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Supplementary information

Heterogenous preferences for living in a hydrogen home: An advanced multigroup analysis

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1 Supplementary Note 1: Comments on meta-review of 54 studies on hydrogen heating

The meta-review article on hydrogen heating by Jan Rosenow[1] – which advances his earlier review of 32 studies[2] – has a somewhat diverse representation of studies, however, the main concentration corresponds to the United Kingdom (N = 17), Germany (N = 10), in addition to a focus on the European Union (N = 12), and global analyses (N = 14). Although 54 articles are retrieved, one study examines Czechia, Italy, Poland, and Spain, while another focuses on Germany, the EU, and globally, which explains the discrepancy in Table S1 and Fig. S1. However, the report conducted by Element Energy[3] for Czechia, Italy, Poland, and Spain has little comparability to the UK context, as inferred within the text:

> One limitation of using hydrogen for heating is that it is reliant on the existence of a hydrogen network. This could be a repurposed existing gas network or a new bespoke hydrogen network. No more than 40% of dwellings are currently connected to the gas grid in any of the countries analysed, with this number dropping to only 10% in Poland, highlighting a possible infrastructural risk for using hydrogen for heating on a large scale.

Other sources collated for the purpose of disproving the economic feasibility of hydrogen for heating present several limitations in their modelling approaches. For example, in the German context, Giehl et al.[4] acknowledge the following:

> "Furthermore, the results are based on the assumption that in all counties parts of the heat demand will be supplied via hydrogen from converted gas distribution grids. However, in the case of using hydrogen to provide decentral heat, this might not be the case. Hydrogen could be used only in preferable regions, and this would lead to a different transition pathway. This issue could be resolved by identifying different regional clusters and modelling the transition pathway of the distribution grids individually."

However, Rosenow extracts one unique point from the article: "*Total annual energy system cost in the hydrogen scenario is more than four times higher than in the electrification scenario*" for 2050.

In the Dutch context, Rosenow cites the study of Scheepers et al.[5] according to a conclusion that 1–9% of heating is provided by hydrogen by 2050. While we could not retrieve the data showing this range, and contend that the upper range is relevant, Scheepers and colleagues[5] acknowledge the following contextual dynamics in their modeling results:

> "Hydrogen also becomes an important energy carrier, notably for transportation and in industry. If import prices are lower than costs of domestic production from natural gas with CCS or through electrolysis from renewable electricity (2.4–2.7 €/kgH_2), the use of hydrogen increases, especially in the built environment."

Additionally, in the Brazilian context (Sao Paulo) Jalil-Vega and colleagues[6] discuss a New Policies Decarbonisation (NP-DEC) scenario where hydrogen boilers reach 40% of the domestic sector capacity during a transition period between 2030 and 2045.

Irrespective of these observations, the meta-review[1] acknowledges that hydrogen heating may play a niche role, as reflected by the following results under cost-optimal conditions: a 10% of EU capacity by 2050 (European Commission); 4% of global capacity by 2050 (Bloomberg New Energy Foundation); 6% of UK capacity by 2050. It follows that dismissing the utility of engaging with the dynamics of the domestic hydrogen transition, whether from a techno-economic or social acceptability perspective, may be somewhat premature and potentially misguided.

Table S1. Summary of contextual dynamics composing the meta-review on hydrogen heating (N = 54).

Context of analysis	Number of studies
European Union	9
European Union 27+UK	3
Germany	10
Global	14
Netherlands	2
Switzerland	1
United Kingdom	14
Brazil (Sao Paulo)	1
United States (California)	1
Spain	1
Italy	1
Czechia	1
Poland	1

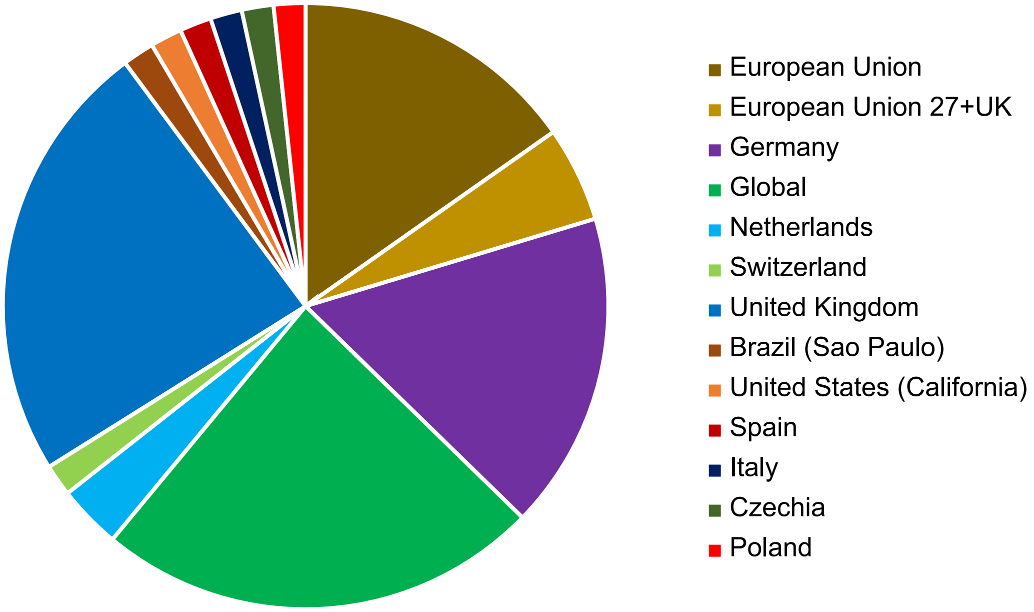

Fig. S1. Visual distribution of research context composing the meta-review (N = 54).

2 Supplementary Note 2: Survey questions and supporting literature

Table S2 provides full details of the survey questions pertaining to each construct and its respective indicators, as well as the scales employed, in addition to the supporting literature for deriving each item.

Table S2. Questionnaire details and literature sources.

Construct	Indicator	Question items and framing	Scale	Supporting literature
Perceived Boiler Performance (BLR)		Please evaluate the following statements about a hydrogen boiler**:**	0–10: Low expectation – High expectation	[7–14]
	BLR1	I expect a hydrogen boiler to provide a higher level of thermal comfort than a natural gas boiler (i.e. satisfactory level and distribution of heat)		
	BLR2	I expect a hydrogen boiler to be more energy efficient than a natural gas boiler		
	BLR3	I expect a hydrogen boiler to be easier to operate than a natural gas boiler		
	BLR4	I expect a hydrogen boiler to provide a smarter heating system than a gas boiler		
Perceived Hob Performance (HOB)		Please evaluate the following statements about a hydrogen hob:	0–10: Low expectation – High expectation	[7,8]
	HOB1	I expect a hydrogen hob to perform more efficiently than a natural gas hob		
	HOB2	I expect a hydrogen hob to provide better cooking control than a natural gas hob		
	HOB3	I expect a hydrogen hob to be easier to maintain and clean than a natural gas hob		
	HOB4	I expect a hydrogen hob to provide a smarter cooking system than a natural gas hob		
Financial Perceptions (FP)	FP1	What is your expectation for the purchasing price of a hydrogen boiler compared to a gas boiler?	1–5: Significantly cheaper –	[15–20]

	FP2	What is your expectation for the purchasing price of a hydrogen hob compared to a gas hob?	Significantly more expensive	
	FP3	What is your expectation when considering potential energy bills for domestic hydrogen compared to natural gas?		
Perceived socio-economic Costs (PSC)		To what extent do you agree or disagree with the following statements:	1–5: Strongly disagree – Strongly agree	[15,16,19,21–23]
	PSC1	Switching from natural gas to hydrogen will have a negative impact on UK energy security (i.e. reliability of energy supply)		
	PSC2	Switching from natural gas to hydrogen will lead to higher levels of fuel poverty across the UK		
Safety Perceptions (SP)		Please evaluate your current safety perceptions of hydrogen compared to natural gas for the following:	0–10: Less safe – More safe	[7,16,24–30]
	SP1	Hydrogen boilers		
	SP2	Hydrogen hobs		
	SP3	Hydrogen pipelines (i.e. transport/transmission)		
	SP4	Underground storage of hydrogen gas		
	SP5	Overall, how do you perceive the safety level of hydrogen compared to natural gas in terms of production, storage, transportation, and domestic use?		
Production Perceptions (PP)	PP1	What is your attitude towards the UK government supporting blue hydrogen production in the short-term (i.e. up to 2030)?	0–10: Opposed – Supportive	[24,25,31–34]
	PP2	What is your attitude towards the UK government supporting blue hydrogen production over the long-term (i.e. after 2030)?		
	PP3	What is your attitude towards the UK government supporting green hydrogen production in the short-term (i.e. up to 2030)?		
	PP4	What is your attitude towards the UK government supporting green hydrogen production over the long-term (i.e. after 2030)?		

	PP5	How do you feel about the government's twin-track strategy? (i.e. with a role for blue and green hydrogen)		
Perceived Adoption Potential (PAP)				
	PAP1	What is your level of willingness to switch to a hydrogen boiler before 2030?	1–5: Not willing at all – Extremely willing	[19,35–37]
	PAP2	What is your level of willingness to switch to a hydrogen hob before 2030?		
	PAP3	What is your level of willingness to switch to a hydrogen home before 2030? (i.e. both hydrogen heating and cooking)		
	PAP4	What is your expectation for hydrogen homes delivering economic benefits such as job opportunities and income security?	0–10: Low – High expectation	[15,38–42]
	PAP5	What is your expectation for hydrogen homes delivering social benefits such as reduced levels of fuel poverty and improved health?		
	PAP6	What is your expectation for hydrogen homes delivering environmental benefits such lower carbon emissions and better air quality?		

3 Supplementary Note 3: Sample characteristics and comparison to UK population

Table S3 describes the breakdown of each consumer sub-group composing our survey sample (N =1845). The ideal target was to secure an equally balanced representation among three of sub-groups (i.e. MEG, VEG, FSG), alongside a larger Baseline Group (BLG) of ~40%. Higher occurrences of incomplete answers and straight-lining responses resulted in a final sample of 677 for the BLG (~36.7%). During the data collection, the Very Engaged Group (VEG) proved harder to reach, leading to partial under-representation (N = 331, 17.9%). By comparison, the Moderately Engaged Group (MEG) was easier to secure and somewhat over-represented (24.8%). Finally, the Fuel Stress Group (FSG) was in line with the original quotas (20.5%).

Table S3. Consumer sub-groups composing the survey sample.

Socio-demographic variable	BLG (N = 677)	MEG (N = 458)	VEG (N = 331)	FSG (N = 379)	Standard deviation	Full sample (N = 1845)	UK population	Difference (%)
Age								
18-34	34.1	31.7	38.7	39.8	3.82	35.5	32.6	+2.9
35-54	41.7	37.3	33.2	42.2	4.22	39.2	30.6	+8.6
55+	24.2	31.0	28.1	17.9	5.67	25.3	36.8	-11.5
Gender								
Male	36.8	42.6	56.5	47.2	8.32	43.9	48.8	-4.9
Female	63.2	57.4	43.5	52.8	8.32	56.1	51.2	+4.9
Other								
Housing tenure								
Owned outright	34.7	36.0	47.4	34.3	6.24	37.2	57.1	-19.9
Mortgage owner	65.3	64.0	52.6	65.7	6.24	62.8	42.9	+19.9
Housing type								
Flat, apartment or bungalow	12.3	9.2	16.6	12.4	3.04	12.3	30.0	-17.7
Detached house	29.1	30.8	30.8	25.3	2.59	29.1	18.0	+11.1
Semi-detached house	36.9	42.1	35.3	39.6	3.00	38.5	25.0	+13.5
Terrace house	21.7	17.9	17.2	22.7	2.73	20.2	27.0	-6.8
No. of occupants								
1	11.7	10.0	9.1	7.9	1.60	10.0	n/a	
2	30.6	32.3	26.0	30.6	2.70	30.2	n/a	

3+	57.8	57.6	65.0	61.5	3.51	59.8	n/a	
Education level								
GCSE/O-Level or lower	24.2	17.9	18.7	24.5	3.51	21.7	n/a	
Vocational/NVQ	27.0	25.8	17.5	23.2	4.23	24.2	n/a	
Postgraduate qualification	17.7	23.1	26.3	21.4	3.58	21.4	n/a	
Degree or equivalent	31.0	33.2	37.5	30.9	3.09	32.7	n/a	
Annual income bracket (before tax)								
Less than £23,500	30.1	27.1	16.9	28.0	5.89	26.6	n/a	
More than £23,500 but less than £31,500	20.7	19.4	16.9	26.1	3.88	20.8	n/a	
More than £31,500 but less than £41,500	18.9	18.6	19.0	19.0	0.19	18.9	n/a	
More than £41,500 but less than £62,500	20.7	23.1	23.9	19.8	1.94	21.7	n/a	
More than £62,500	9.6	11.8	23.3	7.1	7.16	12.1	n/a	
Location								
Southwest and Wales	11.7	15.3	11.5	11.6	1.85	12.5	13.4	-0.9
Midlands and East of England	27.8	25.8	22.1	25.3	2.36	25.7	26.2	-0.5
Southeast and London	26.0	28.6	35.3	22.2	5.52	27.5	27.2	+0.3
North of England and Scotland	34.6	30.3	31.1	40.9	4.83	34.2	33.0	+1.2
Area type								
Inner City or industrial	6.5	7.6	12.7	11.6	3.01	8.9	n/a	
Suburban	54.7	56.3	44.7	48.8	5.36	52.1	n/a	
Urban	19.1	17.7	28.4	24.8	4.99	21.6	n/a	
Rural	19.8	18.3	14.2	14.8	2.71	17.4	n/a	

Source: Authors' compilation based on[43–45].

[a] n/a denotes the decision to exclude these variables when setting quotas, therefore population data is not reported here.

The sample was composed of respondents owning a property outright (57.1%) and mortgage owners (42.9%), following the logic that home ownership will raise the stakes for decision-making and consumer engagement regarding domestic hydrogen.[46] Moreover, all respondents were users of natural gas boiler and hobs; attributing at least moderate levels of important to being able to choose these technologies, while having at least moderate levels of financial involvement in the decision-making process.[7,11,47]

The sampling decision reflects the under-representation of respondents living in a bungalow, flat, or apartment within the sample (12.3% compared to the national average of 30.0%). Relatedly, in the Welsh context, Thomas et al.[48] reported that "bungalows (11.5%) and flats (11%) represent a smaller proportion of the overall housing stock, with the latter less reliant on gas heating due to safety and planning regulation." Notably, 40.9% of fuel stressed respondents in this study are from the North of England and Scotland, compared to the sample average of 34.2%, which reflects the decision to adjust the location filter for the FSG to be broadly nationally representative of fuel poverty in the UK.[49]

Fig. S2 reports the composition of the sample in relation to levels of involvement in financial decision-making, and the level of importance attributed towards choosing between household heating and cooking technologies.

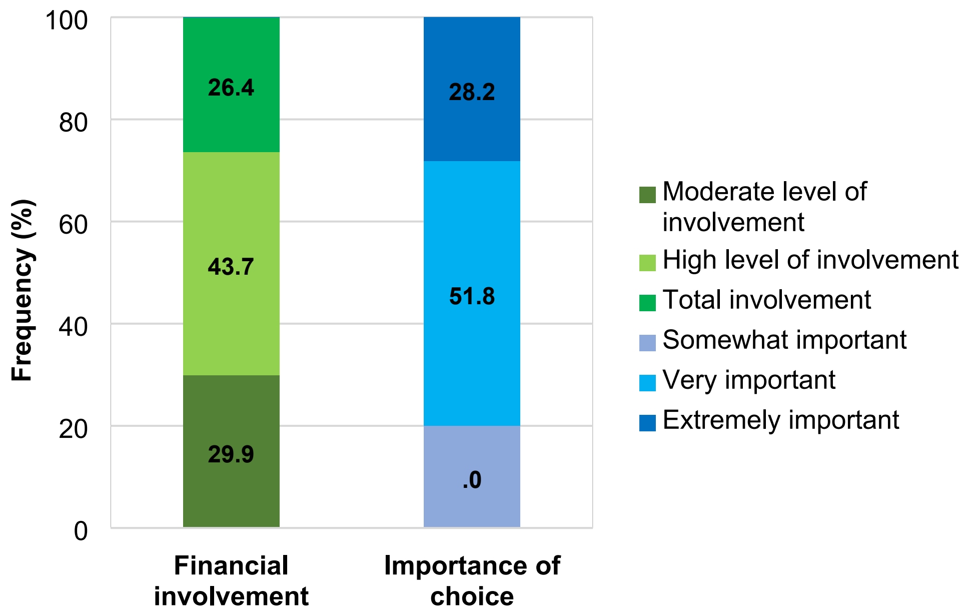

Fig. S2. Financial involvement in appliance purchase and choice perceptions across sample.

4 Supplementary Note 4: Statistical tests for validating sample size specifications

Fig. S3a and Fig. S3b provide results on sample size requirements for testing effect sizes. We used G*Power software to verify the parameters. Since our sample was relatively large (N = 1845), it was suitable for PLS-SEM, however, we checked the results from G*Power to clarify the reliability of (small) effect sizes, as described in Section 2.1

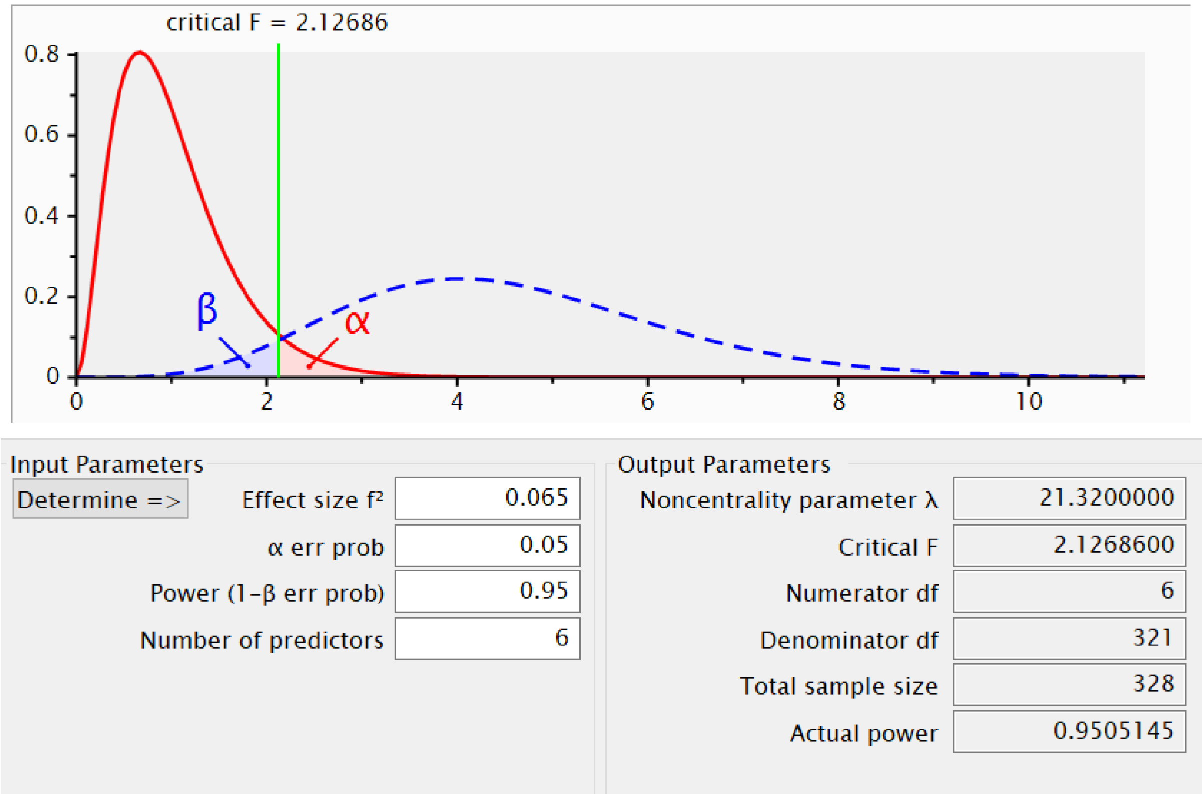

Fig. S3a. Power test to determine the minimum sample size for an effect size of 0.02 at 95% significance.

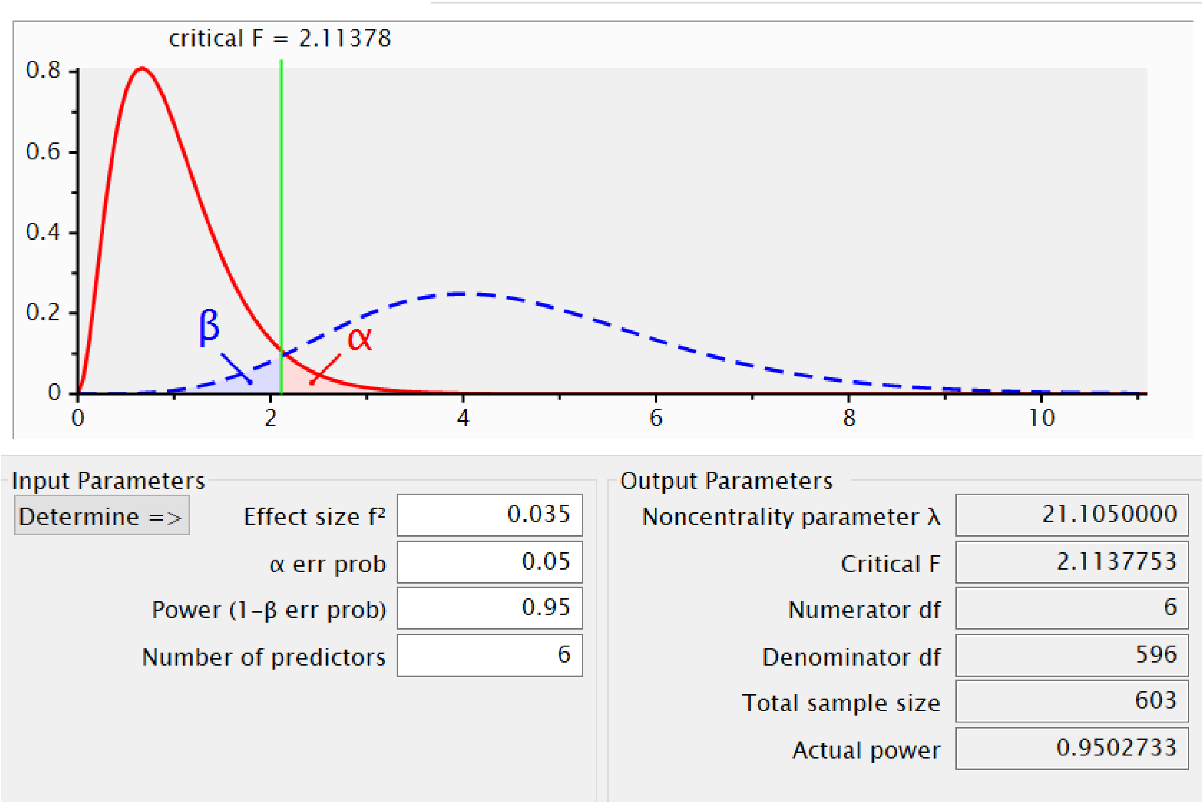

Fig. S3b. Power test to determine the minimum sample size for an effect size of 0.02 at 95% significance.

5 Supplementary Note 5: Common method bias

Table S4 tests each indicator for common method bias (CMB) across the full sample, which was ruled out by the results. The ranges for CMB held consistent across the sub-samples.

Table S4. Harman single factor test for common method bias.

Total Variance Explained						
Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	8.519	29.376	29.376	8.519	**29.376**	**29.376**
2	2.868	9.89	39.265			
3	2.322	8.006	47.272			
4	2.05	7.069	54.341			
5	1.627	5.611	59.952			
6	1.58	5.447	65.399			
7	0.944	3.257	68.656			
8	0.911	3.143	71.799			
9	0.784	2.703	74.501			
10	0.721	2.488	76.989			
11	0.612	2.109	79.099			
12	0.556	1.918	81.017			
13	0.501	1.726	82.743			
14	0.472	1.626	84.369			
15	0.435	1.502	85.871			
16	0.424	1.462	87.333			
17	0.414	1.426	88.759			
18	0.372	1.281	90.041			
19	0.358	1.233	91.274			
20	0.339	1.168	92.443			
21	0.317	1.094	93.537			
22	0.307	1.057	94.594			
23	0.293	1.01	95.604			
24	0.285	0.984	96.587			
25	0.24	0.827	97.414			
26	0.218	0.75	98.165			
27	0.196	0.678	98.842			
28	0.19	0.654	99.496			
29	0.146	0.504	100			
Extraction Method: Principal Component Analysis.						

6 Supplementary Note 6: Skewness and kurtosis

Table S5 reports the skewness and kurtosis for each indicator to verify the suitability of PLS-SEM, as discussed in Section 2.1.

Table S5. Results for skewness and kurtosis.

	BLG (N = 677)		MEG (N = 458)		VEG (N = 331)		FSG (N = 379)	
	Kurtosis	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**
SP1	-0.127	-0.072	-0.173	-0.189	-0.266	-0.423	-0.013	-0.113
SP2	-0.147	-0.126	-0.262	-0.212	-0.016	-0.605	0.080	-0.098
SP3	-0.053	-0.055	-0.286	-0.161	-0.298	-0.515	-0.033	-0.184
SP4	-0.165	-0.016	-0.373	-0.098	-0.310	-0.597	-0.064	-0.191
SP5	-0.026	-0.141	-0.303	-0.296	-0.002	-0.590	0.500	-0.350
BLR1	-0.211	-0.356	-0.139	-0.530	0.522	-0.967	-0.373	-0.496
BLR2	0.513	-1.063	1.379	-1.333	1.961	-1.455	0.418	-1.098
BLR3	-0.384	-0.272	-0.428	-0.314	-0.305	-0.649	-0.530	-0.436
BLR4	0.076	-0.796	0.169	-0.840	0.905	-1.195	0.011	-0.883
HOB1	-0.007	-0.539	0.114	-0.656	0.445	-0.875	-0.366	-0.343
HOB2	0.177	-0.288	-0.135	-0.372	0.020	-0.580	0.095	-0.282
HOB3	-0.210	-0.289	-0.329	-0.416	-0.079	-0.614	-0.287	-0.157
HOB4	0.040	-0.424	0.157	-0.606	0.109	-0.613	-0.248	-0.360
FP1	1.147	-1.233	0.449	-0.892	-0.070	-0.727	0.217	-0.883
FP2	1.171	-1.173	0.254	-0.709	0.035	-0.653	-0.112	-0.692
FP3	-1.053	-0.034	-0.904	0.088	-0.919	-0.131	-0.905	0.061
PSC1	-0.203	0.294	-0.418	0.362	-0.826	0.371	-0.430	0.153
PSC2	-0.297	0.169	-0.404	0.099	-0.801	0.094	-0.569	0.011
PP1	-0.017	0.014	-0.008	-0.324	-0.682	-0.405	0.258	-0.178
PP2	-0.391	-0.041	-0.504	-0.339	0.245	-0.761	-0.119	-0.277
PP3	-0.611	-0.190	-0.349	-0.583	1.512	-1.207	-0.145	-0.356
PP4	0.316	-0.109	0.276	-0.301	0.293	-0.581	0.380	0.124
PP5	0.050	-0.028	0.294	-0.174	-0.099	-0.388	0.498	0.126
PAP1	-0.131	0.190	-0.418	0.146	-0.324	-0.245	-0.154	-0.094

PAP2	-0.149	0.339	-0.405	0.187	-0.493	-0.217	-0.167	0.060
PAP3	-0.028	0.346	-0.473	0.224	-0.653	-0.220	-0.388	0.104
PAP4	0.054	-0.307	0.177	-0.430	1.240	-0.893	0.128	-0.472
PAP5	-0.091	-0.358	0.252	-0.445	1.027	-0.937	0.106	-0.459
PAP6	0.020	-0.512	-0.048	-0.568	0.198	-0.761	-0.016	-0.408

7 Supplementary Note 7: Limitations of the Kruskal-Wallis H test

The Kruskal-Wallis (K-W) H test can be used to support behavioural and social science research[50] by identifying group-specific differences when the samples are independent,[51] as is the case in this study. For example, Vibrans et al.[52] applied the K-W test when examining heterogeneity among potential solar PV adopters in Germany, as a complementary method to PLS-MGA. Nevertheless, non-parametric tests such as K-W are not without their limitations[50,53] such as potentially lower statistical power.[54] Furthermore, post-hoc tests are required to determine where statistically significant differences are detected[50] and to estimate effect sizes, rendering the K-W test as a means for supporting descriptive research and preliminary hypothesis testing.[54] In response, some researchers have proposed modified versions of the K-W test to increase robustness and statistical accuracy.[53]

8 Supplementary Note 8: Ceiling line results from NCA

Table S6 compares the ceiling line effect size for the CE-FDH and CR-FDH, by construct and consumer sub-group. The results are robust for the BLG and MEG, which suggests using either ceiling line may be appropriate since there is negligible influence on the results. For the FSG, the CR-FDH leads to a decrease of 0.032 on average across the three constructs. However, this deflation does not alter the results dramatically, since each effect size remains small. Finally, for the VEG, effect sizes also remain small in either case. However, the CR-FDH deviates significantly from the CE-FDH in directionality for technology perceptions (TP) and production perceptions (PP), while safety perceptions (SP) is stable. From PLS-SEM, it was established that PP has a more significant effect on adoption potential than TP, which would be reversed when applying the CR-FDH. While such intricacies warrant further attention and interrogation in future analyses, in the current study the CE-FDH is applied following the presented comparison.

Table S6. Ceiling line effect size overview

Construct	**Ceiling envelopment free disposal hull (CE-FDH)**	**Ceiling regression free disposal hull (CR-FDH)**	**Difference**
	Baseline Group		
Safety Perceptions	0.182	0.180	-0.002
Technology Perceptions	0.212	0.219	+0.007
Production Perceptions	0.158	0.154	-0.004
	Moderately technology and environmentally Engaged Group		
Safety Perceptions	0.149	0.152	+0.003
Technology Perceptions	0.150	0.151	+0.001
Production Perceptions	0.159	0.167	+0.008
	Very technology and environmentally Engaged Group		
Safety Perceptions	0.149	0.148	-0.001
Technology Perceptions	**0.163**	**0.235**	**+0.072**
Production Perceptions	**0.259**	**0.214**	**-0.045**
	Fuel Stressed Group		
Safety Perceptions	0.192	0.171	-0.021
Technology Perceptions	0.274	0.235	-0.039
Production Perceptions	0.268	0.230	-0.038

9 Supplementary Note 9: Segmentation-based methods

PLS-MGA functions by testing whether statistically significant differences exist between sub-groups, which the researcher identifies *a priori* during the recruitment stage (i.e. BLG, MEG, VEG, FSG);[55,56] as distinct from *a posteriori* approach wherein the research tests for unobserved heterogeneity within the data to identify the plausibility of different segments or 'clusters'.[57,58] When the research design involves no prespecified targeting of sub-groups, the analyst can instead examine whether the sample data is defined by unobserved heterogeneity, which is motivated "to avert validity threats."[58]

SmartPLS 4.1 supports techniques such as finite mixture partial least squares (FIMIX-PLS)[59] and PLS prediction-oriented segmentation (PLS-POS),[58] as respective latent class and distance-based segmentation methods to uncover unobserved heterogeneity in the structural model. Specifically, FIMIX-PLS uncovers heterogeneity by estimating the probability of segment membership for each observation and simultaneously estimating the path coefficient for all segments.[59,60] PLS-POS follows a clustering approach with a deterministic assignment of observations to groups and uses a distance measure for the reassignment of observations. As such, the method has no distributional assumptions.[58]

Although latent class modelling affords opportunities to identify consumer segments with similar attitudes and perceptions *a posteriori*,[59,61] the method is also prone to limitations in terms of reliably estimating the number of clusters and defining their boundaries (i.e. lack of interpretability regarding the cluster descriptors)[62]. Other methodological challenges may include a high Type I error rate, low statistical power, and limitations in examining higher-order interactions.[63]

For example, Kandiah et al.[64] employed agent-based modelling to show that public opinion dynamics towards water reclamation differ according to membership in opinion clusters (i.e. optimistic, disengaged, alarmed, or conflicted consumers). However, the approach relied on clustering methods with known limitations,[63,65] which reflected the additional identification of sub-groups within the main consumer segments (i.e. *adopter* as a subset of *optimistic*, and *resistor* as a subset of *alarmed*).[62]

Specifically, Ward's hierarchical clustering method was used to create four clusters, wherein the random start point for the iterative clustering process biases the cluster membership of the first individual analysed, which motivated the subsequent use of K-means cluster analysis to create a second clustering solution on the cluster averages from the first step. Additionally, multiple imputation was required since 158 respondents could not be sorted into a cluster directly due to missing values. Nevertheless, latent class analysis – defined in the literature as "a probabilistic modelling algorithm that allows clustering of data and statistical inference"[66,67] – may prove useful for exploratory research when the goal is "to determine groups that are maximally different by some criterion."[68]

In summary, PLS-MGA should be applied when the analysis is of a confirmatory nature following *a priori* identification of sub-groups, whereas other methods should be applied to groups detected via cluster analysis of similar techniques.[69] Moreover, researchers should approach these methods with caution and due diligence, since using clustering techniques as a subsequent input to run PLS-MGA is conceptually flawed.[70] Such a sequencing would discount the path model relationships specified prior to the analysis, which are the very relationships likely to explain potential group differences.[70]

It follows that traditional clustering techniques are subject to conceptual drawbacks, rendering these methods ill-suited for identifying heterogeneity in the relationships between latent variables (i.e. segment-specific differences in structural equation models).[71] In technical terms, "the identifying assumption of latent class models is local dependence," therefore, "data dependencies that fail to be predicted by the local dependence model are absorbed as additional classes," which "may bias model parameters of interest as well as posterior classifications."[68] These constraints are also discussed by Loo and colleagues.[72]

10 Supplementary Note 10: Summary of studies with a multigroup research focus.

Table S7. Seminal technology acceptance studies employing multigroup analysis or moderation analysis.

Author and year of study	Empirical focus and location of study	Research method and sample size	Theoretical foundation(s)	Application of MGA/moderation analysis to structural equation modelling
Lin[73] 2011	• Examines the antecedents of attitude and behavioural intention towards adopting (or continuing to use) mobile banking • Taiwan	• Paper-based questionnaire • N = 368	• DoI theory and knowledge-based trust model	• Group 1 = Potential customers (N = 177) • Group 2 = Repeat customers (N = 191)
Thakur and Srivastava[74] 2014	• Examines the antecedents of usage intention for mobile payments • India	• Paper-based questionnaire • N = 774	• TAM • UTAUT	• Group 1: Users • Group 2: Non-users[a]
Leong et al.[75] 2013	• Examines the determinants of mobile credit card adoption • Malaysia	• Self-administered questionnaire • N = 262	• Extended TAM	• Gender (male, female) • Age (younger, older) • Experience (low, high) • Usage (low, high)
Farooq et al.[76] 2020	• Investigates the impact of online information on the individual-level intention to voluntarily self-isolate during the COVID-19 pandemic • Finland	• Online survey • N = 225	• Protection motivation theory[b]	• Group 1a: Living alone (N = 122) • Group 1b: Living with others (N = 109) • Group 2a: Social media as primary information channel (N = 119) • Group 2b: Other information channels (N = 106)
Tarhini et al.[77] 2017	• Examines the effects of individual-level culture on the adoption and acceptance of e-learning tools by students • Lebanon	• Online survey • N = 569	• Extended TAM	• Power distance[c] • Cultural values (masculinity vs femininity) • Uncertainty avoidance[d] • Individualism/collectivism

Tan et al.[78] 2014	• Investigates the factors influencing mobile credit card adoption • Malaysia	• Self-administered questionnaire • N = 156	• Extended TAM	• Gender (male, female)
Barbarossa & De Pelsmacker[79] 2016	• Examiners the drivers and barriers towards purchasing eco-friendly products • Italy	• Self-administered questionnaire • N = 926	• Social dilemma theory • Psychological egoism theory	• Group 1: Green consumers (N = 453) • Group 2: Non-green consumers (N = 473)
Krasnova et al.[80] 2012	• Examines the role of culture in individual self-disclosure decisions among users of social networking sites • United States • Germany	• Online survey • N = 375	• Privacy calculus perspective[e]	• Group 1: American users (N = 237) • Group 2: German users (N = 138)[f]
Kong et al.[81] 2013	• Examines effects of loneliness and self-esteem for the relationship between social support and life satisfaction among college students	• Self-administered questionnaire • N = 389	• Attachment and stress theory[g]	• Group 1: Female students (N = 260) • Group 2: Male students (N = 129)
Pappas et al.[82]	• Examines the moderating role of experience on repurchase intention among online shoppers • Greece	• Online survey and self-administered questionnaire • N = 393	• UTAUT • Expectation confirmation theory • Social cognitive theory	• Group 1: Low-experienced customers (N = 214) • High-experienced customers (N = 179)

[a] Sample size not provided.

[b] The theory examines motivational reasons for adoption protective measures and divides the causes into threat appraisal and coping appraisal.

[c] The extent to which individuals expect and accept differences in power between different people.

[d] The extent to which ambiguities and uncertainties are tolerated.

[e] Rooted in social exchange theory.

[f] Users were national of each country. In the case of Germany, 99 foreign respondents were excluded from the sample.

[g] Rooted in theories related to attachment and stress.

11 Supplementary Note 11: Evidence on public perceptions of hydrogen from Australia

In 2021, Martin et al.[25] found no significant differences in levels of hydrogen support between respondents identifying with one of Australia's three national parties (Liberal/National, Labour, and Greens), although support proved lower among respondents corresponding to 'other' political party preferences (i.e. Not Liberal/National, Labour or Greens). The authors concluded that the hydrogen industry should therefore garner bi-partisan public support.[25]

However, no speculation was made as to the potential relevance of an association between apolitical beliefs and lower support for the national hydrogen economy or wider energy transition. In terms of gender, males proved significantly more supportive of hydrogen, although this disparity closed considerably following information provision.[25] This result may infer a more cautious or sceptical attitude among female respondents in absence of information, whereas males have a stronger predisposition to supporting emerging hydrogen energy technologies.[32,42,83]

Heterogenous energy preferences in the United Kingdom

Roddis and colleagues[84] found that the Southwest and Eastern England had higher levels of support for most energy types, whereas Scotland and London presented consistently lower approval rates, which reflects an approximate North-South divide. Nevertheless, it was concluded that age and concern for climate change were stronger predictors of public acceptance than regional location.[84] Notably, divergence was also observed between urban and rural locations for specific technologies, while citizens most and least directly exposed to energy technologies[i] (i.e. Scotland and London) had the lowest support levels.[84] The contribution of Roddis et al.[84] reinforces the need to recognise that public perceptions of energy technologies may be characterised by different degrees of consumer heterogeneity.

12 Supplementary Note 12: The role of perceived benefits in technology acceptance models

Perceived benefits plays a prominent role in technology acceptance models, typically acting as an antecedent of attitude toward to use, as conceptualised within the TAM vis-à-vis perceived usefulness.[85] Focusing on the hospitality sector, Wang and Qualls[86] adapted the TAM to examine the relationship between perceived ease of adoption, perceived benefits of adoption, and technology adoption behaviour, wherein perceived benefits also acted as a mediating construct. Lee[87] tested the effect of perceived benefits on both attitude ($\beta = 0.24$, $p < 0.05$) and behavioural intention ($\beta = 0.32$, $p < 0.05$) towards internet banking, reporting a stronger effect size for the latter. Notably, a recent meta-analysis showed that perceived benefits is the most significant predictor of residential PV adoption intention.[88]

However, at the latter stages of the innovation-decision process (i.e. implementation and confirmation), the focus may then shift from perceived benefits to a focus on 'benefits realised', as demonstrated by Daniel and Wilson[89] in the context of e-commerce adoption among small and medium-sized enterprises in the UK. Moreover, in the context of radio frequency identification adoption (RFID), Reyes et al.[90] showed that different stages of the innovation-decision process influence the level of perceived benefits (i.e. customer service, productivity, asset management, and communication) among supply chain professionals. A similar approach was applied by Jiménez-Martínez and Polo-Redondo[91] when examining how perceptions of benefits may change among Spanish administrations in the context of electronic data interchange. The authors made the case that benefits may be hard to perceive at first but become more tangible following adoption.[91] Consequently, increasing trialability of the technology is usually the most direct way to raise perceived benefits and adoption prospects.

As the literature has evolved, researchers have operationalised perceived benefits in several ways, reflecting both the importance and multi-faceted nature of the construct. For example, alongside perceived barriers ($\beta = 0.272$), perceived benefits ($\beta = 0.262$) had the strongest influence on willingness to participate in electronic bidding[ii] in the construction industry, but also moderated the relationship between perceived barriers and participation willingness ($\beta = 0.535$).[92] In the context of technology-enhanced learning, Dubey and Sahu[93] operationalised perceived benefits as both a meditator and moderator of the relationship between adoption intention and student satisfaction, thereby applying an outcome-orientated lens.

Kim et al.[94] supported the hypotheses that the relative benefits of mobile banking positively influence consumer trust ($\beta = 0.30$, $p < 0.01$), in addition to directly predicting usage intention ($\beta = 0.18$, $p < 0.01$), with an overall effect size of 0.28. Additionally, Laforet and Li[95] observed that understanding potential benefits is critical to mobile banking adoption. However, Gong et al.[96] showed that perceived benefits mediates the relationship between trust in online health consultation services and adoption intention. Park and colleagues[97] applied a similar approach when examining the interplay between perceived risk, benefit, and trust on consumer's intention to use mobile payment services in the Midwestern United States.

Critically, it should be noted that in many contexts, perceived benefits is understood in terms of 'relative advantage' vis-à-vis Rogers' seminal classification[iii].[98] For example, the study of Abou-Shouk and colleagues[99] focused on perceived benefits of e-commerce adoption among Egyptian travel agents, wherein relative advantage was characterised via three constructs composed of at least four indicators (i.e. 'essential benefits', N = 4; 'marketing and competition benefits', N = 5; and 'business internal efficiency benefit', N = 6). A more reductive approach may also prevail, as taken by Au and Enderwick[100] when defining 'perceived benefit' in terms of "the adopter's belief of the likelihood that the technology can improve the economic benefits of the organisation and/or of the person."

13 Supplementary Note 13: Kruskal-Wallis H Test results for adoption factors

13.1 Safety Perceptions

In terms of safety perceptions, the VEG expressed the most positive outlook (M = 6.59), followed by the MEG (M = 5.87), the FSG (M = 5.75), and finally, the BLG (M = 5.55). Notably, the VEG registered a more positive perception across all safety metrics compared to other sub-groups, which also held true when comparing the MEG to the BLG and FSG. Based on these patterns, technology and environmental engagement is positively correlated with confidence in hydrogen safety. A K-W test was performed after forming a composite score from the five safety indicators, which supported the presence of consumer heterogeneity: H (3, N = 1845) = 85.97, $p < 0.001$. The groups rank as follows (highest to lowest): VEG: Md = 1156; MEG: Md = 923; FSG: Md = 887; BLG: Md = 829.

13.2 Technology Perceptions

Regarding technological perceptions, the VEG attributed the strongest positive expectation to boiler performance (M = 7.54), followed by the FSG (M = 7.10), MEG (M = 6.99) and BLG (M = 6.81). The VEG also reflected the highest level of confidence in hydrogen cooking (M = 6.81), followed by the MEG (M = 6.22), the FSG (M = 6.15), and the BLG (M = 5.94). Overall, the VEG emerges as the consumer segment with highest level of expectancy regarding the relative advantage of hydrogen appliances, while the BLG is the least conservative sub-group when compared at the descriptive level. Consequently, a K-W test detected group-specific differences regarding perceptions of boiler performance (composite score): H (3, N = 1845) = 31.57, $p < 0.001$. The groups rank as follows (highest to lowest): VEG: Md = 1054; FSG: Md = 939; MEG: Md = 916; BLG: Md = 855. A comparable result is likewise reported for hob performance (composite score): H (3, N = 1845) = 49.12, $p < 0.001$. The groups rank as follows (highest to lowest): VEG: Md = 1094; MEG: Md = 932; FSG: Md = 899; BLG: Md = 846.

13.3 Financial Perceptions

In terms of financial perceptions, the BLG held the most negative perspective or highest level of concern across all three metrics (M = 7.69), followed by the MEG (M = 7.41), FSG (M = 7.25) and VEG (M = 7.21). As a result, consumer heterogeneity was identified: H (3, N = 1845) = 29.93, $p < 0.001$. The groups rank as follows (least negative to most negative financial perception): VEG: *Md* = 848; FSG: *Md* = 862; MEG: *Md* = 901; BLG: *Md* = 1008. The expectation that hydrogen boilers would be significantly more expensive to purchase than natural gas boilers proved largest across the sample (FP1: *M* = 8.08) and for all sub-groups. Nevertheless, respondents perceived the purchasing price of each appliance to be relatively comparable. For example, perceptions proved near equivalent in the case of the BLG: Boiler: *M* = 8.36; Hob: *M* = 8.32. In line with previous findings,[15] there was less expectation across the sample that a switch to hydrogen would adversely impact energy bills FP3: *M* = 6.28).

13.4 Perceived Socio-economic Costs

At the macro-economic level, the FSG relayed the most negative outlook across both metrics (PSC1: *M* = 5.82; PSC2: *M* = 6.12). Consequently, the FSG represents the most concerned sub-group (*M* = 5.97) in respect to perceived socio-economic impacts, followed by the BLG (*M* = 5.82), VEG (*M* = 5.64), and MEG (*M* = 5.52). In view of the FSG expressing higher levels of socio-economic concern, group-specific differences were identified: H (3, N = 1845) = 10.540, p = 0.014. The groups rank as follows (least negative to most negative socio-economic perception): VEG: *Md* = 865; MEG: *Md* = 888; BLG: *Md* = 949; FSG: *Md* = 967.

13.5 Production Perceptions

Finally, regarding production perceptions, the VEG proved outright the most supportive consumer segment (*M* = 7.24), followed by the MEG (*M* = 6.60), FSG (*M* = 6.02), and BLG (*M* = 5.93). As a result, the data suggests technology and environmental engagement is positively associated with support for the twin-track approach. Moreover, in view of descriptive results for each production pathway, support is strongest for green hydrogen production.[101] The mean score for PP1 and PP2 (blue) = 6.17, while the mean score for PP3 and PP4 (green) = 6.86 across the sample. In this case, a substantial level of consumer heterogeneity is observed: H (3, N = 1845) = 207.36, $p < 0.001$. The groups rank as follows (highest to lowest): VEG: *Md* = 1241; MEG: *Md* = 1019; FSG: *Md* = 796; BLG: *Md* = 774.

Table S8. Summary of descriptive statistics for constructs predicting adoption potential.

Construct	Baseline Group (BLG)	Moderately Engaged Group (MEG)	Very Engaged Group (VEG)	Fuel Stress Group (FSG)	Full sample
SP	5.55	5.87	6.59	5.75	5.86
BLR	6.81	6.99	7.54	7.10	7.05
HOB	5.94	6.22	6.81	6.15	6.21
FP[a]	7.69	7.41	7.21	7.25	7.45
PSC[a]	5.82	5.52	5.64	5.97	5.74
PP	5.93	6.60	7.24	6.02	6.35

[a] Values for FP and PSC are converted from a five-point Likert scale for comparative purposes.

13.6 Distribution of accepters and rejecters of hydrogen homes

Fig. S4 provides an alternative representation of the data presented in Section 6.1.1 (see Fig. 9) by adjusting the results to the sample size of each group. Therefore, 15.8% of respondents in the BLG corresponded to a position of outright rejection (i.e. 107/677), while 25.4% of respondents in the VEG could be considered outright 'accepters' of hydrogen homes (i.e. 84/331).

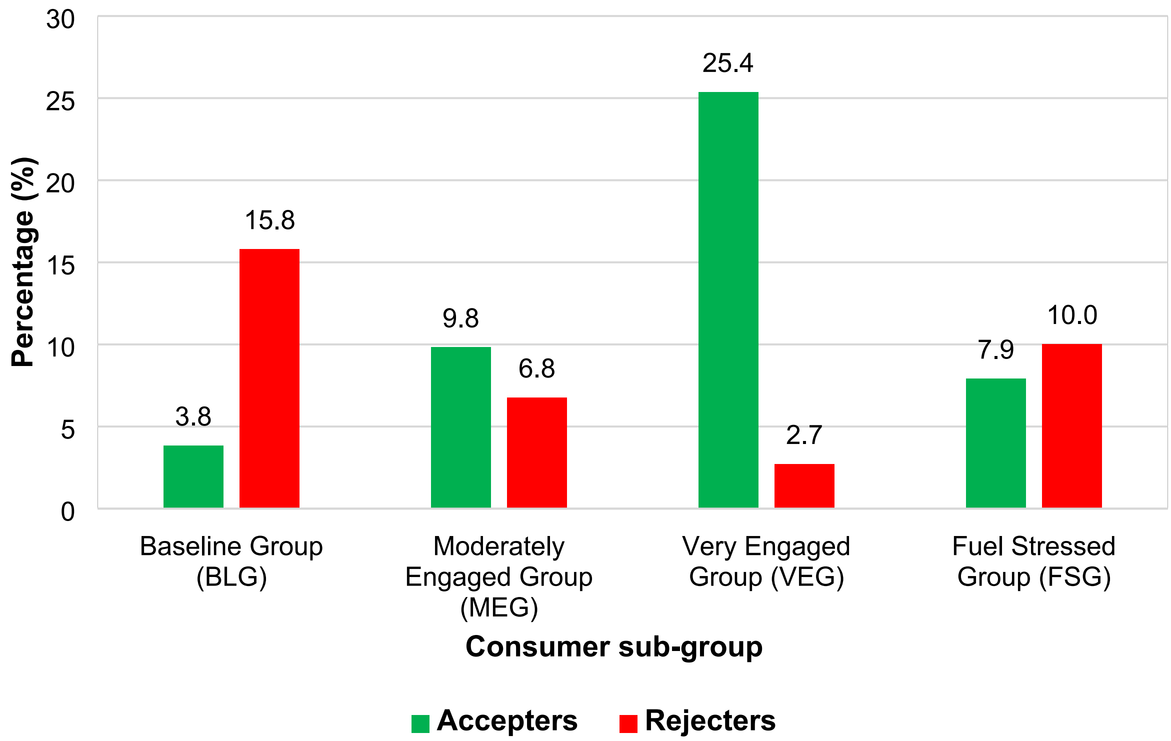

Fig. S4. Breakdown of hydrogen acceptance and rejection by consumer sub-group relative to sample size.

14 Supplementary Note 14: Measurement model assessment

In the case of the BLG, all indicator loadings met the threshold value of 0.708, while one indicator loading failed to satisfy this threshold for the MEG (PP1 = 0.409). Regarding the VEG, three indicators fell marginally below the CA threshold: BLR2 = 0.682; FIN2 = 0.693; ADPT = 0.671. Additionally, and concurring with the result for the MEG, PP1 had a CA value of 0.578. Finally, the FSG reflected a similar pattern, reporting a value of 0.445 for PP1, in addition to 0.668 for PP5, while three other indicators failed to satisfy the recommended threshold: BL3 = 0.596; FP1 = 0.550; FP2 = 0.532. Table S9–S11 report the measurement model assessment for the remaining sub-groups, following the report for the BLG in the main analysis.

Table S9a. Assessment of reliability, convergent validity, and multicollinearity for the Moderately Technology and Environmentally Engaged Group.

Construct	**CA**	**CR (ρ_A)**	**CR (ρ_C)**	**AVE**	**VIF**
Safety Perceptions (SP)	0.924	0.925	0.943	0.768	1.224
Perceived Boiler Performance (BLR)*	0.765	0.768	0.850	0.588	1.657
Perceived Hob Performance (HOB)*	0.861	0.864	0.906	0.706	1.657
Technology Perceptions (TP)**	0.773	0.773	0.898	0.815	1.149
Financial Perceptions (FP)	0.740	0.933	0.812	0.593	1.053
Perceived Socio-economic Costs (PSC)	0.678	0.686	0.861	0.756	1.200
Production Perceptions (PP)	0.762	0.808	0.836	0.516	1.253
Perceived Adoption Potential (PAP)	0.832	0.842	0.870	0.528	n/a

** Higher-order construct
* Lower order constructs

Table S9b. Fornell Larcker results for the Moderately Technology and Environmentally Engaged Group.

	BLR	**FP**	**HOB**	**PAP**	**PSC**	**PP**	**SP**
BLR	0.767						
FP	-0.160	0.770					
HOB	0.630	-0.078	0.840				
PAP	0.382	-0.269	0.376	0.727			
PSC	-0.113	0.164	-0.133	-0.465	0.869		
PP	0.138	-0.095	0.160	0.494	-0.382	0.719	
SP	0.270	-0.162	0.341	0.526	-0.159	0.290	0.876

Table S9c. HTMT results for the Moderately Technology and Environmentally Engaged Group.

	BLR	FP	HOB	PAP	PSC	PP	SP
BLR							
FP	0.182						
HOB	0.773	0.107					
PAP	0.412	0.270	0.373				
PSC	0.181	0.180	0.169	0.609			
PP	0.214	0.106	0.206	0.560	0.498		
SP	0.320	0.160	0.382	0.551	0.194	0.372	

Table S10a. Assessment of reliability, convergent validity, and multicollinearity for the Very Technology and Environmentally Engaged Group.

Construct	CA	CR (ρ_A)	CR (ρ_C)	AVE	VIF
Safety Perceptions (SP)	0.929	0.931	0.946	0.779	1.568
Perceived Boiler Performance (BLR)*	0.735	0.739	0.834	0.558	1.843
Perceived Hob Performance (HOB)*	0.865	0.865	0.908	0.712	1.843
Technology Perceptions (TP)**	0.803	0.804	0.911	0.836	1.417
Financial Perceptions (FP)	0.684	0.798	0.796	0.567	1.054
Perceived Socio-economic Costs (PSC)	0.785	0.833	0.901	0.820	1.063
Production Perceptions (PP)	0.754	0.765	0.834	0.504	1.253
Perceived Adoption Potential (PAP)	0.830	0.838	0.873	0.534	n/a

** Higher-order construct
* Lower order constructs

Table S10b. Fornell Larcker results for the Very Technology and Environmentally Engaged Group.

	BLR	FP	HOB	PAP	PSC	PP	SP
BLR	0.747						
FP	-0.109	0.753					
HOB	0.676	-0.096	0.844				
PAP	0.417	-0.230	0.471	0.731			
PSC	-0.062	0.059	-0.060	-0.205	0.906		
PP	0.243	-0.165	0.304	0.591	-0.177	0.710	
SP	0.411	-0.199	0.537	0.573	-0.055	0.384	0.883

Table S10c. HTMT results for the Very Technology and Environmentally Engaged Group.

	BLR	FP	HOB	PAP	PSC	PP	SP
BLR							
FP	0.205						
HOB	0.846	0.134					
PAP	0.497	0.257	0.500				
PSC	0.214	0.281	0.102	0.250			
PP	0.333	0.265	0.378	0.735	0.277		
SP	0.495	0.234	0.598	0.611	0.064	0.475	

Table S11a. Assessment of reliability, convergent validity, and multicollinearity for the Fuel Stressed Group.

Construct	CA	CR (ρ_A)	CR (ρ_C)	AVE	VIF
Safety Perceptions (SP)	0.892	0.894	0.921	0.699	1.224
Perceived Boiler Performance (BLR)*	0.673	0.685	0.803	0.508	1.657
Perceived Hob Performance (HOB)*	0.836	0.837	0.891	0.671	1.657
Technology Perceptions (TP)**	0.744	0.744	0.886	0.796	1.149
Financial Perceptions (FP)	0.703	0.717	0.733	0.498	1.053
Perceived Socio-economic Costs (PSC)	0.749	0.758	0.888	0.799	1.200
Production Perceptions (PP)	0.772	0.825	0.842	0.527	1.253
Perceived Adoption Potential (ADPT)	0.836	0.843	0.877	0.543	n/a

** Higher-order construct
* Lower order constructs

Table S11b. Fornell Larcker results for the Fuel Stressed Group.

	BLR	FP	HOB	PAP	PSC	PP	SP
BLR	0.713						
FP	-0.170	0.706					
HOB	0.592	-0.127	0.819				
PAP	0.422	-0.295	0.425	0.737			
PSC	-0.267	0.297	-0.253	-0.402	0.894		
PP	0.248	-0.116	0.256	0.472	-0.262	0.726	
SP	0.369	-0.154	0.394	0.499	-0.153	0.301	0.836

Table S11c. HTMT results for the Fuel Stressed Group.

	BLR	FP	HOB	PAP	PSC	PP	SP
BLR							
FP	0.296						
HOB	0.784	0.169					
PAP	0.541	0.270	0.469				
PSC	0.363	0.230	0.319	0.493			
PP	0.344	0.161	0.324	0.545	0.327		
SP	0.486	0.168	0.457	0.558	0.190	0.365	

15 Supplementary Note 15: Measurement model assessment for higher-order construct

Fig. S5a–S5d present the PLS-SEM output for validating the higher-order construct, Technology Perceptions (TP) for each consumer sub-group, following the guidelines presented by Sarstedt and colleagues.[102] The disjoint two-stage approach was applied whereby the latent variable scores for each lower-order construct (Perceived Boiler Performance and Perceived Hob Performance) are calculated and used as indicators for the newly formed first-order construct, Technology Perceptions (TP). The procedure validated the average variance extracted (AVE) in support of convergent validity, while discriminant validity was also established, alongside item reliability and internal consistent reliability.

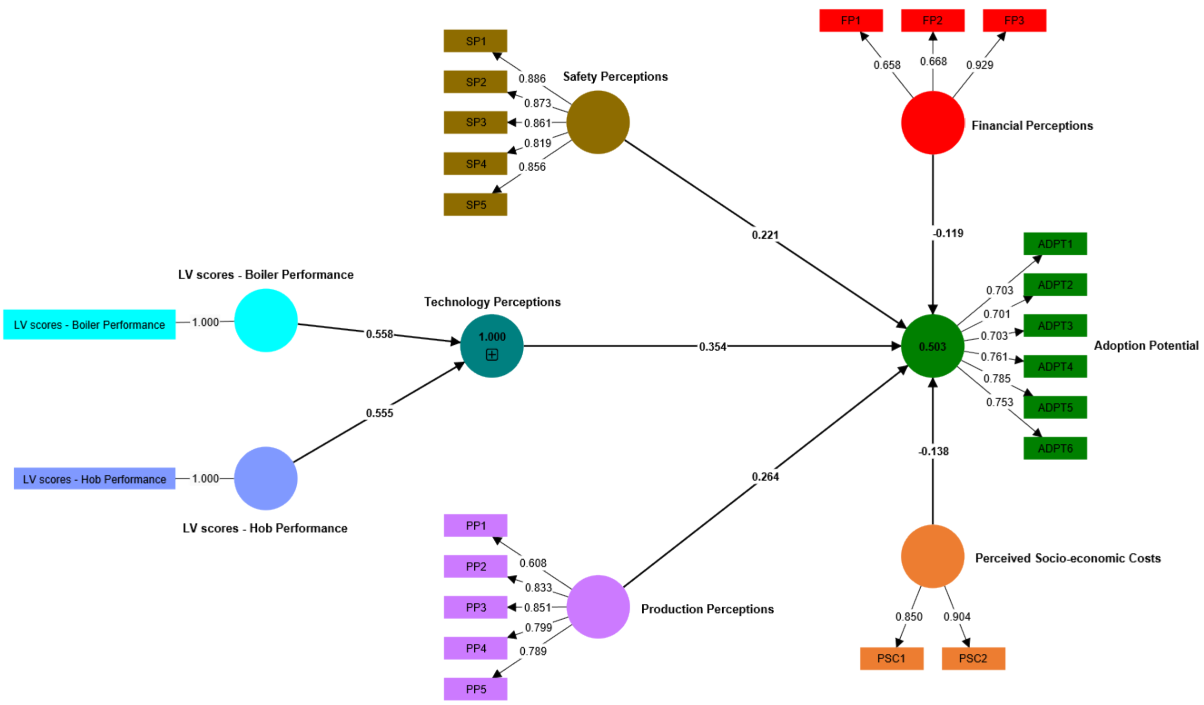

Fig. S5a. Measurement model assessment for reflective-formative construct (TP): Baseline Group.

* The results were visualised in an earlier version of SmartPLS wherein perceived adoption potential was denoted as 'adoption potential' (ADPT). The results are identical.

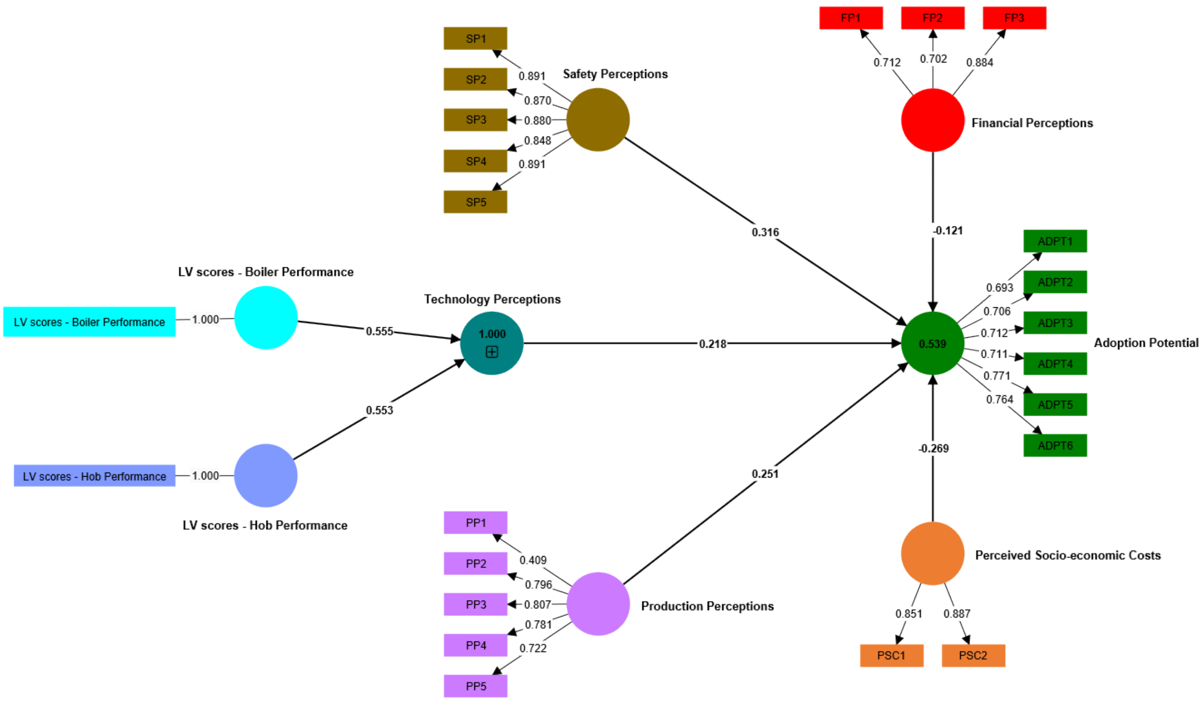

Fig. S5b. Measurement model assessment for reflective-formative construct (TP): Moderately technology and environmentally Engaged Group.

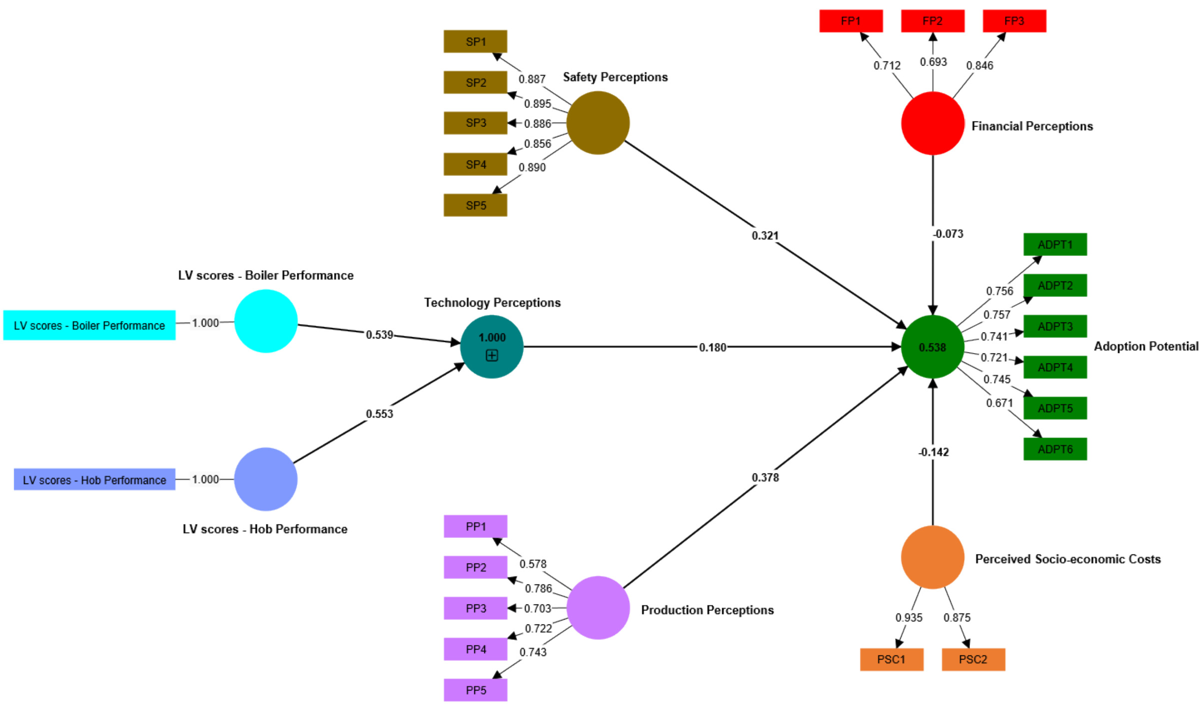

Fig. S5c. Measurement model assessment for reflective-formative construct (TP): Very technology and environmentally Engaged Group.

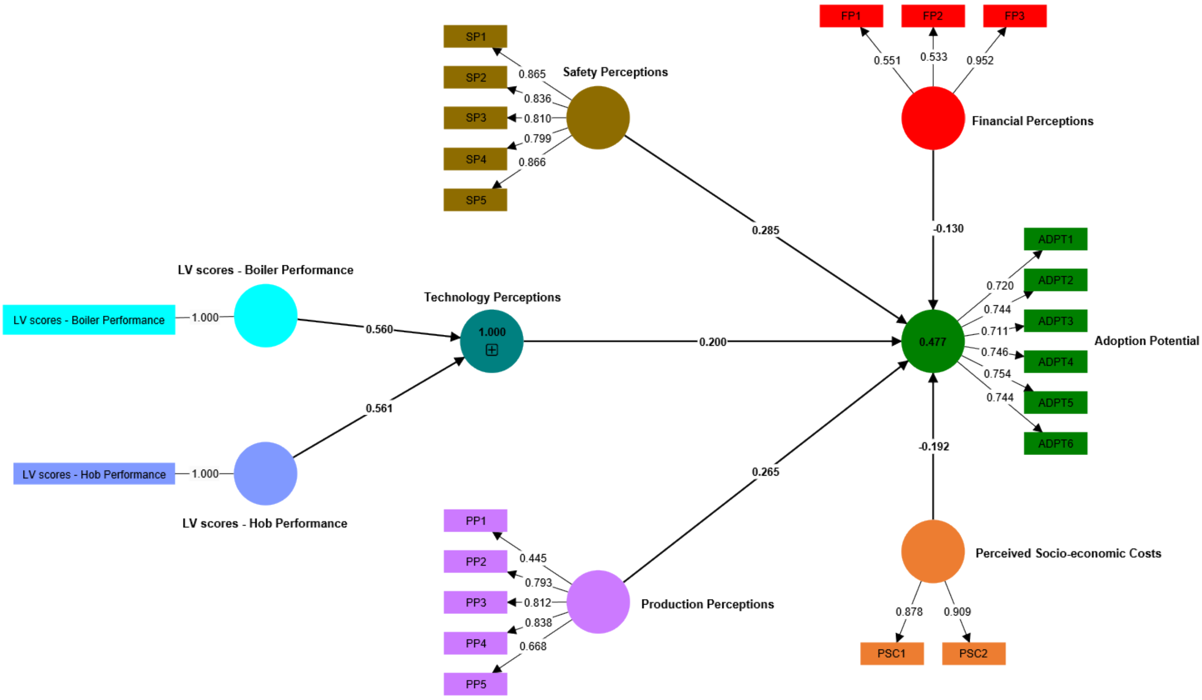

Fig. S5d. Measurement model assessment for reflective-formative construct (TP): Fuel Stressed Group.

16 Supplementary Note 16: Structural model assessment

Fig. S6a–Fig. S6d report the structural model path coefficients for each consumer sub-group.

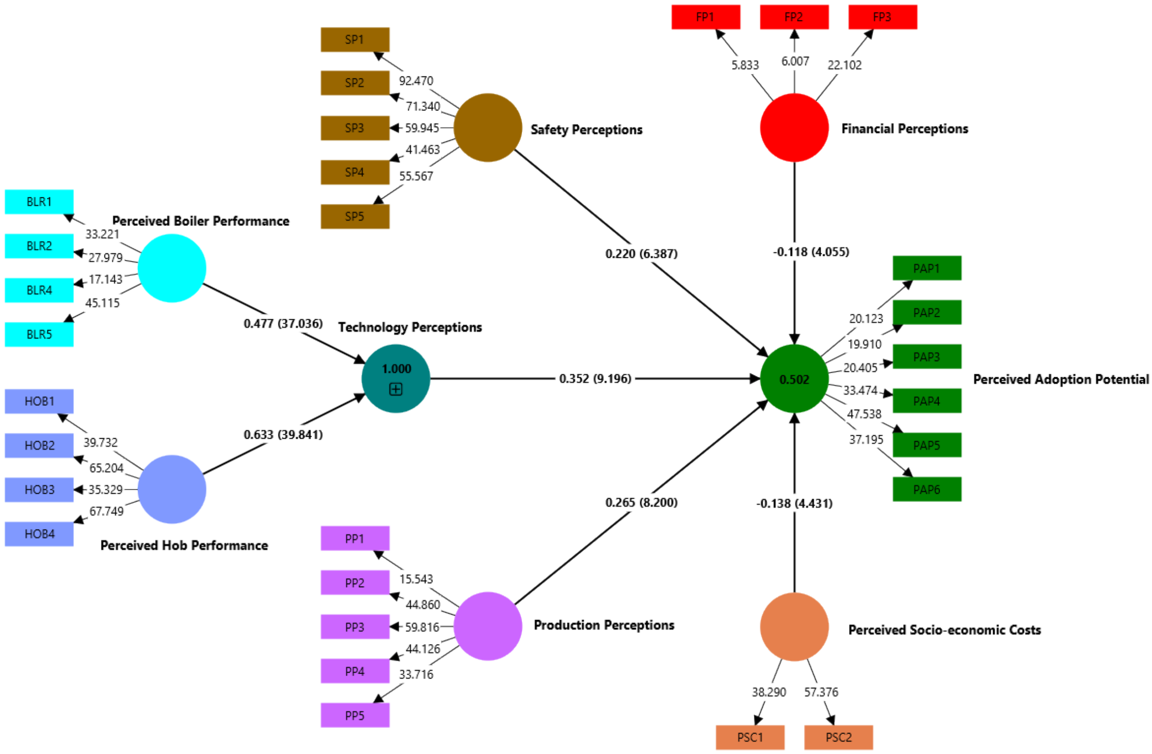

Fig. S6a. Structural model path coefficients for Baseline Group.

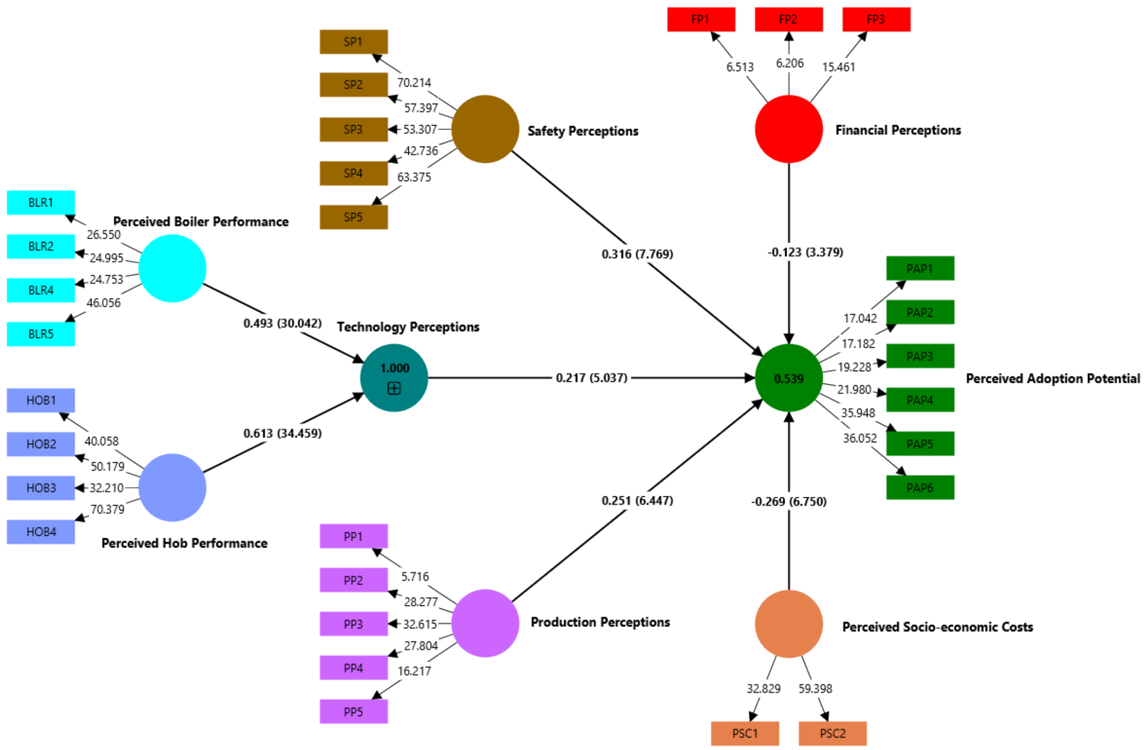

Fig. S6b. Structural model path coefficients for Moderately technology and environmentally Engaged Group.

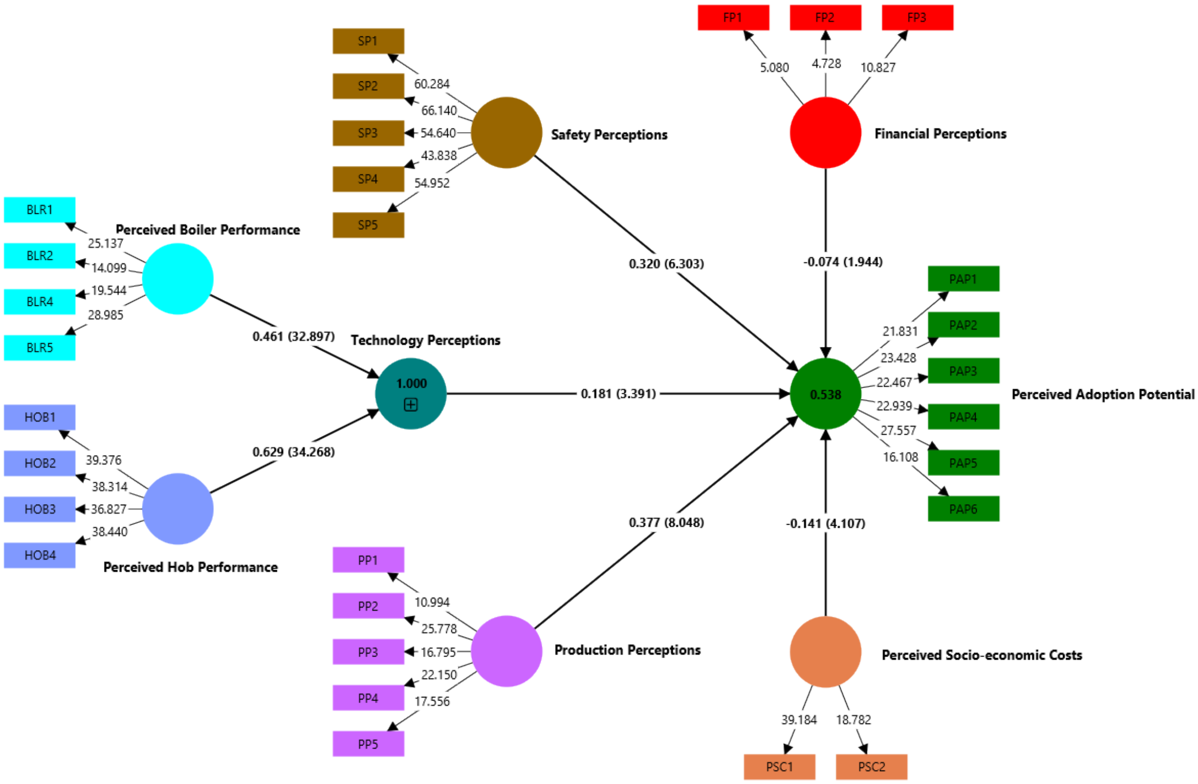

Fig. S6c. Structural model path coefficients for Very technology and environmentally Engaged Group.

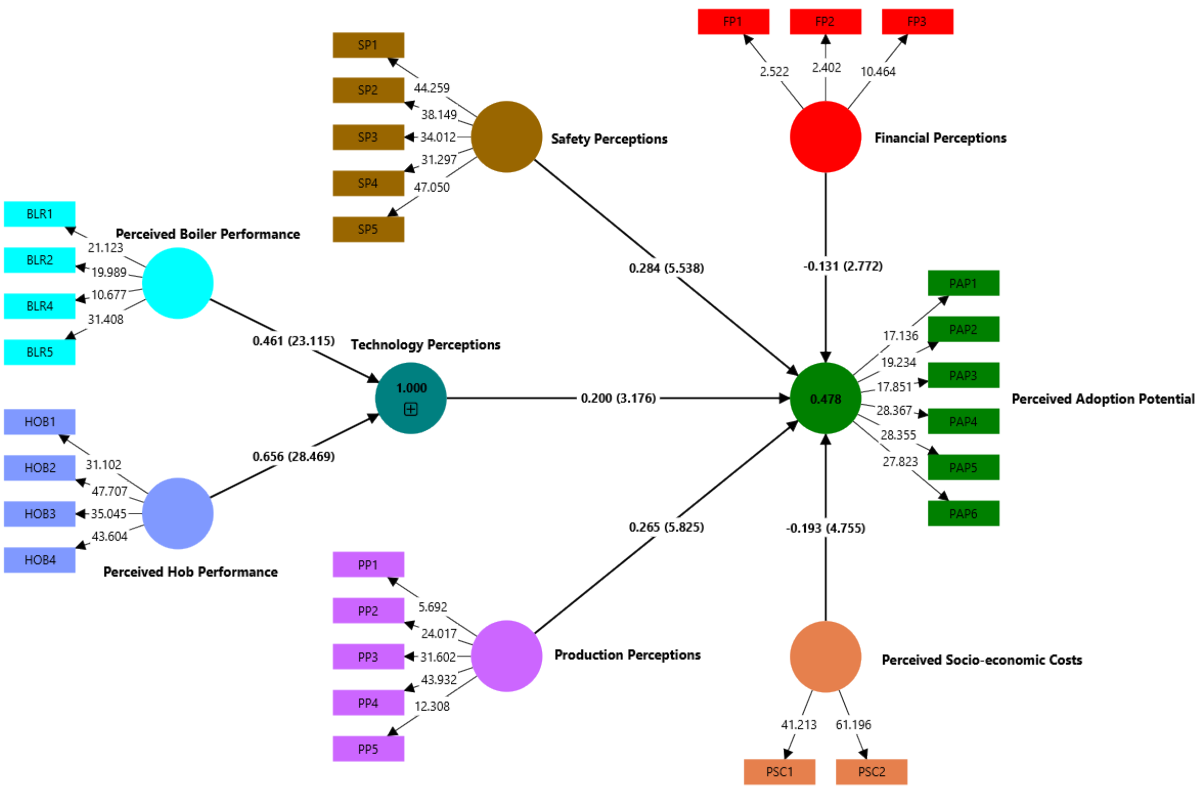

Fig. S6d. Structural model path coefficients for Fuel Stressed Group.

17 Supplementary Note 17: Cross-validated predictive ability test

Table S12 reports the results for the CVPAT, which confirms moderative out-of-sample predictive power for the model across each consumer sub-group.

Table S12. Results for predictive power using CVPAT.

Baseline Group		***PLS-SEM vs Indicator average (IA)***		
		Average loss difference	***t*-value**	***ρ*-value**
	Perceived Adoption Potential (PAP)	-0.852	10.344	<0.001
	Technology Perceptions (TP)	-2.865	14.136	<0.001
	Overall	-2.002	14.678	<0.001
		PLS-SEM vs Linear model (LM)		
		Average loss difference	***t*-value**	***ρ*-value**
	Perceived Adoption Potential (PAP)	0.035	1.475	0.141
	Technology Perceptions (TP)	3.080	29.333	<0.001
	Overall	1.775	29.043	<0.001
Moderately Engaged Group		***PLS-SEM vs Indicator average (IA)***		
		Average loss difference	***t*-value**	***ρ*-value**
	Perceived Adoption Potential (PAP)	-0.785	9.234	<0.001
	Technology Perceptions (TP)	-3.047	12.070	<0.001
	Overall	-2.007	13.131	<0.001
		PLS-SEM vs Linear model (LM)		
		Average loss difference	***t*-value**	***ρ*-value**
	Perceived Adoption Potential (PAP)	0.016	0.519	0.604
	Technology Perceptions (TP)	2.773	23.779	<0.001
	Overall	1.591	24.472	<0.001
Very Engaged Group		***PLS-SEM vs Indicator average (IA)***		
		Average loss difference	***t*-value**	***ρ*-value**
	Perceived Adoption Potential (PAP)	-0.754	6.973	<0.001
	Technology	-3.118	9.566	<0.001

	Technology Perceptions (TP)			
	Overall	-2.105	9.984	<0.001
		PLS-SEM vs Linear model (LM)		
		Average loss difference	***t*-value**	***ρ*-value**
	Perceived Adoption Potential (PAP)	0.026	0.501	0.617
	Technology Perceptions (TP)	2.749	18.925	<0.001
	Overall	1.582	18.456	<0.001
Fuel Stressed Group		***PLS-SEM vs Indicator average (IA)***		
		Average loss difference	***t*-value**	***ρ*-value**
	Perceived Adoption Potential (PAP)	-0.852	10.344	<0.001
	Technology Perceptions (TP)	-2.865	14.136	<0.001
	Overall	-2.002	14.678	<0.001
		PLS-SEM vs Linear model (LM)		
		Average loss difference	***t*-value**	***ρ*-value**
	Perceived Adoption Potential (PAP)	0.035	1.475	0.141
	Technology Perceptions (TP)	3.080	29.333	<0.001
	Overall	1.775	29.043	<0.001

18 Supplementary Note 18: Importance-performance map analysis

Table S13 reports the results for the importance-performance map analysis conducted at the construct level for each sub-group.

Table S13. Total effects and latent variable index values for predictors of perceived adoption potential.

					Adoption construct			
Consumer sub-group	**IMPA measurement**	**BLR**	**HOB**	**TP**	**FP**	**PSC**	**SP**	**PP**
Baseline Group (BLG)	Importance (total effects)	0.168	0.223	0.352	-0.118	-0.138	0.220	0.265
	Performance (LV index values)	68.387	59.426	63.503	64.843	48.056	55.612	59.417
Moderately Engaged Group (MEG)	Importance (total effects)	0.107	0.133	0.217	-0.123	-0.269	0.316	0.251
	Performance (LV index values)	70.113	62.318	66.039	63.206	44.189	58.745	67.131
Very Engaged Group (VEG)	Importance (total effects)	0.083	0.114	0.181	-0.074	-0.141	0.320	0.377
	Performance (LV index values)	75.718	68.281	71.659	62.589	45.081	66.027	73.558
Fuel Stressed Group (FSG)	Importance (total effects)	0.092	0.131	0.200	-0.131	-0.193	0.284	0.265
	Performance (LV index values)	71.404	61.403	65.634	57.759	49.664	57.611	60.395

Fig. S7a–Fig. S7d report the importance-performance map analyses for each consumer sub-group.

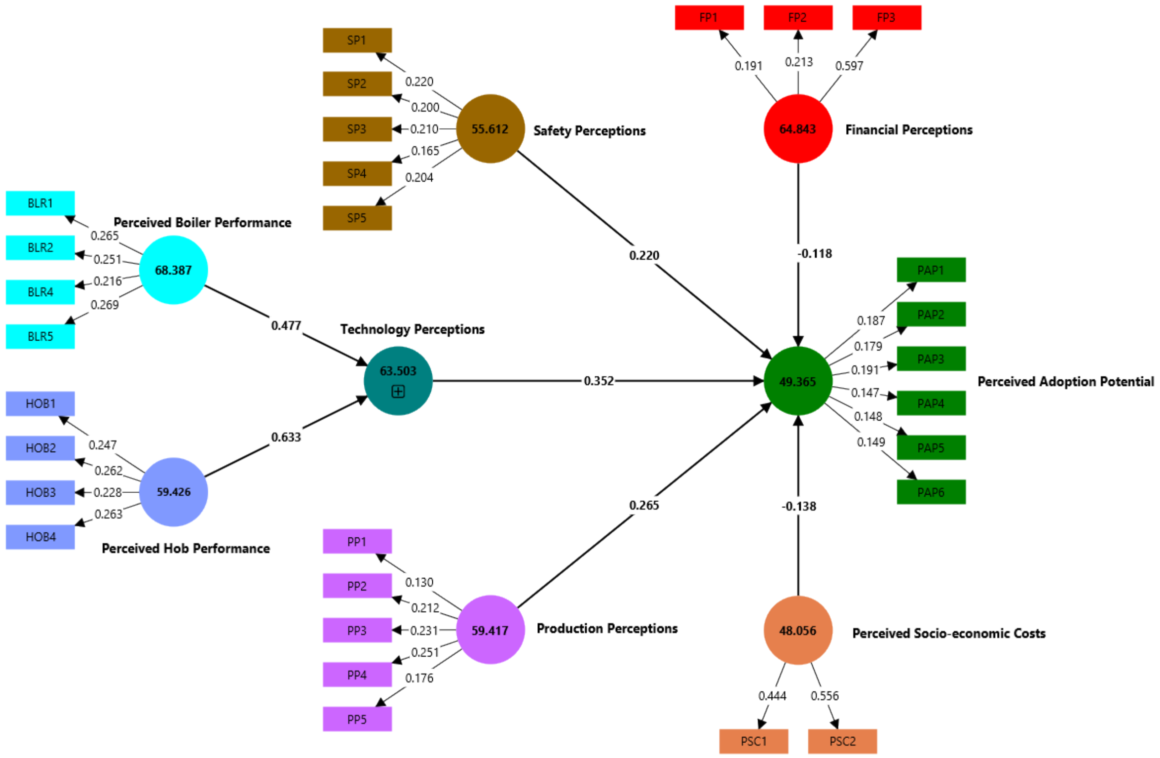

Fig. S7a. Importance-performance map analysis for Baseline Group.

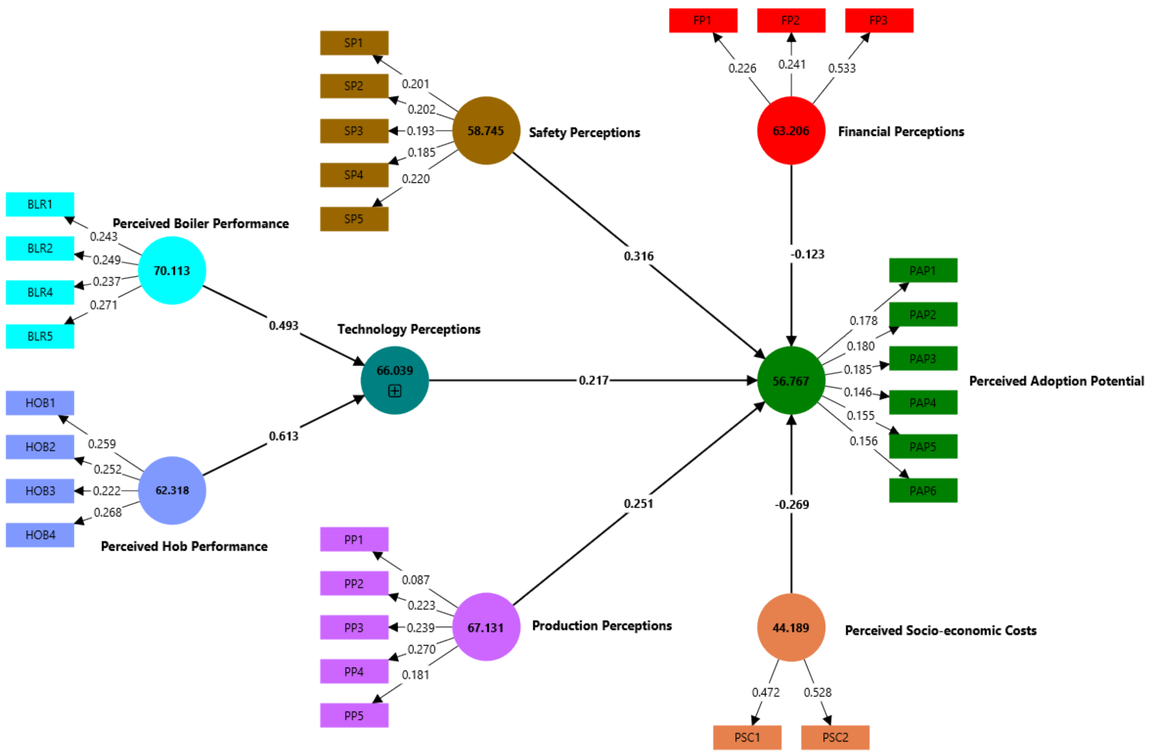

Fig. S7b. Importance-performance map analysis for Moderately technology and environmentally Engaged Group.

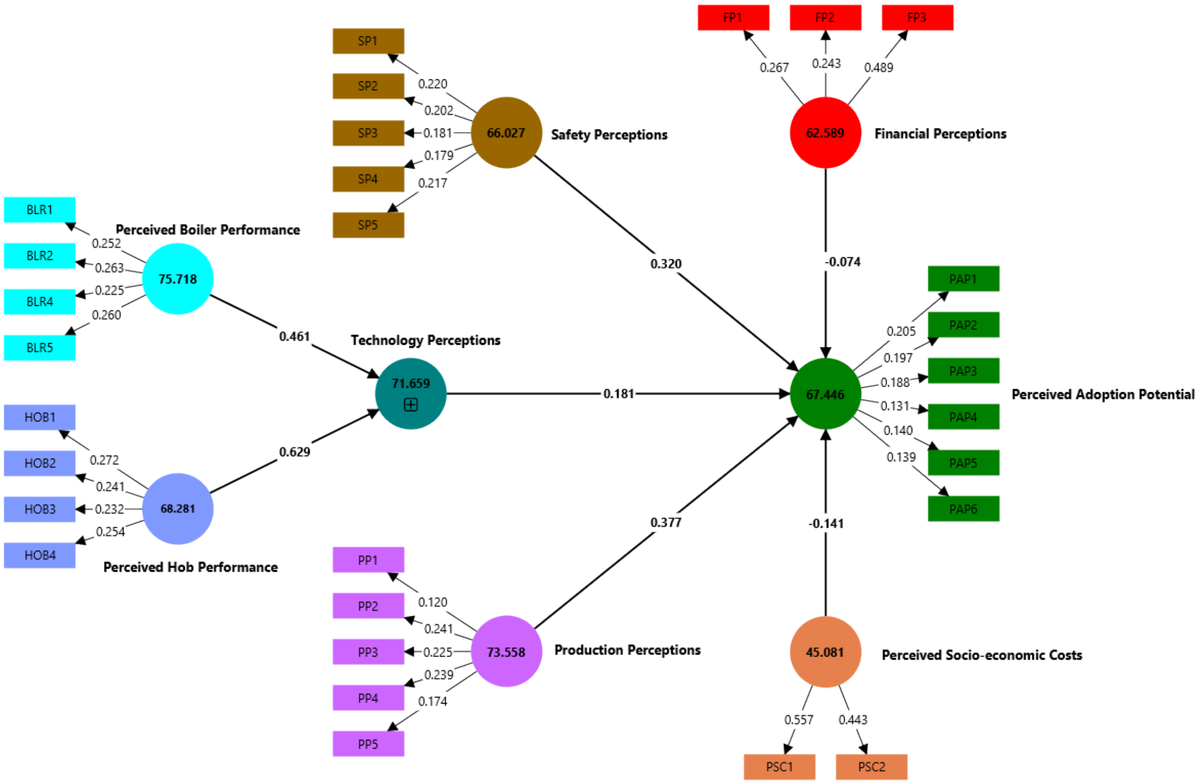

Fig. S7c. Importance-performance map analysis for Very technology and environmentally Engaged Group.

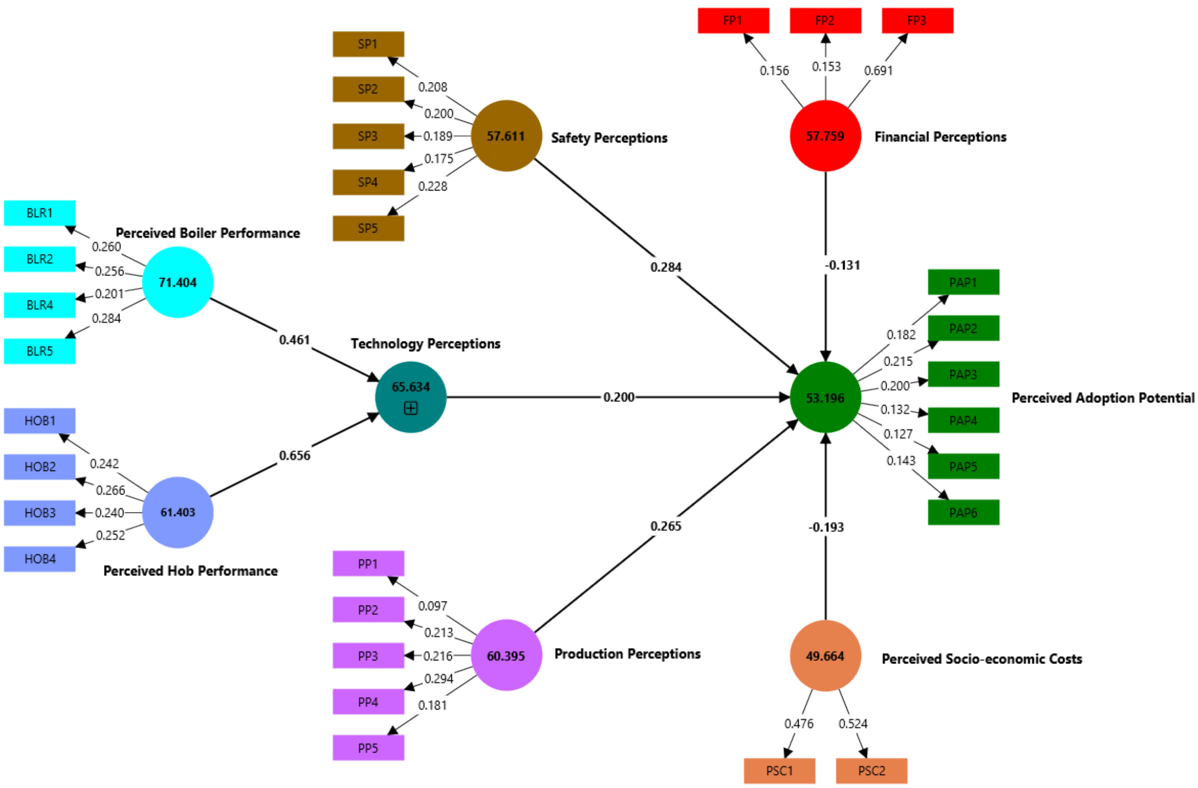

Fig. S7d. Importance-performance map analysis for Fuel Stressed Group.

18.1 Summary of importance-performance map analysis for each consumer sub-group

18.1.1 Baseline Group

For respondents in the BLG, which foreseeably represents the larger proportion of UK society, technology perceptions is the most influential predictor of perceived adoption potential, followed by production and safety perceptions. It follows that more strategic efforts are needed to assure consumers that hydrogen home appliances have a performance advantage over existing natural gas boilers and hobs. In terms of negative predictors, financial perceptions and perceived socio-economic costs have a similar effect on perceived adoption potential. However, more resources should be allocated to mitigating socio-economic concerns, since this construct had the lowest latent variable (LV) index value (i.e. worst performance) in the model (LV = 48.056). By contrast, constructs located at the positive end of the importance-performance matrix are clustered closely together.

18.1.2 Moderately Engaged Group

Following the trend observed with the BLG, positive constructs are also clustered tightly for the MEG in terms of technology performance, albeit with a marginal increase overall. Safety perceptions ranks as the most critical predictor of perceived adoption potential, followed by perceived socio-economic costs. Moreover, these constructs have the lowest performance (SP: LV = 58.745; PSC: LV = 44.189), which reinforces the need for strategic measures to address the safety and macro-economic dimensions of domestic hydrogen adoption. Production perceptions is the next most important positive predictor, followed by technology perceptions, with little discrepancy in terms of their respective performance. In comparative terms, financial perceptions appear to be less relevant to the MEG compared to other constructs, which calls for further interrogation and validation in follow-up studies, for example, by testing for moderating effects related to socio-demographic variables.

18.1.3 Very Engaged Group

Respondents with high levels of technology and environmental engagement attribute most importance to production perceptions (β = 0.377), whereas technology perceptions has more a moderate influence (β = 0.181). Safety perceptions (β = 0.320; LV = 66.027) is the next most critical factor to address after production perceptions, whereas perceived socio-economic costs has a slighter smaller total effect than technology perceptions, but a considerably lower performance (β = -0.141; LV = 45.081). Mirroring results for the MEG, financial perceptions is the least influential factor.

18.1.4 Fuel Stressed Group

In comparison to other sub-groups, fuel stressed respondents present a narrow range within the IMPA, since no positive construct exceeds 0.300, while negative constructs are below -0.200 on the x-axis. This clustering effect corresponds to near equal levels of importance being attributed to the safety and production aspects of the domestic hydrogen transition, which represent the foremost areas of strategic importance. As a result, fuel stressed respondents transmit less overall divergence in perceptions of different adoption factors, which demarcates this sub-group as more homogenous within the overall context of the STEEP framework when tested from a sufficiency perspective.

Technology perceptions (β = 0.200; LV = 65.634) and perceived socio-economic costs (β = -0.193; LV = 49.664) have near equivalent effect sizes. However, there is more scope for improving perceived adoption potential by allocating resources towards mitigating socio-economic concerns, which aligns to the disproportionate livelihood pressures facing fuel stressed citizens. Despite this imperative, when evaluated against other factors, the FSG nevertheless places least weight on the micro-economic dimension associated with the purchasing and running costs of hydrogen appliances. Based on the results, it can be conjectured that citizens facing fuel stress pressures perceive switching to a hydrogen home as a potential mechanism for alleviating safety concerns and improving the environment, which is consistent with prior research.

19 Supplementary Note 19: Bottleneck results for necessary condition analysis

Table S14. Bottleneck tables showing actual IMPA values for enabling domestic hydrogen adoption potential.

	Baseline Group (BLG)		
Perceived Adoption Potential	*Safety Perceptions*	*Technology Perceptions*	*Production Perceptions*
0	0	0	0
10	0.148	0	0
20	0.739	0	0.148
30	0.886	0	0.148
40	0.886	0.886	0.148
50	0.886	0.886	0.148
60	2.806	0.886	0.148
70	2.806	14.771	0.148
80	6.352	14.771	13.442
90	52.290	46.381	33.235
100	77.696	93.058	77.400
	Moderately technology and environmentally Engaged Group (MEG)		
Perceived Adoption Potential	*Safety Perceptions*	*Technology Perceptions*	*Production Perceptions*
0	0	0	0
10	0.218	0	0.218
20	0.218	0	0.218
30	0.218	0	0.218
40	0.218	0	0.873
50	0.218	0.655	0.873
60	0.437	0.873	3.057
70	2.838	0.873	3.057
80	3.493	2.838	3.057
90	8.297	32.751	7.424
100	47.380	80.786	62.445
	Very technology and environmentally Engaged Group (VEG)		
Perceived Adoption Potential	*Safety Perceptions*	*Technology Perceptions*	*Production Perceptions*
0	0	0	0
10	0	0.302	0
20	0	0.302	0
30	0.302	0.302	0.604
40	0.302	0.302	0.604
50	0.604	0.302	0.604
60	0.604	0.906	0.604
70	3.927	0.906	0.604

80	3.927	0.906	3.625
90	6.949	47.734	26.284
100	43.807	86.103	71.299
	Fuel Stressed Group		
Perceived Adoption Potential	*Safety Perceptions*	*Technology Perceptions*	*Production Perceptions*
0	0	0	0
10	0	0	0.264
20	0.792	0	0.264
30	0.792	0	0.264
40	0.792	0	0.264
50	0.792	2.375	0.264
60	2.902	2.639	0.264
70	2.902	8.443	0.792
80	3.430	29.024	8.971
90	14.2480	57.520	78.1
100	85.488	63.588	95.778

20 Supplementary Note 20: Necessary condition analysis scatterplots

Figs. S8–S11 present the individual scatterplot charts using the ceiling envelopment free disposal hull (CE-FDH) for each consumer sub-group by construct. The visualisation supplements the grouped results presented in Figs. 13–16

NCA scatterplots for the Baseline Group

Figs. 8a–8c present the results for the Baseline Group (BLG).

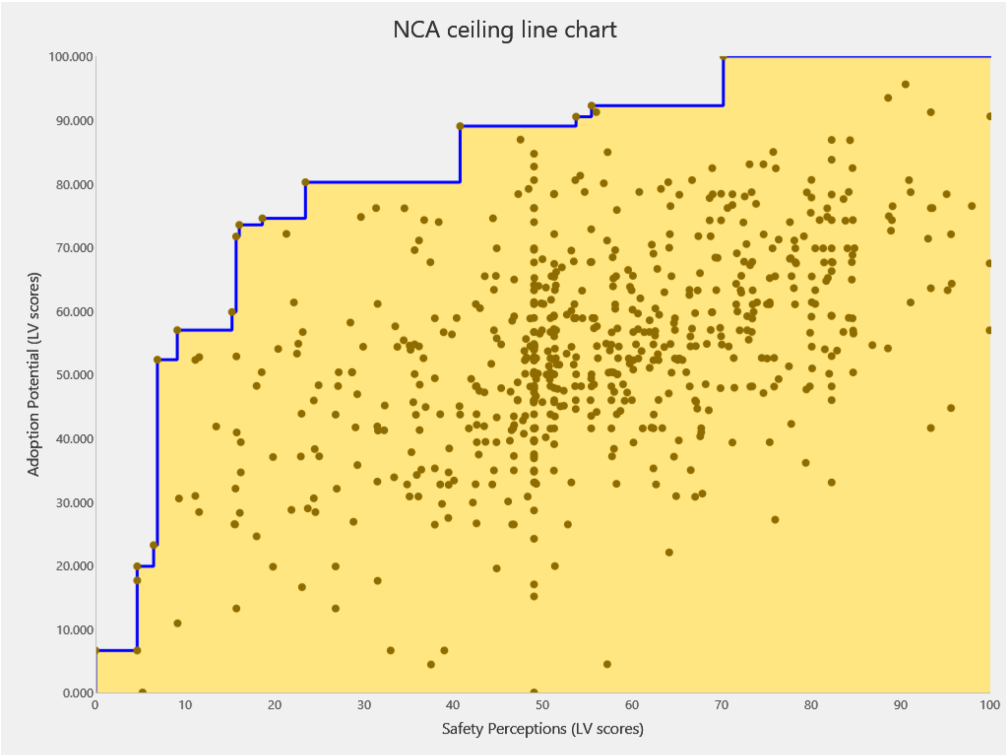

Fig. S8a. NCA chart for technology perceptions as a predictor of perceived adoption potential.

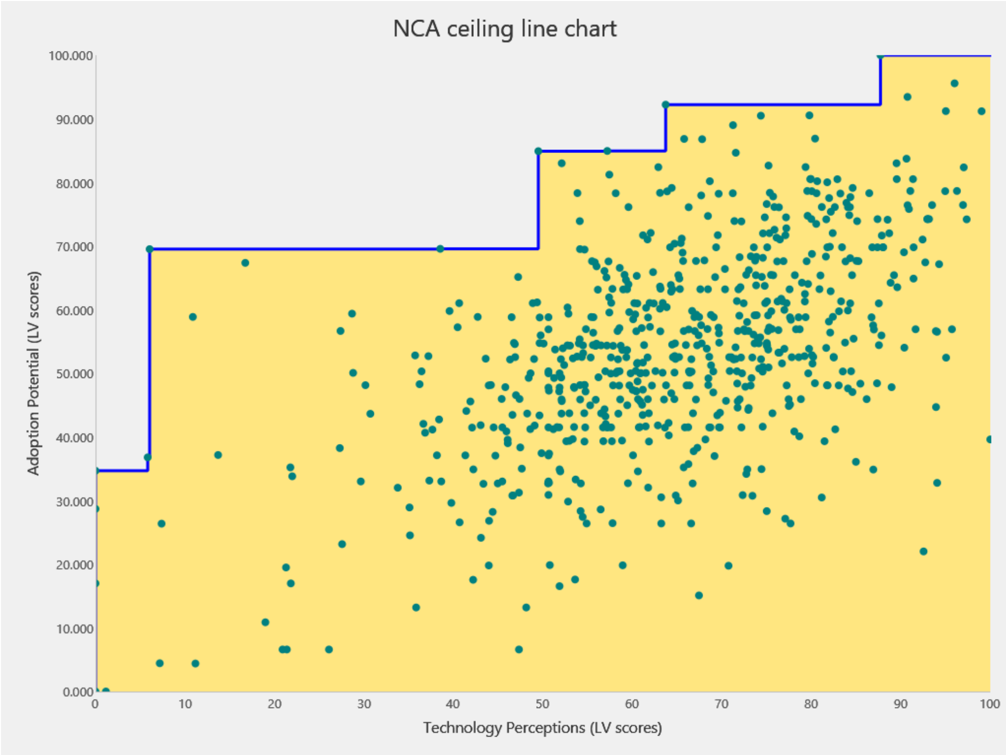

Fig. S8b. NCA chart for technology perceptions as a predictor of perceived adoption potential.

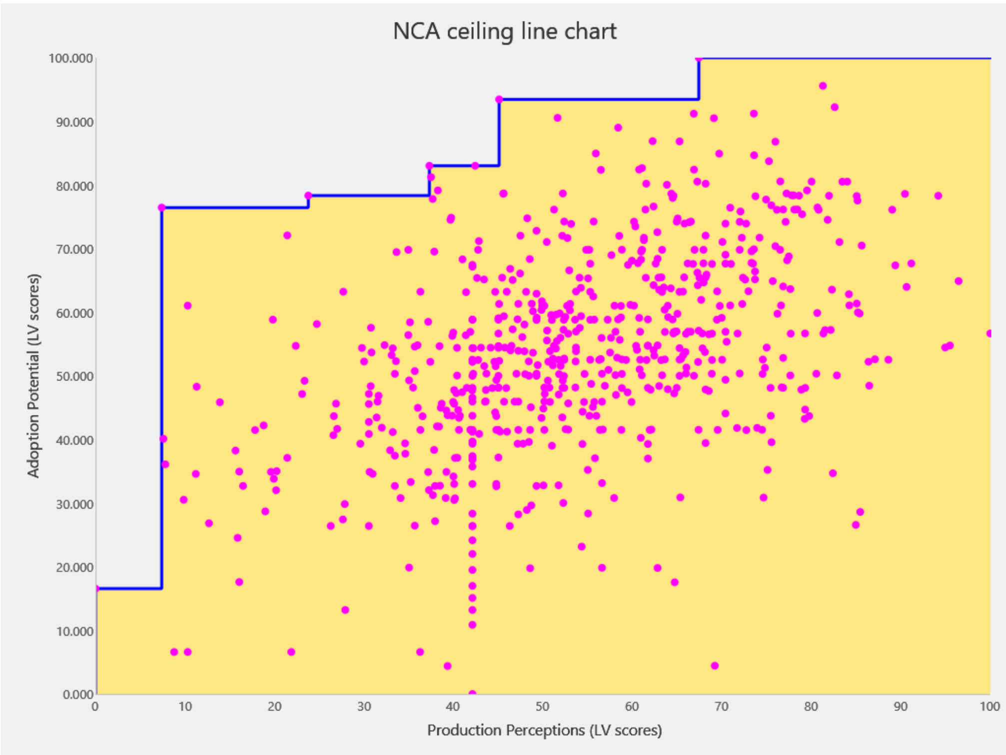

Fig. S8c. NCA chart for productions perceptions as a predictor of perceived adoption potential.

NCA scatterplots for the Moderately technology and environmentally Engaged Group

Figs. S9a–S9c present the results for the Moderately technology and environmentally Engaged Group (MEG).

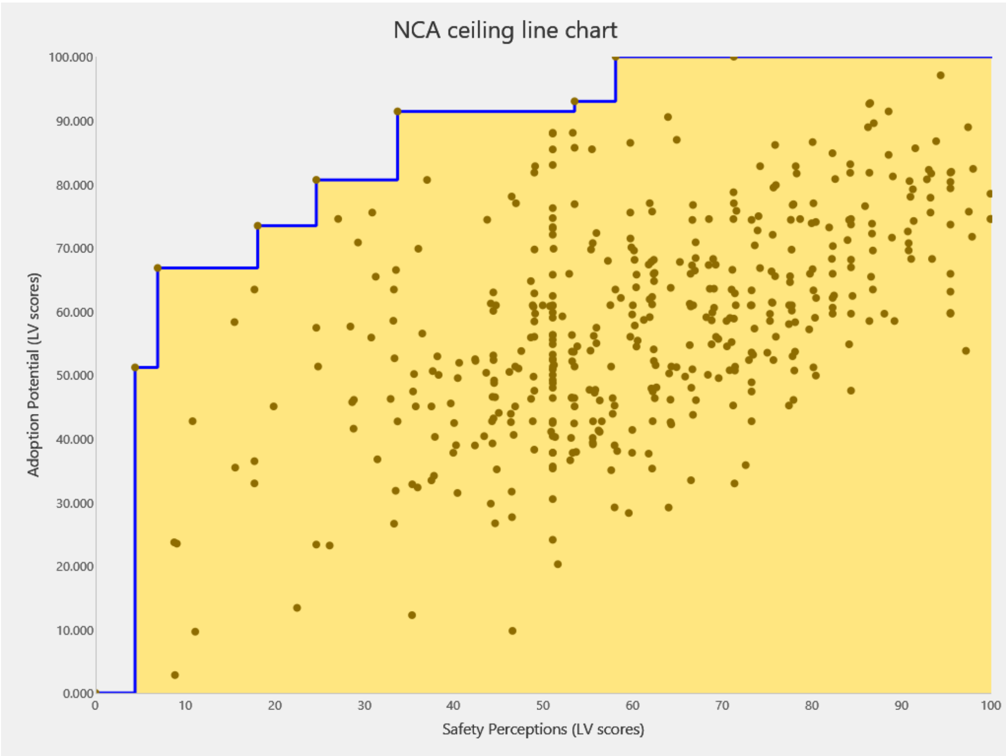

Fig. S9a. NCA chart for safety perceptions as a predictor of perceived adoption potential.

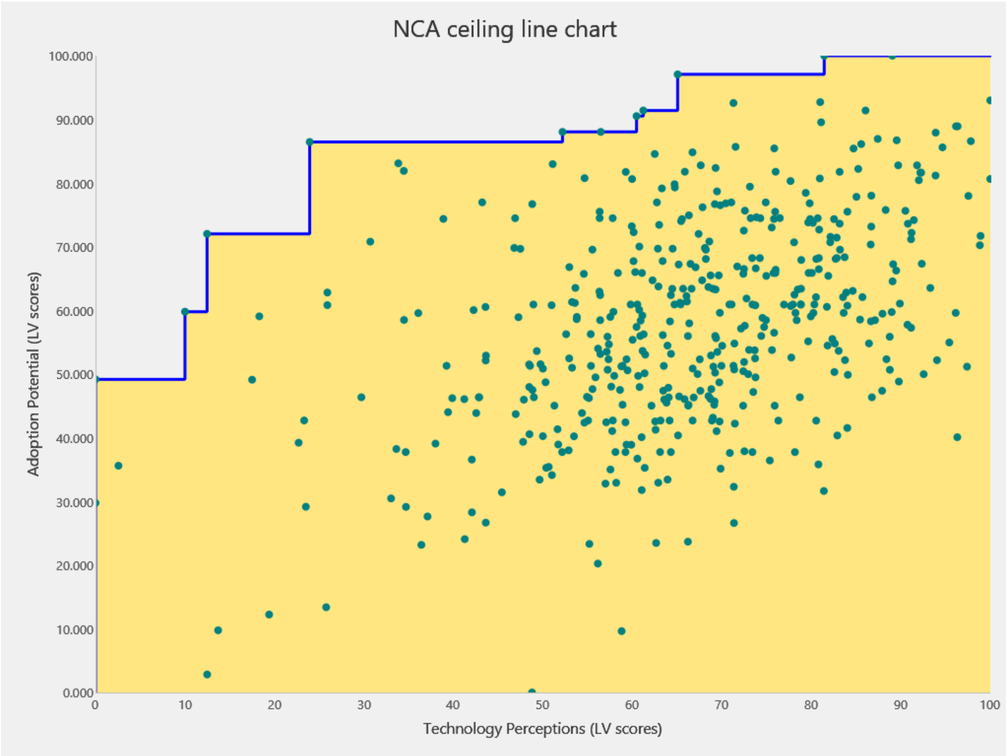

Fig. S9b. NCA chart for technology perceptions as a predictor of perceived adoption potential.

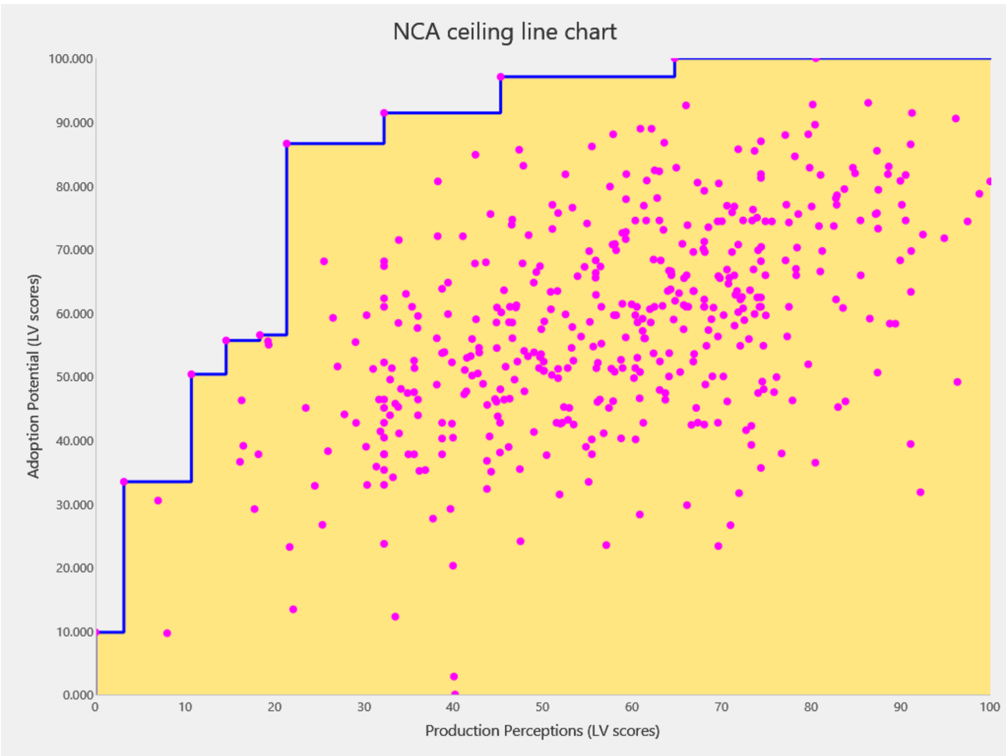

Fig. S9c. NCA chart for production perceptions as a predictor of perceived adoption potential.

NCA scatterplots for the Very technology and environmentally Engaged Group

Figs. S10a–S10c present the results for the Very technology and environmentally Engaged Group (VEG).

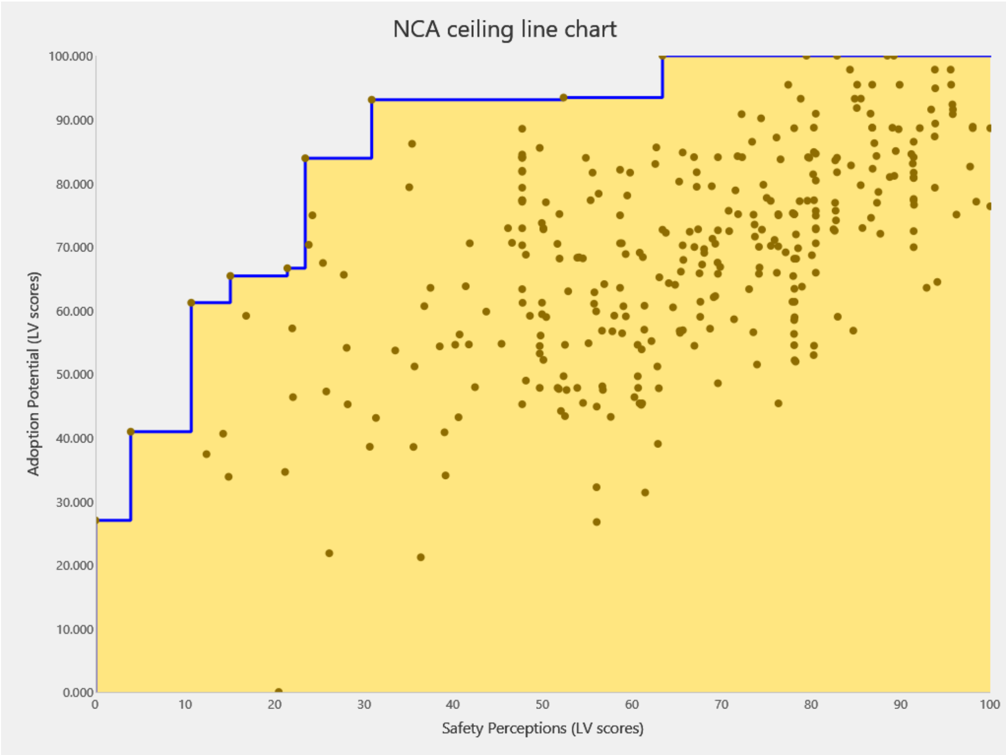

Fig. S10a. NCA chart for safety perceptions as a predictor of perceived adoption potential.

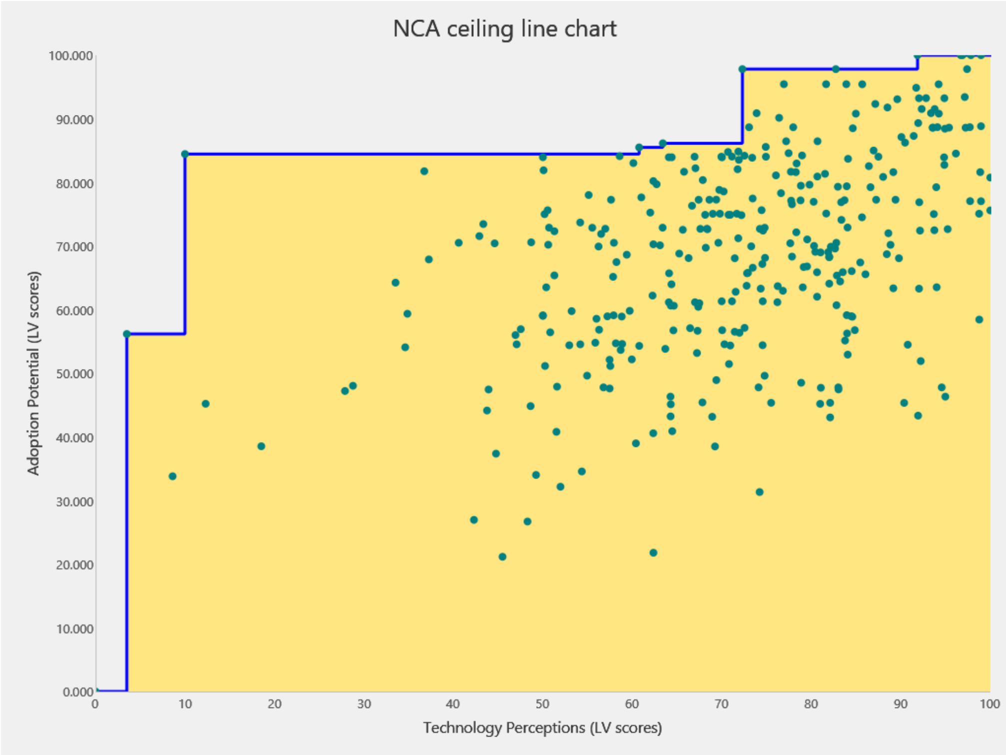

Fig. S10b. NCA chart for technology perceptions as a predictor of perceived adoption potential.

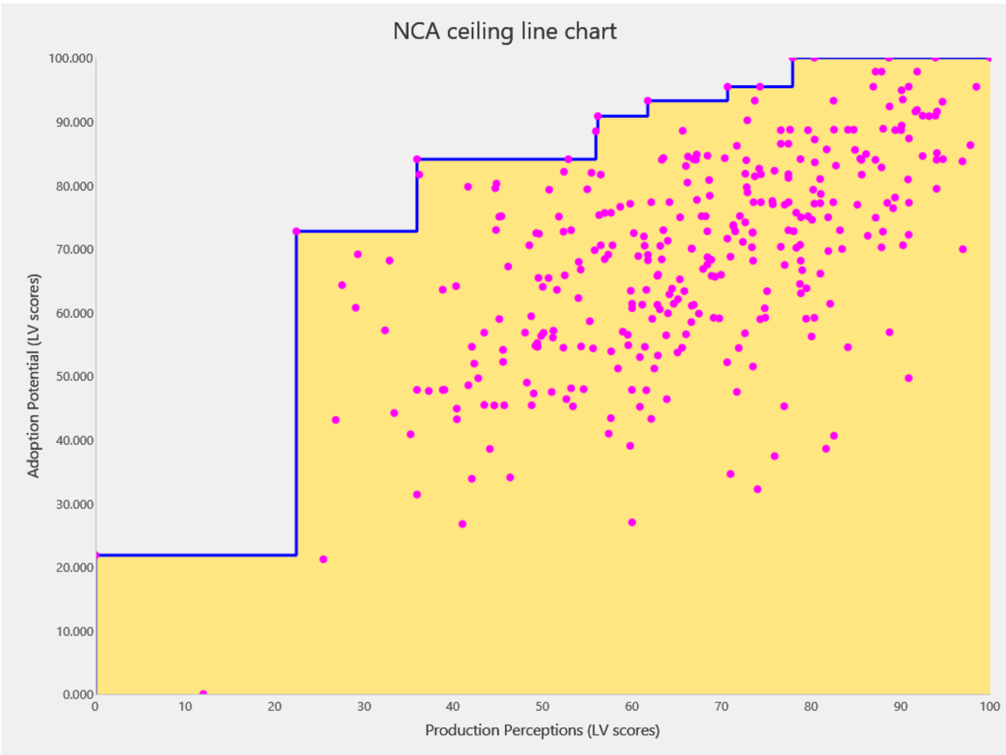

Fig. S10c. NCA chart for production perceptions as a predictor of perceived adoption potential.

NCA scatterplots for the Fuel Stressed Group

Figs. S11a–S11c present the results for the Fuel Stressed Group (FSG).

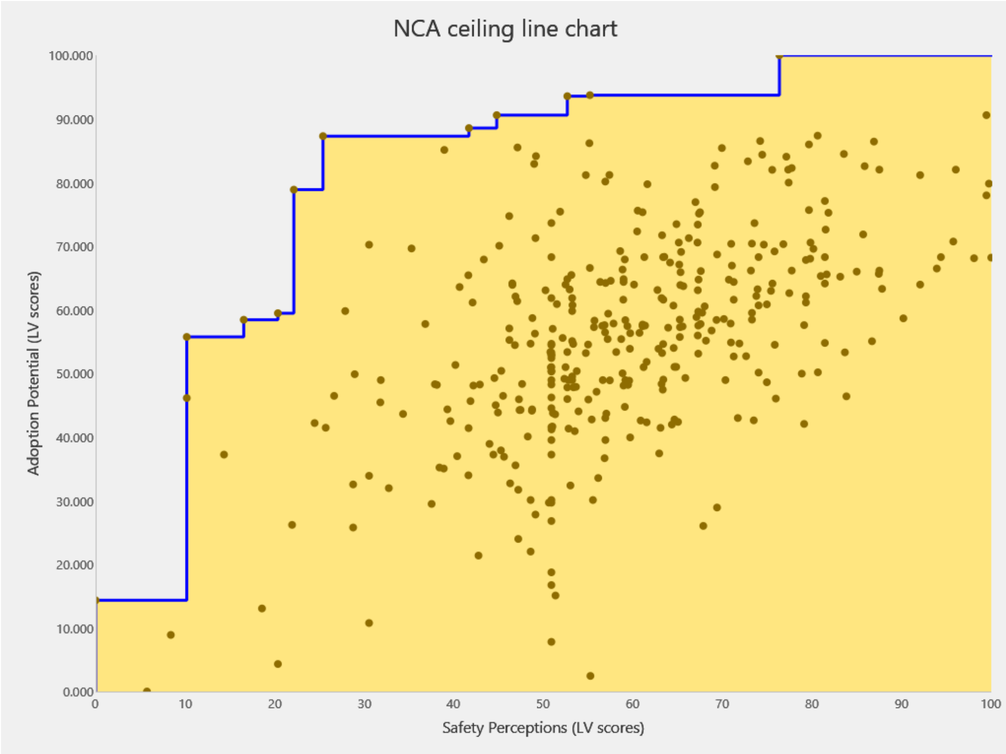

Fig. S11a. NCA chart for safety perceptions as a predictor of perceived adoption potential.

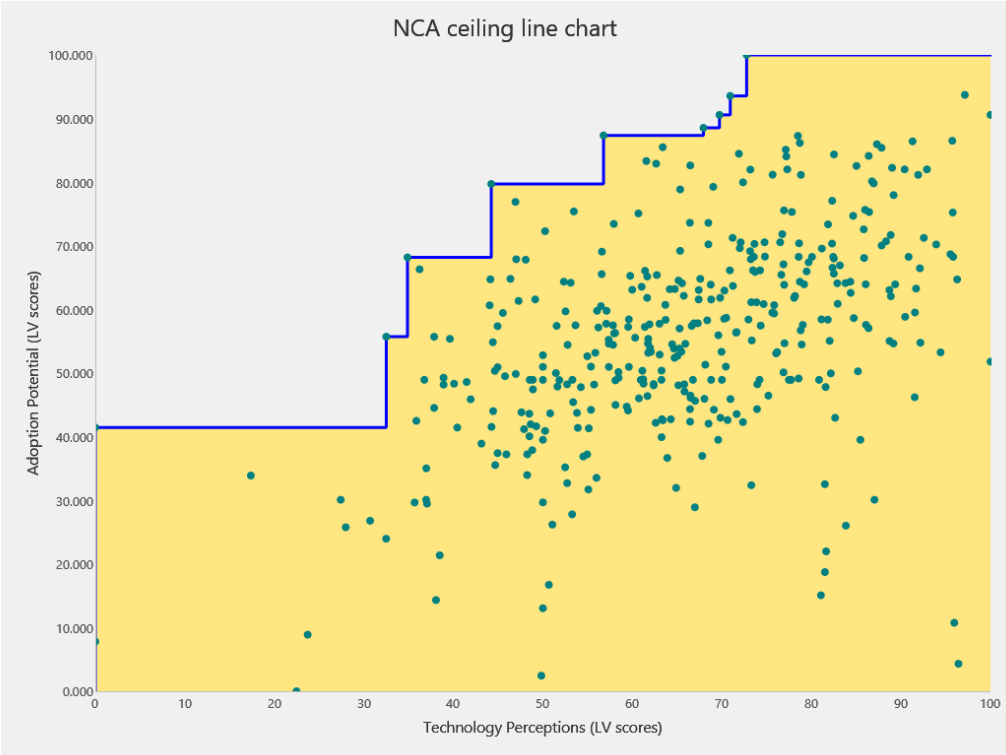

Fig. S11b. NCA chart for technology perceptions as a predictor of perceived adoption potential.

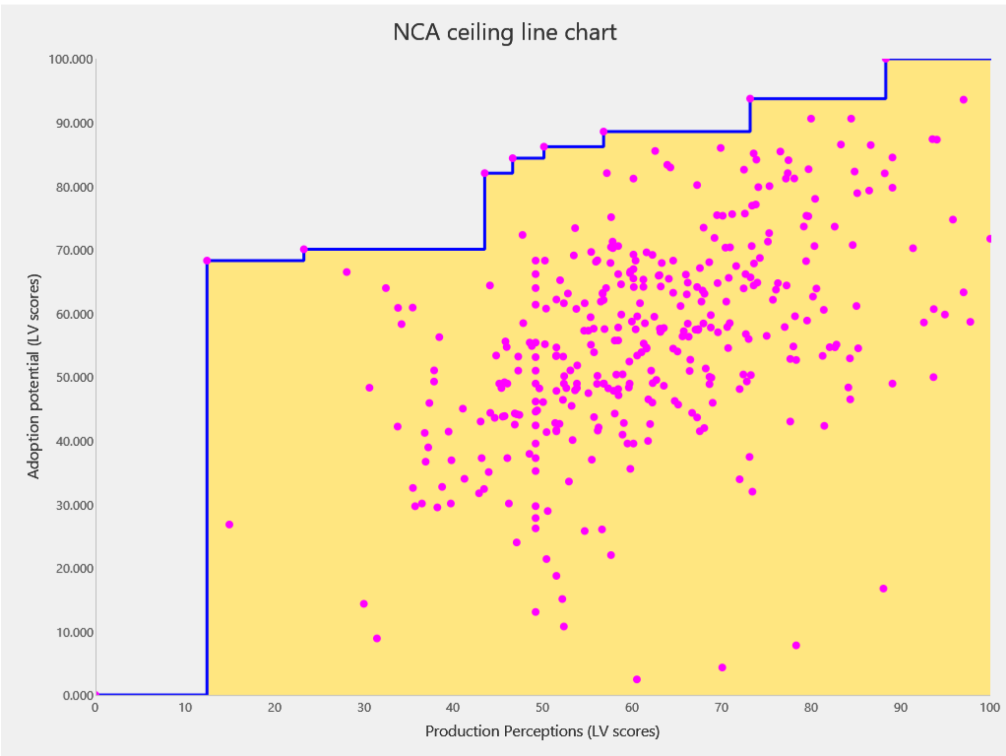

Fig. S11c. NCA chart for production perceptions as a predictor of perceived adoption potential.

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End Notes

[i] Also including onshore and offshore wind, wave/tidal, and biomass.
[ii] i.e. the electronic issuing and receipt of any bid documentation in electronic format as part of the procurement process.[92]
[iii] This study engages with relative advantage by examining technology perceptions vis-à-vis boiler and hob performance.