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Research paper

Stated car choices in Norway and Italy: a comparison based on the integrated choice and latent variable model

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A B S T R A C T

The study investigates whether the large difference in battery electric vehicle (BEV) uptake between Norway and Italy could be explained by differences in car buyers' preference structures, either in terms of their evaluation of the vehicles' characteristics or in terms of their perceptions\attitudes towards BEVs. Based on stated preference data collected in the two countries, we find that car drivers evaluate vehicle attributes very similarly. Norwegians value BEV driving range slightly more and are more sensitive to fuel\electricity costs. *Ceteris paribus*, Italian respondents, in contrast to Norwegian ones, still prefer petrol cars to BEVs. The results of the integrated choice and latent variable (ICLV) model indicate that respondents' perceptions\attitudes influence car choice in both countries. In Norway, BEVs are preferred by those who view them as economically, environmentally, technically, and morally superior. In Italy, the evidence is similar but for the environmental aspects, which are not decisive for BEV choice. Such perceptions\attitudes are correlated with age, sex, and BEV density.

1. Introduction

Norwegian and Italian car drivers make very different car choices. In Italy in 2024 (ACEA, 2025), petrol (PVs), diesel (DVs), and hybrid (HEVs) vehicles constituted most (82.9 % of new registrations) of the passenger-car market, while other fossil fuel-based cars, such as liquefied petroleum gas (LPG) and compressed natural gas (CNG) cars, constituted 9.5 % and 0.1 %, respectively. Electric vehicles (EVs)[1] captured a market share equal to only 7.5 %, of which 4.2 % battery electric vehicles (BEVs) and equally 3.3 % plug-in hybrid electric vehicles (PHEVs). In stark contrast, in 2024 BEVs dominated the Norwegian car market with a market share of 88.9 %. PHEVs declined to 2.7 %. The remaining shares went to HEVs, DVs and PVs, with 5.3 %, 2.3 % and 0.8 %, respectively (others fuel cars were negligible). Our research aims to explore the determinants of such huge difference. The factors are many and may be grouped into demand, supply (including infrastructure) and policy factors. This paper deals mainly with the demand factors. Hence, we studied consumers' choices. The focus of this specific paper is on latent variables (economic, environmental, technical and moral motives), studied jointly with the observed factors associated with the vehicle characteristics.

To the best of our knowledge, few studies have contrasted consumers' car choice in different countries. Tanaka et al. (2014) compared consumers' willingness to pay (WTP) for BEVs and PHEVs in Japan and four United States (US) states, two countries with similar wealth when the EV uptake was in the early stages. They found that US car buyers were more sensitive to fuel-cost reductions and alternative fuel-station availability than Japanese buyers. In a base case, they see no prospect for EV uptake in either country, while in an innovation scenario, the prospects are good in both countries. Helveston et al. (2015) compared US and China; in this case, two countries different in both wealth and car diffusion. They found that differences in consumer preferences led to different outcomes, with China having a greater potential for earlier BEV adoption, given adequate supply. Noel et al. (2019) compared stated car-driver choices in five very similar Nordic countries: Denmark, Finland, Iceland, Norway, and Sweden. They found a high sensitivity to driving range and charging time, the former differing among countries while the latter showed similar values. All these studies have focused on choice determinants such as vehicle characteristics (i.e. purchase price, brand, fuel cost, driving range, acceleration time, and air emissions) or

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[1] Throughout the paper, we will use the acronym 'EV' to mean both BEVs and PHEVs.

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charging-related issues (charging-station availability, fast-charging capability, home-charging costs, and vehicle-to-grid [V2G] capability). Rotaris et al. (2021) compared stated car choices in Italy and Slovenia, two countries similar in terms of wealth and both in the early stages of EV uptake. In addition to the vehicle characteristics and charging issues, they extended the choice model to investigate the role of knowledge and environmental awareness in shaping car choices in the two countries. They found that price sensitivity was higher in Italy, while the sensitivity to driving range and fuel economy was higher in Slovenia. They documented a statistically significant positive impact of environmental awareness on the choice of electric cars, stronger for Italians than for Slovenians.

This study adds to this comparative literature a case study concerning two European countries at very different stages of EV penetration and the development of a fast-charging network. Both countries have high car-ownership levels, slightly higher in Italy than in Norway (670 cars/10^3 inhabitants in Italy vs. 520 cars/10^3 inhabitants in Norway). Italy is, however, a much denser country in terms of population at the national level (195 inhabitants/km[2] vs. 14 inhabitants/km[2] in Norway) and in the major cities (1547 inhabitants/km[2] in Oslo vs. 2142 inhabitants/km[2] in Rome, 7548 inhabitants/km[2] in Milan or 7773 inhabitants/km[2] in Naples). There are also differences in wealth: Italy has a gross national product (GNP) (PPA) per capita of $41,433 while Norway has a GNP (PPA) per capita of $74,356. Importantly, the two countries have adopted very different car fiscal policies, particularly concerning vehicle-registration tax. Norway imposes a car-acquisition tax based on tare weight, CO_2 and NOx emissions, and scrapping cost and, in addition, made the crucial decision to exempt BEVs from value-added tax (VAT). Italy relies on a more traditional registration tax based on engine power and grants slightly differentiated subsidies based on CO_2 emissions.

The main aim of this study, and its contribution to the literature, is to test whether and how such differences and the different paths in the historical variation of the fleet composition are associated with car drivers' preferences, either in terms of their evaluation of the vehicles' characteristics or in terms of their perceptions of\attitudes towards EVs. One might think that in Norway, the larger and almost decade-old EV penetration, denser charging infrastructure, greater direct experience with EVs, deeper knowledge of their pros and cons, and larger social acceptance might be associated with a different evaluation of the vehicles' characteristics and a different attitude towards\perception of BEVs. Our results indicate only minor differences in the former and slightly more pronounced differences in the latter across the various segments of the population, indicating that the considerably different levels of EV uptake are a result of very different contextual and policy factors.

Our analysis exploits a recent survey of 1144 respondents in the two countries. The focus was on the car choices that car drivers stated they would make under a set of hypothetical scenarios. Data collection took place via an internet-based questionnaire. Specific features of our survey were the following.

- The respondents were asked to choose between five powertrains: PVs, DVs, HEVs, PHEVs, and BEVs.
- We deliberately used simplified choice scenarios comprising only three attributes (net purchase price, driving range, and fuel/energy cost) for the reasons discussed in detail in subsection 3.1.
- Such a choice was made to leave respondents more time and attention to answer a set of questions related to the evaluation of EVs' economic, technical, environmental, and moral features.
- Although we also collected information on the household-fleet composition, in contrast to Fevang et al. (2021), our units of analysis are individual respondents.

The motivations and pros and cons of our survey design are discussed below. We modelled car choices using two specifications: a random-parameter logit (RPL) model and an integrated choice and latent variable (ICLV) model. The former is capable of capturing the heterogeneity of respondents' preference structure, while the latter is credited with the potential to explore the cognitive process underlying decision making (Hess, 2012; Mariel & Meyerhoff, 2016; Taye et al., 2018).

The paper is structured as follows: Section 2 reviews the literature on the use of the ICLV model to analyse car choice. Section 3 describes the survey, questionnaire, and sample. Section 4 illustrates some descriptive statistics concerning perceptions of and attitudes towards BEVs and describes the results of the factor analysis. Section 5discusses the modelling framework and the econometric results. Section 6 concludes and discusses the limitations of the study.

2. Literature review on attitudes and perceptions as co-determinants of car choice

There is a widespread consensus stemming from several streams of literature that attitudes and perceptions are co-determinants of any choice. In psychology, the theory of planned behaviour (Ajzen, 1985) clearly states that attitudes, subjective norms, and perceived behavioural control shape individual behavioural intentions. The technology acceptance model (Davis, 1989), derived from the theory of planned behaviour, describes how users come to accept and use a technology (e.g. Thøgersen & Ebsen, 2019). The discrete choice model (Ben-Akiva & Lerman, 1985; McFadden, 1973, 1986; Train, 2009), widely applied in the transport literature, incorporates attitudes and perceptions using several specifications such as a simple multinomial logit model (e.g. Orlov & Kallbekken, 2019), a latent class model (e.g. Hackbarth & Madlener, 2016; Kormos et al., 2019), and an ICLV model (e.g. Jensen et al., 2013).

2.1. The ICLV model

The ICLV model, also known as the hybrid-choice model, which was advocated by McFadden (1986) and Ben-Akiva et al. (2002), set the stage for expanding the traditional discrete-choice framework based on the random utility theory to incorporate several elements of the cognitive process such as history, context, perception formation, and latent variables (LVs). As summarised by Campbell and Sandorf (2020), the popularity of ICLV models is associated with three main claims. First, the inclusion of attitudes and beliefs through LVs might lead to improved forecasts (Vij & Walker, 2016; Yáñez et al., 2010). Second, ICLV models have the potential to shed light on preference heterogeneity (Kassahun et al., 2016; Mariel & Meyerhoff, 2016). Third, the inclusion of attitudes and beliefs might avoid issues related to measurement errors and possible endogeneity bias (Ben-Akiva et al., 2002; Guevara & Ben-Akiva, 2010, pp. 353–370). Over the years, a large variety of methodological features have been tested. We restrict our review to the one exploring car choice.

2.2. LVs and car choice in the ICLV model

We have been able to track 15 journal papers that applied the ICLV models to study car choice. In Table 1, we list them by year of publication and report the powertrains they considered as alternatives to choose from in the stated-choice experiment: the LVs analysed, country where the study was conducted, and whether (confirmatory or exploratory) factor analysis (CFA or EFA) or principal component analysis (PCA) was performed to identify the latent constructs.

Apart from one of them (Mohammadi et al., 2021) that focused on

[2] Segment, Code, and Example. A: mini, Fiat 500; B: small, Dacia Sandero; C: medium, Toyota Corolla; D: large, Peugeot 508; E: executive, Porsche Taycan; F: luxury, Bentley Mulsanne; J: sport utility, Renault Kadjar; M: multi-purpose, Volkswagen Sharan; S: sports, Audi TT.

Table 1
Articles including ICLV models on car choice.

Paper	Powertrains	Latent variables	Country	Factor analysis
Bolduc et al. (2008)	GV, AFV, HEV, HFC	Environmental concern, appreciation of new car features	Canada	no
Jensen et al. (2013)	ICEV, EV	Environmental concern, technology interest, and perception of the car as a status symbol	Denmark	no
Daziano and Bolduc (2013)	GV, AFV, HEV, HFC	Transport-policy support, transport-problem evaluation	Canada	no
Kim et al. (2014)	EV, no-choice	Social-influence variables, environmental aspects, economic aspects, battery aspects, technological aspects, innovation value	Netherlands	no
Kim et al. (2016)	EV, no-choice	Social-influence variables, environmental aspects, economic aspects, battery aspects, technological aspects, innovation value	Netherlands	no
Bahamonde-Birke and Hanappi (2016)	CV, PHEV, HEV, BEV	Wealth, ecological concern	Austria	PCA
Valeri and Cherchi (2016)	GV, DV, CNGV, LPGV, HEV, BEV1, BEV2	Habitual behaviour	Italy	PCA, CFA
Cherchi (2017)	ICEV, EV	Informational and normative conformity	Denmark	no
Smith et al. (2017)	EV, GV, PHEV, DV	Environmental concerns, excitement for new technologies, perceived usefulness, subjective norms	Australia	CFA
Soto et al. (2018)	GV, CNG, HEV, EV, DV	Support for green transport policies, environmental concern, attitudes pro-car use, attitudes pro-technology	Colombia	no
Ghasri et al. (2019)	EV, no choice	Design, environmental impacts, safety	New South Wales (Australia)	
Giansoldati et al. (2020)	ICEV, BEV	EV knowledge	Italy	no
Rotaris et al. (2021)	ICEV, BEV	EV knowledge, environmental awareness	Italy, Slovenia	no
Mohammadi et al. (2021)	Vehicle type: mini, compact, medium, large, and SUV	Lifestyle, transportation attitude, safety attitude	Iran	no

Legend: SGV (standard gasoline vehicle), HFC (hydrogen fuel cell), CV (conventional vehicles), BEV1 (owned battery), BEV2 (leased battery), ICEV (internal-combustion-engine vehicle), PCA (principal component analysis), CFA (confirmatory factor analysis), EV (electric vehicle), BEV (battery electric vehicle), PHEV (plug-in hybrid electric vehicles), CNG (compressed natural gas).

vehicle type, all the studies dealt with the choice of vehicle powertrain and included, among the proposed alternatives, an alternative fuel or electrified vehicle. Many of them focused their attention on electric cars as an alternative to conventional cars. Since electric cars represent a new technology, potentially more environmentally friendly than conventional ones, the ICLV model was deemed a valuable tool to explore the impact on choice of non-measurable and psychological traits.

Not surprisingly, therefore, the most often investigated LV is the attitude towards the environment, phrased either as environmental concern, ecological concern, environmental aspects, environmental impacts, or environmental awareness. In the case of Daziano and Bolduc (2013), the preference for alternative fuel vehicles was mediated via transport-related LVs (transport-policy support and transport-problem evaluation) that exhibited an agreement with policies aiming at reducing transport externalities. All studies found that the LV 'attitude towards the environment' impacted car choice (Bahamonde-Birke & Hanappi, 2016; Bolduc et al., 2008; Ghasri et al., 2019; Giansoldati et al., 2020; Jensen et al., 2013; Kim et al., 2014; Rotaris et al., 2021; Smith et al., 2017; Soto et al., 2018). All agreed that respondents who showed a higher environmental concern tended to choose alternative fuel vehicles, electric cars, or support for green-transport policies (Daziano & Bolduc, 2013; Soto et al., 2018), even when it was not clear whether EVs were actually greener than conventional vehicles (CVs) (Bahamonde-Birke & Hanappi, 2016).

A second extensively researched LV entails social influence and normative conformity. The starting point is that a car is a complex commodity that signals the owner's economic or personality traits to their acquaintances or social environment and is related to the peers' choice. Kim et al. (2014) treated social-influence variables as attributes that directly entered the utility function and identified them as the quality of the reviews or the share of EVs among friends and acquaintances, members of the larger family, colleagues, or the peers' social network. Cherchi (2017) adopted a more general approach underlining that a car buyer's behaviour was affected by what other people did (descriptive norms), what other people thought of their doing something (injunctive norms), and the image the individual wanted other people to have of them (social-signalling). Cherchi (2017) found that social-conformity effects were highly significant and their impact on the overall utility could be sufficiently high to compensate for EVs' low driving range or significant differences in purchase price.

Less clear-cut is how knowledge and perception impact car choice. Cherchi (2017) used the concept of informational conformity: when an individual lacks knowledge and thus turns to members of their group for guidance. She found that informational conformity had a high impact on the EV utility only when the reported experience was negative. Giansoldati et al. (2020) studied the impact of EV knowledge in Italy, concluding that it had a modest effect, mainly on the evaluation of the driving range. Rotaris et al. (2021), analysing a sample of Italians and Slovenians, found that EV knowledge played no statistically significant role.

Another investigated LV is the attitude towards technology, phrased as technical interest, pro-technology attitude, appreciation of new-car features, or innovation value (Bolduc et al., 2008; Jensen et al., 2013;

Kim et al., 2014, 2016; Smith et al., 2017; Soto et al., 2018). Generally, respondents with a strong preference for the latest technological items assign a higher utility to EVs; however, at least in the initial phase of EV uptake, people perceive EVs as technologically not fully developed (Kim et al., 2014).

Other LVs studied by researchers, although less frequently, are cars as status symbols (Jensen et al., 2013); the attitude towards safety (Ghasri et al., 2019; Mohammadi et al., 2021); economic aspects (Kim et al., 2014); battery aspects (Kim et al., 2014); and performance, reliability, and aesthetic aspects (termed design by Ghasri et al. (2019)). Furthermore, the attitude towards a car has been termed habitual behaviour (Valeri & Cherchi, 2016) or pro-car use (Soto et al., 2018). Finally, Bahamonde-Birke and Hanappi (2016) defined wealth as an LV to capture the difficulty of having reliable information on respondents' income.

From a statistical viewpoint, all estimates were performed using classical methods based on maximum simulated likelihood (MSL) estimation, with the exception of Daziano and Bolduc (2013), who used a Bayesian estimation method based on an MCMC Gibbs sampler. Instead of the standard stated-choice procedure in which respondents choose their best/most preferred alternative from a hypothetical scenario, Smith et al. (2017) performed a best-worst analysis in which participants selected their best/most preferred option and their worst/least preferred option from each choice set. All studies were based on stated-preference data collected through one-time surveys. Only Jensen et al. (2013) collected data using a two-wave stated-preference experiment performed before and after the respondents experienced an EV for three months. Such a feature allowed them an interesting analysis of the stability of preferences and attitudes. They reported that individual preferences changed significantly after a real experience with an EV, while the attitude 'environmental concern' and its positive effect on the choice of an EV did not change.

Typically, LVs are detected via statements\questions (indicators) to which respondents are asked to declare their level of (dis)agreement \importance. The number of indicators used to capture LVs varies from a few units (Giansoldati et al., 2020; Mohammadi et al., 2021; Rotaris et al., 2021) to 27 (Jensen et al., 2013, 2014). When the number of indicators is limited, they are all used in the model. Kim et al. (2014, 2016) directly enter them into the utility function as effect-coded variables. When the number of indicators is large, it is advisable to use data-reduction techniques such as factor analysis or PCA (Mariel & Meyerhoff, 2016). Some studies did not report details on how these techniques were used (Cherchi, 2017; Daziano & Bolduc, 2013) or only partially reported them (Soto et al., 2018), thus making it difficult to compare and appreciate the results. Other studies provided more details (Bahamonde-Birke & Hanappi, 2016; Ghasri et al., 2019; Jensen et al., 2014; Smith et al., 2017; Valeri & Cherchi, 2016). Both PCA and EFA/CFA were conducted. In contrast to a well-established tradition in the psychology literature (Trendler, 2022; Wood, 2017), the use of validated scales in the car-choice ICLV-model literature has thus far been rare. Only Ghasri et al. (2019) stated that they adopted existing and tested scales. It is also worth observing that in most instances, the indicators were derived from car- or transport-related issues. Finally, all studies focused on specific countries or regions, with the exception of Rotaris et al. (2021), who contrasted choices and attitudes in Italy and in Slovenia.

Our study will build on this tradition investigating how attitudes co-determine car choice in Italy and Norway, two countries with similarities (European, high car penetration, and medium to high level of wealth) and differences (population and urban density, level of EV uptake, car fiscal policies, electricity costs, and charging infrastructure). We selected 24 statements\questions (indicators) representing attitudes, norms, or intentions to identify LVs via EFA. We compared the results from both the RPL and ICLV model concerning the vehicle attributes, socioeconomic determinants, and LVs.

3. The survey

In the following subsection, we describe the questionnaire and discuss the characteristics of the respondents who participated in the survey, identifying their socio-economic characteristics.

3.1. The questionnaire

We collected data via a web-based survey, administered between November and December 2021 on a sample of Italian (N = 643) and Norwegian (N = 501) respondents using a computer-assisted web-interviewing (CAWI) questionnaire. We entrusted the data collection to two companies specialised in market surveys: SWG for the Italian sample and Norstat for the Norwegian one. The samples were randomly drawn from the two companies' communities so that only persons with a driving license were eligible to fill in the questionnaire. The questionnaire comprised three main parts. The first part contained 10 hypothetical choice scenarios, such as the one shown in Fig. 1. Respondents were asked to *"suppose you have to buy a car"*, without further specifying whether this implied replacing their current vehicle or purchasing an additional one. The intention was to place respondents in a realistic car-purchase situation while keeping the wording as simple and neutral as possible. Moreover, all alternatives referred to new cars.

As is well known, the design of a choice experiment is a balancing act between (at times) conflicting goals including the following.

- presenting the respondents with all the powertrains available in the market;
- describing the alternatives using attribute levels that are close to those of the real world (and at the same time allowing for sufficient variability in the independent variables);
- describing the alternatives with the most important attributes (we opted to use only those referred to the vehicle and to test the contextual ones as covariates);
- trying to be as concise as possible to allow respondents to quickly and fully grasp the characteristics of the alternatives from which we asked them to choose; and
- allowing sufficient space for the attitudinal section.

For each choice task, we asked respondents to choose among five labelled alternatives: PV, DV, BEV, HEV, and PHEV. Alternatively, we could have used unlabelled alternatives and introduced an attribute such as 'fuel type' to specify the powertrain; in previous research, we tested this latter choice. In this study, we opted for the labelled approach because we were convinced that the powertrain provided a strong characterisation of alternatives. Thus, we considered it as a leading characteristic of a car, especially with BEVs, since they entail a completely different ecosystem (new product, battery safety and lifetime issues, charging, and so on). Characterising the alternatives increases, in our view, the realism of the choice experiment. Furthermore, the choice of labelling the alternatives provides a clear meaning to the alternative specific constants (ASCs) since they capture all unspecified characteristics. Another advantage is that attribute levels can be easily customised to the powertrain.

Researchers have made difference choices regarding the number of alternatives with which to confront respondents. Some of them have asked respondents whether they would buy an EV (Kim et al., 2014, 2016), while others have asked them to choose between an internal-combustion-engine vehicle (ICEV) and an EV (Cherchi, 2017; Giansoldati et al., 2020; Jensen et al., 2013; Rotaris et al., 2021). Our choice is more similar to that of Bahamonde-Birke and Hanappi (2016), Valeri and Cherchi (2016), and Smith et al. (2017), who chose to reassemble the actual variety of powertrains existing in the car market. To facilitate comparability between the two countries, we opted, however, to focus only on the main powertrains on sale in Norway, thus disregarding the CNG and LPG powertrains which have a modest but not

	PETROL	DIESEL	BEV	HEV	PHEV
Price (net of taxes and subsidies)	€12,000	€27,000	€34,000	€26,000	€22,000
Driving range	700 km	1000 km	300 km	1100 km	1300 km
Fuel/energy costs (per 100 km)	€9	€10	€7	€9	€14
YOUR CHOICE	☐	☐	☐	☐	☐

Fig. 1. Example of a choice task (for the small segment) proposed to the Italian respondents.

insignificant share in Italy. The main disadvantage of using labelled alternatives was that respondents had to choose among five alternatives, which was a serious challenge, considering that the respondents' attention in filling up an online questionnaire could not be taken for granted and that the choice experiment was part of a larger set of questions.

Regarding the number of attributes used to characterise the hypothetical scenarios, our choice was very conservative. We opted to restrict our selection to only three attributes, which, based on our previous experience (Danielis et al., 2020; Rotaris et al., 2021), have a strong influence on car choice: net purchase price, fuel\electricity cost, and driving range. Thus, they can be considered the 'salient attributes' (Clark & Mathisen, 2020). Net purchase price includes taxes\subsidies, VAT and registration taxes. Fuel\electricity costs are those incurred to travel 100 km, while driving range is the maximum distance in km with a full tank\battery (tank plus battery for PHEVs). They were calculated based on the variation of fuel economy within each powertrain.

Such a choice most likely has limitations since the choice of a car depends on many vehicle- and non-vehicle-related attributes (Coffman et al., 2017; Danielis et al., 2020; Greene et al., 2018; Liao et al., 2017). Excluded non-vehicle-related attributes include acceleration, advanced driver-assistance systems, charging time, maintenance costs, and resale value. Non-vehicle-related attributes include charging-network density, free or reduced circulation tax and parking fees, and access to bus lanes.

A second motivation for focusing on some attributes and disregarding others is the difficulty of technically incorporating them in a meaningful and credible manner in a choice experiment among alternative powertrains that we experienced in previous studies (Slovenia); for instance, charging, which is well known to be a very important topic for BEVs' users. BEVs can be charged in many different locations: during a trip on a highway, while shopping, at work, or at home. Depending on the travel type, time available, and electricity cost, BEV users will make their choices and accordingly evaluate the importance of this attribute. Consequently, it is very difficult to meaningfully characterise the charging-density attribute in a general experiment concerning five powertrains but less so if a choice-experiment is specifically constructed for exploring only the charging issue. This also applies to charging time. The importance of charging time depends on where it occurs and the type of trip. When one charges at home at night, 5 h or 7 h make little difference. On a long trip, minutes matter. Similar difficulties arise with insurance cost because it depends on the car size and car driver. Our previous experience with these attributes suggested that we leave them out unspecified, capturing them with the ASC. Of course, this does not mean that the not included attributes play no role in car choice decisions. On the contrary, these excluded variables add to the error terms (captured by the alternative specific constants) and might cause an omitted variable bias.

It should also be noted that net purchase price contains at least three financial variables. Alternatively, we could have separately specified the list price (or manufacturer-suggested retail price, MSRP), upfront registration taxes (possibly extrapolating the CO2 tax for Norway), and car subsidy enacted in Italy. We opted for the synthetic attribute, net purchase price, because we believe that, when choosing among powertrains, buyers consider the final upfront cost and not the various components. If the goal were to understand the impact of a specific policy instrument, then treating it as a separate variable would be more appropriate.

To summarise, although we are aware that we left out many important attributes, our motivations were the following: a) since we opted to include five alternatives, we wanted to keep the number of attributes to a minimum; thus, we focused only on the salient attributes; b) some attributes are very challenging to meaningfully and realistically introduce in a general choice experiment; and c) as the questionnaire contained other important parts, we did not want to impose too large a cognitive burden on the respondents.

Finally, because the car market comprises very different car types (e.g. compact car, mid-size, convertible, sport utility vehicle [SUV], etc.), we opted to identify two car segments: small to medium cars and large cars. Using a conventional European classification system ranging from A to J[2], we identified the small-to medium-car segment as comprising the segments A, B, and C, and the large-car segment as comprising the segments D to J. We concisely provided such information to the respondents and confronted them with five scenarios referring to the small-to medium-car segment and five scenarios referring to the large-car segment. The underlying motivation was to confront respondents with cars with different powertrains but similar size and costs to enhance the realism of the choice scenario, also considering that a household might use small/medium cars for day-to-day travel and large cars for long trips. Such a choice would also allow us to test whether the car choice depended on the car segment. Such an analysis will not be performed in this study.

The attribute levels used in the choice experiment, reported in Table 2, were country- and powertrain-specific and were tested with a pre-test experiment with 200 respondents in Italy and Norway. The pre-test experiment allowed us to develop an efficient design (Bliemer & Rose, 2011) and to assess the consistency and realism of the choice scenarios. The efficient design has been separately performed for the two market segments.

In the second part of the questionnaire, we asked for respondents' demographic and socio-economic data, such as sex, age, educational level, occupation, household composition and income, house type (apartment vs. detached house), house ownership (for rent or as an owner), garage availability, home charging availability, and area of residence (urban, suburban, rural).

In the third and final part of the questionnaire, we asked respondents about their level of agreement\disagreement on a 5-point Likert-scale (completely disagree, partially disagree, neither agree nor disagree, partially agree, and completely agree) using 24 statements regarding EVs (see Table 3), encompassing several economic, technical, environmental, and moral aspects.

3.2. The sample

We could collect online questionnaires from 1144 respondents: 501 Norwegians and 643 Italians. Although the absolute number is not large, we devoted great care to achieve good sample representativeness along various dimensions. The questionnaire administration was performed by two reputable survey firms whom we asked to ensure representability along some social dimensions. After the data collection, we checked the data representativeness along many dimensions.

Table 2
Attribute levels by car segment.

	Norway		Italy	
	Small segment	Medium/ Large Segment	Small segment	Medium/ Large Segment
Petrol				
Price (1000 € or NOK)	250, 300, 350, 400, 450	400, 500, 600, 700, 800	12, 14, 16, 18, 20	30, 32, 34, 36, 38
Driving range (km)	700, 850, 1000	700, 850, 1000	700, 850, 1000	700, 850, 1000
Fuel\electricity cost (€/NOK per 100 km)	50, 75, 100, 125	75, 100, 125, 150	9, 11, 13, 15	11, 13, 15, 17
Diesel				
Price (1000 € or NOK)	300, 350, 400, 450, 500	500, 600, 700, 800, 900	16, 19, 21, 24, 27	35, 40, 45, 50, 55
Driving range (km)	800, 1000, 1300	800, 1000, 1300	800, 1000, 1300	800, 1000, 1300
Fuel\electricity cost (€/NOK per 100 km)	45, 70, 95, 120	70, 95, 120, 145	6, 8, 10, 12	8, 10, 12, 14
BEV				
Price (1000 € or NOK)	250, 300, 350, 400, 450	400, 500, 600, 700, 800	18, 22, 26, 30, 34	40, 50, 60, 70, 80
Driving range (km)	300, 400, 500	400, 500, 600	200, 300, 400	400, 500, 600
Fuel\electricity cost (€/NOK per 100 km)	10, 30, 50, 70	30, 50, 70, 90	3, 5, 7, 9	5, 7, 9, 11
HEV				
Price (1000 € or NOK)	300, 350, 400, 450, 500	400, 500, 600, 700, 800	13, 17, 20, 23, 26	35, 40, 45, 50, 55
Driving range (km)	900, 1100, 1300	900, 1100, 1300	900, 1100, 1300	900, 1100, 1300
Fuel\electricity cost (€/NOK per 100 km)	50, 75, 100, 125	75, 100, 125, 150	9, 11, 13, 15	11, 13, 15, 17, 19
PHEV				
Price (1000 € or NOK)	350, 400, 450, 500, 550	400, 500, 600, 700, 800	22, 25, 28, 31, 34	45, 50, 55, 60, 65
Driving range (km)	800, 1000, 1300	800, 1000, 1300	800, 1000, 1300	800, 1000, 1300
Fuel\electricity cost (€/NOK per 100 km)	40, 65, 90, 115	65, 90, 115, 140	8, 10, 12, 14	10, 12, 14, 16

The reference population comprises driving-license holders who have or plan to buy a passenger car. In the absence of disaggregate information on this specific population target, we checked the representativeness with reference to the population above 18 years of age. The detailed results are reported in SM 1.0, distinguishing between the Italian and Norwegian samples. The Italian sample has good representativeness by sex, while by age class it slightly over-represents the under-30 age class (20 % vs. 14 %) at the expense of the over-60 age class. By occupation, the retired group is also under-represented (20.2 % vs. 27.3 %). By household type, single households are under-represented while families with more than four members are over-represented (28.6 % vs. 15.3 %). By geographical area, the sample is quite representative while it is not in terms of educational attainment. Indeed, the highly educated groups are over-represented (47.9 % vs. 17.8 %) at the expense of the lower-educated ones (6.1 % vs. 39.4 %), most likely because of the computer-based method used to administer the survey. The representativeness by income is difficult to assess because the official data are by individuals and not by households, as in our survey. By type of housing, the sample over-represents the people living in apartments (68.3 % vs. 53.4 %) vs. those in detached houses, while it fits the national data rather well in terms of house ownership. By place of residency, rural respondents are under-represented (13.4 % vs. 24.5 %), while in terms of parking, the respondents with private/reserved parking space are only slightly over-represented (71.8 % vs. 68.1 %). Unfortunately, there are no national statistics on the number of cars per household and commuting distance.

Overall, we consider the sample representativeness satisfactory along the above-described socio-economic dimensions except for two closely linked dimensions: an under-representation of the population with lower educational attainment (up to 7–8 years of education) and that above 60 years of age. If the results of this study are to be used for market-share forecasting at national level, we would recommend that our estimates be complemented by those derived from a survey focusing on this specific segment of the population.

With reference to the same variables, the Norwegian sample represents the total population in a generally satisfactory manner. However, male respondents are slightly over-represented (56 % vs. 50 %). Similar to the Italian sample, there is an over-representation of people under the age of 30 years at the expense of those older than 60 years. Other age categories, occupation, geographical area, and the proportion of single households are correctly represented. By household size, we could not find a detailed distribution; however, we know that the average size is 2.13 persons per household vs. 2.4 in the sample. As with the Italian case, we find that respondents living in apartments are somewhat over-represented in the Norwegian sample (38.3 % vs. 27.5 %) at the expense of those living in houses. In contrast, house ownership and parking options reflect the population data. Respondents living in rural areas are over represented (34.9 % vs. 17.4 %). The number of cars in a household is similar to that reported in a national travel survey (Hjorthol, 2013); however, we find no national figures on commuting distance with which to compare our sample. Regarding parking availability, the sample representativeness is quite satisfactory. In the sample, 83.8 % of the respondents own private\reserved parking spaces (32.3 % of which have charging stations), compared to the national statistics of 82.7 %. Note that this figure is much higher than the corresponding figure for Italy of 68.1 %.

4. Perceptions of and attitudes towards BEVs

We started by presenting a descriptive analysis on how our respondents replied to the statements presented to them. Next, we applied EFA to identify the main LVs to be used in the ICLV model.

4.1. Perceptions of and attitudes towards BEVs: descriptive statistics

Table 3 reports some statistics on the responses to the statements with which we asked the respondents to agree\disagree. The first two columns report the average results for the two countries. The third and fourth columns estimate the significance of the differences between the two countries' results using analysis of variance (ANOVA) and estimating the scale effect (eta-squared).[3] We find several significant differences between the countries, the main ones being the following.

- Italians are more sceptical than Norwegians about whether BEVs are economically convenient (Q2).
- Italians are more in agreement with the statement that driving a BEV is more environmentally friendly (Q4; Q23) than driving an ICEV and that they would reduce the depletion of natural resources (Q6).

[3] Instead of the conventional *t*-test of the difference between the means, we applied one-way Anova to obtain the sum of square totals to estimate the effect size (eta-square). The scale effect measures the amount of variance explained by the model's terms. Conventionally, $\eta^2 = 0.01$ indicates a small effect; $\eta^2 = 0.06$ indicates a medium effect; and $\eta^2 = 0.14$ indicates a large effect.

Table 3
Statements regarding BEVs.

N°	Statements	Average		Signif.	Effect size	IT	NOR
		IT	NOR		η^2	% of 5[a]	% of 5[a]
Q1	Driving a BEV, one can save money in the long run	3.72	3.76		0.00	23.3 %	26.9 %
Q2	I think there is no economic benefit from driving a BEV	2.58	2.28	***	0.02	8.1 %	5.0 %
Q3	BEVs have lower maintenance costs than conventional cars	3.13	3.27	*	0.00	12.6 %	16.2 %
Q4	Driving a BEV is more environmentally friendly than driving an ICEV	4.01	3.75	***	0.01	43.7 %	34.5 %
Q5	BEVs would reduce environmental pollution caused by traffic	4.11	4.21		0.00	47.0 %	51.7 %
Q6	BEVs would reduce the depletion of natural resources	3.82	3.26	***	0.06	32.2 %	16.6 %
Q7	The limited BEV driving range is a disadvantage relative to that of an ICEV	3.98	4.26	***	0.02	41.2 %	51.1 %
Q8	It is not practical to drive a BEV because of the lack of charging points	3.71	3.9	**	0.01	30.9 %	34.9 %
Q9	It is not practical to drive a BEV because of the long charging time	3.68	3.78		0.00	26.9 %	26.9 %
Q10	I think the performance of a BEV is inferior to that of an ICEV	2.83	2.64	*	0.01	10.4 %	6.8 %
Q11	I would prefer driving a BEV because of the new technology	3.31	3.28		0.00	17.1 %	25.0 %
Q12	The limited luggage capacity is a disadvantage of BEVs	3.21	3.35	*	0.00	14.0 %	17.4 %
Q13	One can save time in traffic by using a BEV	2.66	2.96	***	0.02	6.4 %	6.8 %
Q14	I think BEVs are safer to drive than ICEVs	2.9	2.64	***	0.02	6.1 %	3.0 %
Q15	The chance of a car fire is lower for a BEV than for an ICEV	3.11	2.63	***	0.06	8.2 %	4.2 %
Q16	In case of an accident, I would be safer in an ICEV	2.78	3.01	***	0.01	6.8 %	9.6 %
Q17	I would enjoy driving a BEV more than driving an ICEV	2.95	2.95		0.00	10.1 %	16.2 %
Q18	I would feel strange driving a BEV	2.49	2.38		0.00	5.9 %	5.4 %
Q19	The limited driving range of a BEV would make me feel uncomfortable	3.56	3.66		0.00	23.6 %	25.0 %
Q20	I would feel worried driving a BEV because of the possibility of having no charge in a location where no charging points are available	3.72	3.45	***	0.01	28.8 %	19.8 %
Q21	Many of my family members and\or friends would support my decision to buy a BEV	3.37	3.82	***	0.04	15.9 %	36.5 %
Q22	Owning a car that is not fuel efficient and environmentally friendly would make me feel bad because of its negative impact on the environment.	3.3	2.54	***	0.09	13.2 %	8.2 %
Q23	I feel morally obliged to use a fuel-efficient and environmentally friendly car.	3.46	2.8	***	0.06	19.6 %	10.2 %
Q24	There are many people that I know who use BEVs.	2.46	3.89	***	0.25	7.8 %	37.3 %

Significance in ANOVA: *$p < .05$; **$p < .01$; ***$p < .001$.
[a] Percentage of people who assigned 5 points on the Likert scale (completely agree).

Table 4
Exploratory factor analysis: factor loadings.

Items	ML2	ML1	ML3	ML4
I1 - Driving a BEV, one can save money in the long run	−0.03	0.12	0.08	**0.69**
I2 - I think there is no economic benefit from driving a BEV	0.23	−0.07	0.03	**0.52**
I3 - BEVs have lower maintenance costs than conventional cars	0.04	0.11	0.04	**0.40**
I4 - Driving a BEV is more environmentally friendly than driving an ICEV	0.02	**0.82**	0.00	0.07
I5 - BEVs would reduce the environmental pollution caused by traffic	−0.10	**0.62**	−0.01	0.21
I6 - BEVs would reduce the depletion of natural resources	0.06	**0.75**	0.08	−0.12
I7 - The limited BEV driving range is a disadvantage relative to that of an ICEV	**0.69**	−0.06	0.10	−0.10
I8 - It is not practical to drive a BEV because of the lack of charging points	**0.54**	−0.18	0.09	0.02
I9 - It is not practical to drive a BEV because of the long charging time	**0.69**	0.00	0.04	−0.01
I19 - The limited driving range of a BEV would make me feel uncomfortable	**0.77**	0.13	−0.04	0.02
I20 - I would feel worried driving a BEV because of the possibility of having no charge in a location where no charging points are available	**0.70**	0.00	−0.11	0.12
I22 - Owning a car that is not fuel efficient and environmentally friendly would make me feel bad because of its negative impact on the environment	0.04	0.05	**0.76**	0.02
I23 - I feel morally obliged to use a fuel-efficient and environmentally friendly car	−0.03	−0.01	**0.86**	0.02
SS loadings	2.42	1.85	1.42	1.17
Proportion Var	0.19	0.14	0.11	0.09
Cumulative Var	0.19	0.33	0.44	0.53
Proportion Explained	0.35	0.27	0.21	0.17
Cumulative Proportion	0.35	0.62	0.83	1.00

- Norwegians are more in agreement with the statements regarding driving range and charging issues (Q7; Q8), although they are less worried about running out of charge (Q20).
- Norwegians, however, more than Italians, believe that BEVs can save driving time (Q13, most likely because of the policy of free access to bus lanes).
- Regarding safety, the results are equivocal (Q15; Q16).
- Norwegians feel social support more when buying an EV (Q21) and are certainly surrounded by more BEVs (Q24).
- Italians feel a moral obligation to buy a BEV more than Norwegians (Q22; Q23).

However, most of the differences are not very large in magnitude, as indicated by the low η^2 values: some can be classified as medium (Q6 'BEVs would reduce the depletion of natural resources'; Q22 and Q23 regarding the feeling of moral obligation), while there are very large differences in the diffusion of BEVs between the Italian and Norwegian respondents.

To have an aggregate overview of the differences in attitudes between Italian and Norwegian respondents, we averaged the respondents' choices after recoding them to have a consistent meaning. Fig. 2 indicates that, on average and on aggregate, there appears to be no major difference between the two countries' respondents, apart from the much greater familiarity with BEVs in Norway than in Italy. Italians are slightly less worried about the safety issues and feel more obliged to switch from an ICEV to a BEV. How Italians view BEVs, however, is not much different from how Norwegians do. This finding indicates, in our opinion, that the much larger uptake in Norway is a result of the policies and not of the attitudes. Overall, Italians evaluate BEVs not dissimilarly from Norwegians, notwithstanding their lower direct experience. Economic and infrastructural factors most probably play a larger role than attitudes.

It is also interesting to contrast the views of different segments of the sample, for instance BEV and ICEV owners. Both in Norway and in Italy, their views differ (Fig. 3). As expected, BEV owners think that BEVs are

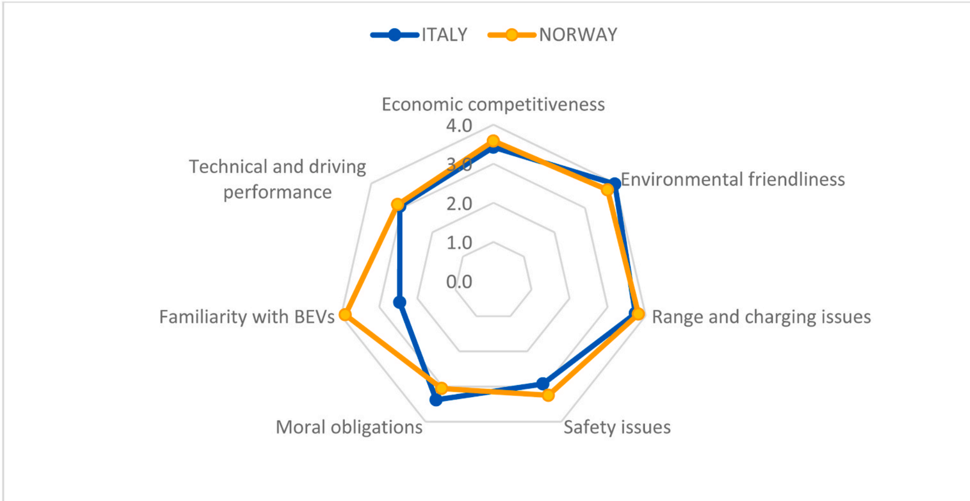

Fig. 2. A comparison of aggregate attitudes between Italian and Norwegian respondents *Legend:* Economic competitiveness (Q1, Q2, and Q3); Environmental friendliness (Q4, Q5, and Q6); Range and charging issues (Q7, Q8, Q8, Q19, and Q20); Safety issues (Q14, Q15, and Q16); Moral obligations (Q21, Q22, and Q23); Familiarity with BEVs (Q24); Technical and driving performance issues (Q10, Q11, Q12, Q13, Q17, and Q18).

cheaper, more environmentally friendly, have a superior technical and driving performance, suffer less range and charging issues, and are safer. They also feel a higher moral obligation and have a greater familiarity with BEVs. The main difference between Italian and Norwegian respondents is that the former are not more convinced than ICEV drivers of the fact that BEVs are cheaper, while the latter are.

4.2. Factor analysis

As recommended by Mariel and Meyerhoff (2016), to understand the role of LVs in ICLV models, it is important to apply exploratory multivariate analyses to the attitudinal responses before including them in the model. We followed their suggestion and conducted an EFA of the 24 collected indicators to capture their correlations in terms of a potentially lower number of unobserved variables and to identify which indicators were appropriate for each LV. We performed the analysis separately for each country to determine potential differences (see SM 2.0). Since we found a high degree of similarity, we then conducted a joint EFA for the entire sample. Following the usual data screening, we checked for accuracy and reverse-scored items. Multivariate assumptions (additivity, normality, linearity, homogeneity, and homoscedasticity) were met.

We tested the goodness of fit for our dataset for the EFA and the correlation adequacy using Bartlett's test, and found that it was significant, $X^2(276) = 9714.295$, $p < .001$, which implied that we had sufficiently large correlations to group them together into meaningful factors. Moreover, we investigated the sampling adequacy by applying the Kaiser-Meyer-Olkin (KMO) test. The mean sampling adequacy (MSA) was 0.89, indicating a sufficiently large sample.

Fig. 4 illustrates the parallel analysis. The dark line is set at 1, implementing the conventional Kaiser criterion, which suggests considering eigenvalues greater than 1 (in recent studies, the value of 0.70 is also indicated as a threshold). The red, dotted line represents the random dataset used for this analysis. The blue line and triangles are the eigenvalues from the real dataset. Following the Kaiser criterion, the number of factors to consider is three or four. The parallel analysis (establishing where the blue and red lines cross) suggests six factors. The scree plot has an 'elbow' and the eigenvalues level off after the fourth factor, indicating that four factors should be retained as significant.

We thus performed the EFA assuming four factors. We structured the analysis using an oblique factor rotation (oblimin), thus allowing factors to be correlated when they were rotated, and maximum likelihood as fitting estimation. We excluded indicators with loadings smaller than 0.4 and re-performed the analysis. We then focused on the internal reliability and adopted Cronbach's alpha. As a rule of thumb, a Cronbach's alpha of 0.50–0.80 is considered an acceptable value. We thus computed a Cronbach's alpha test for each group of items by considering all the items and eventually dropping one item at a time to maximise the internal consistency. By dropping Items I12 and I24,[4] we could achieve alpha values of 0.81, 0.81, 0.81, and 0.59 for the four factors, respectively, which can be considered acceptable, meaning that the items in the four groups have shared covariance and measure the same underlying concept.

It turns out that 53 % of the variance is cumulatively explained (see Table 4). Factor ML2 accounts for 19 % of the total variance. It is primarily defined by Items I7, I8, I9, I19, and I20 and it could be interpreted as a factor describing the driving-range and charging issues. The proportion of the variance explained by Factor ML1 is 14 %; it is described by Items I4, I5, and I6 and concerns a BEV's environmental friendliness. Factor ML3 explains 11 % of the total variance, with Items I22 and I23 having high positive loadings. Thus, it may be a latent factor describing the moral obligation in choosing a BEV. Factor ML4 accounts for 9 % of the total variance; it is defined by Items I1, I2, and I3 and describes a BEV's economic competitiveness. As a result of the factor analysis, the ICLV model to be tested is graphically illustrated in Fig. 5.

5. Modelling framework and econometric analysis

ICLV models comprise three components: (1) the choice model, (2) structural-equation model, and (3) measurement-equation model.

An individual n is assumed to consider the full set of J proposed alternatives in each choice situation $t \in T$ and to choose the alternative with the highest utility. The (relative) utility U_{njt} a person receives from choosing alternative $j \in J$ in the choice task t is defined as follows:

$$U_{njt} = \beta_{nj}^{'} X_{njt} + \gamma_j^{'} Z_n + \alpha_{nl}^{'} LV_{nl} + \varepsilon_{njt} \tag{1}$$

where X is the vector of the attributes presented in the stated-choice experiments; Z is the vector of socioeconomic characteristics; LV is the vector of LVs. β_n differs across individuals, accounting for preference heterogeneity, qualifying our model as a mixed ICLV model. ε is an error

[4] The decision to drop these indicators was based mainly on statistical criteria, having tested that their inclusion\exclusion did not significantly alter the overall results.

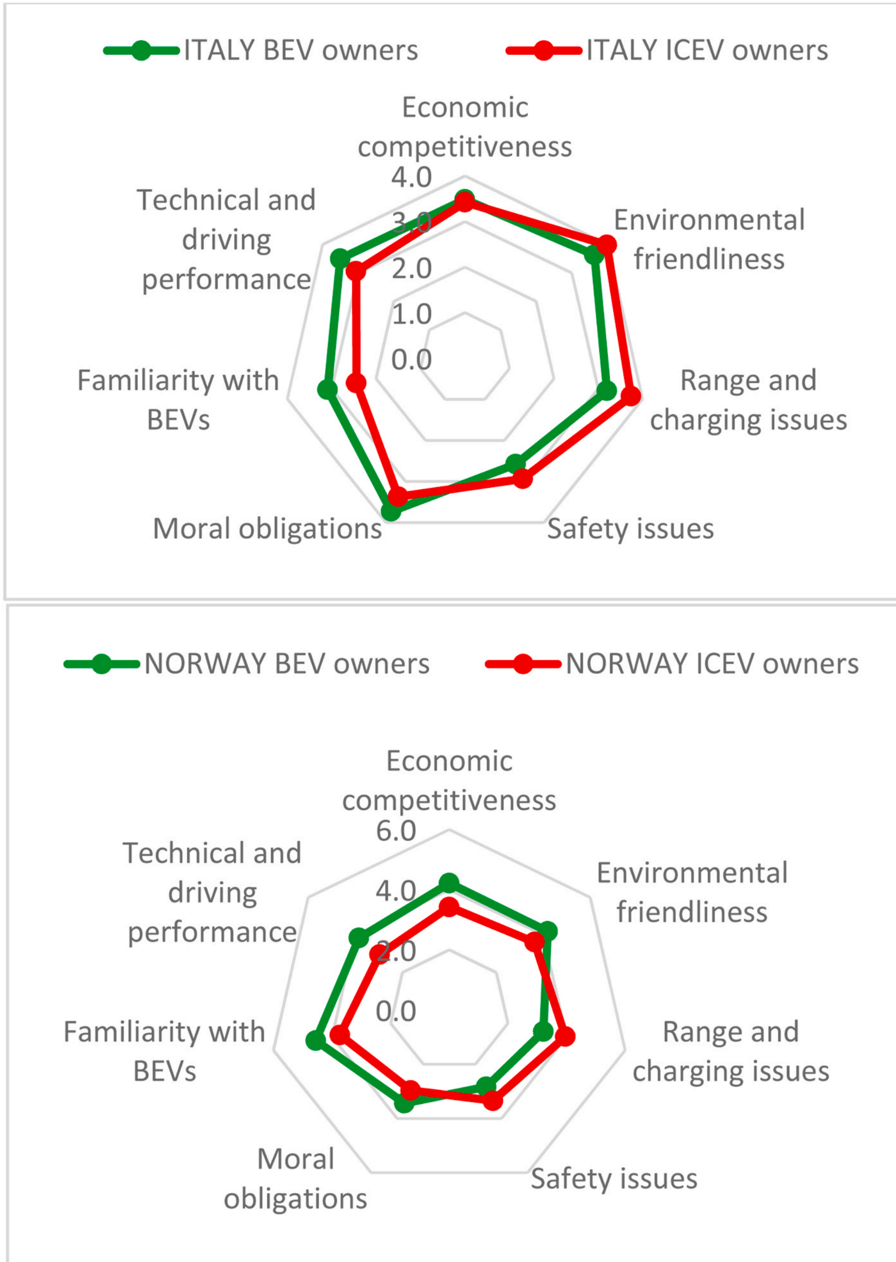

Fig. 3. A comparison of aggregate attitude between BEV and ICEV owners in Italy and Norway.

term with an EV1 i.i.d. distribution with mean zero and a diagonal covariance matrix, Σ_U.

The structural-equation model for LV, $l = 1,\ldots,L$, and for individual n is as follows:

$$LV_{nl} = \vartheta_l^{'} Z_n + \eta_{LV_{nl}} \tag{2}$$

where Z_n is a vector of socioeconomic characteristics, ϑ is a coefficient vector, and $\eta_{LV_{n,l}}$ follows a normal distribution (with mean zero and a covariance matrix, Σ_{LV}) across respondents, capturing the random component of the latent attitude.

The measurement-equation model is as follows:

$$I_{wn} = \overline{I_w} + \tau_{I_w} LV_{nl} + \nu_{w,n} \tag{3}$$

Respondents were asked to evaluate several statements using a 5-point Likert scale; thus, the measurement equation is represented by an ordered discrete variable, I, which assumes the values $I_1, I_2, \ldots, I_w$ for each LV, l, and $\omega_1, \omega_2, \ldots, \omega_{W-1}$ are parameters to be estimated:

$$I_l = \begin{cases} I_1 \text{ if } LV_l < \omega_1 \\ I_2 \text{ if} \omega_1 \le LV_l < \omega_2 \\ \quad \ldots \\ I_i \text{ if} \omega_{i-1} \le LV_l < \omega_i \\ \quad \ldots \\ I_w \text{ if} LV_l \ge \omega_{W-1} \end{cases} \tag{4}$$

In Equation (3), $\overline{I_w}$ is the intersect, τ_{I_w} measures the impact of the LV, LV_l, on I_w, and $\nu_{w,n}$ is assumed to be normally distributed with mean zero and a diagonal covariance matrix, Σ_I.

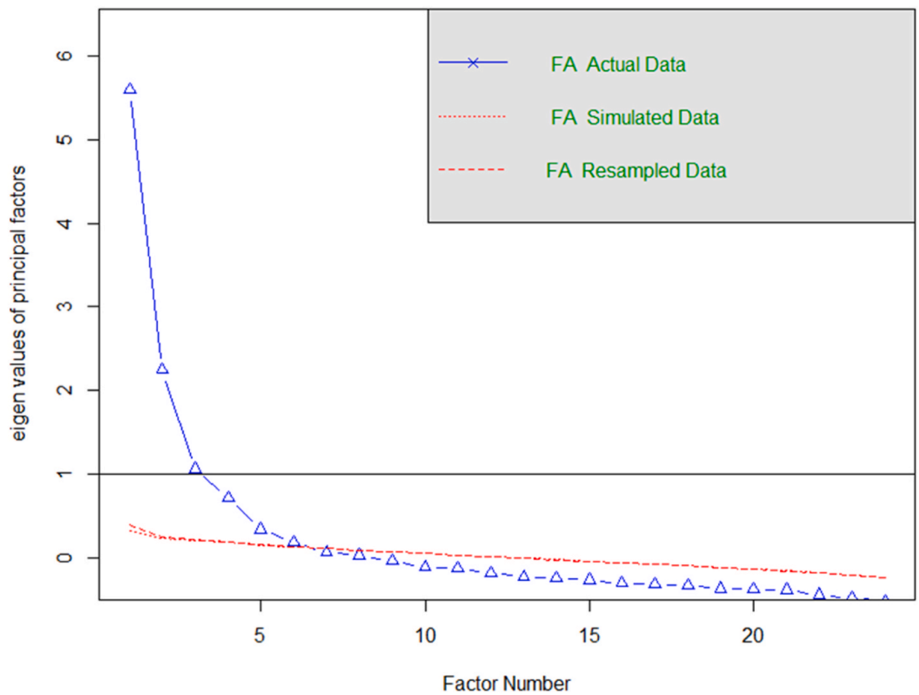

Fig. 4. Parallel-analysis scree plots.

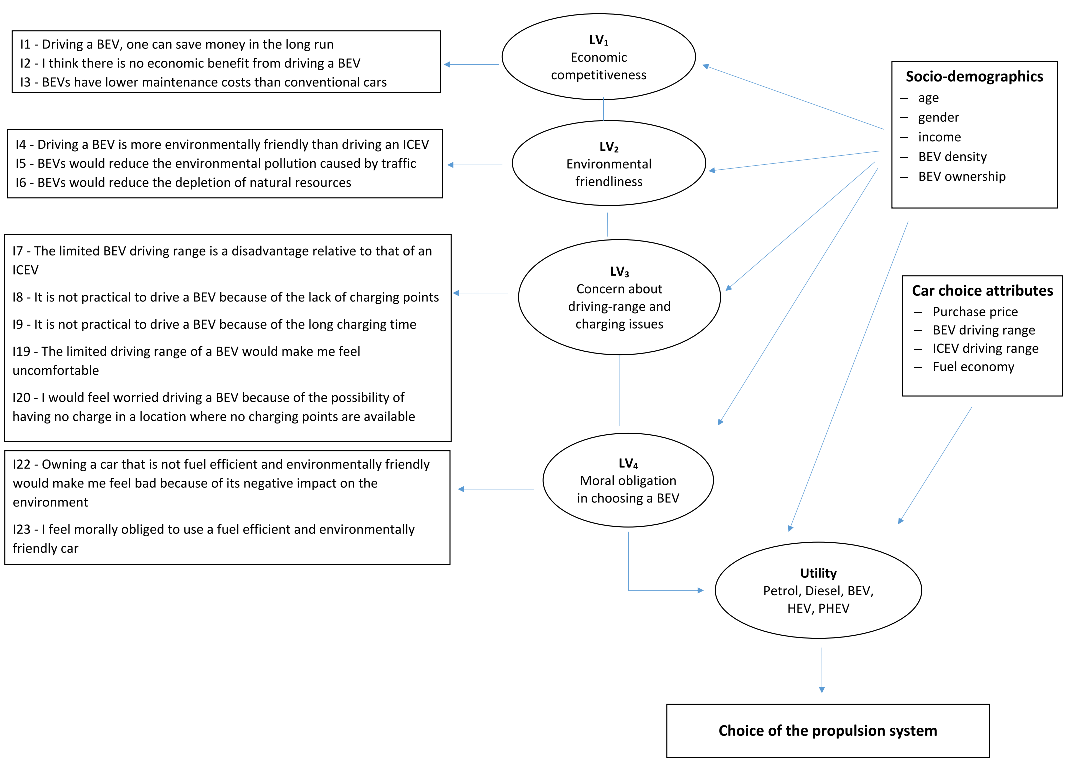

Fig. 5. ICLV model flowchart.

Table 5
RPL and ICLV model estimates.

	RPL	RPL	ICLV	ICLV
	Italy	Norway	Italy	Norway
	Coeff.(t-stat)	Coeff.(t-stat)	Coeff.(t-stat)	Coeff.(t-stat)
Choice				
Net purchase price$_{\text{All cars}}$ (in €1000)	−0.053*** (−15.3)	−0.053*** (−15.3)	−0.044*** (−16.4)	−0.044*** (−16.4)
SD of price	0.067*** (17.1)	0.067*** (17.1)	0.058*** (19.1)	0.058*** (19.1)
Range$_{\text{All but BEVs}}$ (in km)	0.0004*** (4.0)	0.0002 (0.8)	0.0003*** (4.2)	0.0003 (1.4)
SD of Range$_{\text{All but BEVs}}$	0.001*** (10.2)	0.002*** (10.7)	0.001*** (9.9)	0.001*** (9.4)
Range$_{\text{BEV}}$	0.001** (2.4)	0.003*** (3.2)	0.001*** (4.7)	0.002*** (3.1)
SD of Range$_{\text{BEV}}$	0.003*** (7.0)	0.005*** (8.8)	0.002*** (7.7)	0.004*** (7.8)
Fuel\electricity cost$_{\text{All cars}}$	−0.137*** (−11.2)	−0.207*** (−12.0)	−0.111*** (−11.5)	−0.199*** (−13.1)
SD of Fuel\electricity cost$_{\text{All cars}}$	0.144*** (11.8)	0.225*** (13.4)	0.123*** (12.6)	0.201*** (14.2)
ASC$_{\text{Diesel}}$ (relative to petrol)	0.117*** (2.8)	0.736*** (8.5)	0.102*** (2.7)	0.71*** (8.4)
ASC$_{\text{HEV}}$ (relative to petrol)	0.6*** (10.8)	0.547*** (5.8)	0.526*** (11.3)	0.54*** (5.8)
ASC$_{\text{PHEV}}$ (relative to petrol)	−0.054 (−0.9)	0.593*** (7.2)	−0.03 (−0.6)	0.561*** (6.99)
ASC$_{\text{BEV}}$ (relative to petrol)	−0.825** (−2.0)	−2.411** (−2.2)	−0.507* (−1.7)	−1.326 (−1.6)
SD of error term with mean ASC$_{\text{BEV}}$	0.896*** (4.2)	2.386*** (5.5)	0.452*** (3.4)	1.126*** (7.8)
Socio-demographics for the BEV utility function				
• Age	−0.014*** (−2.9)	−0.003 (−0.3)	−0.008** (−2.2)	0.004 (0.6)
• Female	0.095 (0.5)	−0.923** (−2.4)	−0.171 (−1.3)	−1.06*** (−3.8)
• Income class 2 (relative to class 1)	−0.028 (−0.1)	0.222 (0.4)	−0.034 (−0.3)	0.789** (2.3)
• Income class 3 (relative to class 1)	−0.112 (−0.4)	0.074 (0.1)	−0.358* (−1.7)	0.825** (2.3)
• Income class 4 (relative to class 1)	0.208 (0.6)	−0.717 (−1.0)	0.474* (1.8)	0.347 (0.8)
• EV density	0.343** (2.5)	0.036*** (3.7)	0.342*** (3.9)	0.019*** (2.8)
• BEV owner	2.036*** (3.4)	3.792*** (8.1)	1.6*** (4.6)	1.577*** (4.1)
Scale parameter	1.552*** (5.1)	1	1.723*** (6.6)	1
Diagnostics				
LL(0)	−15,805		−36,185	
LL at observed shares, LL(C)	−21,744		−39,823	
LL(final)	−11,354		−27,542	
LL(0, Choice)			−15,805	
LL(final, Choice)			−11,395	
Adj.Rho-squared vs equal shares	0.279		0.237	
Adj.Rho-squared vs observed shares	0.476		0.306	
AIC	22,785		55,503	
BIC	23,066		57,006	
Estimated parameters	39		209	
Number of individuals	982[a]		982[a]	
Number of observations	9820		9820	
Draws (Sobol[b])	1000		1000[a]	

Legend: Age: continuous variable. Female: coded as 1 for females and 0 for males. Income class coded. For the Italian sample, 1: less than €30,000; 2: from €30,000 to €70,000; 3: from €70,000 to €100,000; 4: more than €100,000. For the Norwegian sample, 1: Less than NOK 400,000; 2: Between NOK 400,001 and NOK 800,000; 3: Between 800,001 and NOK 1,200,000; 4: More than NOK 1,200,001. BEV density expressed as the number of BEVs per 1000 inhabitants. BEV owner coded as 1 if the respondent has a BEV, 0 otherwise.

***, **, * indicate significance at 1 %, 5 % and 10 %, respectively.

[a] Some questionnaires were not considered because information about income was not provided.

[b] We chose to use Sobol draws since they are more appropriate, as demonstrated by Czajkowski and Budziński (2019).

The unconditional choice probabilities are given by the following:

$$P_n = \int_\eta P(y_n|\mathrm{X}_n, \mathrm{Z}_n, \mathrm{LV}_n;\ \beta, \gamma, \alpha, \vartheta, \Sigma_U, \Sigma_{LV})\cdot \mathrm{P}(\mathrm{I}_n|LV_n; \tau_n, \vartheta_n, \Sigma_I, \Sigma_{LV})\cdot \mathrm{f}(\mathrm{LV}_n|Z_n; \vartheta_n, \Sigma_{LV})\ d\eta_n \quad (5)$$

Our goal was to compare the preferences in the two countries. A separate estimate for each country would not allow comparability of coefficients since the scale parameter, reflecting the unspecified attributes, might differ between the two countries (only parameter ratios could be compared). Thus, we normalised the scale parameter with respect to Norway (Train, 2009, p. 25). Consequently:

$$\begin{cases} U_{njt}^{NOR} = \left(ASC_{nj}^{NOR} + \beta_{nj}^{NOR} X_{njt} + \gamma_j^{NOR} Z_n + \alpha_{nl}^{NOR} LV_{nl} + \varepsilon_{njt}\right) \\ U_{njt}^{IT} = \theta\left(ASC_{nj}^{IT} + \beta_{nj}^{IT} X_{njt} + \gamma_j^{IT} Z_n + \alpha_{nl}^{IT} LV_{nl} + \varepsilon_{njt}\right) \end{cases} \quad (6)$$

where $\theta = \theta^{IT}/\theta^{NOR} = \sigma^{NOR}/\sigma^{IT}$.

However, the parameters of the equation for Italy are over-specified. One cannot simultaneously estimate θ and the remaining parameters of the equation which are multiplied by θ (any product might result from an infinite combination of factors). At least one parameter of the

Table 6
Latent variables and the measurement model.

	Italy	Norway
	Coeff.(t-stat)	Coeff.(t-stat)
Latent variables		
LV1 'Economic motivation for choosing a BEV'	0.502*** (5.6)	0.898*** (5.2)
LV2 'Environmental motivation for choosing a BEV'	−0.018 (−0.3)	1.177*** (7.4)
LV3 'Technical motivation for not choosing a BEV'	−0.432*** (−6.2)	−1.182*** (−7.4)
LV4 'Moral motivation for choosing a BEV'	0.151** (2.4)	0.278** (2.3)
Measurement model		
Economic motives		
Q1 - Driving a BEV, one can save money in the long run	1.077*** (5.5)	2.302*** (7.7)
Q2 - I think there is no economic benefit from driving a BEV	−0.618*** (−4.1)	−2.197*** (−8.5)
Q3 - BEVs have lower maintenance costs than conventional cars	0.694*** (4.2)	1.134*** (8.1)
Environmental motives		
Q4 - Driving a BEV is more environmentally friendly than driving an ICEV	3.346*** (8.8)	4.331*** (7.2)
Q5 - BEVs would reduce the environmental pollution caused by traffic	3.338*** (9.3)	2.251*** (9.8)
Q6 - BEVs would reduce the depletion of natural resources	1.972*** (11.4)	2.383*** (10)
Technical motives		
Q7 - The limited BEV driving range is a disadvantage relative to that of an ICEV	2.209*** (11.03)	2.074*** (9.8)
Q8 - It is not practical to drive a BEV because of the lack of charging points	2.267*** (11.6)	0.738*** (6.4)
Q9 - It is not practical to drive a BEV because of the long charging time	2.027*** (11.8)	1.746*** (10.5)
Q19 - The limited driving range of a BEV would make me feel uncomfortable	2.091*** (11.7)	3.512*** (8.7)
Q20 - I would feel worried driving a BEV because of the possibility of having no charge in a location where no charging points are available	1.931*** (10.9)	2.171*** (10.7)
Moral motives		
Q22 - Owning a car that is not fuel efficient and environmentally friendly would make me feel bad because of its negative impact on the environment.	2.006*** (8.7)	2.767*** (9.1)
Q23 - I feel morally obliged to use a fuel-efficient and environmentally friendly car.	2.212*** (7.8)	3.123*** (7.8)

***, **, * indicate significance at 1 %, 5 % and 10 %, respectively.

equation for Italy should be set generic, that is, equal to one of the parameters of the equation for Norway, so as 'to anchor' that parameter to the Norwegian dataset. A similar procedure has been applied by Jensen et al. (2013) to compare preferences and attitudes before and after experiencing an EV and by Noel et al. (2019) to compare preferences among Nordic countries.

After testing different specifications, we opted for the following model that produced the best goodness of fit; we opted for not interacting the socio-demographic variables with non-BEVs based on statistical evidence (no significant difference among non-BEV powertrains), model parsimony, and research focus on BEVs:

$$\begin{cases} U^c_{n,PV} = ASC^c_{PV} + \beta_{Price}Price^c_{PV} + \beta^c_{Range}Range^c_{PV} + \beta^c_{F/E\ costs}F/E\ costs^c_{PV} + \varepsilon^c_{n,PV} \\ U^c_{n,DV} = ASC^c_{DV} + \beta_{Price}Price^c_{DV} + \beta^c_{Range}Range^c_{DV} + \beta^c_{F/E\ costs}F/E\ costs^c_{DV} + \varepsilon^c_{n,DV} \\ U^c_{n,HEV} = ASC^c_{HEV} + \beta_{Price}Price^c_{HEV} + \beta^c_{Range}Range^c_{HEV} + \beta^c_{F/E\ costs}F/E\ costs^c_{HEV} + \varepsilon^c_{n,HEV} \\ U^c_{n,PHEV} = ASC^c_{PHEV} + \beta_{Price}Price^c_{PHEV} + \beta^c_{Range}Range^c_{PHEV} + \beta^c_{F/E\ costs}F/E\ costs^c_{PHEV} + \varepsilon^c_{n,PHEV} \\ U^c_{n,BEV} = ASC^c_{BEV} + \beta_{Price}Price^c_{BEV} + \beta^c_{RangeBEV}Range^c_{BEV} + \beta^c_{F/E\ costs}F/E\ costs^c_{BEV} + \beta^c_{Age}\mathrm{Age}^c + \\ \qquad \beta^c_{Gender}\mathrm{Gender}^c + \beta^c_{Income\_class}\mathrm{Income\_class}^c + \beta^c_{EVdensity}\mathrm{EVdensity}^c + \beta^c_{BEVowner}\mathrm{BEVowner}^c + \\ \qquad \alpha^c_{LV1}LV1^c + \alpha^c_{LV2}LV2^c + \alpha^c_{LV3}LV3^c + \alpha^c_{LV4}LV4^c + \varepsilon^C_{n,BEV} \end{cases} \tag{7}$$

for every individual, n, and for each country, c.

The econometric analysis was performed using the Apollo package in R (Hess & Palma, 2019).

5.1. Results from the RPL and ICLV models

We use tables to present the results and facilitate the discussion. Table 5 focuses on the choice model. For comparative purposes, the first two columns of Table 5 report the estimates for the RPL model, disregarding the LVs and focusing only on the car attributes and socio-demographic variables. The remaining two columns report the parameters of the choice part of the ICLV model. For identification purposes, in the joint model representing the two countries, the price attribute is assumed to be generic across countries[5] while the remaining model parameters are sample-specific (Jensen et al., 2013; Noel et al., 2019). It can be seen that the parameters concerning the car attributes (the net purchase price of the car, driving range, and fuel\electricity costs) have the expected sign and are statistically significant in both models (RPL and ICLV). We assumed them to be normally distributed, and thus we estimated their mean values and standard deviations. They show significant levels of unexplained heterogeneity. We tested several covariates (income, garage ownership, commuting distance, etc.);

[5] Because of the difference in purchase power between Italy and Norway, such an assumption might affect the results.

Table 7
Structural model.

	Italy	Norway
	Coeff.(t-stat)	Coeff.(t-stat)
Economic motives		
Age	−0.005 (−1.1)	−0.006* (−1.8)
Female	0.009 (0.1)	−0.477*** (−4.6)
Income class 2	0.146 (0.96)	0.236 (1.4)
Income class 3	0.505** (2.2)	0.407** (2.4)
Income class 4	−0.143 (−0.4)	0.263 (1.3)
Environmental motives		
Age	−0.004* (−1.9)	−0.006** (−2.6)
Female	0.495*** (5.9)	0.379*** (4.3)
Income class 2	0.26*** (2.8)	0.123 (0.96)
Income class 3	0.031 (0.2)	0.206 (1.6)
Income class 4	−0.165 (−1.01)	−0.059 (−0.4)
Technical motives		
Age	0.011*** (4.8)	0.006** (2.2)
Female	−0.158* (−1.9)	0.324*** (3.6)
EV density	−0.129** (−2.1)	−0.007*** (−3.8)
Moral motives		
Age	0.01*** (3.6)	−0.001 (−0.2)
Female	0.065 (0.7)	0.267** (2.5)
EV density	−0.109 (−1.6)	0.017*** (6.8)

***, **, * indicate significance at 1 %, 5 % and 10 %, respectively.

however, we could not find statistically significant correlations. The parameters of the ASC for DVs, HEVs, and PHEVs are also similar between the two model specifications. In contrast, there is a large difference between the two models regarding the ASC_{BEV} for reasons that we will explain below. The scale parameter, statistically significantly different from 1, revealed relevant differences in unobserved heterogeneity in the two samples.

Let us now turn to the comparison of the estimated parameters between the two countries. It can be seen that the magnitude of the country-specific parameters for the ICEV driving range are similar between the two countries, implying a WTP for an additional driving-range km equal to €7 (Rob. SE 2, calculated using the Delta method) in Italy and €3 (Rob. SE 4) in Norway in the RPL model, and to €7.5 (Rob. SE 2) in Italy and €6.4 (Rob. SE 5) in Norway in the ICLV model.[6] Regarding the driving range for BEVs, the implied WTP for an additional driving-range km is equal to €17 (Rob. SE 9) in Italy and €50 (Rob. SE 19) in Norway in the RPL model and €27.7 (Rob. SE 7.5) and €51.2 (Rob. SE 24.6), respectively, in the ICLV model. The fact that the Norwegian drivers value the driving range more might be due to the longer daily travel distances in Norway than in Italy (Scorrano et al., 2019) and the colder winter temperatures.

Compared with previous estimates concerning Italy, our results are lower. Indeed, Valeri and Danielis (2015) found a value of €50 per additional km of driving range, Valeri and Cherchi (2016) a value of €42, Giansoldati et al. (2018) a value ranging from 37 to 106 €/km, and Danielis et al. (2020) a value in the range 29–66 €/km. There seems to be a decreasing trend, indicating a growing sensitivity to the driving range of BEVs offered in the market. In Norway's case, a comparison can be made with the results obtained by Noel et al. (2019) and Fridstrøm and Østli (2022). Noel et al. (2019) conducted a survey between September 2016 and November 2017. In their model specification, they assumed a non-linear specification of range, providing different WTPs per each additional km range for five Nordic countries. For Norway, the values started at $300 per additional km for an initial driving range of 150 km and declined at slightly less than €100 for an initial driving range of 150 km. Fridstrøm and Østli (2022) used revealed-preference data up to May 2019. They also estimated a diminishing return to the range function and found that in a car with an initial range of 150 km, the revealed WTP for a 100 km longer-range BEV was approximately €24,000. When the initial range was 500 km, the value of another 100 km of range dropped to approximately €5100. Considering that in 2021 the Tesla Model 3, the best-selling car in Norway, had a driving range slightly lower than 500 km, we can conclude that our estimates are consistent with those obtained by Fridstrøm and Østli (2022) and that they indicate that in Norway, as in Italy, the drivers' satisfaction with the BEV driving range is improving.

The respondents are also quite sensitive to fuel/electricity savings, with Norwegians having higher absolute values than Italians. The explanation might not be related to the fuel\energy prices, which are similar for petrol but lower in Norway for electricity, but again to higher driving distances and larger sizes of the car models in Norway than in Italy.

Finally, Table 5 reports the results concerning the ASCs for the different powertrains relative to petrol. The ASC is to be interpreted as the (dis)utility of all the variables not modelled in the systematic utility, thus capturing the relative utility of a powertrain *ceteris paribus* (i.e. all other modelled variables being equal). The respondents prefer diesel to petrol cars in both countries, more strongly so in Norway. HEVs are also strongly preferred to petrol cars in both countries, while PHEVs are preferred to petrol only in Norway.

In the case of BEVs, the interpretation of the results is more complex because the ASC_{BEV} is assumed to be normally distributed and is interacted with several socio-economic covariates that explain its heterogeneity. In our specification of the ICLV model, the socio-economic variables enter Equation (5) interacted with the ASC both in the choice model and in the structural model. The former captures the direct effect of the socio-economic characteristics on utility, while the latter measures their impact 'mediated' via the LVs (Kløjgaard & Hess, 2014; Schmid & Axhausen, 2019). We discuss these results in detail in the next subsection.

Table 6 illustrates the impact on utility associated with BEVs of the LVs identified via factor analysis and their corresponding measurement items. The meaning of the LVs can be grasped by reading the items associated with each LV, listed in the measurement model, in association with the sign and statistical significance of their estimated parameters. In both countries, the first LV, LV1, is positively and significantly associated with Item Q1 'Driving a BEV, one can save money in the long run'; it is negatively and significantly associated with Item Q2 'I think there is no economic benefit from driving a BEV'; and it is positively and significantly associated with Item 'Q3 - BEVs have lower maintenance costs than conventional cars'. Thus, high values of LV1 represent respondents who believe that BEVs are economically advantageous. Therefore, we termed LV1 'Economic motivation for choosing a BEV'. With similar reasoning, we termed LV2 'Environmental motivation for choosing a BEV', LV3 'Technical motivation for not choosing a BEV', and LV4 'Moral motivation for choosing a BEV'. Note that all the items have strongly and statistically significant parameters.

Let us now focus on the parameters of the LVs. These parameters measure the impact of the LVs on the utility of BEVs (relative to the other powertrains) since they are specified only in the utility function for BEVs. In the case of Norway, all four LVs are statistically significant and have the expected sign. In the case of Italy, only LV1, LV3, and LV4 are statistically significant. More specifically, both in Norway and in Italy, respondents who have a high economic motivation for choosing a BEV (since they believe that BEVs offer the possibility of saving money in the long run, generate economic benefits, and have lower maintenance costs) assign them a relatively higher utility. Consequently, they are more likely to choose a BEV among the different powertrains.

In contrast, we find different results concerning the environmental motivation (LV2). Those who think that BEVs generate environmental benefits assign them a relatively higher utility and, hence, are more likely to choose them in Norway. That is not the case in Italy: respondents who think that BEVs generate environmental benefits do not

[6] Please also note that we converted Norwegian price and cost variables from the Norwegian krone (NOK) to the Euro (one Euro corresponds to 10 NOK) to have parameter comparability across the countries.

Table 8
Direct, indirect, and total impact of the socio-demographic variables.

	Direct Effect	LV1 Economic motives	LV2 Environmental motives	LV3 Technical motives	LV4 Moral motives	
		Indirect effect	Indirect effect	Indirect effect	Indirect effect	Total effect
	Coeff.(t-stat)	Coeff.(t-stat)	Coeff.(t-stat)	Coeff.(t-stat)	Coeff.(t-stat)	Coeff.(t-stat)
Italy						
Age	−0.008** (−2.2)	−0.003 (−0.7)	0.0001 (0.2)	−0.005*** (−2.7)	0.001 (1.4)	−0.014*** (−3.53)
Female	−0.171 (−1.3)	0.004 (0.1)	−0.009 (−0.2)	0.068 (1.2)	0.01 (0.5)	−0.098 (−0.42)
Income class 2	−0.034 (−0.3)	0.073 (0.7)	−0.005 (−0.2)			0.035 (0.21)
Income class 3	−0.358* (−1.7)	0.254 (1.4)	−0.001 (−0.1)			−0.105 (−0.39)
Income class 4	0.474* (1.8)	−0.072 (−0.4)	0.003 (0.2)			0.405 (1.54)
EV density	0.342*** (3.9)			0.056 (1.4)	−0.016 (−0.99)	0.381*** (3.03)
Norway						
Age	0.004 (0.6)	−0.005 (−1.1)	−0.007* (−1.7)	−0.007 (−0.9)	−0.0002 (−0.2)	−0.015 (−0.77)
Female	−1.06*** (−3.8)	−0.429* (−1.7)	0.446** (2.6)	−0.383** (−2.1)	0.074 (0.8)	−1.351*** (−3.25)
Income class 2	0.789** (2.3)	0.212 (0.9)	0.144 (0.7)			1.145** (2.46)
Income class 3	0.825** (2.3)	0.366 (1.5)	0.243 (1.1)			1.433*** (3.23)
Income class 4	0.347 (0.8)	0.236 (0.6)	−0.069 (−0.2)			0.514 (0.4)
EV density	0.019*** (2.8)			0.009** (2.2)	0.005 (1.5)	0.033* (1.85)

***, **, * indicate significance at 1 %, 5 % and 10 %, respectively.

significantly choose them more than those who think that BEVs dot not generate environmental benefits. In other words, we can say that beliefs do not translate into choices. Italian respondents do not seem to choose BEVs based on their environmental concerns.

With reference to LV3 ‘Technical motivation for not choosing a BEV’, the sign and significance is similar in the two countries. Those who think that BEVs have technical limitations (driving range, public-charger availability, charging time, etc.) assign them a relatively lower utility and, hence, are less likely to choose them. The magnitude of the coefficient is much higher for Norway than for Italy, most likely due to the greater experience with BEVs of the Norwegian respondents.

Finally, regarding LV4 ‘Moral motivation for choosing a BEV’, the variable is also significant in both countries. Those who feel morally obliged to own a fuel-efficient and environmentally friendly car do assign BEVs a relatively higher utility; thus, they tend to opt for a BEV in the stated-choice experiments.

Table 7 reports the results of the structural model, which illustrates the impact of a selected number of socio-economic variables on the LVs. Of the many demographic variables collected in the first part of the interview, we retained the ones that were more interesting and statistically significant. It can be seen that the impact is quite differentiated between the two countries. A more detailed analysis is presented in the next subsection.

5.2. Direct, indirect, and total impact of the socio-demographic variables

As argued by Schmid and Axhausen (2019), the ICLV model has two main advantages: i) it allows consideration of the socio-economic variables that were not significant in the RPL model; ii) it allows the possibility to disentangle the direct and indirect effects of socio-economic characteristics.

Since we have introduced the same socio-economic variables as separate explanatory variables in the ICLV model, as suggested by Vij and Walker (2016) and Schmid and Axhausen (2019), by applying the Delta method, we could decompose the total effect of the socio-economic characteristics into their direct and indirect components. The former measures the direct effect of a socio-economic variable on utility (also reported in Table 5), while the latter measures the impact mediated via the LV. Table 8 summarises the results.

In contrast with Fevang et al. (2021), we find that in Norway age has no overall significant impact on BEV utility. On the contrary, in Italy, age plays a role: younger respondents appear to be more inclined to buy BEVs also because of their stronger moral obligation.

Gender has no impact on BEV utility in Italy: male and female respondents assign equal utility levels to BEVs. In contrast, female respondents in Norway value BEVs less than male respondents, both directly and as mediated via the economic (LV1), environmental (LV2) and technical (LV3) motives, but not via the moral ones (LV4). The finding that males have a stronger preference than females for BEVs in Norway is consistent with that obtained in previous studies (Coffman et al., 2017; Liao et al., 2017) but in contrast with the finding by Anfinsen et al. (2019), specific for Norway, that males and females seem to be equally interested in BEVs. However, it should be borne in mind that buying a car is often a family decision, so that it is uncertain how the sex difference plays out in actual car-buying decisions.

The coefficients for the income classes are to be interpreted relative to the lower income class. Overall, income has no statistically significant impact on BEV utility in Italy, indicating that even rich people do not believe in BEVs. In contrast, in Norway, income classes 2 and 3 are more prone to buy a BEV than income class 1, while there is not a statistically significant difference between income class 4 and 1. This result is in line with that obtained by Fevang et al. (2021).

Finally, EV density has a strong and statistically significant direct effect both in Italy and in Norway: those who live in EV-dense regions seem to have a higher preference for BEVs than those who live in less EV-dense regions. In Norway, the impact of EV density is reinforced by the technical motives. A possible interpretation is that it captures both an agglomeration effect and a peer effect. The fact that the coefficient is

Table 9
Sample’s and estimated choice shares.

	NOR					ITA				
	PV	DV	BEV	HEV	PHEV	PV	DV	BEV	HEV	PHEV
Sample’s choice share (%)	10.7	16.6	39.2	16.6	16.9	21.7	25.1	18.1	26.4	8.7
Estimated choice share (%) RPL	10.8	16.3	39.8	16.2	16.9	22.2	24.9	18.7	26.3	8.0
Sample’s minus estimated RPL	−0.1	0.3	−0.6	0.5	0.0	−0.5	0.2	−0.5	0.1	0.7
Estimated choice share (%) ICLV	10.7	16.9	38.4	16.5	17.5	21.8	24.2	19.0	26.6	8.5
Sample’s minus estimated ICLV	−0.1	−0.3	0.8	0.2	−0.6	−0.1	0.9	−0.8	−0.2	0.2

positive and statistically significant might indicate that BEV uptake tends to agglomerate in certain areas and that phenomena such as imitation and word-of-mouth effects do play a role in BEV acquisition. Another interpretation, more consistent with contentions by Fevang et al. (2021), is that certain regulatory advantages (zero toll roads, access to bus lanes, free parking, access to limited traffic zones, etc.) are area-specific and hence explain the higher propensity to choose a BEV in a given area.

5.3. Goodness-of-fit of the RPL and ICLV models at aggregate level

As explained by Walker and Ben-Akiva (2002), a comparison of the RPL and ICLV models should be made with reference to the log likelihood of the choice part only (e.g. Kløjgaard & Hess, 2014). The Apollo software provides the user with the estimate of the individual components of the overall LL function in the ICLV model, that is the choice component and the various measurement components. The former is termed LL(final, Choice) and is equal to −11,395, while, as reported in Table 5, the LL(final) of the RPL model is equal to −11,354. Such result is consistent with Vij and Walker (2016), who demonstrated theoretically and via simulation that a reduced-form model without LVs may fit the data at least as well as a the LV model if the observable explanatory variables are good predictors of the LVs.

Thus, if used for forecasting, the ICLV model might be inferior to the RPL model from a statistical viewpoint. We tested the difference by comparing the ability of the two models to estimate, at an aggregate level, the choices made by the respondents in the hypothetical scenarios. The results are reported in Table 9.

The RPL model estimates the choices made by the respondents quite well, while the ICLV model under-estimates the Norwegian BEV share and over-estimates the Italian one. Thus, as discussed in the literature, the ICLV model presents a trade-off: a higher ability to explain the psychological factors of a choice and its socio-economic determinants comes at the expense of lower, even if marginal, estimation power.

6. Conclusion and discussion

The research question that motivated our study was to explore whether the huge difference in BEV uptake between Norway and Italy could be explained by differences in the car buyers' preference structures, either in terms of their evaluation of the vehicles' characteristics or in terms of their perceptions of\attitudes towards EVs. Although we found some differences, our general feeling is that what determined the radically different outcome in terms of the market shares of the different powertrains in the two countries cannot be explained by demand factors only. Policy and supply factors, not investigated in this paper, most likely play a large role.

Regarding the evaluation of the vehicles' characteristics, Norwegians value the BEV driving range more and are more sensitive to the fuel \electricity costs. Among powertrains, *ceteris paribus*, Italian respondents, in contrast to Norwegian ones, still prefer PVs to BEVs. A limitation of our choice experiment is certainly that relevant features associated with BEVs such as, for instance, public-charging availability, charging time, maintenance costs, and resale value, were not specified in the choice scenarios, although they are potential aspects that could reveal differences in experience and available charging infrastructure between Italy and Norway. The desire to not overburden respondents with too much information and to leave some room for the evaluation of the perceptions\attitudinal questions refrained us from constructing scenarios that were more realistic. The unspecified contextual variables were consequently captured by the ASCs and scale parameter, which revealed the relevant differences in unobserved heterogeneity in the two samples in both model specifications (RPL and ICLV).

Concerning the impact of socio-economic determinants on BEVs' utility, some interesting differences could be detected. Age was slightly more significant in Italy than in Norway, indicating that in Norway, BEVs are well accepted across generations. Sex played a role only in Norway; that is, males were more BEV-oriented than females. The finding about Norway is consistent with previous studies' findings (Coffman et al., 2017; Liao et al., 2017) and is often motivated by males' stronger interest in new technology but contrasts with the finding by Anfinsen et al. (2019) that males and females seem to be equally interested in BEVs. EV density, a rough metric capturing peer imitation and peer pressure, played a role both in Italy and in Norway. Interestingly, in both countries BEV owners confirmed their preference for BEVs, other things being equal. We also conducted an additional robustness check by estimating the model without the "BEV owners" variable. The signs, magnitudes, and significance levels of the main parameters—including the latent variables—remained essentially unchanged, indicating that the results are not driven by the current BEV owners in the sample. Figenbaum et al. (2019) arrived at a similar conclusion via a direct survey. They documented that in 2018, 94 % of BEV owners would repurchase a BEV. A similar finding is confirmed by Hasan (2021) using a structural-equation model.

The impact of income is unclear. In Italy, there seems to be no statistically significant difference in BEV propensity between the four identified income classes. On the contrary, in Norway, income plays a role, but only with respect to the intermediate income classes. However, this finding should be interpreted with caution since it might depend on the unreliable income self-reporting typical of many surveys (Bahamonde-Birke & Hanappi, 2016) or the well-known hypothetical bias that affects stated-choice data (Haghani et al., 2021a, 2021b). Several other socio-economic variables were available from the survey, such as home-charging availability, place of residence, and journey distance; however, they were not included in the final specification because of insufficient statistical significance.

One of the central areas of research to which this paper was devoted is the question of whether there are significant differences in the attitudes towards and/or perceptions of BEVs between the Italian and Norwegian respondents. We expected differences due to the contextual differences (charging infrastructure, BEV-incentivising policies, greater attention to reduce air pollution, noise from transport in Norwegian cities, etc.) and the greater experience with BEVs. Overall, the short answer to our research question is negative. When asked to dis\agree with the statements regarding BEV perception, on average, the two groups provided similar responses, with the only exception being that of familiarity with BEVs. In our view, this result indicates that, due to social networks and the internet, the information is spread evenly in the two countries, so that direct experience is sufficiently well-compensated for by indirect experience. The implication of this finding might be relevant: it indicates that the information barrier is not particularly strong and that, provided the necessary ecosystem exists, EV penetration can also proceed at a fast pace in countries that are currently lagging behind, such as the southern and eastern European countries.

The ICLV model allowed us to statistically test the relationship between stated choice and BEV-related LVs. In both countries, the respondents' perceptions\attitudes influence car choice. In Norway, the respondents who believe that BEVs are superior from economic, environmental, technical, and moral viewpoints assign a relatively higher utility to BEVs. In Italy, the evidence is similar but for the environmental aspects, which are not decisive for the BEV choice. Such perceptions \attitudes are correlated with age, sex and EV density. Overall, we do not detect striking differences in perceptions\attitudes, thus confirming our previous conclusion that Italian drivers' preferences should allow an EV-penetration path similar to the Norwegian one if the necessary ecosystem in terms of charging infrastructure and incentivising policies is provided.

Importantly, the policy frameworks in the two countries have been radically different. Norway has promoted a wide range of BEV-incentivising financial and regulatory policies such as a no-VAT exemption on purchase, no or reduced annual road tax, no charges on toll roads or ferries, free municipal parking, and access to bus lanes

(Cincotta & Thomassen, 2025; Green and Østli, 2025; Fridstrøm & Østli, 2017; Steinsland et al., 2016). Fossil fuel-based cars, in contrast, have been taxed based on the tare weight and CO2 and NOx emissions. Italy has also promoted BEVs but to a lower extent and less consistently. The registration taxes are much lower than in Norway and are only weakly differentiated by powertrain. All cars emitting less than 135 g CO_2/km are eligible for a purchase subsidy, motivated by the need to spur car renewal, although declining with the CO_2-emission factor.

The combination of demand, supply, and policy factors lead to the current difference in powertrain uptake in the two countries, with the latter ones playing, in our view, a major role.

Although from a technical viewpoint the ICLV model proved useful to estimate the LV marginal effects, in a recent study using Monte-Carlo simulations Campbell and Sandorf (2020) concluded that the ICLV model was appropriate only if there was a strong degree of correlation between attributes, LVs, and indicators. In our specific case, the estimates indicate that the socio-economic variables are good predictors of the LVs, the measurement indicators are appropriate, and there is a significant correlation between preferences, the latent constructs, and the indicators. Nonetheless, as expected (Campbell & Sandorf, 2020; Vij & Walker, 2016), the advantages of disentangling the choice components came at the cost of a lower fit and predictive ability of the ICLV model relative to the RPL model. We tested that this affected mainly the ability of the model to correctly predict the choice of a BEV: it underestimated it in Norway's case and slightly overestimated it in Italy's case.

A further concern is the use of the ICLV model to inform policymakers. While the ICLV model allows an understanding of the cognitive process underlying decision making (Hess, 2012; Mariel & Meyerhoff, 2016; Taye et al., 2018), it cannot simply be used to propose policies that aim at influencing perceptions\attitudes, e.g. via information campaigns on the BEVs' economic and environmental properties. Chorus and Kroesen (2014) cautioned that such a simplistic use might be inappropriate because an LV might be endogenous to choice while data on the LVs are cross-sectional; thus, they cannot be used to predict within-individual changes.[7] In a series of studies, they explained their reasoning and proposed an alternative method based on travel behaviour (private car vs. public transport) (Kroesen & Chorus, 2018, 2020; Kroesen et al., 2017). On the issue of endogeneity, Kroesen and Chorus (2018) pointed out that attitudinal variables needed to satisfy two criteria for causal inference: empirical association and exogeneity. They distinguished between generic and specific attitudes and demonstrated that generic attitudes suffered less from the issue of endogeneity but were only weakly correlated. In contrast, specific attitudes were more strongly correlated but suffered from the endogeneity issue. In our car-choice application, the economic and technical motivations can be considered specific: the extent of the motivation varies depending on the direct experience with BEVs (hence, likely higher for BEV owners), while the environmental and moral motivations can be considered generic and unrelated to BEV ownership. Consequently, the latter would suffer less from the endogeneity issue.

One of the main limitations of our study is, in our view, the stated-preference nature of the choice data. Apart from the commonly quoted hypothetical bias, in a cross-country comparison, our stated-preference scenarios suffered from the difficulty of explicitly and credibly representing the contextual and policy variables via specific attributes. The former concern the diffusion of charging infrastructure and its fast-charging capabilities. The latter concern the numerous fiscal and regulatory incentives of a country. Such difficulty is due to the obvious need to limit the number of attributes in each choice scenario and to the fact that the importance of these variables depends on the respondents' place of residence and their travel needs. For instance, a respondent might find the diffusion of the fast-charging infrastructure important for some of the trips and if the BEV is their only car. Incentives such as the discounted tolls on roads and ferries, free municipal parking, and access to bus lanes enacted in Norway or the access to limited traffic zones in some places in some Italian cities play a role depending on individuals' place of residence and travel habits. Such considerations do certainly influence the actual choice but are very difficult to mimic in a hypothetical choice scenario. Consequently, all these contextual and policy variables remained unspecified in our model and were captured by the mean and variance of the ASC_{BEV}, which were found positive for Norway and not statistically significantly different from zero for Italy.

Although we collected data on the number of cars in households and their use, their place of residence, and garage availabilty, we could not detect statically significant correlations between these variables and the stated choices. It is not unlikely that respondents disregarded such real world limitations in selecting their preferred choice. A person-to-person interview instead of an internet-based online questionnaire might allow the interviewer to remind the respondent of the real-world contraints. However, person-to-person interviews suffer from major drawbacks: it is extremely time and resource consuming to conduct several interviews sufficient to satisfy the statistical representativeness criterion; moreover, the interviews can enhance the social desirability bias due to the interaction between the interviewer and the respondent. The latter issue is particularly severe when the interview, as in our case, proposes questions on the perceptions of\attitudes towards BEVs which contain elements related to the enviroment and moral obligations.

Among the hypothetical bias-mitigation strategies suggested in the literature (see Haghani et al., 2021b; Haghani et al., 2021b.g. cheap talk, solemn oath, opt out and budget remainder, pooled revealed and stated preference estimation, referencing, and pivoting), we prefer the pooling of revealed and stated preference data. Such a strategy allows the merging of the pros of the two datasets: the realism of the former and the attribute variation of the latter. We plan to perform such a task in our next research effort. Finally, future research could also extend the analysis to examine the perceptions and attitudes associated with PHEV purchase, particularly in cross-country settings where the motivations for choosing PHEVs may diverge substantially due to the different stage of development of the charging infrastructure.

CRediT authorship contribution statement

Mariangela Scorrano: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Terje Andreas Mathisen:** Writing – review & editing, Validation, Supervision, Conceptualization. **Romeo Danielis:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Ozlem Simsekoglu:** Writing – review & editing, Investigation. **Giuseppe Marinelli:** Writing – review & editing, Investigation.

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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[7] Chorus & Kroesen (2014) leave open the possibility of using LVs 'as input for scenario studies that involve changes in the population over time'.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.retrec.2025.101695.

Data availability

Data will be made available on request.

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