Analysing risky choice preferences in electric vehicle charging

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SHORT SUMMARY

With continuing growth of electric vehicle (EV) sales and intermittent renewable baseload power supply, EVs can help balance future power grids, through charging and vehicle-to-grid discharging. Understanding charging behaviour will assist flexibility incentive and policy design. We gathered strategic and tactical charging choice attribute preferences and risky choice charging scenario data from 203 EV and petrol/diesel vehicle users. Empirical analysis revealed a risk-averse majority, particularly around range, with varying, evolving risk attitudes across heterogeneous groups. The most context relevant risk attitude predictor was time sensitivity. Flexibility incentives can target range, cost, time and charge location feature aspects of 'where', 'when' and 'how much' to charge/discharge choices, segmenting EV users by risk attitude. Policymakers can target EV adoption interventions at risk-averse groups. Non-expected utility theory methods, focusing on heterogeneous risk attitudes across attributes and segments appear appropriate for explaining risky choices in this context.

Keywords: battery electric vehicle; power system flexibility; vehicle-to-grid (V2G); EV charging behaviour; risky choice.

1. INTRODUCTION

With global installed clean power capacity forecast to exceed 1,600 GW by 2030, electricity grid power supply is increasing in variability. Worldwide electricity demand is predicted to double to around 50,000 TWh by 2050 (International Energy Agency 2024). These trends mean a growing need for grid-scale and distributed energy storage. EVs batteries can help optimise grid loads, providing flexibility through charging and vehicle-to-grid (V2G) discharging (International Energy Agency 2024).

Accurate forecasting of bi-directional charging energy flows, and effective EV energy demand and supply flexibility incentivisation, grounded in an understanding of consumer choice, can improve grid efficiencies. The Random Utility Model (RUM) is a well-established choice modelling paradigm, however real-world decisions often depart from RUM's rational utility maximisation approach (McFadden 2001). Prospect Theory (PT)-based methods have been used to model loss aversion and non-linear probability weightings in risky EV charging choice scenarios (Latinopoulos, Sivakumar and Polak 2017) (Hu, Dong and Lin 2019) (Li, et al. 2022) (Shen, et al. 2025). Extensive heterogeneity has been observed in EV charging behaviour (Potoglou, Song and Santos 2023). Accounting for heterogeneity, and risk attitudes, can improve flexibility incentive design (Marxen, et al. 2023).

This study empirically assesses behaviour of 203 EV and petrol/diesel vehicle users, examining vehicle use patterns, attribute selection in tactical and strategic charging choice modelling and risk attitudes. The inclusion of petrol/diesel vehicle users is seen as important, with EV market growth dependent on non-EV user conversions. Tactical charging choice attributes from the

literature have been reviewed, including those referenced by Potoglou, Song and Santos (2023), Andrenacci and Valentini (2023), Pan, Yao and Mackenzie (2019), and Hoen, et al. (2023). Potoglou, Song and Santos (2023) classify attributes in vehicle, individual, charging infrastructure and temporal attribute groups. Charging energy cost, state of charge and charge duration related attributes are frequently included in choice models in the literature. Here, as illustrated in Fig. 1, cost, time, range and charge location features groups have been found to encompass most attributes featured in the literature. Risk attitudes are examined for cost, time and range, in addition to attribute importance in tactical 'when', 'where' and 'how much' to charge choices and strategic home charging package decisions.

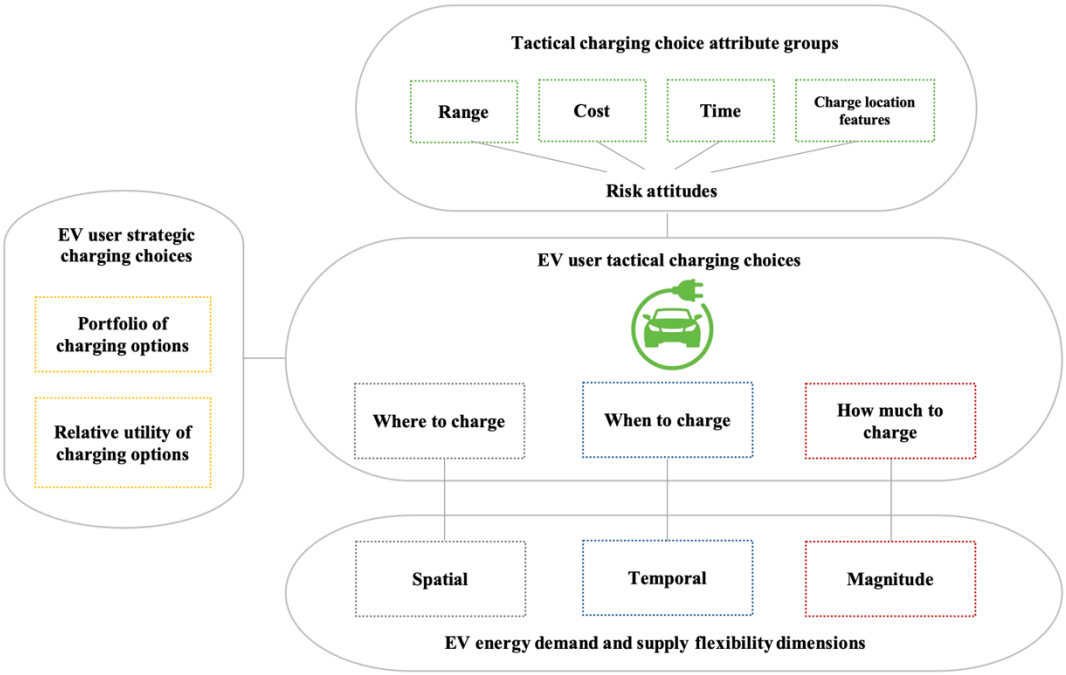


Fig. 1. EV charging choice and energy flexibility dimensions.

Papers exploring tactical charging risk attitudes mostly focus on range, finding range anxiety to affect charging decisions. PT-based choice models from Hu, Dong and Lin (2019) and Li, et al. (2022) combine different attribute types in a single cost function, meaning these studies don't assess range, cost or time attribute risk attitudes in isolation. Wang, et al. (2026) found range anxiety to affect charging choices more significantly than time-based anxiety. Latinopoulos, Sivakumar and Polak (2017) studied price risk aversion, discovering non-linear risk attitudes, particularly as price increased. The reviewed literature hasn't covered charge location feature risk attitudes. Some studies, however, note the importance of greater infrastructure availability in increasing charging demand and reducing range anxiety (Wang, Yao and Yang 2024) (Shen, et al. 2025).

Flexibility incentive targeting can benefit from consumer classification. Several papers have segmented EV users by risk attitude (Pan, Yao and MacKenzie 2019) (Wang, Yao and Pan 2021) (Shen, et al. 2025). Risk attitudes have been linked to sociodemographic characteristics, shown in Table 1. Findings vary, however significant gender and income results found females and high income groups to be more risk averse. A significant majority found older vehicle users to be more risk averse. Findings for EV experience and employment have been mixed.

Table 1: Risk-seeking groups in EV charging

Sociodemographic category	Groups identified as risk seeking	Papers	Total Papers
Gender	Males	Wang et al. (2021), Li et al. (2023)	2
Age	Younger people	Daina (2014), Latinopoulos et al. (2017)*, Wang et al. (2026)	5
	<45s	Daina & Polak (2016)	
	<50s	Thorhauge et al. (2024)	
	>40s	Wang et al. (2021)	2
	Older people	Zhang et al. (2022)	
EV experience	Experienced EV users	Li et al. (2023), Latinopoulos et al. (2017)*	3
	Already paying to charge	Latinopoulos et al. (2017)*	
	Energy literacy	Marxen et al. (2023)	
	Smart charging experience	Marxen et al. (2023)	
	Inexperienced EV users	Yuan et al. (2018), Wang et al. (2021), Wang et al. (2026)	4
	Purchased EV within one year	Pan et al. (2019)	
Income	Low income	Wang et al. (2021), Zhang et al. (2022), Li et al. (2023)	3
Employment	Unemployed people	Latinopoulos et al. (2017)*	3
	Tourism travellers	Wang et al. (2024)	
	Not in full time employment	Daina (2014)	
	High time cost drivers	Li et al. (2022)**, Li et al. (2023)	2
Other	Extraverted people	Wang et al. (2026)	1
	Lower emotional control	Yuan et al. (2018)	1

Note: Risk seeking is around range unless stated. * Risk seeking around cost. ** Risk seeking across range, cost and time combined.

Visaria, et al. (2022) classify EV charging choices into long-term strategic package selection choices and infrequent, tactical charging choices, made during trips. Strategic charging and V2G package choice attributes feature in the literature, including studies by Daziano (2022), Huang, et al. (2021) and Kubli (2022). Le Vine (2011) presents travel choices as a 'portfolio' of options. It may be considered that in EV charging, strategic choices affect the composition and relative utility of tactical choice options, in a portfolio that evolves as EV users move through locations, over time.

2. METHODOLOGY

An online survey was designed. Section 1 included consent questions. Sections 2 and 3 gathered driving and charging/refuelling revealed preference data. Section 4 asked participants to rate attribute importance for 'where', 'when' and 'how much' to charge choices, with attributes selected with reference to the literature.

Section 5 first involved obtaining full charge cost and time reference points, plus certainty levels. Reference point selection is important in PT model development. Participants were then presented with scenarios, summarised in Table 2, testing risky choice attitudes, across charge cost, time and range. Fig. 2 shows example scenarios, as presented to participants. Each randomly presented scenario included a certain, reference outcome and an uncertain outcome, with a possible relative gain or loss. Each situation included a scenario with equally valued certain and risky options, and two scenarios with increasingly favourable risky option expected values. Loss and gain likelihoods and relative sizes differed for each situation, increasing the information obtained. This was intended to explore risk attitudes to different attributes, testing the suitability of a PT-based choice modelling approach in further research, as such models account for risk aversion.

Table 2: Overview of charging scenarios

Situation	Description	Scenario	Option	Option Characteristics	Expected Value
A	You would normally expect to pay around £20 for the amount of charge you need. At Charging Station A, the energy price is fixed and known in advance. At Charging Station B, pricing is variable, depending on demand and time - you won't know the exact cost in advance.	1	A	£20 (100%)	£20
			B	£18 (75%), £25 (25%)	£19.75
		2	A	£20 (100%)	£20
			B	£15 (75%), £25 (25%)	£17.50
		3	A	£20 (100%)	£20
			B	£15 (50%), £25 (50%)	£20
B	You would normally expect the amount of charge you need to take around 1 hour. Charging Station C offers consistent charge speeds, with charge time expected to be close to 1 hour. At Charging Station D, charge speeds vary and charging can be faster or slower depending on demand.	1	C	1 hour (100%)	1 hour
			D	45 mins (50%), 1 hour 15 mins (50%)	1 hour
		2	C	1 hour (100%)	1 hour
			D	50 mins (80%), 1 hour 20 mins (20%)	56 mins
		3	C	1 hour (100%)	1 hour
			D	40 mins (80%), 1 hour 30 mins (20%)	50 mins
C	For remaining ranges above 80 miles you can be certain of getting home. For ranges below 80 miles, there is an increasing chance of running out of energy before arriving. Charging Stations E and F both have 45-minute charging session limits due to high demand. Charging Station E has consistent charge speeds, allowing you to charge to 90 miles of range for sure during the session. At Charging Station F, charging can be faster or slower depending on demand, so there is some uncertainty about how much you can charge in the time available.	1	E	90 miles (100%)	90 miles
			F	120 miles (75%), 75 miles (25%)	108.8 miles
		2	E	90 miles (100%)	90 miles
			F	105 miles (50%), 75 miles (50%)	90 miles
		3	E	90 miles (100%)	90 miles
			F	100 miles (90%), 65 miles (10%)	96.5 miles

Section 6 required participants to rate strategic charging package selection attributes, chosen with reference to the literature. Section 7 gathered attitudinal and sociodemographic information. Throughout, petrol/diesel users were asked to answer some questions imagining an EV was their main vehicle.

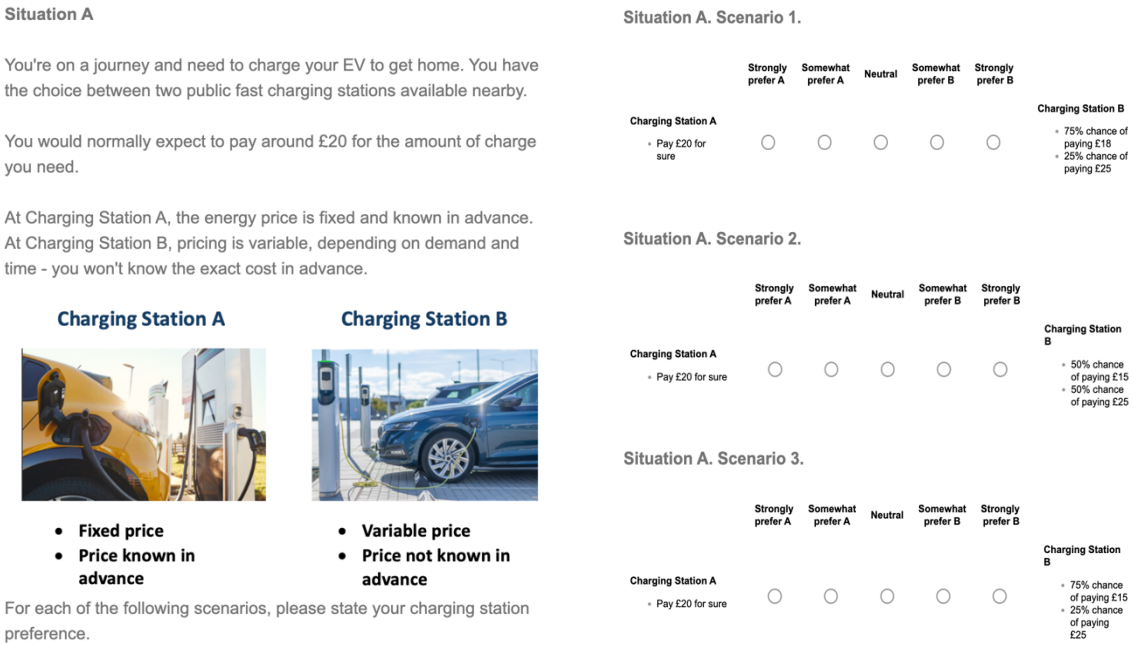


Fig. 2. Example scenario questions.

3. RESULTS AND DISCUSSION

The data was collected during November/December 2025, from 123 electric and 80 petrol/diesel vehicle users, who were diverse across gender, age, education, income and UK location (see Appendix A). 84% of EV users had completed 100+ journeys, with 92% of males and 64% of females being mostly the main driver, compared to a more equal split for petrol/diesel. 24 EV brands and many models, including 30% discontinued, reflect a diverse, evolving EV market. The median EV range was 256 miles, which was 56% of the petrol/diesel median. Table 3 shows that majorities of participants rated themselves generally cost-, energy- and technology-conscious, and risk-averse, with some spare time. Appendix B regression analysis shows EV users, males, younger and more educated vehicle users as significantly more comfortable taking risks.

Table 3: Attitudinal response summary

	Total		EV Users		Petrol / Diesel		Males		Females		Age <40		Age >40	
Question	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
I'm very cost conscious	7.5	2.3	7.4	2.2	7.7	2.4	7.4	2.1	7.6	2.5	7.0	2.5	7.7	2.2
I have little spare time	4.5	2.9	4.3	3.0	4.8	2.9	4.3	2.9	4.7	3.0	5.1	2.7	4.3	3.0
I feel comfortable taking risks	4.1	2.9	4.5	2.9	3.4	2.8	4.6	2.8	3.5	2.8	5.1	2.8	3.8	2.8
It is important the world transitions to sutainable energy sources	6.8	3.2	7.3	3.0	6.1	3.4	6.7	3.2	7.0	3.2	6.5	2.8	6.9	3.3
I try to be as energy efficient as possible	7.3	2.6	7.8	2.3	6.6	2.9	7.3	2.5	7.4	2.7	6.3	2.4	7.6	2.6
Technology innovation is very important	6.9	2.5	7.5	2.1	6.1	2.7	7.3	2.4	6.5	2.5	7.4	2.1	6.8	2.5
I prefer to stay with the same home energy provider	5.8	2.9	5.9	3.1	5.6	2.7	5.7	3.0	5.9	2.9	6.0	2.4	5.7	3.1
I would switch home energy provider if offered a a slightly lower price	5.7	2.8	5.7	2.7	5.8	2.8	5.9	2.7	5.5	2.8	5.8	2.5	5.7	2.8

Response scale: 0 (strongly disagree) to 10 (strongly agree). SD = standard deviation.

68% of EV user charge events were at home, averaging 3.08 weekly charges. Public fast, public slow, work and peer-to-peer chargers each averaged <0.5 weekly charges. Fig. 3 shows EV users targeted lower minimum charges levels, with 69% targeting 10-20%. Fig. 4 shows EV users preferring lower range buffers.

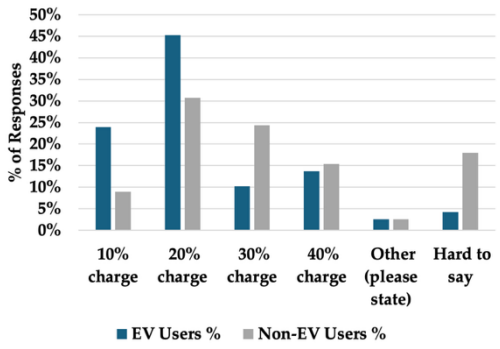


Fig. 3. Minimum EV charge levels.

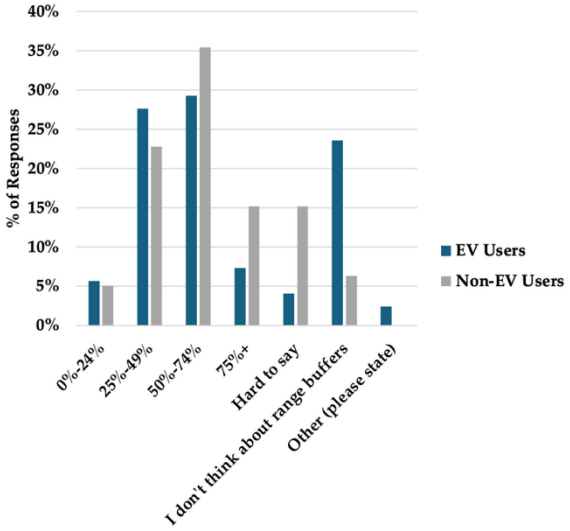
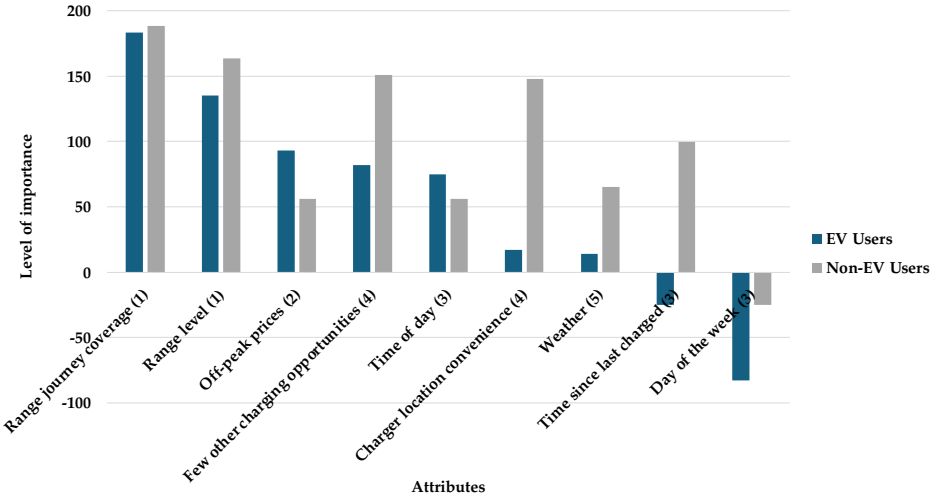


Fig. 4. Range buffer preferences.

'When to charge' attribute importance is ranked in Fig. 5. Likert scale responses were scored from -2 to 2, aggregated per attribute and scaled according to vehicle group sample sizes. Range-related

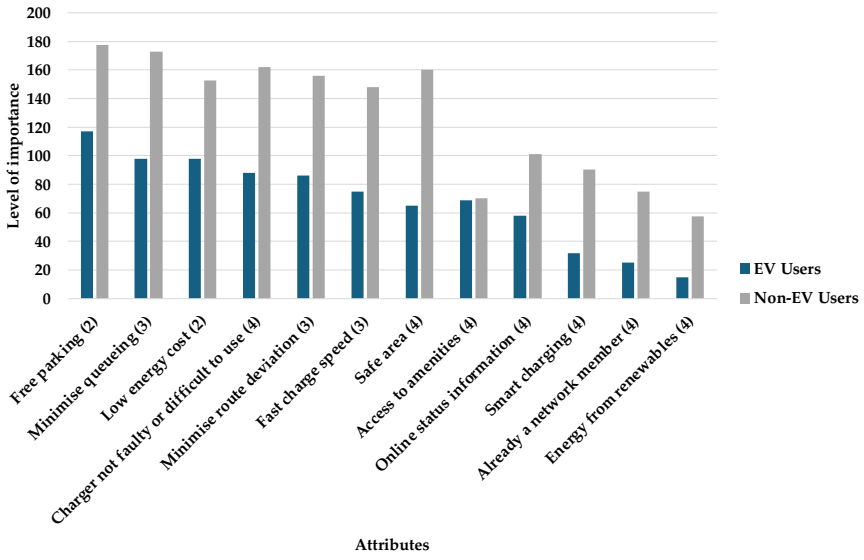
attributes were the most important. Additionally, charge cost, charging opportunities and time of day were priorities for EV users. Petrol/diesel vehicle users valued charge location factors highly. EV users were less concerned by these, possibly due to having trusted charging options. EV user rankings were similar across genders, but females consistently scored attributes somewhat higher.



Attribute groups: (1) range, (2) cost, (3) time, (4) charge location features, (5) other.

Fig. 5. 'When to charge' attribute importance.

'Where to charge' attribute importance rankings, shown in Fig. 6, are similar across vehicle users. Non-EV users generally rated attributes higher, possibly due to less experience or hypothetical bias.

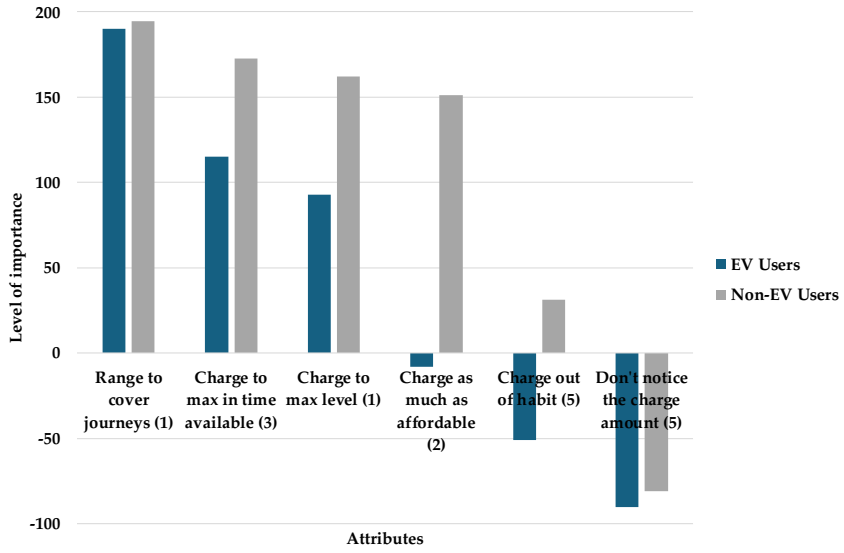


Attribute groups: (1) range, (2) cost, (3) time, (4) charge location features, (5) other.

Fig. 6. 'Where to charge' attribute importance.

Costs of parking and energy, time spent queueing, in detours and charging, and charger functionality were all important. Several charge location feature attributes scored lower, consistent with these appearing in fewer choice models in the literature. Attribute importance rankings for 'how

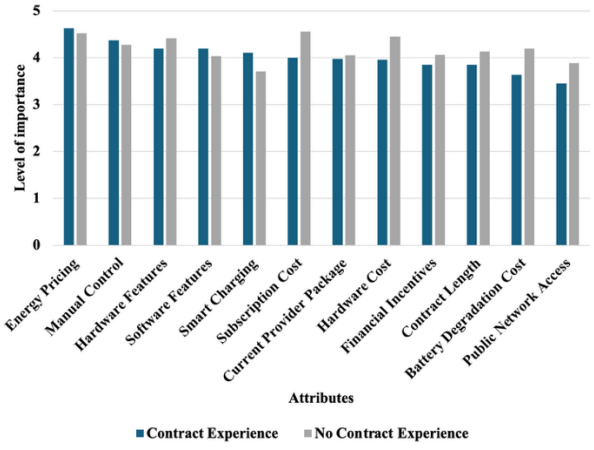
much to charge' decisions, shown in Fig. 7, are consistent across vehicle user types and genders. Non-EV users once more scored attributes more highly. EV-users valued journey range coverage higher than simply charging to the maximum.



Attribute groups: (1) range, (2) cost, (3) time, (4) charge location features, (5) other

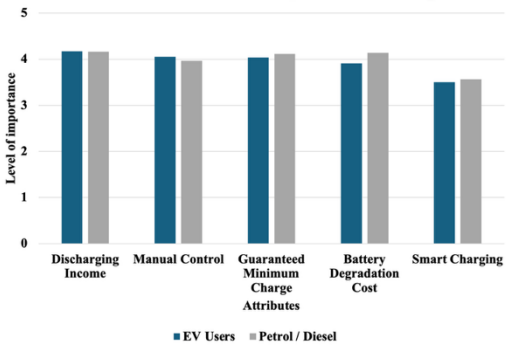
Fig. 7. 'How much to charge' attribute importance.

Figures 8 and 9 show that participants scored most strategic attributes highly. Financial factors ranked highest. Results show a desire for manual control, especially from those not previously in charging contracts. Charging hardware and software characteristics ranked highly. For those with experience, battery degradation was somewhat less important, as was public network access, possibly due to some charging primarily at home.



Responses on a 1-5 scale from 'not important' to 'important'.

Fig. 8. Home charging contract attribute preferences.



Responses on a 1-5 scale from 'not important' to 'important'.

Fig. 9. V2G contract attribute preferences.

Mean and median reference point estimates, shown in Table 5, were reasonable across groups, given sample battery capacities, typical charge costs and speeds. Male EV users had much higher certainty levels and less variation in estimates than other groups.

Table 5: Estimated charge costs, times and certainty levels

		EV full charge cost estimate (£)			Charge cost certainty (0-10)			EV full charge time estimate (hours)			Charge time certainty (0-10)		
		Public Fast	Public Slow	Home	Public Fast	Public Slow	Home	Public Fast	Public Slow	Home	Public Fast	Public Slow	Home
EV	**Mean**	27.3	20.5	13.9	4.6	3.9	6.6	2.5	5.6	8.4	5.0	4.2	6.8
	Median	25.0	19.0	8.0	5.0	4.0	8.0	1.0	4.7	7.0	7.0	4.0	8.0
	SD	15.8	12.9	17.9	3.5	3.0	3.5	3.7	4.5	6.5	3.7	3.3	3.2
Petrol / Diesel	**Mean**	32.9	25.9	22.3	1.8	1.8	2.0	5.2	7.7	8.4	1.7	1.7	1.7
	Median	29.5	20.0	13.0	1.0	1.0	1.0	2.0	4.6	6.0	0.0	0.0	0.0
	SD	24.3	22.6	22.9	2.3	2.3	2.7	7.7	8.6	8.7	2.5	2.5	2.5

SD = standard deviation.

The scenario question responses, shown in Table 6, revealed majorities of respondents to be risk-averse over losses, preferring known outcomes to risky choices with equal or more favourable, expected values. 73% were risk-averse for range, compared to 59% for time and 58% for cost. This suggests stronger loss aversion for the potential loss scenarios around range, given the severity of the possible consequences of running out of energy. Increased expected values generally led to more risk-seeking, however. For all situations, on average, more females and >40 year olds chose the safest option, and more males, <40 year olds and EV users were risk-seeking. In ordinal regression analysis, shown in Appendix B, gender was a significant predictor of risk attitude for all situations, and age significant for cost. Interestingly, higher time sensitivity was highly significantly associated with risk-averse choices in all situations. Other studies, including Zhang et al. (2022) and Wang et al. (2024), have also connected risk aversion in EV charging to high value of time. Four heterogeneous segments, presented in tables 7 and 8, were identified using K-means clustering, with scenario question responses as clustering variables. A dominant weighting was assigned to time sensitivity, given its significance in the regression analysis.

Table 6: Scenario question response summary

Scenario	Expected Value - Safe	Expected Value - Risky	Total		EV Users		Petrol / Diesel		Males		Females		Age <40		Age >40	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A1	£20	£19.75	2.28	1.23	2.35	1.25	2.16	1.18	2.42	1.19	2.10	1.26	2.45	1.35	2.23	1.20
A2	£20	£17.50	2.55	1.28	2.66	1.31	2.38	1.23	2.72	1.24	2.34	1.31	2.69	1.37	2.51	1.26
A3	£20	£20	2.13	1.11	2.18	1.12	2.06	1.09	2.26	1.15	1.98	1.04	2.21	1.24	2.11	1.07
A (Total)			2.32	0.99	2.40	1.00	2.20	0.98	2.47	0.96	2.14	1.01	2.45	1.10	2.28	0.96
B1	1 hour	1 hour	2.17	1.20	2.15	1.23	2.20	1.16	2.20	1.19	2.13	1.22	2.29	1.37	2.14	1.16
B2	1 hour	56 mins	2.35	1.33	2.37	1.39	2.31	1.24	2.48	1.31	2.20	1.34	2.36	1.39	2.35	1.32
B3	1 hour	50 mins	2.43	1.32	2.45	1.36	2.41	1.26	2.59	1.31	2.24	1.31	2.69	1.46	2.37	1.28
B (Total)			2.32	1.11	2.32	1.16	2.31	1.05	2.42	1.09	2.19	1.13	2.44	1.19	2.28	1.09
C1	90 miles	108.8 miles	1.88	1.12	1.93	1.20	1.81	0.98	1.99	1.12	1.75	1.11	2.24	1.28	1.79	1.05
C2	90 miles	90 miles	1.78	1.04	1.87	1.16	1.65	0.80	1.92	1.09	1.62	0.95	2.10	1.10	1.70	1.01
C3	90 miles	96.5 miles	2.05	1.27	2.11	1.32	1.96	1.21	2.18	1.30	1.89	1.23	2.48	1.50	1.94	1.19
C (Total)			1.90	1.02	1.97	1.09	1.81	0.90	2.03	1.02	1.75	0.99	2.27	1.12	1.81	0.97
A, B & C (Total)			2.18	1.2	2.23	1.28	2.11	1.16	2.31	1.2	2.03	1.2	2.39	1.34	2.13	1.20

Response scale: 1-5, from 'strongly prefer first option' to 'strongly prefer second option'. SD = standard deviation.

Here, some nuanced segment characteristics varied from high-level trends. Group 4 on average includes younger, higher-income, more educated workers who are time sensitive and, despite identifying as more risk-seeking, are less likely to choose the uncertain charging options. Group 1 is somewhat opposite to this. Groups 2 and 3 sit in between these groups in terms of their sociodemographic profiles but differ from one another in terms of time sensitivity.

Table 7: Group characteristics

Group	Average of A	Average of B	Average of C	Time Sensitivity	Cost Sensitivity	Risk Attitude	Gender	Age	Education	Vehicle	Income
1	2.5	2.5	2.0	0.8	6.9	3.5	0.42	3.82	4.20	0.76	2.22
2	2.3	2.4	2.0	3.0	7.0	4.4	0.43	2.57	4.35	0.51	3.10
3	2.4	2.2	1.9	5.8	8.1	3.9	0.47	2.88	4.29	0.65	2.94
4	2.1	2.1	1.8	8.3	8.0	4.6	0.49	2.33	4.84	0.51	3.47

Scenario responses (A, B and C): 1-5 scale, from 'strongly prefer safe' to 'strongly prefer gamble'. Time sensitivity, cost sensitivity and risk attitude: 0-10 scale. Gender: male (0), female (1). Ordinal categorical variables: age (1-7), education (1-8), income (1-7), lowest to highest.

Time sensitivity is a key differentiator across groups and may to some degree be a multi-dimensional predictor of behaviours (Small 2012), that is context relevant here. With charging costs still relatively low, EV users are currently more likely to experience anxiety around time-based inconveniences.

Table 8: Vehicle use profiles by group

Group	Weekly work trips (median)	Weekly EV user home charges (median)	Weekly total EV user charges (median)
1	0	1.8	2.0
2	2	2.0	2.1
3	2	2.8	3.1
4	5	4.0	4.5

A limitation to note is that with a sample of n=203, the four-cluster analysis and regression analyses may have had limited statistical power. A further limitation was that net loss risky options were not included due to the need to minimise the number of tasks for participants and the lower likelihood of these being selected. Further research may target a larger sample and include net loss scenarios.

4. CONCLUSIONS

Understanding the roles of range, cost, time and charge location feature related choice attributes, and risk attitudes towards these, in tactical 'when', 'where' and 'how much' to charge and discharge choices, can inform the development of demand flexibility incentives and policy design. Majorities of vehicle users have shown risk-averse attitudes to choice scenarios, particularly for range, but with some increased risk taking as incentives become more favourable. At a high level, there is some evidence of EV users, males and younger vehicle users being more risk-seeking, and evidence of nuanced sub-segments, whose differing flexibility profiles may warrant targeted tariff structures. A key thread through all the risky choice scenario responses was the influence of higher time sensitivity on risk aversion, which may be a context-relevant predictor of tactical

choice outcomes here. Time-based levers, such as maximum session time tariffs, could be included alongside price and range-based levers, to incentivise these different groups. Additionally, given the evidence of attitudes evolving with experience, individual flexibility profiles may change over time.

Policy measures can aim to address observed common pain points within these choices to reduce anxiety. Such measures can focus on infrastructure improvements, taking a consumer-centric approach, aiming to build long-term trust by ensuring simplicity, transparency and reliability in public and home charging, and V2G services. A differentiated approach can be taken across segments, including appropriate information and experiential sessions for identified risk-averse groups. If successful, such measures can help boost EV adoption and equity of access.

From a choice modelling perspective, non-EUT methods, such as PT-based models, would appear suited to explain risky choices in this context, given the risk aversion observed. A differentiated approach to reference points may be taken in such models, gathering reference values from experienced EV users with high certainty, and using latent reference points, or a more involved initial phase, to obtain reference points for less experienced groups. Given the heterogeneity in risk attitudes across range, cost and time, PT-based models can seek to explain each independently, in addition to considering risk attitudes towards charge location features.

APPENDIX A

Sociodemographic Data Category	Response Options	Total (#)	Total (#)	Males (%)	Females (%)	EV Users (%)	Petrol / diesel Vehicle Users (%)
Gender	Male	110	54%			59%	47%
	Female	93	46%			41%	53%
	Prefer to self-describe	0	0%			0%	0%
	Prefer not to say	0	0%			0%	0%
Age Range	17-19	0	0%	0%	0%	0%	0%
	20-29	8	4%	2%	6%	2%	8%
	30-39	35	17%	21%	12%	15%	20%
	40-49	40	20%	21%	18%	19%	20%
	50-59	51	25%	26%	25%	27%	23%
	60-69	33	16%	13%	20%	18%	14%
	70-79	30	15%	17%	12%	18%	10%
	80+	6	3%	1%	5%	2%	5%
	Prefer not to say	0	0%	0%	0%	0%	0%
Highest Education Level	No formal qualifications	4	2%	2%	2%	2%	1%
	GCSE / O level	22	11%	13%	9%	9%	14%
	A level	20	10%	5%	15%	9%	11%
	Vocational or technical	17	8%	8%	8%	6%	11%
	HNC, HND or foundation degree	12	6%	7%	4%	8%	3%
	Bachelor's degree	73	36%	38%	34%	37%	34%
	Master's degree	32	16%	15%	17%	18%	13%
	PhD	6	3%	5%	1%	2%	4%
	Professional qualification	17	8%	8%	9%	8%	9%
Income	<£20k	22	11%	8%	14%	6%	18%
	£20k-£34k	31	15%	12%	19%	10%	23%
	>£35k-£49k	35	17%	21%	13%	18%	16%
	>£50k-£74k	49	24%	26%	20%	29%	16%
	>£75k-£99k	21	10%	10%	11%	13%	6%
	£100k-£150k	18	9%	9%	10%	8%	10%
	>£150k	17	8%	11%	5%	12%	3%
	Prefer not to say	10	5%	4%	6%	3%	8%
Location*	Rural	17	8%	9%	8%	7%	10%
	Semi-urban	42	21%	17%	25%	22%	19%
	Urban	144	71%	74%	68%	71%	71%
Vehicle Type	EV	123	61%	66%	55%		
	ICE	80	39%	34%	45%		

**Location types derived from postcode data.*

APPENDIX B

		Risk Attitude			Cost Sensitivity			Time Sensitivity		
		Coefficient	Standard Error	P-value	Coefficient	Standard Error	P-value	Coefficient	Standard Error	P-value
Attitudinal variables	Time Sensitivity	0.0922	0.05	0.064						
	Cost Sensitivity	-0.1198	0.061	0.051						
	Risk Attitude				-0.0774	0.052	0.137	0.061	0.051	0.233
Socio-demographic variables	Gender	-0.54	0.254	0.034*	0.232	0.258	0.369	0.3055	0.253	0.227
	Age	-0.228	0.092	0.013*	0.03	0.09	0.739	-0.2732	0.092	0.003**
	Income	0.0868	0.077	0.261	-0.0824	0.072	0.252	0.1683	0.073	0.021*
	Education	0.2282	0.069	0.001**	-0.0522	0.066	0.427	0.0175	0.067	0.794
	Vehicle	0.681	0.272	0.012*	-0.1203	0.27	0.656	-0.4448	0.267	0.096

	All Situations			Situation A - Cost			Situation B - Time			Situation C - Range		
	Coeffi-cient	Standard Error	P-value	Coeffi-cient	Standard Error	P-value	Coeffi-cient	Standard Error	P-value	Coeffi-cient	Standard Error	P-value
Gain framing	0.512	0.112	0.000***	0.056	0.090	0.533	0.059	0.124	0.634	0.161	0.088	0.066†
Gain magnitude	-0.180	0.065	0.005**	0.276	0.119	0.021*	0.097	0.134	0.472	-0.040	0.075	0.590
Gain framing * magnitude	0.469	0.140	0.001**	-	-	-	-	-	-	-	-	-
Time Sensitivity	-0.093	0.017	0.000***	-0.112	0.029	0.000***	-0.100	0.029	0.001**	-0.076	0.031	0.014*
Cost Sensitivity	0.009	0.020	0.655	0.024	0.035	0.498	0.046	0.035	0.190	-0.050	0.037	0.177
Risk Attitude	0.033	0.017	0.056†	0.055	0.030	0.064†	0.023	0.030	0.440	0.016	0.032	0.605
Gender	-0.406	0.088	0.000***	-0.455	0.151	0.003**	-0.341	0.151	0.024*	-0.450	0.160	0.005**
Age	-0.104	0.032	0.001**	-0.018	0.054	0.749	-0.100	0.055	0.067†	-0.224	0.059	0.000***
Education	0.010	0.023	0.673	0.024	0.039	0.539	0.046	0.040	0.249	-0.046	0.041	0.267
Income	-0.005	0.026	0.844	0.053	0.044	0.225	-0.054	0.045	0.237	-0.015	0.047	0.749
Vehicle	0.029	0.093	0.754	0.087	0.160	0.588	-0.092	0.160	0.566	0.126	0.169	0.457

Confidence levels: *** Significant at >99.9%, ** Significant at >99%, * Significant at >95%, † Significant at >90%

REFERENCES

Andrenacci, N, and M.P. Valentini. 2023. “A Literature Review on the Charging Behaviour of Private Electric Vehicles.” *Applied Sciences* 13.

Daina, N. 2014. *Modelling Electric Vehicle Use and Charging Behaviour* . Accessed March 19th, 2026. https://spiral.imperial.ac.uk/home.

Daina, N, and J.W Polak. 2016, June 1-4. “Hazard Based Modelling Of Electric Vehicles Charging Patterns.” *IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC).* Busan, Korea.

Daziano, Ricardo A. 2022. “Willingness to delay charging of electric vehicles.” *Research in Transportation Economics* 94.

Hoen, Fredrik Solvi, María Díez-Gutierrez, Sahar Babri, Stephane Hess, and Trude Tørset. 2023. “Charging electric vehicles on long trips and the willingness to pay to reduce waiting for charging. Stated preference survey in Norway.” *Transportation Research Part A* 175.

Hu, Liang, Jing Dong, and Zhenhong Lin. 2019. “Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach.” *Transportation Research Part C* 102: 474-489.

Huang, Bing, Aart Gerard Meijssen, Jan Anne Annema, and Zofia Lukszo. 2021. “Are electric vehicle drivers willing to participate in vehicle-to-grid contracts? A context-dependent stated choice experiment.” *Energy Policy* 156.

International Energy Agency. 2024. “World Energy Outlook 2024.” Accessed March 26th, 2026. https://www.iea.org/reports/world-energy-outlook-2024.

Kubli, Merla. 2022. “EV drivers’ willingness to accept smart charging: Measuring preferences of potential adopters.” *Transportation Research Part D* 109.

Latinopoulos, C, A Sivakumar, and J.W Polak. 2017. “Response of electric vehicle drivers to dynamic pricing of parking and charging services: Risky choice in early reservations.” *Transportation Research Part C* 80: 175-189.

Le Vine, Scott. 2011. *Strategies for personal mobility: A study of consumer acceptance of subscription drive-it-yourself car services.* PhD thesis. https://spiral.imperial.ac.uk/home.

Li, Hao, Lu Yu, Yu Chen, Huizhao Tu, and Jun Zhang. 2023. “Uncertainty of available range in explaining the charging choice behavior of BEV users.” *Transportation Research Part A* 170.

Li, Yujing, Su Su, Biao Liu, Koji Yamashita, Yan Li, and Liang Du. 2022. “Trajectory-driven planning of electric taxi charging stations based on cumulative prospect theory.” *Sustainable Cities and Society* 86.

Marxen, Hanna, Mohammad Ansarin, Raviteja Chemudupaty, and Gilbert Fridgen. 2023. "Empirical evaluation of behavioral interventions to enhance flexibility provision in smart charging." *Transportation Research Part D* 123.

McFadden, Daniel. 2001. "Economic Choices." *American Economic Review* 91 (3): 351-378.

Pan, Long, Enjian Yao, and Don MacKenzie. 2019. "Modeling EV charging choice considering risk attitudes and attribute non-attendance." *Transportation Research Part C* 102: 60-72.

Potoglou, Dimitris, Rongqiu Song, and Georgina Santos. 2023. "Public charging choices of electric vehicle users: A review and conceptual framework." *Transportation Research Part D* 121.

Shen, Yuxi, Alyssa Ryan, Melrose Pan, Xiaoqin Fu, and Liang Zhang. 2025. "Behavioral and infrastructure influences on electric vehicle charging and grid impact." *Transportation Research Part D* 149.

Small, Kenneth A. 2012. "Valuation of travel time." *Economics of Transportation* 1 (1-2): 2-14.

Thorhauge, M, J Rich, and S.E Mabit. 2024. "Charging behaviour and range anxiety in long-distance EV travel: an adaptive choice design study." *Transportation.*

Visaria, Anant Atul, Anders Fjendbo Jensen, Mikkel Thorhauge, and Stefan Eriksen Mabit. 2022. "User preferences for EV charging, pricing schemes, and charging infrastructure." *Transportation Research Part A* 165.

Wang, Jiyao, Wenbo Zhang, Xiao Luke Wen, Ran Tu, and Dengbo He. 2026. "Modeling battery electric vehicle users' charging decisions in scenarios with both time-related and distance-related anxiety." *Travel Behaviour and Society* 42.

Wang, Yue, Enjian Yao, and Long Pan. 2021. "Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction." *Journal of Cleaner Production* 286.

Wang, Zhaohui, Enjian Yao, and Yang Yang. 2024. "An analysis of EV charging and route choice behavior considering the effects of planning ability, risk aversion and confidence in battery in long-distance travel." *Transportation Research Part F: Psychology and Behaviour* 104: 186-200.

Yuan, Quan, Wei Hao, Haotian Su, Guanwen Bing, Xinyuan Gui, and Abolfazl Safikhani. 2018. "Investigation on Range Anxiety and Safety Buffer of Battery Electric Vehicle Drivers." *Journal of Advanced Transportation.*

Zhang, Yiyuan, Xia Luo, Zengrui Wang, Qixin Mai, and Ruixin Deng. 2022. "Estimating charging demand from the perspective of choice behavior: A framework combining rule-based algorithm and hybrid choice model." *Journal of Cleaner Production* 376.