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Modelling the innovation-decision process for hydrogen homes: An integrated model of consumer acceptance and adoption intention

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ABSTRACT

As the global energy transition progresses, a range of drivers and barriers will continue to shape consumer attitudes and behavioural intentions towards emerging low-carbon technologies. The innovation-decision process for technologies composing the residential sector such as hydrogen-fuelled heating and cooking appliances is inherently governed by the complex interplay between perceptual, cognitive, and emotional factors. In response, this study responds to the call for an integrated research perspective to advance theoretical and empirical insights on consumer engagement in the domestic hydrogen transition. Drawing on online survey data collected in the United Kingdom, where a policy decision on 'hydrogen homes' is set for 2026, this study systematically explores whether an integrated modelling approach supports higher levels of explanatory and predictive power. Leveraging the foundations of the unified theory of domestic hydrogen acceptance, the analysis suggests that production perceptions, public trust, perceived relative advantage, safety perceptions, knowledge and awareness, and positive emotions will shape consumer support for hydrogen homes. Conversely, perceived disruptive impacts, perceived socio-economic costs, financial perceptions, and negative emotions may impede the domestic hydrogen transition. Consumer acceptance stands to significantly shape deployment prospects for hydrogen boilers and hobs, which are perceived to be somewhat advantageous to natural gas appliances from a technological and safety perspective. The study attests to the predictive benefits of adopting an integrated theoretical perspective when modelling the early stages of the innovation-decision process, while acknowledging opportunities for leveraging innovative research approaches in the future. As national hydrogen economies gain traction, adopting a neuroscience-based approach may help deepen scientific understanding regarding the neural, psychological, and emotional signatures shaping consumer perspectives towards hydrogen homes.

Abbreviations: ADV, Perceived Relative Advantage; AVE, Average variance extracted; BIC, Bayesian information criterion; BLR, Perceived Boiler Performance; CA, Cronbach Alpha; CCS, Carbon capture and storage; CMB, Common method bias; COP, Conference of the Parties; CR, Composite Reliability; C-TAM-TPB, Combined Technology Acceptance Model-Theory of Planned Behaviour; CVPAT, Cross-validated predictive ability test; DESNZ, Department for Energy Security and Net Zero; DHA, Domestic Hydrogen Acceptance; DHAM, Domestic Hydrogen Acceptance Model; DoI, Diffusion of Innovation; ECG, Electrocardiogram; FP, Financial Perceptions; fMRI, functional Magnetic Resonance Imaging; GOV, Trust in the government; HKA, Hydrogen Knowledge and Awareness; HOB, Perceived Hob Performance; HTMT, Heterotrait-monotrait; IA, Indicator Average; IMPA, Importance-performance map analysis; LM, Linear Model; LV, Latent variable; MAE, Mean absolute error; NAM, Norm Activation Model; NE, Negative Emotions; NeuroH2, Neuroscience for hydrogen systems; NeuroIS, Neuroscience for information systems; NGN, Northern Gas Networks; NRG, Trust in the energy sector; PLS-SEM, Partial least squares structural equation modelling; PDI, Perceived Disruptive Impacts; PSC, Perceived Socio-economic Costs; PE, Positive Emotions; PP, Production Perceptions; PT, Public Trust; QUAL, Trust in product and service quality; R&D, Trust in Research & Development; R^2, Coefficent of determination; RMSE, Root mean squared error; SETA, Sustainable Energy Technology Acceptance; SP, Safety Perceptions; SMR, Steam methane reformation; TAM, Technology Acceptance Model; TPB, Theory of Planned Behaviour; TRA, Theory of reasoned action; STEEEP, Safety-Technological-Economic-Environmental-Emotional-Perspectives; ST, Social Trust; UTAUT, Unified Theory of Acceptance and Use of Technology; UTAUT2, Unified Theory of Acceptance and Use of Technology 2; VIF, Variance inflation factor; WTA, Willingness to Adopt a Hydrogen Home.

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1. Introduction

Following the emergence of seminal contributions to the field of social psychology [1–3], scholars have explicitly recognised the predictive benefits that integrated theoretical approaches can yield when modelling human decision-making and behaviour [4–9].[1] Early recognition of this advantage is well reflected in the Combined Technology Acceptance Model-Theory of Planned Behaviour (C-TAM-TPB) framework advanced by Taylor and Todd [10], which continues to gain traction among scholars after nearly three decades [11–13].[2] Arguably, the most emblematic theoretical contribution of this nature can be traced to the 2003 publication of Ventakesh and colleagues' [14], which inaugurated the Unified Theory of Acceptance and Use of Technology (UTAUT).

Subsequently, researchers have frequently adapted or extended the UTAUT to examine emerging phenomena [15], such as consumer attitudes towards mobile phone apps [16–18], driverless vehicles [19,20], smart home technologies [21,22], and rooftop solar PV [23,24]. Marking an improvement to its predecessor [14], the UTAUT's next iteration, UTAUT2, incorporated three additional constructs to the modelling approach. Notably, this change strengthened the in-sample predictive power of the model by 18% ($R^2 = 0.740$) and 12% ($R^2 = 0.520$) when explaining behavioural intention and technology use in relation to mobile internet [25].

In the intervening decade between UTAUT and UTAUT2, contemporaries of Ventakesh et al. [14] consolidated the premise that integrated or unified modelling approaches may better explain and predict the critical success and resistance factors of technology acceptance [26–29]. Crucially, theory development can help support more robust causal explanations and predictions, in addition to facilitating design and action via explicit policy or managerial prescriptions [30]. As a general guideline, sound theories should ensure comprehensiveness without resorting to excessive levels of complexity, which can occur when numerous constructs or moderating relationships are postulated [31], as critically discussed in Supplementary Note 1 (see SN1).

As exemplified by the Sustainable Energy Technology Acceptance (SETA) model pioneered by Huijts et al. [32] (see SN2) and reflected within recent meta-analyses [33,34], various conceptual approaches have emerged for modelling different components of energy technology acceptance [35–38]. Nevertheless, theory development in the context of the hydrogen economy remains somewhat limited [39]. To date, most regression-based models engaging with hydrogen acceptance – primarily engaging with fuelling stations and fuel cell vehicles [40,41] – have lacked explicit theoretical foundations or limited their scope to just a few variables [39,42]. Acknowledging limitations in the literature, Gordon et al. [42] posited a unified theory of domestic hydrogen acceptance, wherein perceptual antecedents of rational thought and emotional response shape consumer attitudes and behavioural intentions in the context of transitioning to a 'hydrogen home' [43].

In its totality, the unified theory advanced by Gordon and colleagues [42] draws from Roger's Diffusion of Innovation (DoI) theory [44], Schwartz's Norm Activation Model (NAM) [45], the Theory of Planned Behaviour (TPB)[3] [46], and Davis' Technology Acceptance Model) (TAM [47], alongside risk perceptions literature [48,49], trust-based [50–54] and affective-based models [26,55–57], in addition to specific energy acceptance frameworks [32,58,59]. While the unified theory presents an important juncture for understanding hydrogen acceptance [42], knowledge is ultimately advanced through the building and subsequent operationalisation of models [60]. To date, several constructs hypothesised by Gordon et al. [42] are yet to be tested as originally formulated, following an initial focus on the respective antecedents of social acceptance [61] and perceived technology adoption potential [62,63].

In response, the conceptual innovation of this study lies with developing an integrated model of domestic hydrogen acceptance and adoption, which is grounded in the following approaches: the Domestic Hydrogen Acceptance Model (DHAM) [61]; the Safety-Technological-Economic-Environmental-Emotional-Perspectives (STEEEP) Framework [63]; and a trust-based model exploring the relationships between perceived community benefits, domestic hydrogen acceptance, and adoption willingness [64]. The novelty of the contribution involves leveraging insights from emerging theoretical foundations [64] and recent empirical contributions [65–68] to comprehensively examine interrelations between the perceptual, cognitive, and emotional antecedents shaping consumer perspectives towards hydrogen homes. To support the core research motivation, the following research questions are formulated:

- What are the critical drivers and barriers shaping domestic hydrogen acceptance?
- What are the critical drivers and barriers shaping willingness to adopt a hydrogen home before 2030?
- Does an integrated modelling approach support higher predictive capabilities?

Following this introduction, Section 2 contextualises recent developments regarding the contested transition to hydrogen homes in the UK context. Section 3 describes the research design and modelling approach, and further outlines the structure of the study. Next, Section 4 elucidates the conceptual approach, while Section 5 develops hypotheses to test the proposed framework. Subsequently, Section 6 relays and discusses findings from partial least squares structural equation modelling (PLS-SEM) and importance-performance map analysis (IMPA). Finally, Section 7 concludes by acknowledging the limitations of the study, highlighting opportunities for further research, and emphasising critical lessons for steering the domestic hydrogen transition towards a socially acceptable trajectory.

2. The contested transition to hydrogen homes

Historically, rapid energy transitions for the residential sector have proved feasible in select cases [69], as witnessed via the deployment of heat pumps in Scandinavian countries [70,71], district heating in Denmark [69], and solar thermal systems in China [72]. Of most relevance to the context of this study, the UK achieved a rapid national energy transition between 1960–1977[4] [69] by switching from manufactured 'town gas'[5] to natural gas [73,74]. However, as scholars continue to debate the temporal dynamics of the clean energy transition [75–77], public opposition is but one of several socio-technical barriers [78] that may counteract decarbonisation efforts [79–81]. As reflected across different national contexts [82–84], social resistance can substantially undermine ambitions to scale up low-carbon energy technologies [85–87], casting doubt over the feasibility of net-zero targets in countries such as the UK [88–90].

[1] Parts of the manuscript including the introduction are adapted from the lead author's PhD dissertation [349].

[2] Generally, the early 2000s marked the proliferation of 'decomposed' models of the TPB and extended versions of the TAM, which integrated constructs from Diffusion of Innovation (DoI) Theory such as perceived technology attributes [350–352].

[3] Based on the Theory of Reasoned Action (TRA) which Ajzen developed alongside Fishbein [2].

[4] Scholars acknowledge and debate the difficulty of tracing the formative phase of energy transitions when formalising national case studies [31,32]. For example, Arapostathis et al. [74] discuss the transition from town gas to natural gas for the period 1948–1977.

[5] Made up of methane (CH4), carbon monoxide (CO) and up to 50% hydrogen [30].

Although a relatively nascent development, domestic hydrogen presents an emblematic case of a contested energy transition [91–93], which partly captures historical developments regarding hydrogen-based energy futures [94–96]. Mapping recent developments in the German context, Kern et al. [97] discuss how developing a national hydrogen economy will involve navigating multiple contested pathways regarding both production pathways and technology applications. Moreover, leading political parties may hold diametrically opposed views over the future of heat pumps and hydrogen, which has been reflected in emerging media narratives in Germany [97]. Reviewing global developments, Vezzoni [98] further unpacks "contested aspects of hydrogen off-take, transportation, infrastructural investments, and production processes," calling for stronger participatory processes in the energy transition.

In August 2021 the UK government released its Hydrogen Strategy [99] ahead of the Conference of the Parties in Glasgow (COP26). Following recognition of a potential role for low-carbon hydrogen in UK buildings since the mid-2010s [100,101], the strategy included a focus on domestic hydrogen [99]. Specifically, it was announced that a policy decision on hydrogen homes should be taken in 2026 [99], as further consolidated within the Heat and Buildings Strategy in October 2021 [102]. Notably, following the destabilising effects of Russia's invasion of Ukraine [103,104], the British Energy Security Strategy increased the hydrogen production from 5 GW to 10 GW [105], in conjunction with advancing plans for hydrogen village trials in industrial locations [106–108].

Despite initial signs of momentum, the socio-political feasibility of hydrogen homes currently hangs in the balance, following the recent cancellation of anticipated village trials [92] for the North of England [109,110] and growing policy support for electrifying the UK housing stock [111]. Nevertheless, in its latest update on hydrogen heating, the Department for Energy Security and Net Zero (DESNZ) [112] affirmed that a policy decision would still be taken in 2026, while drawing more directly on international evidence from countries such as the Netherlands and Germany, as national research continues:

> "Unlike other technologies, 100% hydrogen for heating is not yet an established technology. Further work is required to understand the feasibility, costs, and convenience of transporting 100% hydrogen in the gas grid and using hydrogen for heating and cooking" [112].

Mirroring the motivation of this study, the DESNZ update cited the value of consumer research gathered by Northern Gas Networks (NGN) in the context of the planned trial for Redcar in North Yorkshire [112]. Additionally, first-hand evidence of the consumer experience of hydrogen homes in the UK may yet be provided through the prospective H100 Fife neighbourhood trial in East-central Scotland [112]. However, supply-chain and procurement challenges, alongside a potential lack of consumer buy-in continue to challenge the timeline and feasibility of the Fife trial [113], while the environmental and safety credentials of domestic hydrogen remain subject to scrutiny [114,115].

Recent developments in the UK suggest any prospective pathway to deploying hydrogen homes is likely to incur a degree of consumer resistance, as reflected in the bottom half of Fig. 1. In parallel, both the heat pump transition and switch to smart meters have faced and continue to confront significant barriers to social acceptance [116–119], which has delayed progress on residential decarbonisation. Fig. 1 cautions that transitioning to hydrogen homes may fail to prove a viable near-term policy pathway. At the same time, the historical record reflects the dynamic nature of social acceptance [120,121], which is perhaps best exemplified by diverging support for nuclear power across parts of Europe [122–125]. To an extent, domestic hydrogen echoes some of the characteristics of nuclear power in presenting a contested and costly technology pathway [126], which will be largely determined by techno-economic, political, and socio-technical capacities at the national level [127].

3. Material and methods

3.1. Questionnaire design and data collection

This study employs an online survey to examine how UK consumers perceive the prospect of transitioning to a hydrogen home before 2030. The survey instruments (see SN3) were supported by findings from online focus groups [43,128,129] and extensive literature review on the subject matter [42,78,120], as reflected in Table 1. Piloting for the survey took place over the summer of 2022, supported by additional inputs from hydrogen experts and social scientists. Once content and face validity had been firmly established [61,130] data collection commenced in October 2022. The survey closed towards the end of 2022 with more than 2000 responses, leading to a sizeable final sample after data cleaning was completed ($N = 1845$).[6]

3.2. Characteristics of the survey sample

The sample proved largely nationally representative of the UK population, while entailing four distinct consumer sub-groups demarcated by their socio-economic profile, and levels of engagement in technology and the environment (see SN4), as further detailed in the context of multigroup analysis [62,63]. This configuration helps support national representativeness in a more nuanced way (i.e. compared to relying exclusively on socio-demographic variables), since early adoption potential and environmental attitude are embedded into the sample characteristics [165].

At the aggregate level, just over one-third of respondents are outright property owners, while close to two-thirds are mortgage owners, with all participants dwelling in homes reliant on natural gas heating and cooking. Additionally, the filtering approach targets respondents that are liable to be directly affected by the domestic hydrogen transition through two conditions: all respondents reported an at least moderate level of financial participation in purchasing decisions, while assigning at least moderate importance to deciding between available heating and cooking technologies. Accordingly, the sampling approach internalises the need to account for agency and choice when examining energy technology acceptance [166]. Additional details of the sample breakdown are provided in Supplementary Note 5 (see SN5).

3.3. Data analysis

3.3.1. Partial least squares structural equation modelling

Given that domestic hydrogen presents an emerging technology, this study utilises PLS-SEM to advance theoretical and empirical insights in a nascent research context [167–169]. PLS-SEM supports a predictive-oriented modelling approach [170,171] by minimising the unexplained variance of predictors [172]. The method has gained increasing popularity across the social sciences for supporting theory development and prediction [170,173] in areas such as information technology and business management [174–177]. Increasingly, energy transition scholars have leveraged PLS-SEM to examine multiple areas [43], such as smart home technologies [178–180], solar PV [181,182], energy-efficient heating appliances [183], and hydrogen fuel cell vehicles [140,152,184].

This study applied SmartPLS 4.1 software [185] to test the predictive capabilities of an integrated model of domestic hydrogen acceptance and adoption intention. Following conventions in the literature, the two-stage approach is implemented by firstly validating the measurement (or outer) model, ahead of testing the path relationships composing the structural (or inner) model [186]. To uphold methodological rigour, this study adheres to up-to-date guidelines when

[6] i.e. removal of straight-lining responses, fast responses, and other irregularities which impeded the integrity of the data.

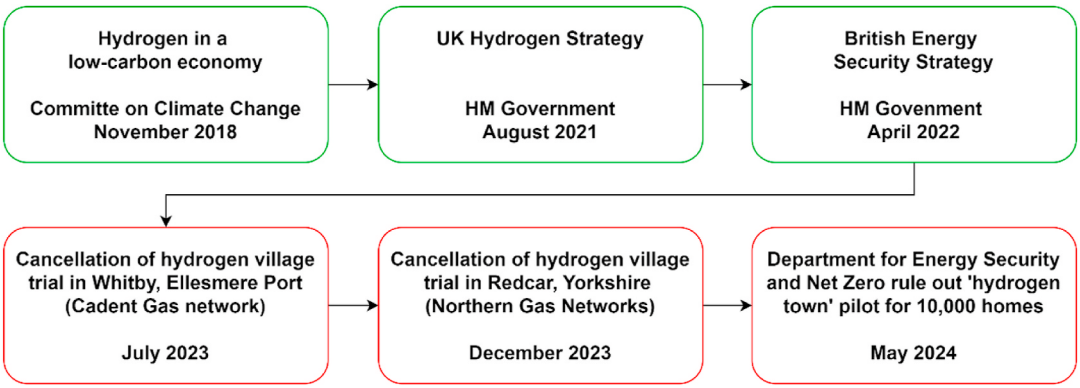

Fig. 1. Overview of key policy developments shaping the domestic hydrogen transition.

justifying the decision to use PLS-SEM [177,187]. Accordingly, validity checks for sample size and statistical significance levels are firstly performed, in addition to testing for common method bias (CMB), skewness, and kurtosis [188,189].

The robustness of the sample size was verified using G-Power software analysis [190,191] to calculate model-specific estimates for effect size [192]. Given the parameters of the proposed model, the sample size proved more than sufficient for detecting a small effect size ($f^2 = 0.02$) at a 95% significance level ($\rho < 0.05$), as reported in SN6. Additionally, CMB was tested using Harman's single factor test [193], which returned a variance of 26.97%, substantially below the guideline of 50% (see SN7). Lastly, data integrity was further supported since results for skewness and kurtosis fell comfortably within the suggested threshold of ±1 (see SN8).

3.3.2. *Importance-performance map analysis*

To derive further insights from PLS-SEM, importance-performance map analysis (IMPA) [194,195] is undertaken at the construct level for domestic hydrogen acceptance, and at the construct and indicator level for willingness to adopt a hydrogen home before 2030. Within an X–Y plot, IMPA provides a means to compare importance (i.e. unstandardised total effects) and performance (i.e. latent variable scores rescaled from 0 to 100) [194] to help inform strategic decision-making [196,197]. When interpreting results, constructs positioned at the bottom right quadrant represent the foremost area of strategic value [194,198]. Constructs within this quadrant display a high level of importance but significant scope for improving their contribution (i.e. performance) towards realising the target outcome [199–202].

3.3.3. *Summary of data analysis procedure*

Fig. 2 outlines the structure of the study by visualising the research steps and data analysis techniques. Following the description of the conceptual framework in Section 4, Section 5 develops hypotheses for testing the integrated model, which is described and visualised in Section 6. Subsequently, Section 6.1 presents the descriptive results at the indicator level, ahead of assessing the measurement and structural models in Sections 6.2 and 6.3, respectively. Following IMPA in Section 6.4, the predictive capabilities of model are reported in Section 6.5. Finally, Section 6.6 crystallises the analysis through a comparative assessment of modelling results on the acceptance and adoption dynamics of hydrogen homes.

4. Conceptual framework

Following increased recognition that cognitive, psychological, and emotional processes are deeply intertwined in energy-related decisions and behaviours [203], integrated approaches for modelling residential energy acceptance have emerged in the literature [204–206]. The foundations of integrated models of domestic energy acceptance [38,207] can be traced to the UTAUT [14] and its derivatives [25,208], as discussed in Section 1 and SN2. The energy transitions literature has since evolved to reflect a more comprehensive focus on socio-psychological, emotional, behavioural, cultural, ethical, and contextual factors [207,209–211]. Critically, by adopting a more integrated perspective [26,212,213] researchers can enhance the explanatory and predictive power of their models [14,22,205].

While early efforts have been taken to embed an interdisciplinary research perspective into hydrogen acceptance studies [61,133], the need for innovative and sustained exploration has been duly acknowledged [39,42]. In response, the proposed model examines the direct effects of four exogenous constructs (production perceptions, safety perceptions, perceived socio-economic costs and perceived disruptive impacts) and two higher-order constructs (public trust and perceived relative advantage) on domestic hydrogen acceptance, which in turn predicts willingness to adopt a hydrogen home before 2030. Additionally, adoption willingness is predicted by four exogenous constructs (hydrogen knowledge and awareness, financial perceptions, positive emotions, and negative emotions), as depicted in Fig. 3.

Through this approach, the integrated model departs from its predecessors in a fundamental way, namely, domestic hydrogen acceptance consists of three indicators measuring support for hydrogen homes at the household, community, and socio-political level, and three indicators measuring perceived economic, social, and environmental benefits at the local level. Following exemplars of developing new measurement items [214,215], this line of thinking has been previously applied when constructing a hybrid construct for perceived adoption potential [63], but is yet to be incorporated when operationalising social acceptance as an endogenous construct.[7] Accordingly, the dimension of community acceptance [58,216] is explicitly represented within this study, which is critical given the spatial dynamics of developing hydrogen homes [120] and recent failure to secure local support for village trials in the North of England [109,110].

In total, excluding the lower-order constructs composing public trust and perceived relative advantage, twelve constructs comprise the integrated model (eight exogenous and four endogenous). The constructs are measured reflectively since corresponding indicators are correlated and do not form the construct [217,218]. To increase model parsimony and predictive power, public trust and perceived relative advantage are operationalised as reflective-formative constructs [219].[8] As a result, the proposed framework answers the call for theoretical rigour and

[7] Exogenous constructs are independent variables (i.e. arrows pointing away from the construct) whereas endogenous constructs are dependent variables (but can also function as predictors as is the case with domestic hydrogen acceptance in the presented model).

[8] i.e. all indicator items are measured reflectively while the lower-order constructs point towards the higher-order constructs [353].

Table 1
Summary of questionnaire framing, construct items, and supporting literature.

Construct and scale	Indicators and question framing	Supporting literature
Public Trust (PT) (HOC)[a] 11-point	➢ In supporting a cost-effective, efficient, and fair transition to hydrogen homes	[43,131–135]
Trust in government	• GOV1: Central government • GOV2: Regional authorities • GOV3: Local councils	
Trust in the energy sector	• NRG1: Fuel/gas supply companies • NRG2: Electricity and/or gas suppliers • NRG3: Renewable energy producers	
Trust in product and service quality	• QUAL1: Trades bodies/associations • QUAL2: Boiler manufacturers • QUAL3: Gas engineers and technicians	
Trust in research & development	• R&D1: Non-governmental organisations • R&D2: Universities • R&D3: Other research institutes and organisations	
Social trust	• ST1: Gas distribution network operators • ST2: Financial institutions • ST3: Office of gas and electricity markets • ST4: Media	
Production perceptions (PP) 11-point	➢ *Support for hydrogen production pathways over different time-horizons* • PP1: Blue hydrogen up to 2030 • PP2: Blue hydrogen after 2030 • PP3: Green hydrogen up to 2030 • PP4: Green hydrogen after 2030 • PP5: The twin-track production approach	[65,134–138]
Safety perceptions (SP) 11-point	➢ *Compared to natural gas* • SP1: Hydrogen boilers • SP2: Hydrogen hobs • SP3: Hydrogen pipeline transport • SP4: Underground hydrogen storage • SP5: Overall safety level	[134,135,139–145]
Perceived disruptive Impacts (PDI) 5-point	➢ *Concern about impacts during the hydrogen switchover period* • PDI1: Noise, traffic, and inconvenience during the switchover • PD2: Temporary disconnection from the gas grid • PDI3: Visits from gas engineers and technicians	[43,132,134,135,146]
Perceived socio-economic costs (PSC) 5-point	➢ *Negative macro-economic risks* • PSC1: Negative impact on UK energy security • PSC2: Higher levels of fuel poverty across the UK	[39,43,68,144,147,148]
Perceived Relative Advantage (ADV) HOC[a] 11-point	➢ Perceived performance advantage compared to a natural gas boiler or a natural gas hob	[134,145,149–151]
Perceived boiler performance	• BLR1: Higher level of thermal comfort • BLR2: Higher energy efficiency • BLR3: Smarter heating system	
Perceived hob performance	• HOB1: More efficient performance • HOB2: Better cooking control • HOB3: Smarter cooking system	
Domestic hydrogen acceptance (DHA) 11-point	➢ *Socio-political, community, and household-level acceptance, and perceived community benefits* • DHA1: Hydrogen becoming a critical part of the UK's energy future • DHA2: Hydrogen replacing natural gas in your local area before 2030 • DHA3: Switching your home to both hydrogen heating and cooking before 2030 • DHA4: Economic benefits such as job opportunities and income security • DHA5: Social benefits such as reduced level of energy poverty and improved health • DHA6: Environmental benefits such as lower carbon emissions and better air quality	[43,99,132,152–154]
Hydrogen knowledge and awareness (HKA) 5-point	➢ *Subjective Knowledge of hydrogen fuel and awareness of low-carbon and hydrogen energy* • HKA1: Subjective knowledge • HKA2: Awareness of low-carbon residential energy technology • HKA3: Awareness of the UK hydrogen strategy • HKA4: Awareness of hydrogen homes	[133,135,138,139,141,152,155]
Financial perceptions (FP) 5-point	➢ *Expectations compared to natural gas* • FP1: Purchasing a hydrogen boiler • FP2: Purchasing a hydrogen hob • FP3: Energy bills	[134,145,149–151,156–158]
Positive emotions (PE) 5-Point	➢ Feelings about using a hydrogen boiler and hob within your home • PE1: Satisfied • PE2: Calm • PE3: Confident • PE4: Optimistic	[140,155,159–162]
Negative emotions (NE) 5-point	➢ *Feelings about using a hydrogen boiler and hob within your home* • NE1: Discontent	[140,155,159–162]

(*continued on next page*)

Table 1 (*continued*)

Construct and scale	Indicators and question framing	Supporting literature
	• NE2: Worried • NE3: Fearful • NE4: Pessimistic	
Willingness to adopt a hydrogen home (WTA) 5-point	➢ *Before the year 2030* • WTA1: Hydrogen boiler • WTA2: Hydrogen hob • WTA3: Hydrogen home	[39,120,163,164]

[a] Higher-order construct.

multi-dimensional integration in hydrogen acceptance studies [39]. Foremost, the combined model leverages the building blocks of the unified theory of domestic hydrogen acceptance [42] to examine perceptual, cognitive, and emotional factors shaping consumer perspectives of hydrogen homes, culminating in a mid-range theory that is context-specific yet firmly rooted in seminal literature [9].

5. Hypotheses development

5.1. Public trust in the domestic hydrogen transition

Energy transitions researchers have engaged with the multi-dimensional nature of public trust across a range of contexts and technology cases [220], such as onshore and offshore wind power [221], marine energy futures [222], nuclear power [223] and nuclear fusion [224], among other examples [225–227]. The dynamics of public trust have also attracted the attention of hydrogen acceptance scholars, following early engagement from Huijts et al. [228] in the Dutch context. Subsequently, several studies conducted in Germany have included trust metrics in their modelling approaches [153,229,230], with researchers in Australia [134,149,231] and the UK extending the evidence base [43,137,158].

Although a growing literature has steadily emerged spanning different country contexts and hydrogen applications [39], Gordon et al. [42,64] argue that trust-related research on energy acceptance remains far from saturated, motivating the need for high-level conceptual and empirical engagement. In response, a trust-based model of domestic hydrogen acceptance and adoption intention has been developed in supporting research [64], which is leveraged in this analysis. The following hypotheses are developed to validate the antecedents of public trust in hydrogen homes:

H1a. Trust in the government will significantly and positively affect public trust in the domestic hydrogen transition.

H1b. Trust in the energy sector will significantly and positively affect public trust in the domestic hydrogen transition.

H1c. Trust in product and service quality will significantly and positively affect public trust in the domestic hydrogen transition.

H1d. Trust in research and development will significantly and positively affect public trust in the domestic hydrogen transition.

H1e. Social trust will significantly and positively affect public trust in the domestic hydrogen transition.

Subsequently, the interactions between public trust and domestic hydrogen acceptance is explored in **H2a**. Accordingly, the proposed model reflects similar trust-acceptability models [232], which have been applied in contexts such as carbon capture and storage (CCS) [233,234] and hydrogen-powered transportation in the Netherlands [131,228], electricity generation sources in Chile [235] and South Korea [236], and nuclear power in Switzerland [237] and China [238]. In response, hypotheses are also formulated to test whether public trust effectively mediates the relationship between its lower-order constructs and domestic hydrogen acceptance, as posited in **H2b**–**H2f**.

H2a. Public trust in key stakeholders and actors will significantly and

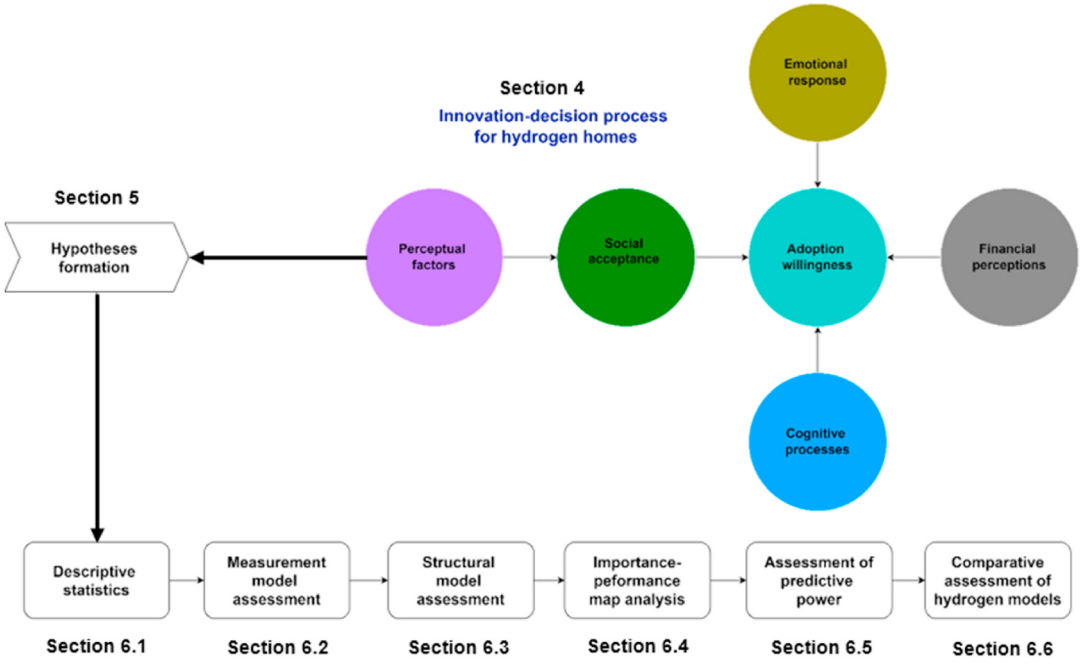

Fig. 2. Research procedure and data analysis methods.

Fig. 3. Conceptual framework for examining the innovation-decision process for hydrogen homes.

positively affect domestic hydrogen acceptance.

H2b. Public trust in key stakeholders and actors will significantly and positively mediate the relationship between trust in the government and domestic hydrogen acceptance.

H2c. Public trust in key stakeholders and actors will significantly and positively mediate the relationship between trust in the energy sector and domestic hydrogen acceptance.

H2d. Public trust in key stakeholders and actors will significantly and positively mediate the relationship between trust in product and service quality and domestic hydrogen acceptance.

H2e. Public trust in key stakeholders and actors will significantly and positively mediate the relationship between trust in research and development and domestic hydrogen acceptance.

H2f. Public trust in key stakeholders and actors will significantly and positively mediate the relationship between social trust and domestic hydrogen acceptance.

5.2. Perceptions of hydrogen production pathways

Prior mixed-methods research conducted in the UK context [129] highlights the likelihood that public perceptions of hydrogen production pathways will influence social acceptance. To date, results suggest more support for a 'green' production pathway [61] utilising "electrolytic hydrogen predominantly powered by renewables" [99], as opposed to a 'blue' pathway reliant on steam methane reformation (SMR) and CCS [239]. While this preference is largely reflected in the European [65, 240] and Australian contexts [150], survey results from Japan observe less comparative support for green hydrogen when cost considerations trump environmental concerns [66]. In response, the subsequent hypothesis examines how production perceptions will shape public support vis-à-vis the UK's 'twin-track' approach [99], which aims for at least 50% green production by 2030 [105]:

H3. Production perceptions will significantly and positively affect domestic hydrogen acceptance.

5.3. Hydrogen safety perceptions

The initial feasibility of launching hydrogen homes in proximity to industrial clusters will rest firmly on safety-related parameters [241]. Consequently, hydrogen pipelines and infrastructure must be non-hazardous, and the fuel must prove safe for transporting and storing [242]. The current scientific consensus is that hydrogen has a comparable risk profile to natural gas and gasoline [243,244]. Against this backdrop, safety perceptions of hydrogen are examined in comparison to natural gas, positing a positive impact on social acceptance in line with prior research findings [61,130]:

H4. Safety perceptions will significantly and positively affect domestic hydrogen acceptance.

5.4. Perceived disruptive impacts of the hydrogen switchover

Switching parts of the national gas grid to hydrogen will entail a degree of short-term disruption to consumers at street level and within their properties [164]. Nevertheless, 'soft' risks associated with increased traffic, noise, and inconvenience may arouse significant concerns at both the community and individual level [61,156], especially if the switchover period exceeds three to four days [43,146]. The perceived disruptive impacts of converting to a hydrogen home will be heightened and may prove intolerable among vulnerable consumers such as the elderly and fuel poor [43,146]. In response, the following hypothesis is developed to capture these important dynamics:

H5. The perceived disruptive impacts of the hydrogen switchover will significantly and negatively affect domestic hydrogen acceptance.

5.5. Perceived socio-economics costs of the domestic hydrogen transition

The perceived socio-economic costs of the domestic hydrogen transition will rest on how consumers anticipate macro-level impacts on energy security and fuel poverty [61]. One study conducted in the North of England suggested mostly neutral perceptions concerning macro-economic impacts [144]. However, the regional survey was conducted before the COVID-19 pandemic [245] and outbreak of war in Ukraine [246], which have contributed towards an unprecedented period of political and economic instability [247,248], aggravating fuel poverty in the UK context [249]. In view of the ensuing energy crisis [43] and its cascading global implications [104], the following hypothesis is posited:

H6. The perceived socio-economic costs of transitioning to hydrogen homes will significantly and negatively affect domestic hydrogen acceptance.

5.6. Perceived relative advantage of hydrogen homes

The UK Hydrogen Strategy [99] cites the importance of establishing a robust evidence base ahead of a policy decision on domestic hydrogen in 2026, which includes gauging how consumers perceive and experience hydrogen heating and cooking relative to other low-carbon solutions [112]. Relatedly, studies examining low-carbon energy technology acceptance in the residential context [250–252] reflect the importance of perceived relative advantage [44] in guiding consumer decision-making. The rationale is that early adopters will expect hydrogen boilers and hobs to perform equally well as, or to otherwise surpass, the incumbent technology [42].

Although the deployment of hydrogen homes remains hypothetical, there appears to be a general belief among the UK public that hydrogen-fuelled technologies would outperform natural gas boilers and hobs in terms of efficiency and smartness [128]. However, scholars such as Scott and Powells [145] have also documented that consumers may have a more explicit preference for hydrogen heating due to less immediate impacts on the lived experience of residential energy consumption compared to hydrogen cooking. Following recent consumer-oriented research on domestic hydrogen [130], this analysis examines the connection between technology perceptions for hydrogen heating and cooking, perceived relative advantage, and domestic hydrogen acceptance through a series of hypotheses:

H7a. The perceived performance of hydrogen boilers will significantly and positively affect the perceived relative advantage of hydrogen homes.

H7b. The perceived performance of hydrogen hobs will significantly and positively affect the perceived relative advantage of hydrogen homes.

H7c. The perceived relative advantage of hydrogen homes will significantly and positively affect domestic hydrogen acceptance.

H7d. The perceived relative advantage of hydrogen homes will significantly and positively mediate the relationship between the perceived performance of hydrogen boilers and domestic hydrogen acceptance.

H7e. The perceived relative advantage of hydrogen homes will significantly and positively mediate the relationship between the perceived performance of hydrogen hobs and domestic hydrogen acceptance.

5.7. Social acceptance and adoption intention

Following Ajzen's [46] theory of planned behaviour (TPB) and its forerunner, the theory of reasoned action (TRA) [2], the link between attitude and behavioural intention has been well-established in seminal technology acceptance models [14,253]. This interplay has been acknowledged and explored by energy scholars for more than a decade [32], lending support to the notion that acceptance predicts adoption intention and subsequent decision-making [182,183,238]. At the same time, researchers have documented the underlying prevalence of an intention-behaviour gap across different contexts [254,255], which may undermine actual low-carbon energy adoption [256,257]. This study sets out to quantify the strength of the relationship between domestic hydrogen acceptance and adoption willingness, in addition to testing the mediating role of domestic hydrogen acceptance within the integrated model:

H8a. Domestic hydrogen acceptance will significantly and positively affect consumer willingness to adopt a hydrogen home before 2030.

H8b. Domestic hydrogen acceptance will significantly and positively mediate the relationship between public trust and willingness to adopt a hydrogen home before 2030.

H8c. Domestic hydrogen acceptance will significantly and positively mediate the relationship between production perceptions and willingness to adopt a hydrogen home before 2030.

H8d. Domestic hydrogen acceptance will significantly and positively mediate the relationship between safety perceptions and willingness to adopt a hydrogen home before 2030.

H8e. Domestic hydrogen acceptance will significantly and negatively mediate the relationship between perceived disruptive impacts and willingness to adopt a hydrogen home before 2030.

H8f. Domestic hydrogen acceptance will significantly and negatively mediate the relationship between perceived socio-economic impacts and willingness to adopt a hydrogen home before 2030.

H8g. Domestic hydrogen acceptance will significantly and positively

mediate the relationship between perceived relative advantage and willingness to adopt a hydrogen home before 2030.

5.8. Hydrogen knowledge and awareness

In accordance with DoI Theory [44], knowledge and awareness mark the initial stage of the innovation-decision process, ahead of persuasion, decision, implementation, and confirmation (see Fig. 1 in Ref. [63]). Since hydrogen homes remain at the pre-deployment stage [258], consumers are yet to experience associated technologies for heating and cooking [146]. This status quo is reflected through low levels of domestic hydrogen awareness both in the UK [259] and internationally [134,260]. As a result, awareness of hydrogen boilers lags other sustainable heating technologies [259], which may partially explain higher levels of willingness to switch to a heat pump or solar heating across the UK, Germany, Italy, Spain, and Sweden [261].

Prior research suggests knowledge and awareness will increase underlying consumer support and adoption prospects for hydrogen homes [165], although a non-significant direct effect on domestic hydrogen acceptance was recorded in prior research [61]. To address the extant research gap, this analysis explores the relationship between cognitive processes and adoption willingness by integrating hydrogen knowledge and awareness into a single construct:

H9. Knowledge and awareness of hydrogen will significantly and positively affect consumer willingness to adopt a hydrogen home before 2030.

5.9. Financial perceptions of hydrogen homes

Financial factors will invariably shape consumer decision-making when choosing between low-carbon technologies for the home [261] such as hydrogen boilers and heat pumps [262]. Moreover, financial considerations become increasingly important as consumers progress along the innovation-decision process [263,264]. Survey research indicates that around 45% of the UK population may be worried about the potential costs of installing a low-carbon heating system, while this number drops to approximately 25% when considering potential running costs [265]. In the context of transitioning to hydrogen homes, evidence suggests purchasing costs could pose the main short-term bottleneck to technology adoption [156,266]. Engaging with deprived households in the North of England, Scott and Powells [151] also identified affordability as the primary barrier to consumer acceptance, with 77% of respondents citing inability or unwillingness to pay for higher energy bills [158]. The following hypothesis is formulated to reflect dynamics underpinning financial factors at the household level, which may induce rational decision-making on the part of consumers [42]:

H10. Financial perceptions regarding the purchasing and running costs of hydrogen boilers and hobs will significantly and negatively affect consumer willingness to adopt a hydrogen home before 2030.

5.10. Positive and negative emotions

Emotions critically shape consumer perspectives towards emerging energy technologies [267,268], which has been increasingly recognised by sustainability scholars in recent years [159,162,269] especially in the context of community-level projects [270–273]. Notably, researchers have developed affective-based models to advance understanding of emotional response to energy projects and technologies [161,162,274,275], which may fall across a wide spectrum of feelings such as hope, optimism, indifference, scepticism, and pessimism [165]. For example, in the context of hydrogen-related safety concerns and risk perceptions, negative imagery and emotions such as fear and dread may prove pervasive [131,142,276]. Alternatively, feelings of pride and gratitude may emerge among citizens of pioneering hydrogen energy communities [155]. Positive emotions may reflect a shared sentiment that hydrogen represents a fuel of the future [165,277], which is largely mirrored within the scientific community [278]. Accordingly, the

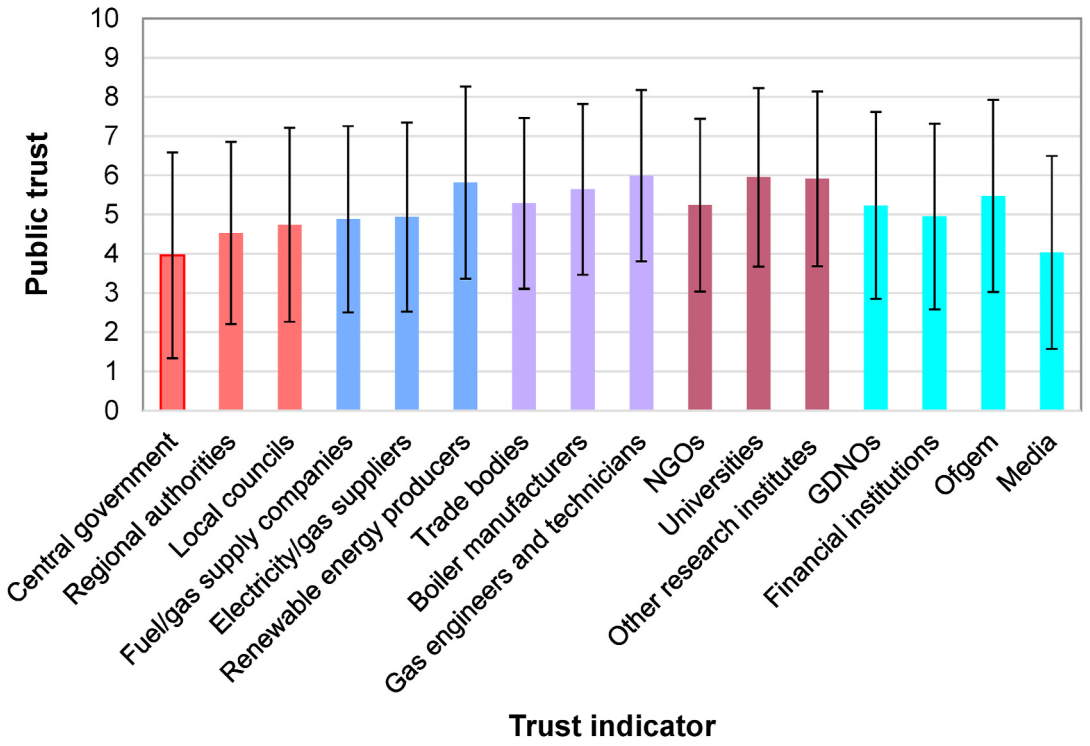

Fig. 4a. Mean score for indicators predicting public trust in the domestic hydrogen transition.
Salmon = Trust in the government (GOV); Indigo = Trust in the energy sector (NRG); Mauve = Trust in product and service quality (QUAL); Grape = Trust in R&D; Turquoise = Social trust (ST).

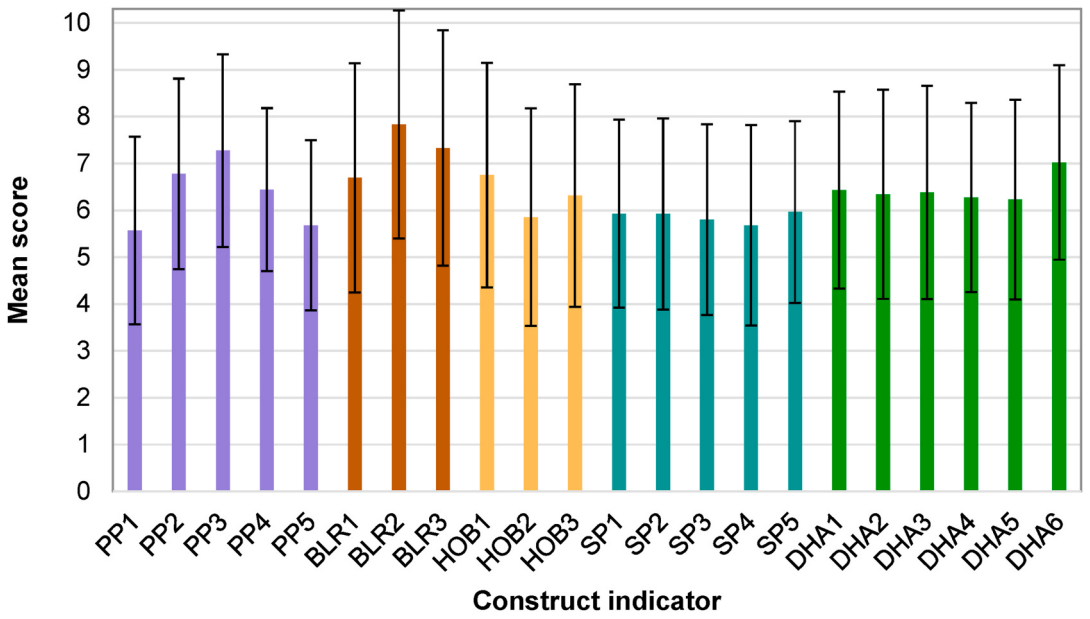

Fig. 4b. Constructs evaluated using an eleven-point Likert scale.
Purple = Production Perceptions (PP); Brown = Perceived Boiler Performance (BLR); Apricot = Perceived Hob Performance (HOB); Emerald = Safety Perceptions (SP); Green = Domestic Hydrogen Acceptance (DHA). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

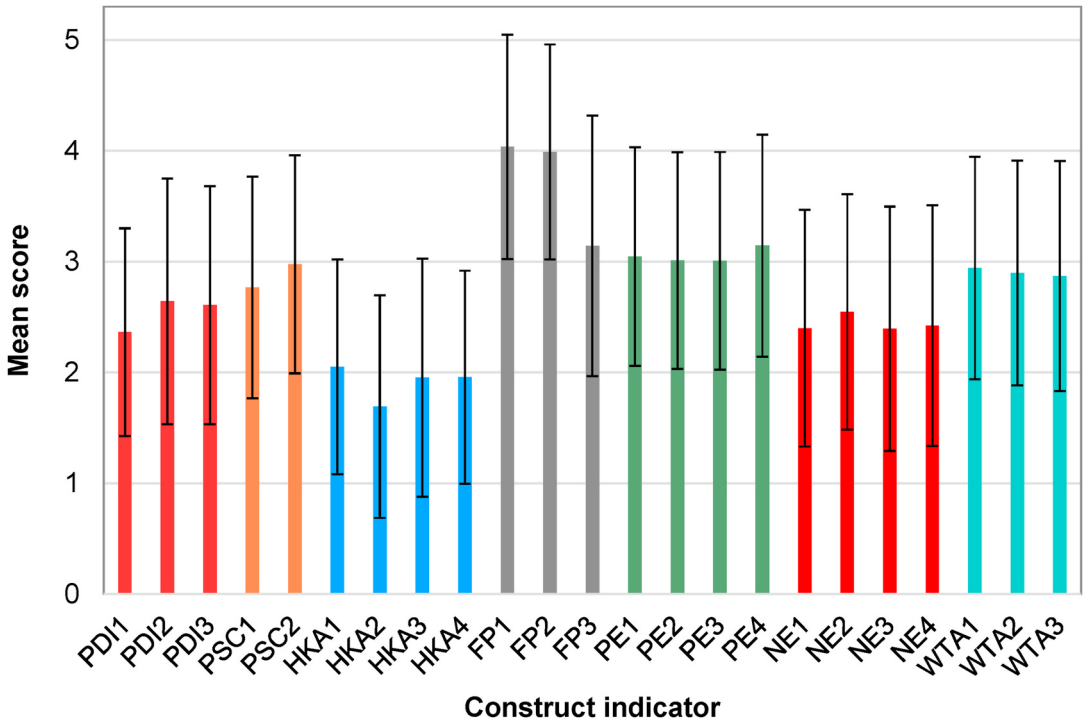

Fig. 4c. Constructs evaluated using a five-point Likert scale.
Ruby red = Perceived Disruptive Impacts (PDI); Orange = Perceived Socio-economic Costs (PSC); Blue – Hydrogen Knowledge and Awareness; Grey = Financial Perceptions; Lime = Positive Emotions (PE); Red = Negative Emotions; Teal = Willingness to Adopt Domestic Hydrogen (WTA). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

following hypotheses are tested to complete the analysis:

H11a. Feelings of satisfaction, calm, confidence, and optimism will significantly and positively affect consumer willingness to adopt a hydrogen home before 2030.

H11b. Feelings of discontent, worry, fear, and pessimism will significantly and negatively affect consumer willingness to adopt a hydrogen home before 2030.

6. Results and discussion

6.1. Descriptive statistics

Ahead of testing the conceptual framework via PLS-SEM, a summary

Table 2
Assessment of construct reliability, convergent validity, and multicollinearity.

Construct	CA	CR (ρ_A)	CR (ρ_C)	AVE	VIF
Trust in Government[a]	0.889	0.893	0.932	0.819	2.369
Trust in the Energy Sector[a]	0.887	0.890	0.931	0.818	3.645
Trust in Product and Service Quality[a]	0.862	0.863	0.916	0.784	2.784
Trust in Research & Development[a]	0.832	0.833	0.899	0.749	1.978
Social trust[a]	0.842	0.846	0.894	0.678	4.853
Public trust[b]	0.916	0.918	0.937	0.749[c]	1.466
Production Perceptions	0.816	0.844	0.870	0.578	1.385
Safety Perceptions	0.918	0.920	0.939	0.754	1.487
Perceived Disruptive Impacts	0.758	0.815	0.859	0.673	1.112
Perceived Socio-economic Costs	0.730	0.730	0.881	0.788[c]	1.192
Perceived Boiler performance[a]	0.708	0.711	0.837	0.632	1.590
Perceived Hob performance[a]	0.822	0.824	0.894	0.738	1.590
Perceived Relative advantage[b]	0.757	0.757	0.892	0.805	1.263
Domestic H2 Acceptance	0.898	0.907	0.922	0.665	1.634
H2 Knowledge and Awareness	0.816	0.827	0.877	0.641	1.127
Financial Perceptions	0.732	0.726	0.850	0.655	1.046
Positive Emotions	0.881	0.883	0.918	0.737	1.560
Negative Emotions	0.869	0.916	0.906	0.708	1.163
Willingness to Adopt H2 Home	0.934	0.934	0.958	0.883	n/a

[a] Lower-order construct.
[b] Higher-order construct: validated via the disjoint two-stage approach.
[c] Since PSC has two indicators, the AVE is larger than 0.50 by default.

analysis of descriptive statistics is carried out to support the investigation, as further detailed in Supplementary Note 9 (see SN9). Taken together, the sub-constructs of public trust account for 16 indicators (see Fig. 4a), which were measured using an 11-point scale and returned a moderate average ($M = 5.16$). By contrast, the mean score for perceived relative advantage (see Fig. 4b), as derived from six selected indicators, proved considerably higher ($M = 6.80$), suggesting relatively positive perceptions of hydrogen appliances from a technological perspective. Similarly, respondents are somewhat supportive of hydrogen production, but clearly favour a green pathway while expressing comparatively less backing for the twin-track approach.

Across all metrics, hydrogen is deemed safer than natural gas, while the perceived socio-economic costs of transitioning to a hydrogen home are considered more substantial than the potential disruptive (short-term) impacts, as reflected in Fig. 4c. Furthermore, consumers have largely negative perceptions of hydrogen in terms of financial investment and running costs. Nevertheless, positive emotions prevail over negative emotions (see Fig. 4c), Overall, consumers hold moderate levels of domestic hydrogen acceptance and willingness to adopt a hydrogen home before 2030, as largely dictated by perceptions of environmental benefits, and a lesser extent socio-economic benefits (see Fig. 4b). However, it should be emphasised that the level of hydrogen knowledge and awareness remains low across the UK population (see Section 5.8), thus current perceptions could prove short-lived. Importantly, the results should be gauged within a context where information provision materials may have influenced certain trends, as discussed when analysing the simplified STEEP Framework [63].

6.2. Measurement model assessment

Four conditions should be satisfied when measuring reflective constructs: item reliability, internal consistency reliability, convergent validity, and discriminant validity [279]. Across the 61 indicators composing the model, item reliability (i.e. scale reliability) is clearly supported in most cases since loadings exceed the suggested Cronbach Alpha (CA) threshold of 0.708. Satisfying this condition infers that the construct explains at least 50% of the variance in a respective indicator [186]. In one case, CA falls marginally below the cut-off value (NE1 = 0.697), which is unproblematic. Although PP1 has a lower than desirable CA value (0.552), other reliability and validity conditions were fulfilled, therefore the indicator is included to support content validity [280].

Internal consistency between each set of indicators is established since Composite Reliability (CR) exceeds 0.70 for all values without breaching the upper conservative limit of 0.95 [217], as best measured via Henseler and Dijkstra rho_a (ρ_A) [281]. Additionally, convergent validity is confirmed since each construct converges to explain more than 50% of the variance in its indicators (see Table 2), as demonstrated by average variance extracted (AVE) values greater than 0.50 [186]. Critically, each construct can be regarded as empirically distinct since the heterotrait-monotrait (HTMT) ratio of correlations returns values comfortably below 0.85 for each construct, as reported in Table 3 [282].[9] Furthermore, variance inflation factor (VIF) scores fall below the threshold of 3.0 in all but two instances and do not exceed the more conservative threshold of 5.0, which suggests minimal risk of multicollinearity [283].

6.3. Structural model assessment

The proposed hypotheses were tested in SmartPLS 4.1 [185] via the bootstrapping procedure (10000 sub-samples). Except for **H10** (FP → (−) DHA, $p = 0.006$), all relationships proved significant at the less than 0.1% level ($p < 0.001$), as reported in Table 4. Firstly, each lower-order construct has a strong and comparable influence on shaping public trust ($\beta = 0.210–0.261$; SD = 0.021), thereby confirming **H1a–H1e**. Among the five lower-order constructs, social trust has the strongest influence on public trust. In turn, public trust positively predicts domestic hydrogen acceptance (**H2a**: $\beta = 0.277$, $f^2 = 0.160$), in addition to mediating the relationship between each trust dimension and domestic hydrogen acceptance (**H2b–H2f**). Accordingly complementary partial mediation is observed within the trust-based component of the model [284,285].

Compared to public trust, the positive effect of production perceptions on domestic hydrogen acceptance is larger (**H3**: $\beta = 0.304$, $f^2 = 0.204$), while the influence of safety perceptions is comparatively smaller (**H4**: $\beta = 0.197$, $f^2 = 0.080$). However, the negative effect of perceived disruptive impacts (**H5**: $\beta = -0.121$, $f^2 = 0.041$) and perceived socio-economic costs (**H6**: $\beta = -0.175$, $f^2 = 0.079$) on domestic hydrogen acceptance is slightly smaller compared to safety perceptions. Finally, perceived relative advantage has the third most significant effect on domestic hydrogen acceptance (**H7c**: $\beta = 0.226$, $f^2 = 0.124$). Regarding the lower-order constructs of perceived relative advantage, perceived hob performance (**H7b**: $\beta = 0.613$, $t = 69.916$) is slightly more influential than perceived boiler performance (**H7a**: $\beta = 0.500$, $t = 65.432$), resulting in a marginally weaker mediating effect on domestic hydrogen acceptance for the latter sub-construct (**H7e**: $\beta = 0.138$, $t = 12.068$; **H7d**: $\beta = 0.113$, $t = 11.666$).

The direct effect of domestic hydrogen acceptance on willingness to adopt a hydrogen home carries the third strongest effect size across the model (**H8a**: $\beta = 0.333$, $f^2 = 0.137$), thereby confirming the positive association between social acceptance and adoption intention. The indirect effect of public trust, production perceptions, safety perceptions, perceived disruptive impacts, perceived socio-economic costs, and perceived relative advantage on adoption willingness (**H8b–H8g**) is approximately 66% smaller as compared to the direct effect on domestic hydrogen acceptance.

Alongside domestic hydrogen acceptance, positive emotions has a substantial influence on willingness to adopt a hydrogen home before 2030 (**H11a**: $\beta = 0.367$, $f^2 = 0.174$), whereas the effect of hydrogen knowledge and awareness (**H9**: $\beta = 0.226$, $f^2 = 0.037$) and negative emotions (**H11b**: $\beta = -0.109$, $f^2 = 0.021$) is more moderate. Lastly, financial perceptions is the least significant construct in the model, given

[9] The lower-order constructs are excluded when assessing discriminant validity.

Table 3
Heterotrait-monotrait results for assessment of discriminant validity.

	DHA	FP	HKA	NE	PDI	ADV	PSC	PE	PP	PT	SP	WTA
DHA												
FP	0.200											
HKA	0.157	0.235										
NE	0.345	0.119	0.132									
PDI	0.298	0.092	0.094	0.511								
ADV	0.591	0.148	0.087	0.103	0.071							
PSC	0.470	0.224	0.148	0.530	0.392	0.235						
PE	0.614	0.211	0.335	0.115	0.153	0.335	0.249					
PP	0.705	0.104	0.246	0.237	0.193	0.330	0.329	0.404				
PT	0.632	0.149	0.284	0.112	0.149	0.302	0.127	0.452	0.495			
SP	0.617	0.170	0.115	0.125	0.036	0.473	0.159	0.403	0.413	0.505		
WTA	0.646	0.227	0.324	0.240	0.219	0.270	0.287	0.674	0.418	0.378	0.368	

its relatively modest effect on adoption willingness (**H10**: $\beta = 0.226$, $t = 2.773$, $f^2 = 0.005$). To summarise the findings, Fig. 5 visualises the results from the measurement and structural models, in addition to illustrating the in-sample explanatory power of the model for predicting domestic hydrogen acceptance ($R^2 = 0.674$) and adoption willingness ($R^2 = 0.503$), which is further discussed following IMPA. Additionally, Fig. 6 shows the relationships between latent constructs with *p*-values and *t*-statistics.

6.4. Insights from importance-performance map analysis

The modelling results can be further interpreted via IMPA, which aids in revealing areas of strategic importance for realising the target outcome. Among the four positive constructs predicting domestic hydrogen acceptance, improving consumer perceptions of hydrogen production presents the foremost strategic priority and still has significant room for improvement (Latent variable (LV) score = 63.833). However, there is more scope for improving public trust in the domestic hydrogen transtion (LV = 52.056), which presents the second priority (see Fig. 7 and SN10). While perceived relative advantage is the best perfoming construct in this part of the model (LV = 67.678), there is more value in targeting the technological dimension of domestic hydrogen acceptance compared to the safety dimension, given the difference in effect size (0.029).

Notably, negative constructs have a smaller effect size and an inferior performance to each positive construct, as illustrated in Fig. 7. Although perceived disruptive impacts and socio-economic costs should be curbed to help mitigate potential social resistance to hydrogen homes, it is more

Table 4
Results of path analysis and hypothesis testing.

Hypothesis	β-coefficient (*SD*)	95% bootstrap confidence intervals	*t*-statistic	*p*-value	f^2
H1a: GOV → (+) PT	0.211 (0.003)	[0.205; 0.218]	64.973	<0.001	n/a
H1b: NRG → (+) PT	0.237 (0.003)	[0.231; 0.244]	74.076	<0.001	n/a
H1c: QUAL → (+) PT	0.233 (0.004)	[0.226; 0.240]	66.216	<0.001	n/a
H1d: R&D → (+) PT	0.210 (0.003)	[0.203; 0.216]	60.785	<0.001	n/a
H1e: ST → (+) PT	0.261 (0.003)	[0.255; 0.266]	90.658	<0.001	n/a
H2a: PT→ (+) DHA	0.277 (0.020)	[0.238; 0.315]	13.969	<0.001	0.160[a]
H2b: GOV → PT→ (+) DHA	0.059 (0.004)	[0.050; 0.067]	14.116	<0.001	n/a
H2c: NRG → PT → (+) DHA	0.066 (0.005)	[0.056; 0.075]	13.958	<0.001	n/a
H2d: QUAL → PT → (+) DHA	0.065 (0.005)	[0.055; 0.074]	13.771	<0.001	n/a
H2e: R&D → PT→ (+) DHA	0.058 (0.004)	[0.049; 0.066]	13.347	<0.001	n/a
H2f: ST → PT → (+) DHA	0.072 (0.005)	[0.062; 0.082]	14.002	<0.001	n/a
H3: PP → (+) DHA	0.304 (0.009)	[0.267; 0.339]	16.379	<0.001	0.204[a]
H4: SP → (+) DHA	0.197 (0.019)	[0.161; 0.234]	10.540	<0.001	0.080[b]
H5: PDI → (−) DHA	−0.121 (0.016)	[-0.153; −0.092]	7.600	<0.001	0.041[b]
H6: PSC → (−) DHA	−0.175 (0.015)	[-0.205; −0.146]	11.721	<0.001	0.079[b]
H7a: BLR → (+) ADV	0.500 (0.008)	[0.485; 0.515]	65.432	<0.001	n/a
H7b: HOB → (+) ADV	0.613 (0.009)	[0.597; 0.631]	69.916	<0.001	n/a
H7c: ADV → (+) DHA	0.226 (0.019)	[0.189; 0.263]	11.947	<0.001	0.124[b]
H7d: BLR → ADV → (+) DHA	0.113 (0.010)	[0.094; 0.132]	11.666	<0.001	n/a
H7e: HOB → ADV → (+) DHA	0.138 (0.011)	[0.116; 0.161]	12.068	<0.001	n/a
H8a: DHA → (+) WTA	0.333 (0.021)	[0.293; 0.373]	15.991	<0.001	0.137[b]
H8b: PT → DHA→ (+) WTA	0.092 (0.009)	[0.075; 0.110]	10.577	<0.001	n/a
H8c: PP → DHA→ (+) WTA	0.101 (0.009)	[0.085; 0.118]	11.587	<0.001	n/a
H8d: SP → DHA→ (+) WTA	0.066 (0.008)	[0.051; 0.082]	8.573	<0.001	n/a
H8e: PDI → DHA→ (−) WTA	−0.041 (0.006)	[-0.053; −0.030]	6.890	<0.001	n/a
H8f: PSC → DHA→ (−) WTA	−0.058 (0.006)	[-0.071; −0.047]	9.340	<0.001	n/a
H8g: ADV → DHA→ (+) WTA	0.075 (0.008)	[0.061; 0.091]	9.748	<0.001	n/a
H9: HKA → (+) WTA	0.144 (0.017)	[0.110; 0.178]	8.302	<0.001	0.037[b]
H10: FP → (−) WTA	−0.049 (0.018)	[-0.083; −0.015]	2.773	0.006	0.005
H11a: PE → (+) WTA	0.367 (0.021)	[0.325; 0.409]	17.422	<0.001	0.174[a]
H11b: NE → (−) WTA	−0.109 (0.018)	[0.146; 0.072]	5.921	<0.001	0.021[b]

[a] Moderate effect size ($0.15 \leq f^2 < 0.35$).
[b] Small effect size ($0.02 \leq f^2 < 0.15$).

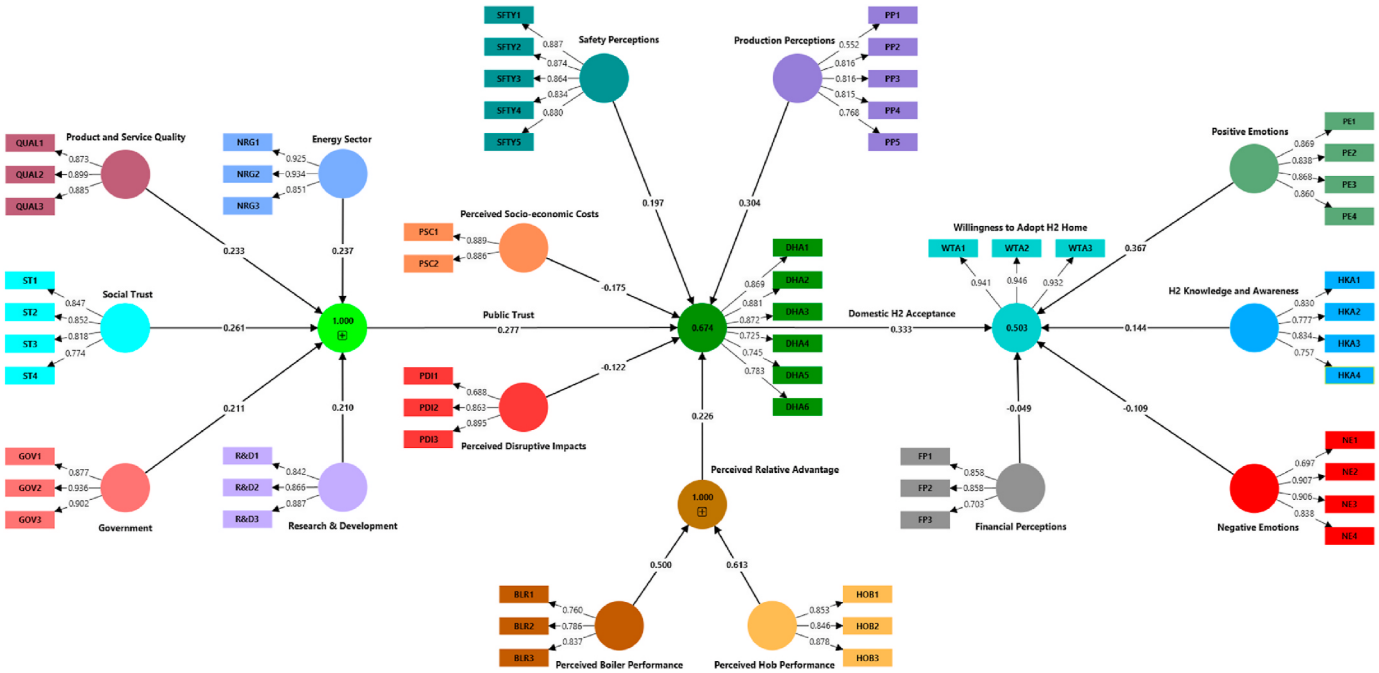

Fig. 5. Structural model path coefficients and indicator loadings.

justified to focus on the economic dimension at this juncture of the domestic hydrogen transition. Despite perceived disruptive impacts presenting the largest scope for improvement (LV = 38.878), consumers appear less concerned about associated risks such as noise and inconvenience, at least when the transition remains hypothetical and potentially several years away.

Whereas the respective positive and negative predictors of domestic hydrogen acceptance are clustered somewhat closely together within the IMPA, there is more divergence when considering the antecedents of adoption willingess. Hydrogen knowledge and awareness is the worst performing construct by a significant margin, but also has the smallest effect size (see Fig. 8 and SN10). Consequently, allocating resources towards raising hydrogen knowledge and awareness, although a likely requirement for strengthening long-term prospects for national hydrogen economies [165,286], may prove strategically unsound for increasing near-term deployment prospects for hydrogen homes [130].

Key stakeholders including policy makers should take stock that increasing domestic hydrogen acceptance is a necessary step for improving consumer willingness to adopt a hydrogen home before 2030 [64]. However, it is critical to raise the overall level of social acceptance via the perceptual pathways identified in Fig. 7, in conjunction with strengthening positive sentiment about hydrogen homes. Consolidating feelings of satsifaction, calm, confidence, and optimism towards hydrogen homes will inevitably help offset negative emotions, which is more important than addressing (negative) financial perceptions at this juncture of the prospective transition. Moreover, there is comparatively less scope to improve financial perceptions (LV = 68.390) compared to other constructs in the model.

Targeting communication campaigns across specific segments of the population such as industrial towns and socio-economically deprived communities [62], in conjunction with increasing the trialability and observability of hydrogen homes [42], presents a tangible 'intervention point' [287,288] for mitigating pessimism and scepticism. In parallel to directly circumventing negative emotions, decision-makers can take stock that reinforcing feelings of confidence (PE3) and optimism (PE4) towards hydrogen homes will naturally present the most direct means for bolstering technology adoption. Taken together, Figs. 7–9 present an initial snapshot of which success factors are likely to prove critical to establishing a sense of hope and curbing fears for domestic hydrogen futures.

6.5. Predictive capabilities of the model

6.5.1. In-sample predictive power

The coefficient of determination (R^2) indicates how much variance in an outcome variable can be explained by its predictors [289,290]. While in-sample predictive power should be assessed on a case-by-case basis [291,292], a general guideline is that R^2 values of 0.25, 050, and 0.75 approximate weak, moderate, and substantial levels of predictive power [293]. As shown in Fig. 5, the proposed model displays a higher level of explanatory power for predicting domestic hydrogen acceptance (R^2 = 0.674) compared to willingness to adopt a hydrogen home (R^2 = 0.503). Given the nascency of modelling consumer perspectives of domestic hydrogen [130], in-sample predictive power can be considered at least moderate in both cases.

To better position the results of this study in the context of the PLS-SEM literature, Table 5 leverages findings from SN1 to provide the R^2 values for 38 target constructs retrieved from 16 studies spanning a range of country contexts. Across the sample, six constructs display substantial in-sample predictive power, whereas 13 and 17 constructs exhibit moderate and weak explanatory power, as depicted in Fig. 10. Additionally, two constructs fall below the cut-off of $R^2 = \geq 0.25$, corresponding to the studies of Hasheem et al. [294] and Pan et al. [302], thereby marginally increasing the variance of the sample (SD = 0.202), while the average R^2 value is moderate (M = 0.537).

It follows that the constructs of DHA (R^2 = 0.674) and WTA (R^2 = 0.503) from the integrated model fall above 26 and 19 of the 38 target constructs reported in Table 5 and visualised in Fig. 10. This stands to reason since the in-sample predictive power of WTA lies close to the suggested guideline of 0.50, implying that the small sample is broadly representative of results across the PLS-SEM literature. Validating the results in the context of the PLS-SEM literature (see SN1) further demonstrates that both model parsimony and predictive power are achieved through an integrated approach, with the relationship between attitude and intention proving comparable to the context of solar PV acceptance and adoption in Saudi Arabia [296].

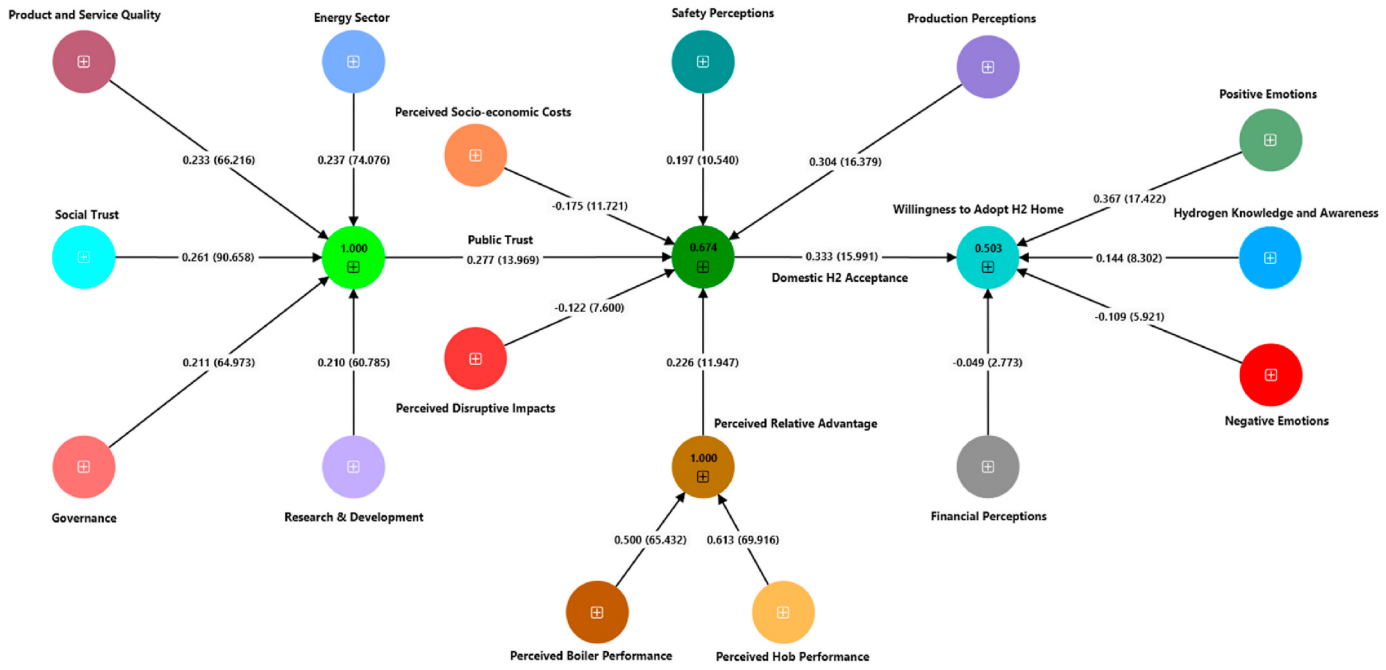

Fig. 6. Structural model path coefficients and t-statistics.

6.5.2. *Out-of-sample predictive power*

Assessing out-of-sample predictive power helps determine the reliability of modelling results for informing strategic decision-making and future research [173]. Shmueli et al. [309] developed the $PLS_{predict}$ tool which calculates the Stone-Geisser's Q^2 value [310,311] for each endogenous construct using a blindfolding procedure in SmartPLS. The predictive relevance of the PLS-path model for domestic hydrogen acceptance proved substantial ($Q^2 = 0.670$), while the result for adoption willingness was slightly below the desired cut-off ($Q^2 = > 0.50$) but nevertheless moderate ($Q^2 = 0.445$) [186].[10]

Since $PLS_{predict}$ is not strictly a statistical test (i.e. a comparative assessment), the cross-validated predictive ability test (CVPAT) provides a more robust method for evaluating out-of-sample predictive power [173]. The integrated model surpasses the indicator average (IA) prediction benchmark, given that the average loss difference between the PLS-SEM model and the IA is negative and significantly below zero, as reported in Table 6. However, the model failed to outperform the more conservative linear model (LM) prediction benchmark, which is necessary for achieving strong predictive accuracy [312] Additionally, Table 6 shows that each endogenous construct outperformed and underperformed compared to the IA and LM benchmarks, respectively.

6.6. *Comparative findings between domestic hydrogen models*

6.6.1. *Impacts of the integrated model on explanatory and predictive power*

The integrated model of domestic hydrogen acceptance and adoption intention demonstrates the scope for increasing explanatory and predictive power by operationalising a range of perceptual, cognitive, and emotional predictors. Notably, while the DHAM explained 66.9% of the variance in domestic hydrogen acceptance via ten exogenous constructs[11] [61], the integrated model explains 67.4% of observed variance via four exogenous constructs (i.e. PP, SP, PDI, and PSC) and two higher-order constructs (i.e. PT and ADV). This level of similarity demonstrates the additional explanatory power afforded by increasing construct bandwidth via higher-order constructs to capture respective sub-dimensions of public trust and perceived relative advantage.

The integrated model also demonstrates stronger explanatory power compared to the STEEEP Framework, which explained 61.2% of the variance in perceived adoption potential via five exogenous constructs (i.e. SP, FP, PSC, PP, and PE) and one higher-order construct (i.e. ADV). While the outcome variables are distinct (i.e. social acceptance and perceived adoption potential), it is nevertheless noteworthy that the integrated model outperforms the STEEEP Framework in this regard since the number of constructs is comparable.

Moreover, the predictive benefits of the approach taken in this study become more apparent when contrasted against the trust-based model, which also specified a path relationship between social acceptance (DHA1–DHA3) and adoption willingness [64]. Whereas this study explains 67.4% of the variance in domestic hydrogen acceptance, the trust-based model explained 56.1% of the variance in perceived community benefits (i.e. DHA4–DHA6) and a more modest 45.4% of variance in domestic hydrogen acceptance,[12] in addition to 39.4% of the variance in adoption willingness [64]. As a result, the predictive superiority of the integrated model is attested to, since 50.3% of the variance in adoption willingness could be explained by domestic hydrogen acceptance, hydrogen knowledge and awareness, financial perceptions, positive emotions, and negative emotions, as captured in Fig. 5.

Mirroring the observations for explanatory predictive power, Table 7 demonstrates the benefits of adopting an integrated approach in terms of out-of-sample predictive power. Additionally, PLS-SEM supports a robust method for statistically comparing predictive performance using a range of metrics and techniques including the root mean squared error (RMSE) and mean absolute error (MAE) vis-à-vis $PLS_{predict}$ [170], the CVPAT [173,312], and the Bayesian information criterion (BIC) [313]. The BIC helps identify the model that best optimises predictive accuracy, while balancing model fit and complexity to avert overfitting [313] (i.e.

[10] At the indicator level, Q^2 measured 0.366 and 0.507 for domestic hydrogen acceptance ($M = 0.446$), and 0.391 and 0.395 for willingness to adopt a hydrogen home before 2030 ($M = 0.393$).

[11] Hydrogen energy awareness (i.e. HKA2, HKA4), subjective knowledge of hydrogen fuel (i.e. HKA1), Public Trust (i.e. NRG3, ST1–ST4), PP, SP, PDI, PSC, Perceived Community Benefits (i.e. DHA4–DHA6), PE, and NE.

[12] As directly predicted by perceived community benefits and its mediating path relationships (i.e. to PT, TP, SP, and PP).

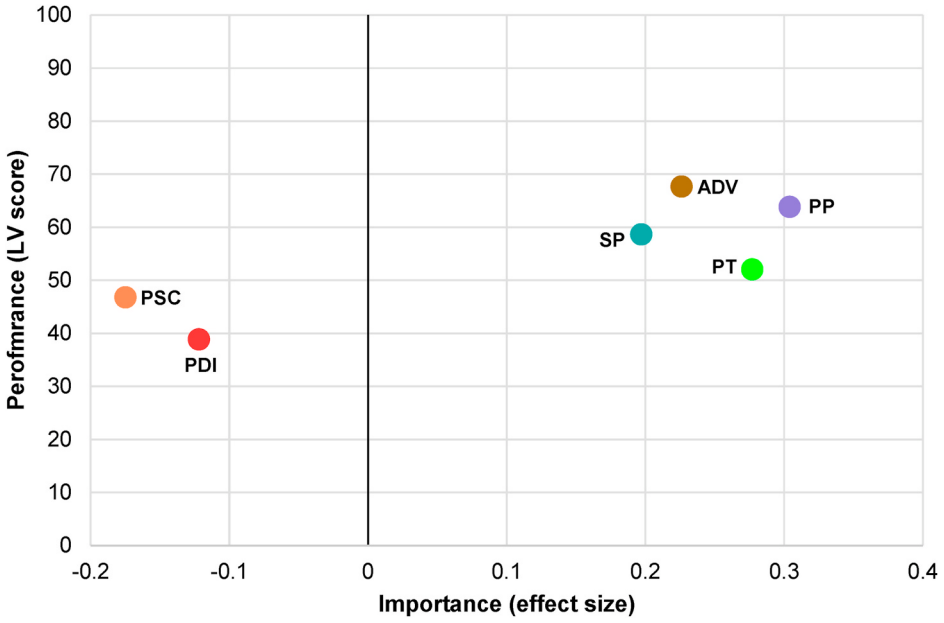

Fig. 7. Importance-performance map analysis for domestic hydrogen acceptance.

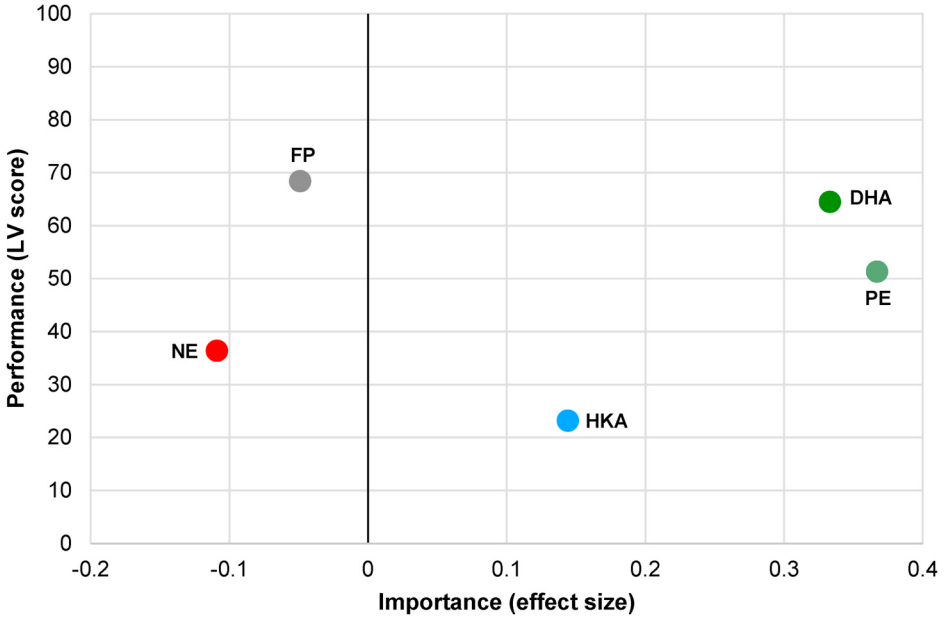

Fig. 8. Importance-performance map analysis for willingness to adopt a hydrogen home before 2030.

a model with a BIC of −250 is preferred over a BIC of −25) [313].

Given that willingness to adopt a hydrogen home is operationalised identically within the corresponding trust-based model [64] and the integrated framework depicted in Fig. 3, comparative analysis across different metrics is feasible. Table 8 confirms the superior predictive capabilities of the integrated approach across each statistical benchmark. This improvement supports the premise that cognitive and emotional factors, alongside rational thought, will take on increasing importance as consumers move through the innovation-decision for hydrogen homes, wherein a range of perceptual antecedents shape initial acceptance dynamics.

6.6.2. *Impacts of the integrated model on path coefficients*

To extend the comparative assessment, Table 9 considers specific changes in path coefficients between the integrated model and prior approaches, thereby providing a systematic breakdown at the construct level. To help interpret the results and enable comparison across predictors, the observed difference between beta coefficients (β) is also calculated in percentage terms, leading to the following cut-offs: <25% $\Delta\beta$ = non-significant; 25% ≤ $\Delta\beta$ < 50% = small change in statistical significance; 50% ≤ $\Delta\beta$ < 100% = moderate change in statistical significance; 100% ≤ $\Delta\beta$ < 250% = large change in statistical significance; ≥250% $\Delta\beta$ = very large change in statistical significance. The following patterns are observed in the modelling results: 4 results are non-significant; 7 results show a small change in statistical significance; 2 results present a moderate change; 1 result demonstrates a large change; and 2 results correspond to a very large change.

The most significant changes (>1110%) are observed in relation to hydrogen knowledge awareness, which is non-significant in predicting domestic hydrogen acceptance [61], whether modelled as a combined

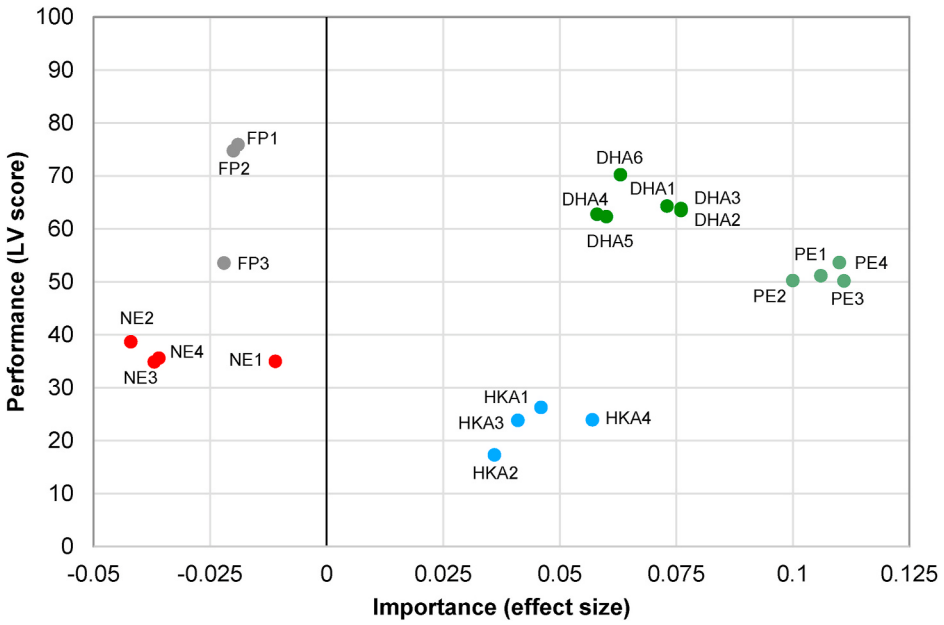

Fig. 9. Importance-performance map analysis for adoption willingness at the indicator level.

construct or separated into its constituent parts (see Table 9). Although subjective knowledge of hydrogen fuel (HKA1) remains non-significant in predicting social acceptance (i.e. DHA1–DHA3) or adoption willingness (i.e. WTA1–WTA3), both hydrogen awareness (i.e. HKA2–HKA4) and the combined construct conceived in this study (i.e. HKA1–HKA4) become statistically significant predictors of adoption willingness ($p < 0.001$).

In practical terms, this discrepancy means that as consumers navigate the innovation-decision process [44] and begin to consider the suitability of adopting a hydrogen home, knowledge and awareness of the technology takes on increasing importance. Statistical analysis of qualitative responses to this dataset supports this rationale, since knowledge and awareness of renewable energy technologies also proved more significant in predicting adoption willingness compared to social acceptance [165].

The more granular findings presented in Fig. 9 further demarcate the interactions between knowledge, awareness, and adoption willingness, revealing that awareness is more influential than subjective knowledge. Notably, the literature supports the notion that technical or objective knowledge may fail to translate into higher technology adoption intention [314,315], which infers limitations regarding the potential influence of subjective knowledge. By contrast, perceived familiarity (i.e. a combined sense of subjective knowledge and awareness) and subsequent experience can support enabling conditions for market uptake [315–317], reflecting the imperative to bolster the observability and trialability of hydrogen homes [62].

The integrated model also reveals more intricate dynamics regarding the role of safety perceptions in shaping consumer attitudes towards hydrogen homes. A substantial change is detected between operationalising safety perceptions as a direct predictor in the DHAM ($\beta = 0.057$, $t = 2.833$) [61] compared to integrating perceived community benefits into the acceptance construct as presented in Fig. 6 ($\beta = 0.197$, $t = 10.540$). This result is consistent with the associated trust-based model, wherein safety perceptions positively and significantly predicted perceived community benefits ($\beta = 0.232$, $t = 10.537$) [64], which is further reflected via alignment to the STEEEP Framework (see Table 9).

The main implication is that perceptions of hydrogen safety – as represented by both infrastructural and technological developments (see Section 5.3) – will have a strong bearing on the degree to which the public anticipates potential environmental health benefits from the hydrogen switchover. A similar dynamic is observed for perceived socio-economic costs, which becomes significantly more influential in the integrated model compared to the DHAM ($\beta = +0.177$, $t = +8.289$). It follows that perceptions of energy security and fuel poverty risks will feed more directly into shaping community-level acceptance, as partly dictated by mechanisms of distributional (in-)justice [157,318]. Thus, the highlighted critical success and resistance factors (i.e. SP and PSC) become more prominent predictors when perceived community benefits is factored into the social acceptance equation.

A moderate amplifying effect is also observed at the emotional level. The change is specific to positive emotions which is approximately 69% more influential in the integrated model compared to the DHAM, as reported in Table 9, whereas the influence of negative emotions remains relatively consistent between models. Thus, feelings of calm, confidence, satisfaction, and optimism will tangibly transmit towards perceptions of economic, social, and environmental benefits associated with the domestic hydrogen transition. By empirically validating this logical relationship, the integrated model attests to the importance of human emotions in shaping behavioural intentions towards emerging, low-carbon energy technologies [155,159,319], while underscoring the multi-dimensional nature of domestic hydrogen acceptance [120].

7. Conclusion

7.1. Practical and theoretical contributions

Through an integrated conceptual framework, this study advances insights on the critical drivers and barriers shaping social acceptance and early adoption prospects for domestic hydrogen in the UK. Departing from previous modelling approaches [61–63], a dual focus on acceptance and adoption dynamics is presented to capture the initial stages of the innovation-decision process for hydrogen homes. In doing so, the underlying premise of the unified theory of domestic hydrogen acceptance [42] is explicitly captured for the first time by juxtaposing perceptual, cognitive, and emotional factors, while expanding previous insights from a more concise, trust-based model [64].

Addressing the first research objective, the critical drivers of domestic hydrogen acceptance include perceptions of hydrogen production pathways, public trust, perceived relative advantage, and safety perceptions. Fig. 7 affirms that the environmental tenets of the domestic

Table 5
In-sample predictive power of different target constructs in PLS-SEM studies.

Study	Research focus and context	Target construct(s)	R^2
[295]	Factors affecting university students' new technology entrepreneurial performance in China	• Entrepreneurial intention • Entrepreneurial performance	0.568 0.568
[296]	Consumer acceptance of solar PV in Saudi Arabia	• Consumer attitude • User behaviour (intention)	0.760 0.563
[294]	Consumer acceptance of solar PV in Pakistan	• Consumer attitude • Purchase intention	0.400 0.211
[297]	Consumer acceptance of a home energy management system in South Korea	• Perceived ease of use • Perceived usefulness • Intention to use	0.486 0.814 0.703
[21]	Consumer acceptance of smart meter technology in Malaysia	• Behavioural intention	0.962[a]
[298]	Entrepreneurial tendencies among engineering students in Pakistan	• Entrepreneurial behaviour	0.488
[299]	Determinants of active online learning in the Chinese smart learning environment	• Active online learning	0.445
[300]	Drivers of data-drive innovation by organisations in Australia	• Data-driven innovation development	0.655
[301]	Determinants of cultural orientation among Malaysian entrepreneurs	• Cultural orientation	0.505
[302]	Acceptance and use of electric bicycle-sharing systems in China	• Perceived environmental value • Perceived pleasure • Perceived usefulness • Behaviour attitude • Behaviour intention • Actual behaviour	0.393 0.279 0.143 0.475 0.328 0.277
[303]	Determinants of E-banking customer satisfaction and loyalty in Pakistan	• Trust in Islamic e-banking • Religiosity • E-customer loyalty	0.488 0.692 0.870
[304]	Examines the impact of interactivity (i.e. computer-mediated environments) on communication quality and process satisfaction among univeristy students in Southern California	• Communication quality • Process satisfaction	0.485 0.688
[305]	Predictors of network embeddedness and innovation performance of small- and medium-sized enterprises in Pakistan	• Absorptive capacity • Innovation performance	0.744 0.396
[306]	Examines the antecedents and relationship between corporate reputation and customer response	• Corporate reputation • Customer satisfaction • Customer loyalty	0.734 0.306 0.565
[307]	Examines the factors influencing the reputation of non-profit organisations	• Competence • Likeability	0.659 0.752
[308]	Examines the relationship between corporate social responsibility, green construction, and sustainable development in China	• Green design • Green procurement • Carbon emissions • Sustainable construction • Sustainable waste management • Ecosystem sustainability	0.349 0.475 0.845 0.343 0.261 0.728

[a] 0.962 can be considered an artificially (or excessively) high R^2 value but is nonetheless included in the sample. Removing this data point has a negligible effect on the sample average ($R^2 = 0.525$) or variance ($SD = 0.192$).

hydrogen transition, as implicit within the twin-track production approach [129], are paramount to enabling social acceptance for hydrogen homes. While this observation is strongly in line with prior models [61,64], the results depart somewhat from previous iterations since public trust and safety perceptions share nearer levels of equivalence in predicting social acceptance.

Notably, this study makes a novel contribution by operationalising perceived relative advantage as an antecedent of acceptance as opposed to adoption potential [62,63], which corresponds to the third most important critical success factor behind production perceptions and public trust. In terms of critical barriers or resistance factors, perceived socio-economic costs is more influential than perceived disruptive impacts, which marks a notable reversal from the DHAM (see Table 9) [61], reflecting the strong interaction between macro-economic risk factors and community-level acceptance.

Regarding the second research objective, the critical success factors of adoption willingness are domestic hydrogen acceptance, hydrogen knowledge and awareness, and positive emotions, while barriers include financial perceptions and negative emotions. Insights from IMPA (see Section 6.4) suggest emotional factors are currently more influential than cognitive processes and associated rational thought when the adoption decision remains hypothetical and distant. This observation aligns to prior results [263,264,320], signalling the more subdued role of consumer knowledge, financial factors, and rational thinking when technologies are yet to reach commercialisation.

While affective drivers of adoption intention feature prominently, alongside underlying perceptions and attitudes shaping social acceptance, there is more scope for increasing positive emotions to enhance deployment prospects for hydrogen homes. At present, negative emotions present more of a barrier to adoption willingness than financial perceptions, further suggesting that emotional response may outweigh rational thought during the formative phase of the transition [42], which sees trust mechanisms strongly shape the formation of consumer attitudes [50,321].

The final research question has been answered emphatically by comparing results from available models. As reported in Section 6.6, the

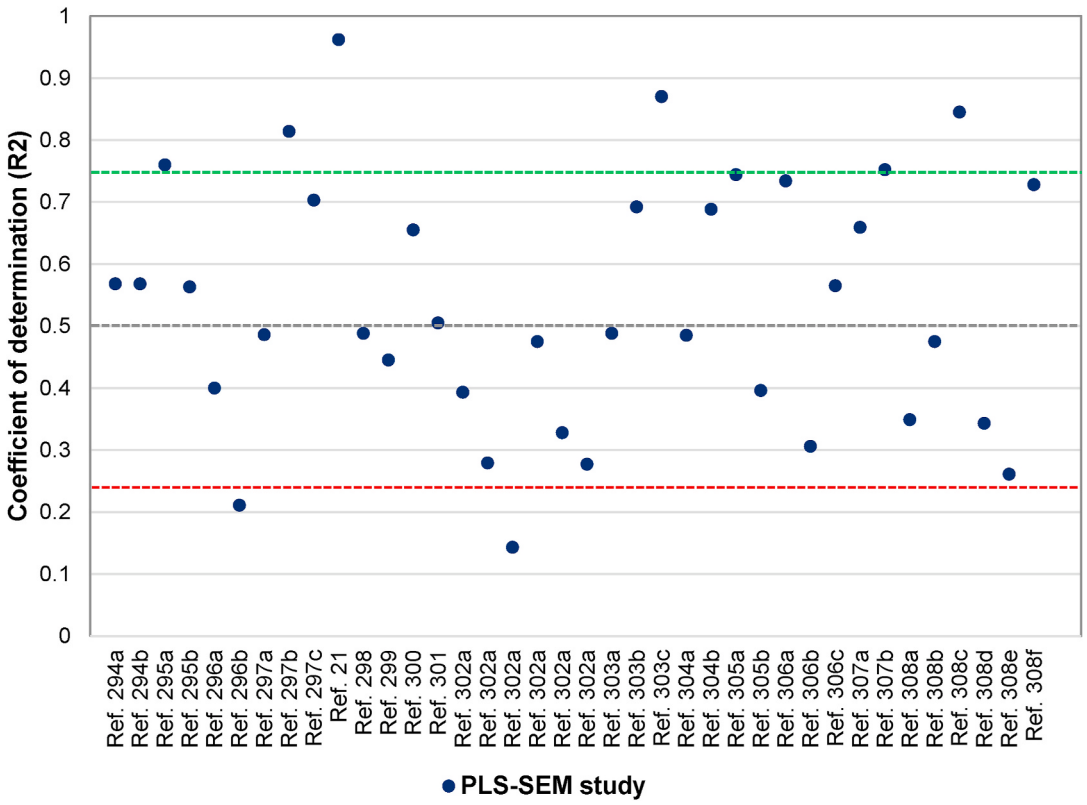

Fig. 10. Scatter plot of in-sample predictive power for target constructs (N = 38) in the PLS-SEM sample (N = 16) discussed in Supplementary Note 1.
The dashed red line demarcates the cut-off for a weak R^2 value ($0.25 > R^2 \leq 0.50$).
The grey dashed line demarcates the cut-off for a moderate R^2 value ($0.50 > R^2 \leq 0.75$).
The green dashed line demarcates the cut-off for a strong R^2 value (≥ 0.75). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 6
CVPAT benchmark and results for predictive ability test.

Target construct	PLS-SEM vs Indicator average (IA)				
	PLS loss	IA loss	Average loss difference	*t*-value	*p*-value
Domestic H2 Acceptance	2.534	4.595	−2.061	20.527	<0.001
Perceived Relative Advantage	2.631	5.840	−3.209	24.881	<0.001
Public Trust	2.347	5.534	−3.187	30.865	<0.001
Adoption willingness	0.631	1.039	−0.408	16.063	<0.001
Overall	2.272	4.976	−2.704	35.622	<0.001
	PLS-SEM vs Linear model (LM)				
	PLS loss	LM loss	Average loss difference	*t*-value	*p*-value
Domestic H2 Acceptance	2.534	2.242	+0.292	9.535	<0.001
Perceived Relative Advantage	2.631	0.000	+2.631	42.915	<0.001
Public Trust	2.347	0.000	+2.347	52.701	<0.001
Adoption willingness	0.631	0.633	−0.002	0.317	0.751
Overall	2.272	0.495	+1.777	60.319	<0.001

Table 7
Comparison of out-of-sample predictive power between modelling approaches.

Model specification	Q^2 value for domestic hydrogen acceptance	Q^2 value for willingness to adopt a hydrogen home	PLS-SEM vs Indicator average for overall model (*t*-value)
Integrated model	0.670	0.445	35.622
DHAM [61]	0.653	n/a	20.971
STEEEP Framework [63]	n/a	0.608	25.985
Trust-based model [64]	0.434	0.178	31.798

Table 8
Model comparison between trust-based and integrated frameworks.

Indicators/construct	Root mean square error[a]		Mean absolute error[b]	
	Trust-based model	Integrated model	Trust-based model	Integrated model
WTA1	0.924	0.783	0.735	0.621
WTA2	0.932	0.790	0.748	0.624
WTA3	0.952	0.810	0.770	0.642

	Cross validated predictive ability test			
	Trust-based model	Integrated model	Average loss difference	*t*-value (*p*-value)
Willingness to adopt a hydrogen home	0.875	0.631	−0.244	13.842 (<0.001)
Overall model	2.114	2.076	−0.038	13.577 (<0.001)

	Bayesian information criterion	
	Trust-based model	Integrated model
Willingness to adopt a hydrogen home	−910.436	−1245.290

Bold text highlights stronger predictive capabilities.
[a] The square root of the average of the squared differences between the predictions and the actual observations.
[b] The average absolute difference between the predicted and the actual values.

integrated model demonstrates higher predictive capabilities than its predecessors. Thus, this analysis aligns to the seminal findings espoused via the UTUAT [14] and subsequent iterations [25,208], with a wealth of studies underscoring the explanatory and predictive advantages of leveraging integrated frameworks [20,322–324] or unified modelling approaches [26,325,326]. This study palpably demonstrates the ability to advance theoretical understanding and empirical insights through the development and testing of models [60], as supported by the exploratory, causal-predictive nature of PLS-SEM [168,289,327].

Importantly, this analysis deviates from the unified theory of domestic hydrogen acceptance [42] by linking cognitive processes with adoption intention, thereby exploring an alternative causal link to what was tested and proved non-significant within the DHAM [61]. More explicitly, the integrated model posits relationships between a group of (positive and negative) perceptual antecedents and social acceptance, which serves as a proxy for consumer attitude. In line with established psychological theories [3,46,47], an individual's attitude towards acceptance, whether endorsing or simply tolerating a given technology [120,328] is a strong predictor of behavioural intention [264,329], which manifests through cognitive processes, financial perceptions, and

Table 9
Comparison of structural path coefficients between modelling approaches.

Construct	Model specification		
	DHAM[a]	Integrated model (DHA)[b]	Change in β (%)
Public Trust	0.198 (10.207)	0.277 (13.969)	0.079[e] (+39.9)
Production Perceptions	0.214 (10.897)	0.304 (16.379)	0.090[e] (+42.1)
Safety Perceptions	0.057 (2.833)	0.197 (10.540)	0.140[g] (+245.6)
Perceived Disruptive Impacts	−0.092 (5.450)	−0.122 (7.600)	0.030[e] (+32.6)
Perceived Socio-economic Costs	−0.058 (3.432)	−0.175 (11.721)	0.117[g] (+201.7)
	STEEP Framework[c]	**Integrated model (DHA)**[b]	
Safety Perceptions	0.193 (9.679)	0.197 (10.540)	0.004 (+2.1)
Perceived Relative Advantage	0.179 (8.674)	0.226 (11.947)	0.047[e] (+26.3)
Perceived Socio-Economic Costs	−0.126 (8.409)	−0.175 (11.721)	0.049[e] (+38.9)
Production Perceptions	0.241 (13.441)	0.304 (16.379)	0.063[e] (+26.1)
	DHAM[a]	**Integrated model (WTA)**[d]	
Subjective Hydrogen Knowledge (HKA1)	−0.008 (0.731)	−0.014 (0.639)	0.006 (+25.0)
Hydrogen Awareness (HKA2–HKA4)	0.010 (0.678)	0.160 (7.020)	0.150[h] (+1500.0)
Hydrogen Knowledge and Awareness (HKA1–HKA4)	0.012 (0.423)	0.144 (8.302)	0.132[h] (+1110.0)
	DHAM[a]	**Integrated model (DHA)**[b]	
Positive Emotions	0.217 (12.599)	0.367 (17.422)	0.150[f] (+69.1)
Negative Emotions	−0.138 (8.325)	−0.109 (5.921)	0.029 (−21.0)
	STEEP Framework[c]	**Integrated Model (WTA)**[d]	
Positive Emotions	0.376 (19.909)	0.367 (17.422)	0.009 (2.5)
Financial Perceptions	−0.082 (5.311)	−0.049 (2.773)	0.033[e] (40.2)

[a] Domestic Hydrogen Acceptance (i.e. DHA1, DHA2, DHA3).
[b] Domestic Hydrogen Acceptance (extended) (i.e. DHA1, DHA2, DHA3, DHA4, DHA5, DHA6).
[c] Perceived Adoption Potential (i.e. WTA1, WTA2, WTA3 combined with DHA4, DHA5, DHA6).
[d] Willingness to Adopt a Hydrogen Home (WTA1, WTA2, WTA3).
[e] Small change in statistical significance.
[f] Moderate change in statistical significance.
[g] Large change in statistical significance.
[h] Very large change in statistical significance.

emotional response.

The strong path relationship between domestic hydrogen acceptance and adoption willingness ($\beta = 0.333$, $p < 0.001$) further corroborates the assertion of Dwivedi et al. [330] that attitudinal parameters should form an integral part of unified approaches towards modelling the link between acceptance, adoption intention, and subsequent decision-making for consumer technologies. In conjunction, it should be recognised that affective response is likely to play a pivotal role in shaping both acceptance and adoption dynamics (see Table 9). Critically, this observation motivates the need for deeper understanding of human emotions in shaping the innovation-decision process for residential energy technologies (see Section 7.2).

7.2. Implications for future research

Certain limitations associated with the research design and sampling characteristics, alongside recognition that actual consumer behaviour could not be captured at this juncture, have been discussed in earlier outputs [62,63]. While a research stream on hydrogen-related developments in the UK provides a useful starting point and is contextually relevant to emerging net-zero policy [112], behavioural-related insights from a single dataset at a specific point in time are naturally limited. Nevertheless, this study provides a stepping-stone for developing a more comprehensive understanding regarding the interplay between perceptual, cognitive, and emotional antecedents in shaping consumer attitudes towards hydrogen homes. The natural evolution of this contribution lies with expanding the longitudinal evidence base on hydrogen acceptance [66,134], in addition to advancing cross-national studies [261,331]. Such additions would enhance understanding of both the temporal [264,332] and cultural dynamics shaping public perceptions [333,334].

As advancements in research methods and computational power continue to shape the trajectory of scholarship on consumer behaviour and technology acceptance [335–337], opportunities beckon to close the gap on understanding the interplay between cognitive processes, rational decision-making, and emotional response. In a notable contribution to the technology acceptance literature, Dimoka and Davis [338] investigated "the neural mechanisms underlying technology adoption" by positing the intriguing question: "Where does TAM reside in the brain?" This innovative trajectory manifested under the umbrella of neuroscience for information systems (NeuroIS) research [339], which was subsequently contextualised in relation to decision-making, and cognitive, emotional, and social processes [340].

Fundamentally, NeuroIS studies leverage state-of-the-art tools such as functional Magnetic Resonance Imaging (fMRI), and psychophysiological technologies such as electrocardiogram (ECG) and eye tracking to capture objective data directly from the human brain and body [335].[13] Dimoka and Davis [338] contend that "by directly asking the brain, not the person, functional neuroimaging tools allow an objective, reliable and unbiased measurement of thoughts, beliefs, and feeling and link them to human choices, decisions, and behaviour." The efficacy of adopting a NeuroIS-based approach has been demonstrated across several novel domains within recent years by scholars such as Benbasat et al. [341],[14] Casado-Aranda et al. [342–344],[15] and Venkatraman et al. [345]. Critically, researchers have also recognised the potential to develop a deeper understanding of human response to climate change and sustainable technologies through neuroscience [346,347]. Acknowledging this trajectory and reflecting the resonance between NeuroIS and the integrated framework depicted in Fig. 3, researchers may leverage tools from the neurosciences – with the requisite guidance and training from specialists – to advance cross-disciplinary evidence on the innovation-decision process for hydrogen homes.

Ahead of the UK government taking a strategic decision on whether homes should play a part in the country's energy future, researchers can seek to better understand the neural, psychological, and emotional signatures underlying domestic hydrogen acceptance and adoption. As a complementary method to qualitative techniques and quantitative modelling [348], implementing a neuroscience for hydrogen systems ('NeuroH2') approach can help address a question that has yet to be asked social scientists, namely, where does (hydrogen) energy technology acceptance reside in the brain and body? Net-zero stakeholders should increasingly support the formation of transdisciplinary research teams to tackle this question, in view of wider implications for advancing a national hydrogen economy and accelerating the energy transition.

[13] See Table 1 in Dimoka et al. [335] for a list of commonly used neuro-psychological tools.

[14] Demonstrating how ethnicity and gender shape consumer preferences in technology-mediated environments.

[15] Showing how trust signals differ between users in an online purchasing environment, and how neural aversive biases may exist towards product labelling.

CRediT authorship contribution statement

Joel A. Gordon: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nazmiye Balta-Ozkan:** Supervision, Project administration, Funding acquisition, Conceptualization. **Anwar Ul Haq:** Supervision, Methodology, Investigation, Conceptualization. **Seyed Ali Nabavi:** Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Joel A. Gordon reports financial support was provided by Engineering and Physical Sciences Research Council in partnership with Cadent Gas Ltd. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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