance[h]	post μ	post σ	post μ	post σ	post μ	post σ
Choice model: Mixed Logit[a]	Frequency[c]	5, 15, 25, 35	13.50 (11.77)	−0.365***	0.034	0.544***	0.024	–	–
	Duration[d]	0.5 h, 1 h, 2 h, 3 h	12.96 (11.54)	−0.445***	0.037	0.499***	0.027	–	–
	Time period[e]	Morning[g]	42.86 (43.77)	–	–	–	–	–	–
		Noon		−0.930***	0.097	1.847***	0.090	–	–
		Afternoon		−1.493***	0.113	1.820***	0.090	–	–
		Evening		−1.265***	0.124	2.091***	0.091	–	–
		Night		1.844***	0.091	2.024***	0.083	–	–
	Compensation[f]	30€, 60€, 90€, 120€, 150€	30.68 (26.15)	−0.233**	0.090	1.084***	0.111	−0.055	0.079
	Left-right effects	Left	–	0.017	0.036	–	–	–	–
		Center		0.065+	0.037	–	–	–	–
		Right		–	–	–	–	–	–
Choice model: Ordered Logit[b]	Frequency[c]	5, 15, 25, 35	13.52 (11.34)	−0.149***	0.032	0.736***	0.035	–	–
	Duration[d]	0.5 h, 1 h, 2 h, 3 h	16.41 (13.56)	−0.197***	0.039	0.923***	0.040	–	–
	Time period[e]	Morning[g]	28.35 (25.93)	–	–	–	–	–	–
		Noon		−0.282**	0.095	1.555***	0.126	–	–
		Afternoon		−0.622***	0.112	1.284***	0.150	–	–
		Evening		−0.245**	0.078	0.923***	0.143	–	–
		Night		1.566***	0.094	2.549***	0.079	–	–
	Compensation[f]	30€, 60€, 90€, 120€, 150€	41.72 (48.53)	0.277***	0.064	2.121***	0.153	−3.458***	0.225

$p < 0.10$: +, $p < 0.05$: *, $p < 0.01$: **, $p < 0.001$: ***, using quantile-based credibility intervals.
[a] Forced choice data.
[b] Free choice data.
[c] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 10 quota events.
[d] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 1 h.
[e] Discrete attribute in preference space with normal distributions; (dis-)utility for a change from the reference level.
[f] Continuous attribute in preference space with nonparametric distribution; (dis-)utility for an increase by 30€.
[g] Reference level.
[h] Mean (median) attribute importance in percent based on the individual part-worth utilities (see Orme, 2002).

today – typically use the least electricity during this *time period* (see, e.g., Mathieu et al., 2011; Sundt et al., 2020). On the other hand, with many of them charging their electric car at home at night, this could change in the future.

A look at the average importance values[19] of the attributes (see Table 3) reveals that when respondents have to choose a quota scheme, their choices are mainly driven by the *time period* (43.77%), followed by the amount of monetary *compensation* (26.15%). *Frequency* and *duration*, on the other hand, show similarly low relative importance values of 11.77% and 11.54%, respectively. This picture changes when looking at the results of the OL model component: even though the relative importance values of *frequency* (11.34%) and *duration* (13.56%) hardly change, *time period* (25.93%) and *compensation* (48.53%) swap places. The latter leads to the conclusion that, at least from an aggregated perspective, monetary incentives are the main motivation for participation in quota schemes when consumers are free to choose whether to participate or not (see also Annala et al., 2014). On the other hand, one should keep in mind that a high (negative) utility of a quota scheme in the forced choices does not necessarily imply that respondents would (not) participate in the respective program.

That said, when looking at the empirical distribution functions of the importance values (see Fig. 3 and Fig. 4), it emerges that 18.86% of our respondents show importance values ≤ 10% for *compensation* in the OL model component (in contrast to 1.16% in the MIXL model component). This suggests that monetary incentives are negligible for a sizeable portion of consumers, speaking in favor of H4. Altogether, the distribution functions show that the curves of *time period* and *compensation* are virtually swapped between the two model components, as indicated by the mean importance values before, while the curves of *frequency* and *duration* are quite similar.

When comparing the model components, it is also important to note

[19] For information on how the importance values are calculated, see Orme (2002).

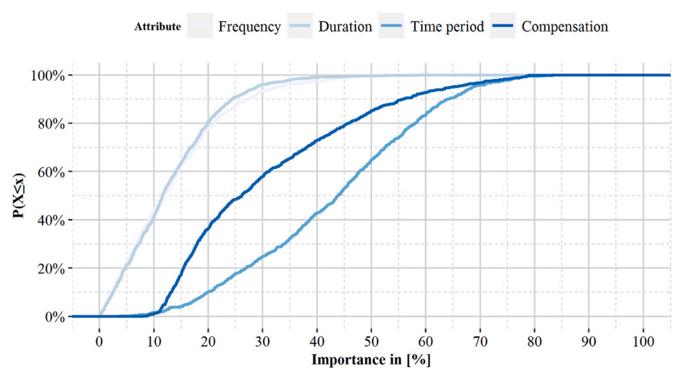

Fig. 3. Empirical distribution functions of conditional attribute importance values of the MIXL model component.

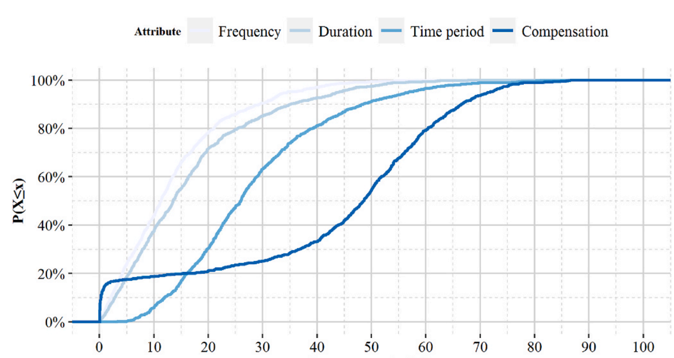

Fig. 4. Empirical distribution functions of conditional attribute importance values of the OL model component.

that the sensitivity in parameters, with the exception of the parameter of *compensation*, decreases substantially in the OL model, whereas the standard deviations do not change by the same factors. These changes in sensitivities may in part be the result of changes in preferences, but may also be attributed to changes in scale, i.e., the responses in the (forced) choice tasks were more deterministic than the responses in the (free) ratings tasks. This gives reason to believe that factors other than the attributes of the alternatives affect respondents' willingness to participate in quota schemes (see also Sloot et al., 2022). These differences in scale, however, do not reflect in importance ratings. Yet, separating these two effects is anything but trivial.[20] Finally, and with regard to the distribution parameters, it remains to say that the standard deviations are high in relation to the means in both model components, pointing towards strong preference heterogeneity in the attributes under investigation. Distribution and density plots of the part-worth utilities and importance values can be found in the Appendix and Supplementary Material.

4.1.2. Covariates analysis

Our results regarding the covariates, i.e., respondents' sociodemographic characteristics and current living conditions, shed some light on the sources of preference heterogeneity (see Table 4). For example, women have a slightly stronger aversion to more frequent quota events (−0.122), and also to quotas at *noon* (−0.323) and in the *afternoon* (−0.394). Since even today women are more likely to stay at home with children compared to men, they are also more likely to be affected by quota events during these *time periods*. On the other hand, model results indicate a lower aversion to quotas in the *evening* (0.335), a lower preference for quotas at *night* (−0.221), and a higher willingness to participate in general (0.326). The latter may be caused by women usually being more environmentally conscious and more engaged in environmentally friendly behavior (see, e.g., Gómez-Román et al., 2021; Afonso et al., 2018). The effect of age is clearly pro-quota: when age increases by ten years, the negative utility of *frequency* and *duration* of quota events decreases (by 0.071 and 0.069, respectively), sensitivity to financial *compensation* is attenuated (by factor $e^{0.065} = 0.937$), and willingness to participate is enhanced (by 0.130). These results may be unintuitive, as older generations are usually more critical of innovations (see, e.g., Berkowsky et al., 2018) and are said to have lower environmental motivations (see, e.g., Gifford and Nilsson, 2014), although some studies refute the latter (see, e.g., Gómez-Román et al., 2021). On the other hand, older individuals often spend more time at home, which may increase their ability to provide flexibility and reduce their (perceived) disutility (see Kessels et al., 2016). Contrary to age is the effect of education, i.e., they are contra-quota: First, the negative sensitivity to *frequency* (−0.087) and *duration* (−0.122) increases with levels of education. Moreover, sensitivity to *compensation* (0.104), but also to the *time periods night* (0.105) and *noon* (0.273), increase. The latter could be related to the fact that as education increases, so does the labor force participation rate (bpb 2021), leading to a preference for *time periods* during working hours. Small differences in the sensitivities to the financial *compensation* (0.055) also appear as respondents' income grows. From a legal perspective, the distinction between homeowners and tenants is essential, as the latter may not be allowed to undertake necessary infrastructure measures to participate in DR programs.[21] However, in our results (in contrast to, for example, Kessels et al., 2016), homeowners show a slightly greater aversion (−0.271) to quota schemes which may hamper their diffusion.

When interpreting the results of the covariate analysis, it is also important to consider the effect of the current electricity mix. Respondents who stated to purchase green electricity (i.e., electricity exclusively from renewables) show a significantly higher willingness to participate in quota schemes (0.571). The conscious purchase of green electricity may be considered as proxy of environmental motivations (Lehmann et al., 2021).

The last covariate, the cheap talk script, shows an attenuating effect by factor $e^{-0.218} = 0.804$ on the sensitivity of the *compensation* coefficients, meaning that respondents who saw the script gain less utility from monetary incentives. This result suggests that the script worked as respondents tend to overestimate positive financial incentives in hypothetical choices (see also Penn and Hu, 2019; Kowalska-Pyzalska, 2016).

4.1.3. Cluster analysis

To identify respondents with similar attribute importance values and to facilitate interpretation, we performed a cluster analysis.[22] To this end, we used a Gaussian Mixture Model implemented in the R-package 'mclust' by Fraley et al. (2020), allowing for probabilistic class assignment (see Izenman, 2008, p. 453). The number of clusters was determined specifically based on two criteria: First, improvements in the Bayesian Information Criterion (BIC) (see Baudry et al., 2010) and second, the ability to interpret cluster centroids (see also Yan, 2005, pp. 4–5). This approach resulted in three and two classes for the MIXL and OL model components, respectively.[23] The cluster centroids and sizes are shown in Table 5. Graphics of the clusters can be found in Figs. 6 and 7 in the Appendix.

In the first and largest cluster of the MIXL model component, respondents place the greatest focus on the *time period* (59.68%), followed at great distance by *compensation* (18.81%), while *frequency* (11.15%) and *duration* (10.36%) play a negligible role. In cluster two, this picture changes: Now *compensation* is the most important attribute (51.01%) compared to the *time period* (32.92%). The analogue in the OL model component is its first and biggest cluster with 859 respondents, i.e., for the majority of consumers *compensation* is the key criterion for (non-)participation in a quota scheme. On the other hand, the remaining 175 respondents in cluster two show no sensitivity to *compensation* at all. This results speaks also in favor of H4 (see Section 4.1.1), that is, financial incentives are important for participation, yet not for all consumers. It is also worth mentioning that in all five clusters, that is, even in the third and most balanced cluster, the *time period* is always ranked first or second. This is another indication that consumers do not want to be (strongly) affected by quotas in their behavior (see Section 4.1.1).

4.2. Hybrid Choice Model

4.2.1. MIXL model component

In the HCM, the effects of the LV on the parameters of the MIXL model component are measured using shrinkage factors λ (see Section 3.4.2), which are shown in Table 6. Starting with the first LV *cognitive complexity and costs*, it is evident that all effects, with the exception of the effects on *night* and *compensation*, are non-significant. In these two cases only, we find a negative correlation between the *cognitive complexity and costs* of an attribute and the sensitivities in parameters, with the latter being reduced by factors $1/e^{(0.165)} = 0.848$ and $1/e^{(0.107)} = 0.899$, respectively. This result may be surprising, since monetary amounts are actually something familiar to respondents and individual consequences of nightly quotas should be easy to assess. On the other hand,

[20] For a discussion on the challenges and pitfalls of separating preference and scale heterogeneity, see, e.g., Hess and Train (2017) and Mariel et al. (2021, pp. 85–86).

[21] For example, as recently as the end of 2020, there was a change in law that gives tenants in Germany the right to a private charging station, as long as they bear the costs for hardware and installation (see German Federal Government, 2020). Prior to that, tenants had to rely on the concession of their landlord.

[22] For a discussion on clustering based on conditional estimates, see, for example, Eagle and Magidson (2020).

[23] We compared solutions with two to five clusters. For more than three (MIXL model component) and two clusters (OL model component), however, meaningful interpretation of the cluster centroids was hampered.

Table 4
Results for the covariates of the Joint Model.

Model component	Attribute	Level	Sociodemographic characteristics				Current living conditions			Other
			δ_{Gender}	δ_{Age}	$\delta_{Education}$	δ_{Income}	$\delta_{CurrentMix}$	$\delta_{Homeowner}$	$\delta_{ExistingDevice}$	$\delta_{CheapTalk}$
Choice model: Mixed Logit[a]	Frequency[c]	5, 15, 25, 35	−0.122**	0.071***	−0.087***	–	–	–	0.106+	–
	Duration[d]	0.5 h, 1 h, 2 h, 3 h	0.053	0.069***	−0.122***	–	–	–	0.030	–
	Time period[e]	Morning[g]	–	–	–	–	–	–	–	–
		Noon	−0.323*	−0.196***	0.273***	–	–	–	0.378***	–
		Afternoon	−0.394**	0.018	0.054	–	–	–	0.660***	–
		Evening	0.335+	0.092+	−0.017	–	–	–	0.284	–
		Night	−0.221+	0.024	0.105+	–	–	–	0.005	–
	Compensation[f]	30€, 60€, 90€, 120€, 150€	−0.024	−0.065+	0.104**	0.055+	–	–	–	−0.218*
Choice model: Ordered Logit[b]	Constant	–	0.326***	0.130***	−0.080	0.054	0.571***	−0.271+	0.155	–

$p < 0.10$: +, $p < 0.05$: *, $p < 0.01$: **, $p < 0.001$: ***, using quantile-based credibility intervals.
[a] Forced choice data.
[b] Free choice data.
[c] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 10 quota events.
[d] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 1 h.
[e] Discrete attribute in preference space with normal distributions; (dis-)utility for a change from the reference level.
[f] Continuous attribute in preference space with nonparametric distribution; (dis-)utility for an increase by 30€.
[g] Reference level.

Table 5
Results of the cluster analyses using Gaussian Mixture models for the Joint Model. Cluster centroids expressed as importance of the attributes (in percent).

	Mixed Logit[e]			Ordered Logit[f]	
Attribute	I	II	III	I	II
Frequency[a]	11.15	7.72	21.71	10.95	26.09
Duration[a]	10.36	8.35	20.27	12.85	33.85
Time period[b]	59.68	32.92	34.52	26.05	39.66
Compensation[c]	18.81	51.01	23.50	50.15	0.39
Cluster size[d]	371	332	331	859	175

[a] Continuous attribute in preference space with normal distribution.
[b] Discrete attribute in preference space with normal distributions.
[c] Continuous attribute in preference space with nonparametric distribution.
[d] Assignment of respondents based on the highest class membership probability.
[e] Forced choice data.
[f] Free choice data.

respondents may have had difficulties in assessing the *compensation* in relation to their income and the constraints in electricity consumption imposed by quota schemes. With regard to complexity of nightly quotas, respondents may have considered future scenarios with electric vehicles (which only 2.32% of our respondents currently have), charging at *night* and needed the next morning.

It is doubtful that the *cognitive complexity and costs* of the other attributes and levels in fact had no influence on individual choice behavior, as for the LV *attribute irrelevance*, a completely different picture emerges: all shrinkage factors, with the exception of the *time period night*, are (highly) significant different from zero and reduce sensitivities by up to factor $1/e^{(0.598)} = 0.550$. These differences in the shrinkage factors between the two LV may have two reasons: First, it is reasonable to believe that respondents who have difficulties or are unwilling to cognitively evaluate attributes are (also) unwilling to admit this, but rather increase their rating on the items of the second LV *attribute irrelevance*. On the other hand, the attributes might indeed not have resulted in cognitive (over-)load. However, respondents' unfamiliarity with DR programs makes the latter seem rather unlikely.

4.2.2. Latent variables: Structural equation model component

Table 7 presents the results of the structural equation model component and should be interpreted against the results from Section 4.2.1. Starting with the first explanatory variable, gender, there is a negative correlation with both *cognitive complexity and costs* and *attribute irrelevance*, except for *compensation*, which proves insignificant. Hence,

Table 6
Effects of the latent variables on the coefficients of the Hybrid Choice Model.

Model component	Attribute	Level	Cognitive complexity and costs		Attribute irrelevance	
			post μ	post σ	post μ	post σ
Choice model: Mixed Logit[a]	Frequency[b]	5, 15, 25, 35	0.088	0.069	0.474***	0.052
	Duration[c]	0.5 h, 1 h, 2 h, 3 h	0.162	0.113	0.598***	0.115
	Time period[d]	Morning[f]	–	–	–	–
		Noon	−0.047	0.082	0.133**	0.073
		Afternoon	0.093	0.077	0.192***	0.063
		Evening	−0.063	0.073	0.251***	0.072
		Night	0.165*	0.078	0.051	0.058
	Compensation[e]	30€, 60€, 90€, 120€, 150€	0.107+	0.058	0.415***	0.046

$p < 0.10$: +, $p < 0.05$: *, $p < 0.01$: **, $p < 0.001$: ***, using quantile-based credibility intervals.
[a] Forced choice data.
[b] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 10 quota events.
[c] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 1 h.
[d] Discrete attribute in preference space with normal distributions; (dis-)utility for a change from the reference level.
[e] Continuous attribute in preference space with nonparametric distribution; (dis-)utility for an increase by 30€.
[f] Reference level.

Table 7
Results of the structural equation model.

		Cognitive complexity and costs								Attribute irrelevance							
		Frequency		Duration		Time period		Compensation		Frequency		Duration		Time period		Compensation	
		post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ	post μ	post σ
Covariates	Gender	−0.084⁺	0.050	−0.108*	0.058	−0.097*	0.043	−0.008	0.065	−0.177*	0.078	−0.131⁺	0.067	−0.150***	0.047	−0.037	0.074
	Age	0.129***	0.024	0.128***	0.022	0.074***	0.021	0.101***	0.026	0.183***	0.035	0.196***	0.033	0.083***	0.029	0.148***	0.033
	Education	−0.129***	0.026	−0.131***	0.025	−0.142***	0.023	−0.113***	0.030	−0.243***	0.038	−0.192***	0.036	−0.164***	0.029	−0.119**	0.041
	Income	–	–	–	–	–	–	−0.063***	0.022	–	–	–	–	–	–	−0.101***	0.034
	ExistingApp	0.089	0.083	0.120	0.094	0.140*	0.069	–	–	0.279***	0.103	0.151	0.097	0.153*	0.071	–	–
	CheapTalk	–	–	–	–	–	–	−0.027	0.073	–	–	–	–	–	–	0.042	0.088
Standard deviation		1.128***	0.038	1.092***	0.037	0.965***	0.034	1.177***	0.042	1.619***	0.065	1.639***	0.042	1.225***	0.038	1.698***	0.046

$p < 0.10$: +, $p < 0.05$: *, $p < 0.01$: **, $p < 0.001$: ***, using quantile-based credibility intervals.

female respondents show lower values in both LV, meaning that women first, state to have a higher cognitive capability and will of assessing the attributes of quota schemes, but also to put a higher emphasis on the attributes in their choices. Contrary to gender are the effects of age, which are positive across both LV and all attributes, but with small differences in the effect sizes: These are somewhat larger for *frequency* and *duration*, i.e., for these attributes differences in the LV between younger and older respondents increase more rapidly as age increases. This is in line with research showing that (perceived) cognitive ability often decreases with advancing age (see, e.g., Deary and Der, 2005; Westerman et al., 1995), but this effect may be even more pronounced for DR programs in general and for the more abstract and less easy to grasp attributes *frequency* and *duration* in particular. As expected, the effects of education are highly significant and negative across all LV and attributes, i.e., as education increases, the values for both *cognitive complexity and costs* and *attribute irrelevance* decrease. This suggests that individuals do not only differ in their cognitive capabilities, but also in their willingness to process complex information (Layer et al., 2017; Hensher et al., 2005), with education being a proxy for cognitive ability.

With regard to appliances with high electric power (e.g., electric vehicles), we only found differences between respondents regarding *time period* and *frequency*. Concerning the former, respondents with at least one such appliance show higher values in both *cognitive complexity and costs* and in *attribute irrelevance*. Yet, it is especially these respondents who should be more capable of assessing the consequences of constraints on their appliances at certain *time periods*, which does not seem to be the case. On the other hand, their higher values regarding the *attribute irrelevance* of *frequency* are in line with our expectations and thus point into the direction that these respondents are more capable of assessing the consequences of quota schemes. To summarize, however, no valid conclusion can be drawn in this regard.

Before moving to the discussion of our overall findings in the next section, it is worth to also take a look at the standard deviations of the LV. The standard deviations are quite homogenous within the reasons for ANA and across attributes, but differences occur between the reasons, with the standard deviations of *attribute irrelevance* being higher than the standard deviations of *cognitive complexity and costs*. This, again, gives reason to believe that heterogeneity in responses, actually attributable to the LV *cognitive complexity and costs*, was self-shifted towards the LV *attribute irrelevance*.

5. Conclusion and policy implications

5.1. Key findings, implications and future research

The increase in fluctuating electricity generation, on the one hand, and the increasing electrification of consumption, on the other, require enhanced coordination between these two sides. With regard to electricity consumption, demand response (DR) programs are becoming increasingly important. DR is defined as a change in usual consumption behavior in time or quantity in response to an incentive signal or when required by system reliability (Albadi and El-Saadany, 2008). More recently, quota schemes, an incentive-based DR program, where consumers are allowed to obtain only a predefined share of their baseline electrical power (e.g., 50%) during a quota event, have received attention from academia, industry, and policy makers (e.g., Sloot et al., 2022). Compared to other DR programs, such as time of use prices, quota schemes put forward the advantages of predictability and reliability for flexibility users (e.g., grid operators), two key factors for preventing local grid congestions. However, little is known about the preferences of household consumers regarding the design aspects of DR programs in general and quota schemes in particular. Furthermore, even less is known about individuals' cognitive processes underlying their decisions about DR programs. To this end, we conducted a representative online survey with 1034 respondents from Germany, which included a choice experiment, where respondents had to choose repeatedly between varying quota schemes and answer questions about their willingness to participate in the quota schemes, as well as behavioral attribute non-attendance (ANA) questions. ANA is defined as non-compensatory choice behavior where certain attributes of alternatives are ignored (Mariel et al., 2021, p. 91).

From an aggregate perspective, our model results show, that, when respondents have to choose their preferred quota scheme, choices are mainly driven by the *time period* of quota events, followed by the financial *compensation*. Far less important are the *frequency* and *duration* of quota events. While *frequency* and *duration* remain unimportant when respondents indicate their willingness to participate in a second step, the order between the *time period* and *compensation* is reversed. This shift in importance values suggests that while respondents may have a clear preference for or against certain (design attributes of) quota schemes, these preferences do not necessarily translate into willingness to participate. Correspondingly, our analysis of individual survey participants and the cluster analysis suggest that about one-sixth to one-fifth of the respondents show negligible importance values for the financial *compensation*, which is in line with other studies suggesting that financial incentives may not always motivate participation (e.g., Gyamfi et al., 2013; Kim and Shcherbakova, 2011; Sloot et al., 2022; Yilmaz et al., 2021).

However, one should keep in mind that the amounts of possible financial compensations depend on both the regulatory framework and the use case of quota schemes. For example, the regulatory framework in Germany might change in the future, possibly giving grid operators more leeway to increase financial compensations beyond the waiver of grid charges. Furthermore, quota schemes could be used by other stakeholders of the energy system such as energy suppliers or aggregators to steer electricity demand into time periods when electricity is abundant and (almost) free (e.g., during excess generation of renewables). While in the second case, determining the amount of compensation is a business decision, changes in the regulatory framework are political ones, i.e., politicians should also consider the costs of alternative measures (e.g., grid reinforcement and expansion instead of using flexibility only). Future research should explore whether the low sensitivities of some respondents to the financial incentives shown in our survey are the result of the financial *compensation* being too small or whether some individuals are simply not motivated by any financial incentive relative to comfort restrictions. With regard to the latter, the use of automation technologies might alleviate some of the negative effects of quota schemes (see Sintov and Schultz, 2015).

From a policy and practitioner's point of view, the results from our cluster analysis suggest that target group-specific appeals may be necessary to spur participation as long as participation is not mandatory. These should focus on those attributes of quota schemes particularly important for a certain subgroup of consumers, for example, communicating minimal comfort restrictions to consumers that are not very sensitive to financial incentives (e.g., quotas mainly at times when electricity is not urgently needed). Moreover, consumers could be targeted based on their individual motivations. The latter can be achieved, for example, through environmental appeals to environmentally conscious individuals (see Sloot et al., 2022). Yet, in practice it remains difficult to identify target groups. Often, only sociodemographic characteristics are observable and known about (potential) participants. In this regard, our results suggest that advertising statements should focus on female and older persons. Both not only show a higher willingness to participate, but also a higher willingness to accept quotas at peak times, something that may be increasingly relevant for preventing grid congestion in the future. In addition, the current type of electricity tariff (a proxy of environmental motivations) is a strong predictor for participation, with respondents currently consciously purchasing green electricity (i.e., electricity exclusively from renewables) being more likely to indicate high participation ratings. Our results are thus consistent with studies regarding preferences for green and local electricity (e.g., Lehmann et al., 2021, 2022; Bigerna and Polinori, 2019; Kowalska-Pyzalska, 2019). When interpreting these model results it should be kept in mind that the effects of respondents' sociodemographic characteristics on their choices are small, suggesting that practitioners should put a stronger focus on psychographic criteria (see Sloot et al., 2022). Even though gathering data on psychographic criteria is only possible at great expense today, this may change in the future as digitalization advances.

With regard to advertising quota schemes, it is important to bear in mind that marketing must convince at least the energy decision-maker of a household to participate in a quota scheme, or even all members of a household. In practice, it is likely that decisions about participation are made collectively rather individually and a household decision to participate may thus be the result of multiple individual preferences and motivations, as well as social influence processes between household members. What is more, marketing often comes with considerable costs, yet without guaranteeing that a sufficient participation rate in every grid segment will be achieved. One option to counter this problem of high costs is to make participation mandatory instead of voluntarily, especially for households with high power appliances that cause grid congestion (e.g., electric vehicles). Setting this default may be a more efficient option than building upon voluntariness, even though it may hamper the acceptance of quota schemes (see Sloot et al., 2022).

Individuals differ both in their capabilities and in their willingness to process (complex) information (see Layer et al., 2017). Van Trijp et al. (1996) use the term 'cognitive misers' to describe consumers' attempts to limit their time and effort devoted to behavior. In contrast, researchers often specify utility functions assuming unlimited cognitive capacities to arrive at a utility-maximizing choice (Hensher et al., 2005). Hence, including ANA in choice models constitutes an important element to better understand decision-making processes. Addressing this research area in the context of DR and building upon the work of Hensher et al. (2005) and Hess and Hensher (2013), we specified a model incorporating two reasons for ANA, these are, (i) the cognitive complexity and costs and (ii) the actual irrelevance of an attribute.

With DR in general and quota schemes in particular being a relatively new concept (at least from the perspective of household consumers), there is reason to believe that unfamiliarity with and complexity of design attributes lead to different degrees of ignoring them when making choices. To this end, we specified a HCM using the responses to behavioral ANA questions as latent variables (LV), which, in turn, are used to explain differences in the sensitivities of parameters. In conclusion, while directly inquiring about the reasons for ignoring certain attributes allows for more flexibility to incorporate ANA and may increase model fit and prediction accuracy, our results also indicate that this method has limitations in terms of revealing the true underlying reasons for ANA. This is most likely due to the fact that individuals are unwilling to admit that they are not (sufficiently) capable or willing of assessing an attribute in a decision-relevant manner. This may indicate that they rather tend to state that an attribute is irrelevant. Future research is needed to delve deeper into individuals' cognitive processes ignoring certain attributes, especially in new (and possibly cognitive-demanding) choice situations. More specifically, future research could use LV not directly addressing the attributes of quota schemes, but rather more general constructs such as LV on respondents' price sensitivity in everyday life or on their amenability to new technologies (cf. Sloot et al., 2022). This could reduce the risk of biased item responses and increase generalizability of results.

5.2. Limitations

First and foremost, as DR programs are something unfamiliar to household consumers, it is possible that at least some of our respondents did not fully understand the design attributes and their consequences on daily life, or may have even been overburdened by the choice situations. We addressed this problem with an adequate survey design (e.g., introduction video, explanatory texts, info buttons, graphics, etc.), yet this risk can never be ruled out (see Coast et al., 2012). In the same vein is hypothetical bias, i.e., since the choice situations were hypothetical, respondents were not incentivized to reveal their true preferences. Even though this applies to the vast majority of today's surveys, especially if the concepts under investigation are not (yet) marketable (see Ryan et al., 2012), hypothetical bias is one of the main criticisms in survey research (see Beck et al., 2016).[24] Especially with online surveys, sample quality is difficult to assess (see Mariel et al., 2021, pp. 54–58). For example, researchers are unable to control for external influences, and self-selection bias may be present (see Bethlehem, 2010). Finally, it is important to keep in mind that our survey represents a snapshot of current preferences of German household consumers, restricting the possibility of making predictions into the future (see Abou-Zeid et al., 2014).

CRediT authorship contribution statement

Nico Lehmann: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Daniel Sloot:** Conceptualization, Methodology, Software, Validation, Investigation, Writing – original draft, Writing – review & editing, Project administration. **Armin Ardone:** Conceptualization, Supervision, Writing – review & editing, Resources, Funding acquisition. **Wolf Fichtner:** Supervision, Writing – review & editing, Resources, Funding acquisition.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2022.113023.

A. Appendix

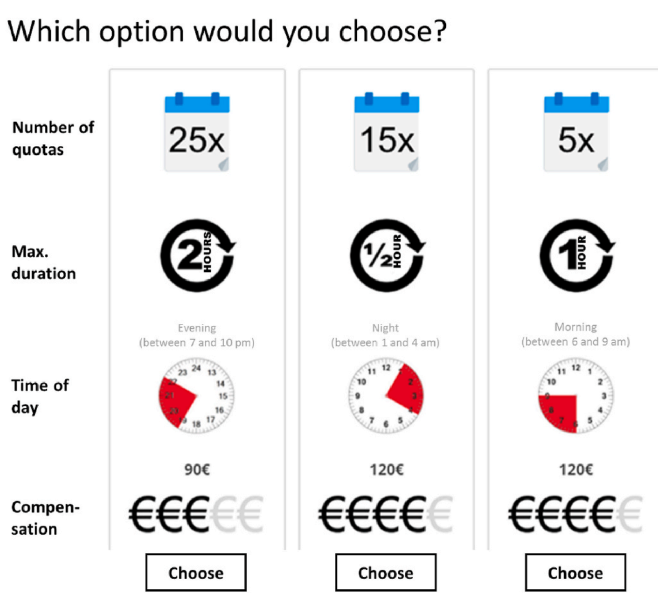

Fig. 5. Exemplary choice set (texts translated from German).

[24] For an overview of measures to reduce hypothetical bias in surveys, see Mariel et al. (2021, pp. 16–23).

Table 8
Descriptions of items and original assignment to the latent variables.

Item		Latent variable		
Name	Description	α_1: Cognitive complexity	α_2: Cognitive costs	α_3: Attribute irrelevance
I_1	*"This attribute was too difficult to evaluate."*	x		
I_2	*"I ignored this attribute because I cannot evaluate its consequences."*	x		
I_3	*"I ignored this attribute to make my decision easier."*		x	
I_4	*"It would have been too much effort to pay attention to this attribute."*		x	
I_5	*"This attribute was completely irrelevant to my decisions."*			x
I_6	*"I ignored this attribute because it had no influence on my decisions."*			x

Table 9
Description of covariates (N = 1034).

	Name of the covariate	Level of measurement	Value range [a]	Transformations	Description [b]
Sociodemographic characteristics	Gender	Nominal scale	{0, 1}	–	Gender, measured in two classes. (1) Male [49.0%] (2) Female [51.0%]
	$\text{Age}_{\text{centered}}$	Ratio scale	[-3.01, 3.69]	Mean centering Division by ten	Age, measured in years. [Min = 18.0, $Q_{0.25}$ = 35.0, $Q_{0.50}$ = 50.0, Mean = 48.1, $Q_{0.75}$ = 61.0, Max = 85.0]
	$\text{Education}_{\text{centered}}$	Ordinal scale	[-2.33, 2.67]	Mean centering	Education, measured in six classes. (1) No graduation [0.6%] (2) Secondary school graduate [36.8%] (3) General certificate of secondary education [26.2%] (4) General higher education qualification [15.6%] (5) Bachelor's degree or equivalent [7.2%] (6) Master's degree (formerly diploma) or higher [13.6%]
	$\text{IncomeClass}_{\text{centered}}$	Ordinal scale	[-3.04, 3.96]	Mean centering	Net household income, measured in eight classes and in euros per month. (1) 900 euros [9.3%] (2) 900–1500 euros [16.2%] (3) 1500–2000 euros [12.6%] (4) 2000–2600 euros [14.2%] (5) 2600–3200 euros [14.3%] (6) 3200–4500 euros [14.6%] (7) 4500–6000 euros [7.8%] (8) 6000 euros [2.4%] (9) No information [8.6%]
Current living conditions	CurrentMix	Nominal scale	{0,1}	–	Current electricity tariff is a green electricity tariff (1) [c]. [36.4%]
	Homeowner	Nominal scale	{0,1}	–	Is (co-)owner of a residential property (1). [37.6%]
	ExistingApp	Nominal scale	{0,1}	–	Has at least one of the following appliances: electric car, heat pump, air conditioner (1). [20.4%]
Other	CheapTalk	Nominal scale	{0,1}	–	Got the CheapTalk script displayed (1). [49.5%]

[a] Value range in the statistical model after transformations.
[b] Relative shares in square brackets.
[c] "Don't know" responses are included as "No" responses.

Table 10
Effects of covariates on the model coefficients considered in the analyses.

				Sociodemographic characteristics				Current living conditions			Other
Model	Component	Attribute	Level/Latent variable	Gender	Age	Education	IncomeClass	CurrentMix	Homeowner	ExistingApp	CheapTalk
Joint Model	Choice model 1: Mixed Logit[a]	Frequency[c]	5, 15, 25, 35	x	x	x				x	
		Duration[d]	0.5 h, 1 h, 2 h, 3 h	x	x	x				x	
		Time period[e]	Morning[g], Noon, Afternoon, Evening, Night	x	x	x				x	
		Compensation[f]	30€, 60€, 90€, 120€, 150€	x	x	x	x				x
	Choice model 2: Ordered Logit[b]	Frequency[c]	5, 15, 25, 35								
		Duration[c]	0.5 h, 1 h, 2 h, 3 h								
		Time period[d]	Morning[g], Noon, Afternoon, Evening, Night								
		Compensation[e]	30€, 60€, 90€, 120€, 150€								
		Constant	–	x	x	x	x	x	x	x	
Hybrid Choice Model	Choice model: Mixed Logit[a]	Frequency[c]	5, 15, 25, 35								
		Duration[d]	0.5 h, 1 h, 2 h, 3 h								
		Time period[e]	Morning[g], Noon, Afternoon, Evening, Night								
		Compensation[f]	30€, 60€, 90€, 120€, 150€								
	Structural equation model	Frequency[c]	Cognitive complexity and costs	x	x	x				x	
			Attribute irrelevance	x	x	x				x	
		Duration[d]	Cognitive complexity and costs	x	x	x				x	
			Attribute irrelevance	x	x	x				x	
		Time period[e]	Cognitive complexity and costs	x	x	x				x	
			Attribute irrelevance	x	x	x				x	
		Compensation[f]	Cognitive complexity and costs	x	x	x				x	
			Attribute irrelevance	x	x	x				x	

Effect considered in the respective model component: yes (x), no ().
[a] Forced choice data.
[b] Free choice data.
[c] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 10 quota events.
[d] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 1 h.
[e] Discrete attribute in preference space with normal distribution; (dis-)utility for a change from the reference level.
[f] Continuous attribute in preference space with nonparametric distribution; (dis-)utility for an increase by 30€.
[g] Reference level.

Table 11
Results of the measurement model of the Hybrid Choice Model.

		Effect[b]		Standard deviation	
		ζ		$\sigma_{k,s}$	
Indicator	Latent variable[a]	post μ	post σ	post μ	post σ
$I_{1,1}$	$\alpha_{1,1}$	1	–	1.160	0.028
$I_{1,2}$	$\alpha_{1,1}$	1.156	0.039	0.942	0.032
$I_{1,3}$	$\alpha_{1,1}$	1.112	0.045	1.070	0.029
$I_{1,4}$	$\alpha_{1,1}$	1.107	0.041	0.882	0.031
$I_{1,5}$	$\alpha_{1,2}$	1	–	1.054	0.060
$I_{1,6}$	$\alpha_{1,2}$	1.007	0.046	1.124	0.051
$I_{2,1}$	$\alpha_{2,1}$	1	–	1.018	0.024
$I_{2,2}$	$\alpha_{2,1}$	1.146	0.040	0.784	0.024
$I_{2,3}$	$\alpha_{2,1}$	1.132	0.037	0.766	0.023
$I_{2,4}$	$\alpha_{2,1}$	1.112	0.038	0.673	0.022
$I_{2,5}$	$\alpha_{2,2}$	1	–	0.783	0.050
$I_{2,6}$	$\alpha_{2,2}$	0.972	0.032	0.921	0.048
$I_{3,1}$	$\alpha_{3,1}$	1	–	0.971	0.023
$I_{3,2}$	$\alpha_{3,1}$	1.198	0.042	0.689	0.021
$I_{3,3}$	$\alpha_{3,1}$	1.130	0.037	0.616	0.019
$I_{3,4}$	$\alpha_{3,1}$	1.135	0.037	0.568	0.020
$I_{3,5}$	$\alpha_{3,2}$	1	–	0.751	0.043
$I_{3,6}$	$\alpha_{3,2}$	1.021	0.043	0.603	0.055
$I_{4,1}$	$\alpha_{4,1}$	1	–	0.957	0.027
$I_{4,2}$	$\alpha_{4,1}$	1.074	0.040	0.809	0.025
$I_{4,3}$	$\alpha_{4,1}$	1.017	0.044	1.082	0.030
$I_{4,4}$	$\alpha_{4,1}$	1.015	0.036	0.804	0.025
$I_{4,5}$	$\alpha_{4,2}$	1	–	0.826	0.048
$I_{4,6}$	$\alpha_{4,2}$	0.975	0.031	0.961	0.049

[a] Frequency: $\alpha_{k,1}$, Duration: $\alpha_{k,2}$, Time period: $\alpha_{k,3}$, Compensation.$\alpha_{k,4}$
[b] For normalization of the latent variables, their scale was set equal to the first indicator (see Ben-Akiva et al., 2002).

Table 12
Results for the threshold parameters of the OL model component.

Thresholds[a]	post μ	post σ
τ_1	−4.825	0.134
τ_2	−3.544	0.132
τ_3	−2.517	0.128
τ_4	−0.820	0.133
τ_5	1.588	0.143
τ_6	5.049	0.170

[a]For normalization: $\tau_0 = -\infty$ and $\tau_7 = \infty$.

Table 13
Results for the parameters of the MIXL model component of the Hybrid Choice Model.

			μ		σ		σ_2	
Model component	Attribute	Level	post μ	post σ	post μ	post σ	post μ	post σ
Choice model:	Frequency[b]	5, 15, 25, 35	−0.313***	0.022	0.337***	0.033	–	–
Mixed Logit[a]	Duration[c]	0.5 h, 1 h, 2 h, 3 h	−0.281***	0.036	0.251***	0.042	–	–
	Time period[d]	Morning[f]	–	–	–	–	–	–
		Noon	−1.065***	0.072	1.890***	0.066	–	–
		Afternoon	−1.549***	0.102	1.733***	0.119	–	–
		Evening	−1.027***	0.126	2.008***	0.091	–	–
		Night	1.613***	0.079	1.939***	0.079	–	–
	Compensation[e]	30€, 60€, 90€, 120€, 150€	0.183	0.128	1.001***	0.185	−0.926***	0.143
	Left-right effects	Left	0.026	0.035	–	–	–	–
		Middle	0.069*	0.035	–	–	–	–
		Right	–	–	–	–	–	–

$p < 0.10$: +, $p < 0.05$: *, $p < 0.01$: **, $p < 0.001$: ***, using quantile-based credibility intervals.
[a] Forced choice data.
[b] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 10 quota events.
[c] Continuous attribute in preference space with normal distribution; (dis-)utility for an increase by 1 h.
[d] Discrete attribute in preference space with normal distribution; (dis-)utility for a change from the reference level.
[e] Continuous attribute in preference space with nonparametric distribution; (dis-)utility for an increase by 30€.
[f] Reference level.

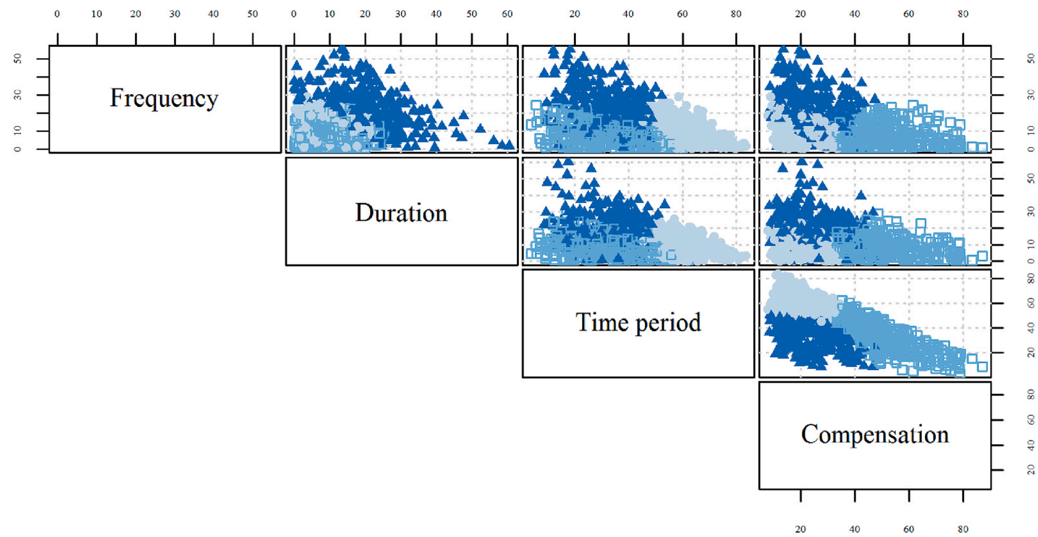

Fig. 6. Result of the cluster analysis of the attribute importance values in the Mixed Logit model component (in percent, including covariates) of the Joint Model using a Gaussian Mixture model and three classes.

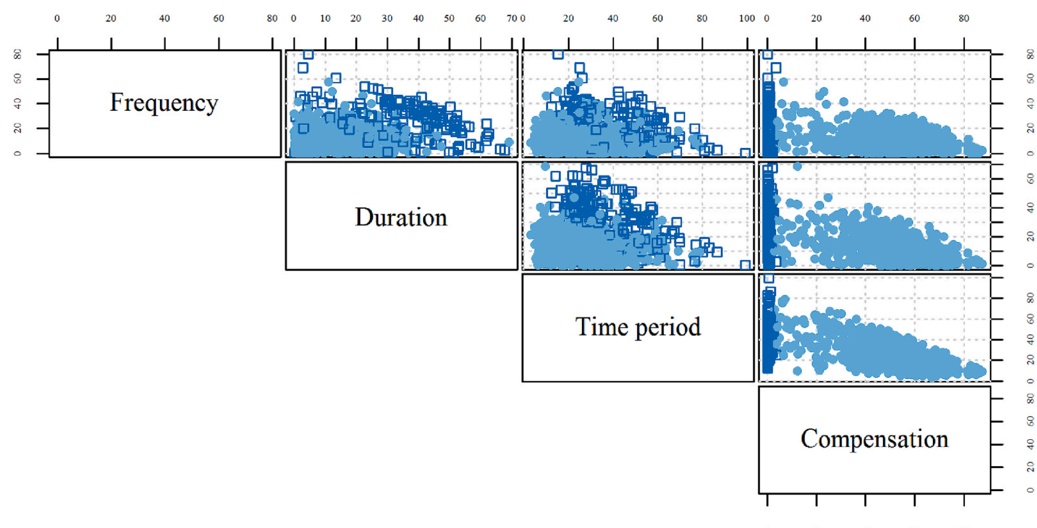

Fig. 7. Result of the cluster analysis of the attribute importance values in the Ordered Logit model component (in percent, excluding covariates) of the Joint Model using a Gaussian Mixture model and two classes.

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