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Trigger my motivations and remove my barriers: Latent class analyses of homeowners' perception about home energy retrofit

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A B S T R A C T

The effectiveness of interventions promoting household energy-efficiency investments depends on the diversity of the target audience. In the context of home energy retrofit, where decision-making is complex and influenced by multiple market and behavioural failures, few studies have rigorously analysed real-world homeowner attitudes and behaviours that enable meaningful policy implications. This study addresses this gap by applying model-based 3-step latent class analyses (LCA) to a sample of 1,011 Dutch homeowners with actual retrofit experience, focusing particularly on various motivations and barriers of home energy retrofit. Five motivation segments and three barrier segments are identified, separately. The motivation segments include *balanced motivation homeowners* (26.7 %), *individual utility maximisers* (6.8 %), *immediate utility seekers* (14.7 %), *environmental and immediate utility maximisers* (6.3 %), and the *environmental-financial sensitive majority* (45.4 %). The barrier segments are labelled as *balanced financial and feasibility barriers* (72.3 %), *lack of demand* (24.3 %), and *prominent non-financial barriers* (3.4 %). Both segmentation solutions demonstrate high classification accuracy and meaningful substantive interpretation. Furthermore, the segments for motivations and barriers show only marginal correlations, offering complementary insights. The findings enhance the understanding of homeowner heterogeneity in the energy retrofit market and support the design of more targeted incentives, information, and de-hassling programmes.

1. Introduction

The effectiveness of policy interventions aimed at encouraging household energy-efficiency investments is subject to the diverse needs and preferences of the target audience. For example, Allcott et al. (2015) showed empirically that energy efficiency subsidies – designed to address market failures such as credit constraints, the landlord-tenant problem, and environmental externalities – were primarily received by wealthy environmentalist homeowners, rather than by the market segment with the highest distortions. In another case, utility companies can identify households likely to have energy-inefficient air conditioners based on their energy-using data, thereby providing information about new energy-efficient models to these targeted households (Allcott and Greenstone, 2012). As these examples suggest, it is important for market and policy interventions to effectively target audiences who are most in need of support and who are subject to relevant market and behavioural failures. The precision with which an intervention targets specific audiences can ultimately determine its effectiveness in terms of energy savings, cost-effectiveness, and social welfare gains (Allcott, 2017; Gillingham et al., 2018).

Recognising the diversity in consumer demand, marketing research has applied segmentation as an alternative marketing strategy to the generalised marketing approach (Smith, 1956). Market segmentation assumes that a heterogeneous market can be disaggregated into several smaller homogeneous markets with consumers having precise demands and specific preferences for products (Smith, 1956). Furthermore, it complements the investigation of individual-level heterogeneity by providing an understanding of the size and characteristics of different audiences (Füchslin, 2019; Kácha et al., 2022). More recently, social marketers have also applied segmentation to inform diversified market and policy interventions that promote socially beneficial behaviours (Gray and Bean, 2011; Grier and Bryant, 2005). Following previous

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research in both marketing and political spheres, we use the term 'segmentation' to refer to the practice of identifying relatively homogeneous and mutually exclusive classes [1] (Hine et al., 2014; Smith, 1956).

Segmentation can be conducted based on multiple factors such as values, behaviours, attitudes, and external constraints (e.g., Kácha et al., 2022; Llorca et al., 2020; Rhead et al., 2018; Thomas et al., 2020). In the home energy retrofit market, where decision-making is complex and various market and behavioural failures must be addressed, the challenge in conducting segmentation lies in selecting factors that enable meaningful implications.

In terms of the complexity of decision-making, the process of home energy retrofit is often considered a multi-stage activity, including the pre-decision stage (e.g., acquiring information), the decision-making stage (e.g., deciding which retrofit measures to take and how to implement them), and the post-decision stage (e.g., implementing and experiencing the retrofit) (Broers et al., 2019; Ebrahimigharehbaghi et al., 2020; Klöckner and Nayum, 2016). Each of these stages is subject to multiple influencing factors such as financial factors, social factors, pro-environmental values, personal background, and external developments (Broers et al., 2019).

Considering practical value of the segmentation, the selected factors should be targetable and meaningful for market and policy interventions. Interventions to facilitate home energy retrofit often follow a personal approach, which involves intensive interaction with professionals. In the Netherlands, local authorities have implemented programmes to perform a free home energy scan, followed by a personalised report providing information on potential energy-efficiency measures (Ebrahimigharehbaghi et al., 2022a). As a second example, one-stop shops are emerging in many countries, offering integrated retrofitting solutions, helping secure financial solutions, and providing guidance throughout the process (Bertoldi et al., 2021). Bearing this personal approach in mind, a practically useful segmentation should be based on factors that are attainable through interpersonal interactions such as during an energy scan or consultation.

To account for the complexity of home energy retrofit decisions while obtaining viable and practically useful segmentation, this study focuses on homeowners' perceived motivations and barriers as the primary segmentation factors. These motivations and barriers directly reflect the underlying drivers and constraints shaping retrofit behaviours across different stages—from pre-decision information acquisition to post-decision implementation. Furthermore, these perceptions are attainable during interpersonal interactions between homeowners and professionals, making them highly actionable targets for market and policy interventions.

The segmentation in this study is based on a sample of 1,011 Dutch homeowners who had personal experiences with home energy retrofit. Although segmentation studies are effectively data driven and exploratory, we made efforts to minimise researcher bias and increase replicability by means of carefully performing model-based latent class analyses (LCAs) and determining the number of segments based on quantitative and qualitative criteria. We identified five segments for homeowners' energy retrofit motivations: *balanced motivation homeowners* (26.7 %), *individual utility maximisers* (6.8 %), *immediate utility seekers* (14.7 %), *environmental and immediate utility maximisers* (6.3 %), and the *environmental-financial sensitive majority* (45.4 %). In addition, three latent classes were identified for homeowners' energy retrofit barriers: *balanced financial and feasibility barriers* (72.3 %), *lack of demand* (24.3 %), and *prominent non-financial barriers* (3.4 %). The identified segments are also described according to socio-demographic characteristics and previous retrofitting behaviours. The segments identified in terms of both motivations and barriers are highly differentiated and provide an informative substantive interpretation. Furthermore, we found that the probabilities of motivation segment membership and barrier segment membership are marginally correlated, suggesting that the segmentation exercises based on motivations and barriers provide complementary implications for market and policy interventions.

This study makes two contributions to the market segmentation literature in the field of residential energy consumption. First, to our knowledge, this study is among the first to examine the segmentation of the real-world home energy retrofit market (e.g., Kerr et al., 2018; Broers et al., 2021) with rigorous data-driven and model-based methods to this market. Second, it enhances the practical utility of segmentation by focusing on factors accessible through real-world, interpersonal intervention channels, thereby offering actionable insights for policy and programme design.

This paper proceeds as follows. Section 2 reviews the literature on segmentation in the context of energy consumption. Section 3 specifies the analytical method and data. The results are presented in Section 4. We discuss the results and implications in Section 5. Section 6 concludes.

2. Market segmentation in the context of energy consumption

In the context of household and individual energy consumption, segmentation studies have contributed to the understanding of heterogeneity in energy consumption patterns (Ben and Steemers, 2018; Ortiz and Bluyssen, 2018; Sütterlin et al., 2011; Tumbaz and Moğulkoç, 2018), energy-saving behaviours (Boudet et al., 2016), energy poverty (Bardazzi et al., 2023; Charlier et al., 2021; Eisfeld and Seebauer, 2022; Robinson et al., 2018), energy performance gap (Charlier, 2021), electric vehicle charging behaviour (Powell et al., 2022), and the decision to change home energy contract (Hall et al., 2021). Based on the segmentation analysis, these studies proposed targeted marketing and policy strategies for identified segments. For example, Hall et al. (2021) identified four consumer segments that differ in the likelihood of changing their home energy contract by conducting a two-stage cluster analysis. The study then investigated preferences for different new utility business model archetypes per household class, which contributes to the discussion of energy market transitions. As an illustration of the relevance of policies, Tumbaz and Moğulkoç (2018) identified four household segments differing in household characteristics, energy consumption patterns, and policy preferences. They suggested that information interventions are preferred by attentive users, who are conscious about their energy efficiency practices, are relatively old, and have lower education levels; whereas another segment of households with relatively high energy efficiency and an average income level is strongly incentivised by reducing their energy bill.

Few studies have investigated homeowner segmentation on home energy retrofit decisions in a real-world setting. Kerr et al. (2018) developed four groups of homeowners in the UK with heterogeneous experiences of home energy retrofit. These groups represent homeowners who are 'organised and seeking greater comfort', 'settled and performing a functional upgrade', 'growing and needing a family home', and '[having] a lot to do and no time like the present'. The study adopted an interview-based, semi-quantitative Q-methodology with a relatively small sample of 40 interviewees. Although this approach allowes for the collection of as many statements about home energy retrofit as possible, it cannot provide information on the share of each segment.

Unlike the above study on an overall upgrade of home energy efficiency, Broers et al. (2021) focused on a specific retrofit measure – photovoltaics. They identified five homeowner segments based on socio-demographic and psychographic variables, including educational or professional background (technical, financial-economic, or neither background) and environmental concern (high versus low). The results show that the perceived complexity and aesthetics of residential photovoltaics, as well as the experiences of taking energy-saving measures at home, differ between segments. However, the homeowner segments

[1] Note that the term 'classes' has also been known as segments (e.g., Hall et al., 2021), clusters (Tumbaz and Moğulkoç, 2018), profiles (e.g., Charlier, 2021), or archetypes (e.g., Ortiz and Bluyssen, 2018) in different studies.

in this study are not determined by data-driven models but are assigned based on pre-defined cut-offs of the criteria.

Several studies investigated heterogeneous consumer preferences in home energy retrofit decisions by means of latent class modelling with data from discrete choice experiments (DCEs) (e.g., Bakaloglou and Belaïd, 2022; Ghasemi et al., 2022; Petrovich et al., 2019). This strand of research differs from the current study in two main aspects. First, latent class modelling with DCEs primarily focuses on heterogeneous preferences for certain attributes of a specific home energy retrofit measure (e.g., the cost and colour of solar panels), whereas the current study focuses on a broader range of attitudinal factors and multiple energy-efficient measures. Second, retrofit decisions are hypothetical in DCEs, but real in the current study.

In sum, segmentation research helps understand the heterogeneity in the energy consumption pattern and can inform market and policy interventions. However, limited knowledge has been gained about the segmentation of the home energy retrofit market in a real market setup with rigorous modelling approaches. This study fills the knowledge gap by rigorously adopting the data-driven LCA while accounting for a wide range of attitudinal factors underlying the retrofitting decision process, and with a sample of homeowners with real retrofitting experiences.

3. Methods

3.1. Dutch household survey and the sample

The main purpose of this study is to identify homeowner segments that demonstrate different patterns in perceived motivations and barriers for home energy retrofit. For this purpose, the study draws on data from an online survey among Dutch homeowners conducted in May 2022. The survey consisted of a broad set of questions on homeowners' behaviours and opinions related to maintaining their homes and implementing energy-efficient measures. The analysis of this study used a subset of these survey questions, including perceived motivations and barriers to undertaking home energy retrofit, previous experiences of implementing retrofit measures, as well as socio-demographic and dwelling characteristics.

The perceived motivations for (reasons for, RF) home energy retrofit were measured with the question 'What were the main reasons for you to implement sustainable measures?'[2] Participants were asked to choose up to three reasons (motivations) from 12 alternative statements. These statements covered different aspects of the motivations underlying homeowners' retrofitting decisions, including financial, hedonic, environmental, practical, and social motivations, which were developed based on insights from the literature as well as our previous qualitative study (Ebrahimigharehbaghi et al., 2022b). These motivation statements are summarised in Table 1. Specifically, financial motivations included saving energy costs, investing in the home, and acquiring a subsidy. Hedonic motivations consisted of the pursuit of home comfort, visual beauty, and enjoyment of the application of new techniques. Environmental motivation was defined by decreasing CO_2 emissions through energy conservation, thus saving the environment. Practical motivations included generating domestic energy to achieve home energy independence, as well as combining the implementation of energy retrofit measures with other (necessary) measures. Lastly, social motivations considered interactions with other people.

Similarly, respondents were asked to select up to three barriers to (reasons against, RA) implementing home energy retrofit from 14 alternatives statements. The survey question was 'What are the main reasons for you to not (yet) implement sustainable measures'. These barrier statements are specified in Table 2. The statements captured five aspects of potential barriers to undertaking retrofit measures: 1) the financial barrier suggested affordability; 2) the transaction cost, in this context, referred to the hidden non-financial costs throughout the life-cycle of home energy retrofit projects (Kiss, 2016; Mundaca T et al., 2013), which included the lack of time and the hassles related to implementing retrofit measures; 3) the practical barrier covered the perceived feasibility related to one's own home and the technology, including the lack of demand to further improve energy efficiency, the

Table 1
The survey question on perceived motivations for implementing home energy retrofit.

Items	Indicator variable
What were the main reasons for you to implement sustainable measures? Choose up to 3 statements.	
Financial motivation	
It resulted in less energy consumption and therefore a lower energy bill.	RF1
I see it as a good investment, for example for the value of my home.	RF2
I was able to get a subsidy for implementing this measure.	RF3
Hedonic motivation	
It provided increased comfort: it now gets warm faster or better indoors, stays cooler in the summer and/or drafts less.	RF4
It made my home more beautiful.	RF5
I like to apply new techniques.	*
Environmental motivation	
It resulted in less energy consumption and therefore lower CO_2 emissions, which is better for the environment.	RF6
Practical motivation	
It ensures that I can generate my own energy and am independent.	RF7
It was easy to combine with other (necessary) measures.	RF8
Social motivation	
I can show it as an example to others, I can inspire people.	*
It was recommended to me by friends/family/colleagues.	*
It was recommended to me by the contractor/supplier.	*

Notes: (1) * denotes items that are not included in the LCA due to the general lack of indication. (2) RF stands for 'reason for'.

Table 2
The survey question on perceived barriers to implementing home energy retrofit.

Items	Indicator variable
What are the main reasons for you to not (yet) implement sustainable measures? Choose up to 3 statements.	
Financial barrier	
I can't afford it.	RA1
Transaction cost	
I don't have enough time for it.	RA2
I don't like the hassle/mess during the installation of the sustainability measures.	RA3
Practical barrier	
My home is already energy efficient.	RA4
My home is not suitable.	RA5
I doubt the benefits of installing sustainability measures.	RA6
I have a negative experience of previously installed measures.	*
External barrier	
I prefer to wait for new developments.	RA7
Other residents do not want to cooperate.	*
I first have to come to an agreement with my neighbours about the installation of sustainability measures.	*
I can't find good information.	*
I can't find a good performance party.	*
Self-ability	
I don't have enough knowledge and skills to apply sustainability measures.	RA8
Installing sustainability measures is too complex for me.	*

Notes: (1) * denotes items that are not included in the LCA due to the general lack of indication. (2) RA stands for 'reason against'.

[2] In the survey questionnaire, sustainable home renovation is defined as 'all measures that ensure physical adjustments to the home that have energy savings as (additional) consequences' such as insulation and solar panels, which is the same with the definition of home energy retrofit in this paper.

home being not suitable, doubts about benefits, and negative past experience; 4) the external barrier referred to the perceived feasibility related to external factors and parties, which included waiting for new developments, non-cooperation of other residents, reaching an agreement with neighbours, and the difficulty in finding good information as well as a good implementer; 5) self-ability considered the lack of knowledge and the complexity of installation. The survey items on barriers were also designed based on the literature and our previous qualitative study (Ebrahimigharehbaghi et al., 2022b).

To understand the probability of each homeowner segment to implement different retrofit measures, we used the survey question on previous experiences about home energy retrofit. Specifically, participants were asked to indicate the measures they had implemented in the past five years from a list of eight measures, including roof insulation, floor insulation, cavity wall insulation, exterior wall insulation, replacement of glass for HR++ or triple glazing, (hybrid) heat pump, solar panels, and solar water heater.

To compare household characteristics between segments, we considered several socio-demographic and dwelling factors. Socio-demographic factors included participants' age, net household monthly income, education level, and household size. In terms of dwelling characteristics, we accounted for the type of dwelling and the energy label reported by the participants.

Data were collected in May 2022 by the *I&O Research Panel*, commissioned by *Milieu Centraal*. A total of 1,738 valid responses were obtained. For the purposes of this study, we focused specifically on homeowners with direct experiences of home energy retrofit, as our aim was to explore their perceptions and behaviours based on actual, rather than hypothetical, experiences. Therefore, we included in our analysis only respondents (N = 1,011) who reported having implemented at least one retrofit measure within the past five years. This purposeful selection was made to ensure that insights into motivations and barriers are grounded in real-world experiences, which is crucial for informing practical policy and market interventions.

All participants were Dutch homeowners. Sample characteristics and a comparison with national statistics are summarised in Table 3. The sample is roughly comparable with national statistics in gender. Furthermore, compared to national statistics, the sample has a larger share of young to middle-aged adults (18–49 years) and a larger share of homeowners aged between 50 and 69 years, and a smaller share of homeowners with medium-level education. Regarding dwelling characteristics, 6.5 % of the respondents resided in an apartment (including ground floor apartment, upstairs apartment, maisonette, gallery, or flat), 45 % lived in a terraced or corner house, and 44 % lived in a detached or semi-detached house. In addition, 18 % of the respondents had homes with an A or A+ label, 31 % had a medium level of home energy efficiency with B/C/D labels, 6.7 % lived in relatively less energy-efficient homes with E/F/G labels, and the remaining 44 % were uncertain about their energy label.

Table 3
Summary of sample characteristics and comparison with national statistics.

The sample (N = 1,011)		National statistics (homeowner) [1]	
Female	46.0 %	Female	49.2 %
Age		Age	
18-29	3.9 %	18-49	48.3 %
30-49	30.0 %		
50-69	51.0 %	50-69	36.9 %
70 and above	15.0 %	70 and above	14.8 %
Household monthly net income			
2,000 euros and below	12.0 %		
2,000–3,000 euros	28.0 %		
3,000–4,000 euros	26.0 %		
4,000–5,000 euros	17.0 %		
5,000 euros and above	17.0 %		
Education		Education	
Below secondary	27.0 %	Below secondary	21.3 %
Secondary	33.0 %	Secondary	43.2 %
Bachelor's degree	20.0 %	Bachelor's degree/Master's degree/PhD degree	35.5 %
Master's degree/PhD degree	20.0 %		
Household size	2.4		
Dwelling type			
Apartment	6.5 %		
Terraced house	45.0 %		
(Semi-)detached house	44.0 %		
Other	3.8 %		
Energy label			
High (A and above)	18.0 %		
Medium (B/C/D)	31.0 %		
Low (E/F/G)	6.7 %		
Unknown	44.0 %		

Notes: (1) Source: Gold Standard 2021 (Gouden Standaard 2021) based on micro data from the Central Bureau of Statistics (Centraal Bureau voor de Statistiek, CBS) of the Netherlands.

3.2. Latent class analysis

LCA is a statistical procedure that can be used to identify unobserved (latent) heterogeneous groups within a population based on patterns of a set of observed variables (also known as manifest variables or indicator variables) (Linzer and Lewis, 2011; Nylund-Gibson and Choi, 2018; Weller et al., 2020). Intuitively, as a person-centred approach, LCA aims to identify groups of individuals who are maximally similar in a set of observed characteristics, while maximizing differences in these characteristics across groups. Furthermore, the decision to perform LCA instead of cluster analysis is because the former is model-based, which enables model evaluation based on statistical indices, and generates probabilities of class membership rather than simple class assignment (Nylund-Gibson and Choi, 2018; Weller et al., 2020). In this study, LCA helps answer the research question: what are the hidden groups among homeowners in terms of their motivations and barriers to undertaking home energy retrofit?

We first decided on the observed indicator variables to be used to identify latent classes. Firstly, according to the behavioural reasoning theory (Westaby, 2005), we expect that latent classes of homeowners in terms of reasons forand reasons against home energy retrofit can be different. In other words, a group of homeowners who demonstrate similar patterns in their motivations for retrofitting may show in-group heterogenous patterns in their perceived barriers to retrofitting. Therefore, we decided to identify latent classes separately for motivations and barriers related to home energy retrofit. Secondly, as shown in Figs. 1 and 2, some of the motivation and barrier statements were less frequently selected by participants, resulting in a low variation between individuals and thus a lack of information for the identification of latent classes (Masyn, 2013). In addition, motivations and barriers that are less frequently indicated can also be less valuable to draw policy implications. Therefore, we only account for the statements indicated by at least 5 % of the participants in the LCAs. As shown in Table 1 and Fig. 1, the motivation statements used as indicator variables are labelled RF1 to RF8. As shown in Table 2 and Fig. 2, the barrier statements used as indicator variables are denoted RA1 to RA8.

Next, an exploratory class enumeration was performed separately for LCAs for motivations and barriers, and a set of criteria was used to determine the optimal number of latent classes. In the class enumeration step, models ranging from one class to eight classes were performed.

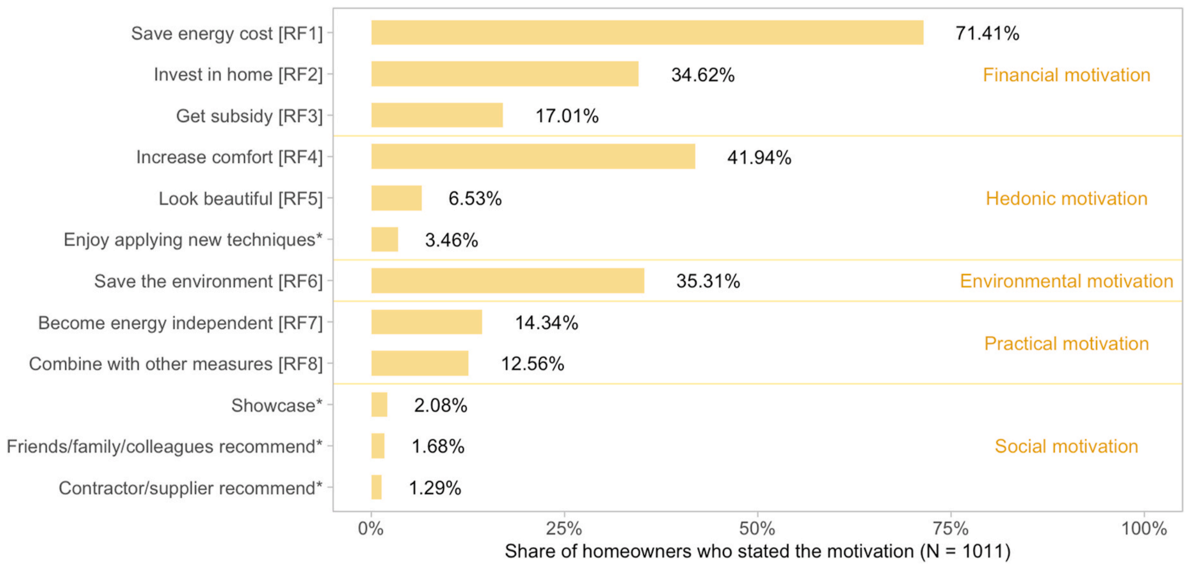

Fig. 1. Percentage of indication of each motivation for implementing home energy retrofit.
(Notes: * denotes items that are not included in the LCA due to the general lack of indication.)

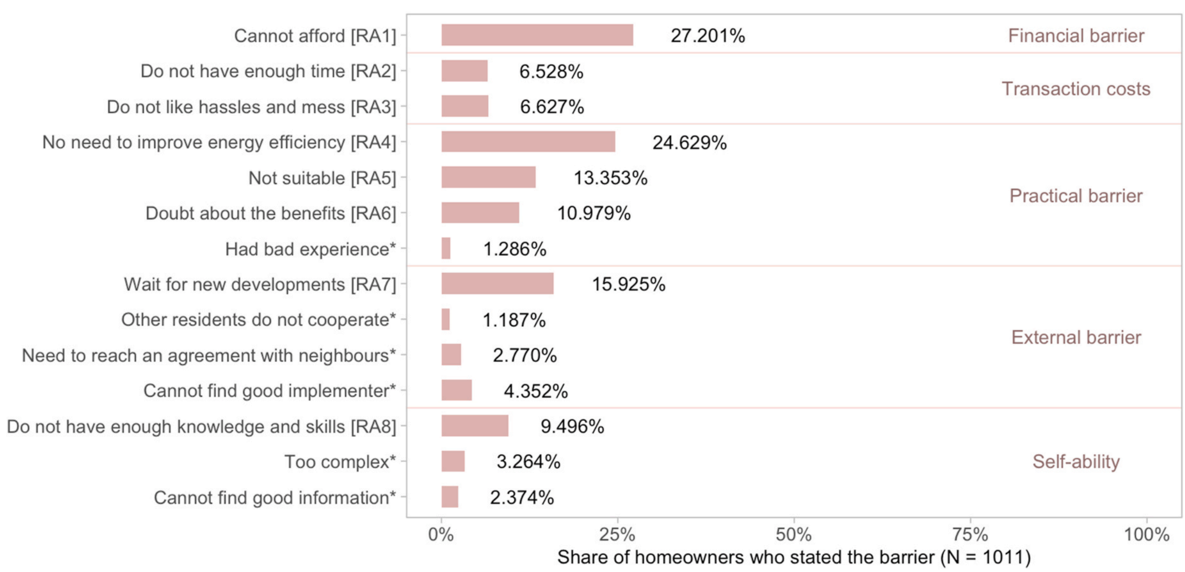

Fig. 2. Percentage of indication of each barrier to implementing home energy retrofit.
(Notes: * denotes items that are not included in the LCA due to the general lack of indication.)

After enumeration, statistical indices, substantive interpretability, and parsimony were considered to determine the final models (Nylund-Gibson and Choi, 2018; Weller et al., 2020).[3] In particular, log-likelihood, Bayesian Information Criterion (BIC), sample-size adjusted BIC (SABIC), Akaike Information Criterion (AIC), consistent AIC (CAIC) (Weller et al., 2020), and Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (VLMR-LRT) (Lo, 2001; Vuong, 1989) were used to evaluate the relative fit of the models. When comparing two nested models, the model with a higher log-likelihood and lower information criteria has a better representation of the data (Masyn, 2013). VLMR-LRT provides a statistical test for the relative fit of a k-class model compared to the model with k-1 classes (Lo, 2001; Vuong, 1989). In addition, the relative entropy is used to evaluate how well the classes are differentiated based on the estimated posterior class probabilities of each individual, which ranges between 0 and 1 (Masyn, 2013). A generally accepted level of relative entropy is above 0.8 (Weller et al., 2020). Where fit statistics suggest multiple plausible solutions, the final model is chosen based on substantive interpretability and parsimony.

Finally, we interpret the segment solutions determined by the above procedure. Furthermore, since we are interested in the association between class membership and previous retrofitting behaviours and household characteristics, following model estimation, we applied 3-step LCAs with distal variables and covariates (Nylund-Gibson et al., 2019). For the analyses of distal outcomes, we included eight binary variables indicating whether each homeowner had implemented a given

[3] It should be noted that model selection in latent class analysis is inherently susceptible to multiple plausible solutions, as different statistical criteria may suggest a different number of classes. Although we mitigated this limitation by combining quantitative fit indices with qualitative interpretability criteria during model selection, some degree of subjectivity remains. Therefore, in addition to the main segmentation results presented in the manuscript, we report alternative solutions in Section A of the Supplementary Information (SI) for reference.

Table 4
Latent class models for energy retrofit motivations with fit indices.

K	Parameters	LL	AIC	BIC	CAIC	SABIC	VLMR-LRT	Entropy	Class sizes
1	8	−4104	8224	8263	8271	8238	/	/	100 %
2	17	−4036	8106	8190	8207	8136	$p < 0.001$	0.629	65 %/35 %
3	26	−4003	8058	8186	8212	8103	$p = 0.037$	0.712	20 %/45 %/35 %
4	35	−3967	8005	8177	8212	8066	$p < 0.001$	0.919	45 %/27 %/7 %/21 %
5	**44**	**−3929**	**7945**	**8162**	**8206**	**8022**	**$p < 0.001$**	**0.956**	6 %/45 %/7 %/15 %/27 %
6	53	−3904	7915	8176	8229	8007	$p < 0.001$	0.861	7 %/6 %/31 %/34 %/14 %/8 %
7	62	−3877	7879	8184	8246	7987	$p = 0.003$	0.937	17 %/21 %/7 %/27 %/5 %/7 %/17 %
8	71	−3856	7855	8204	8275	7979	$p = 0.549$	0.880	11 %/7 %/6 %/21 %/14 %/6 %/17 %/17 %

retrofit measure, including roof insulation, floor insulation, cavity wall insulation, external wall insulation, glazing, heat pump, solar panel, and solar heater. For the analysis of covariates, we assessed associations between latent class membership and the following variables: age, household income, education level, dwelling type, and home energy label.

Class enumeration and 3-step LCAs were performed using *Mplus* (version 8.3 for Mac) with the facilitation of the *MplusAutomation* package in R (Hallquist and Wiley, 2018). For all latent class models performed, we carefully checked for potential convergence issues by following the procedure suggested by Jung and Wickrama (2008).

4. Results

4.1. Latent classes for energy retrofit motivations

We first explored latent class solutions for eight energy retrofit motivations of homeowners. The performance of models with one to eight latent classes was compared according to statistical, substantive interpretability, and parsimony criteria. The statistical indices are presented in Table 4. Models with four or more latent classes have a relative entropy above 0.8. The five-class model has the lowest BIC and CAIC. Although the seven-class model has a better fit according to LL, AIC, and SABIC, and its increased complexity seems to significantly improve the model fit according to the VLMR-LRT, we will focus on interpreting the five-class model considering parsimony.[4]

The homeowners in our sample are grouped into five identified latent classes based on their most likely latent class membership. As shown in Fig. 3, 26.7 %, 6.8 %, 14.7 %, 6.3 %, and 45.4 % of the homeowners in our sample belong to classes 1 to 5, respectively. According to the patterns of item probabilities, the five latent classes are labelled *balanced motivation homeowners* (class 1, 26.7 %), *individual utility maximisers* (class 2, 6.8 %), *immediate utility seekers* (class 3, 14.7 %), *environmental and immediate utility maximisers* (class 4, 6.3 %), and *environmental-financial sensitive majority* (class 5, 45.4 %). In the following, the five latent classes will be described according to the probabilities of each motivation item (Fig. 3), the probabilities of having implemented different retrofit measures (Table 5), and their socio-demographic and dwelling characteristics (Table 6)[5].

The *balanced motivation homeowners* class (class 1) is characterised by a zero probability of identifying the cost-saving motivation, and relatively balanced probabilities across the other seven motivations. In particular, the conditional probabilities of indicating investing in home, getting subsidies, increasing comfort, looking beautiful, saving the environment, becoming energy independent, and combining with other (necessary) measures as a main motivation are 0.363, 0.124, 0.553, 0.127, 0.263, 0.094, and 0.222, respectively. Class 1 is used as the reference class for comparing probabilities of implementing retrofit measures and socio-demographic and dwelling characteristics.

Homeowners belonging to the *individual utility maximisers* class (class 2) are highly homogeneous, with all identifying saving energy costs, investing in their homes, and increasing home comfort as their top three motivations for energy retrofitting. These motivations are directly related to an increase in individual utility in either financial or hedonic forms. Compared to *balanced motivation homeowners* (class 1), *individual utility maximisers* are more likely to have previously implemented floor insulation, cavity wall insulation, and solar panels. The socio-demographic and dwelling characteristics of class 2 do not differ significantly from those of class 1.

Similar to class 2, *immediate utility seekers* (class 3) also identify saving energy costs and increasing home comfort as their main motivations. The difference between classes 2 and 3 lies in that *immediate utility seekers* seem to care less about the long-term investment in their homes. Instead, a third main motivation identified by homeowners of class 3 is distributed across several other relatively instant benefits of home energy retrofit, including acquiring subsidies, increasing visual beauty, generating domestic energy to be able to become energy independent, and combining with other (necessary) measures. The conditional probabilities of these motivations are 0.208, 0.121, 0.154, and 0.195, respectively. Compared to *balanced motivation homeowners* (class 1), a larger share of the *immediate utility seekers* has previously implemented roof insulation, cavity wall insulation, and solar panels. Homeowners who are older (compared to young homeowners of 29 years or younger), live in a (semi-)detached house (compared to an apartment and a terraced house), and have an energy label of B/C/D (compared to E/F/G) have a higher probability of seeking immediate utilities than having balanced motivations.

The *environmental and immediate utility maximisers* class (class 4) is also highly homogeneous in perceived motivation. Similar to classes 2 and 3, homeowners in this class are highly motivated by immediate individual utilities of saving energy costs and increasing home comfort. Differently, class 4 has a probability of 1 in identifying the motivation to save the environment. In terms of retrofitting behaviours, *environmental and immediate utility maximisers* are more likely to have implemented cavity wall insulation and solar panels compared to *balanced motivation homeowners*. Homeowners who have a Bachelor's or higher degree, compared to those with below-secondary education, are more likely to belong to class 4 than class 1.

Finally, the largest identified latent class is the *environmental-financial sensitive majority* (class 5). This class is characterised by relatively high probabilities of indicating the three financial motivations (0.932, 0.398, and 0.231) and the environmental motivation (0.478). However, homeowners in this class are not motivated by an increase in home comfort. Moreover, the probability of identifying the motivation to generate domestic energy to become energy independent is the highest (0.208) among all five latent classes. This energy independence motivation may lead to a high probability of 0.867 in installing solar panels of this class. However, homeowners in this class are less likely to have implemented insulation measures (including the insulation of roof, floor, cavity wall, external wall, and window) compared to *balanced*

[4] An item probability graph for the 7-class model can be found in Section A, SI.

[5] See Table C1, SI, for mean socio-demographic and dwelling characteristics per motivation latent class

[6] Item probabilities for motivation latent classes are summarised in Table B1, SI

motivation homeowners. In terms of household characteristics, homeowners living in an apartment compared to those living in a (semi-)detached house are less likely to be the environmental-financial sensitive type than have balanced motivations. Also, compared to homeowners living in an energy-inefficient house with a label E/F/G, those who have an energy label of medium to high efficiency are more likely to be in class 5 than in class 1.

4.2. Latent classes for energy retrofit barriers

Next, we turn to explore latent class solutions for energy retrofit barriers of homeowners. As shown in Table 7, both two-class and three-class models have an above 0.8 relative entropy, and significantly improve the model with one less class according to VLMR-LRT. The two-class model has relatively low BIC and CAIC, whereas the three-class model has a better fit according to LL, AIC, and SABIC. We examined the substantive interpretability of two-class versus three-class models based on item probabilities by latent classes, and found that the three-class model separated one more latent class (class 2) with meaningful patterns. Therefore, the three-class model was identified as the optimal solution for energy retrofit barriers.[7]

The LCA for energy retrofit barriers is independent of the analysis for motivations. This means that, regardless of the motivation latent classes to which homeowners in the sample belong, they are regrouped into three latent classes based on their most likely latent class membership for energy retrofit barriers. As shown in Fig. 4, 72.3 %, 24.3 %, and 3.4 % of the sample belong to classes 1, 2, and 3, respectively. According to the patterns of item probabilities, the three latent classes are labelled *balanced financial and feasibility barriers* (class 1, 72.3 %), *lack of demand* (class 2, 24.3 %), and *prominent non-financial barriers* (class 3, 3.4 %). In

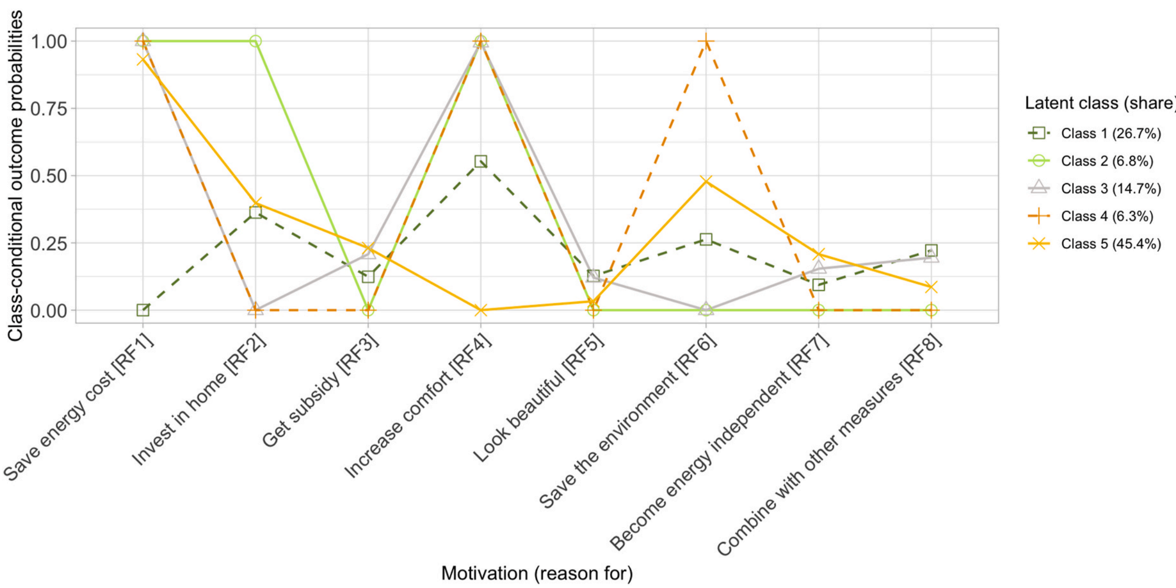

Fig. 3. Item probabilities for latent classes for energy retrofit motivations.[6].

Table 5
Estimated probabilities of implementing retrofit measures by latent classes for energy retrofit motivations.

	Class 1 *Balanced motivation homeowners (Reference)*	Class 2 *Individual utility maximisers*	Class 3 *Immediate utility seekers*	Class 4 *Env. and immediate utility maximisers*	Class 5 *Env.-fin. sensitive majority*
	N = 270	N = 69	N = 149	N = 64	N = 459
Roof insulation	0.265	0.362	0.378*	0.375	0.108***
	(0.030)	(0.058)	(0.039)	(0.061)	(0.017)
Floor insulation	0.294	0.435*	0.330	0.359	0.138***
	(0.032)	(0.060)	(0.038)	(0.360)	(0.018)
Cavity wall insulation	0.196	0.333*	0.383***	0.375**	0.089**
	(0.027)	(0.057)	(0.040)	(0.061)	(0.015)
External wall insulation	0.161	0.217	0.168	0.141	0.047***
	(0.026)	(0.050)	(0.031)	(0.043)	(0.012)
Glazing	0.621	0.667	0.558	0.531	0.229***
	(0.036)	(0.057)	(0.040)	(0.062)	(0.022)
Heat pump	0.034	0.072	0.034	0.062	0.059
	(0.014)	(0.031)	(0.015)	(0.030)	(0.012)
Solar panel	0.280	0.536***	0.420**	0.469**	0.887***
	(0.034)	(0.060)	(0.039)	(0.062)	(0.018)
Solar heater	0.011	0.014	0.007	0.000	0.030
	(0.011)	(0.014)	(0.007)	(0.000)	(0.009)

Notes: (1) Results were estimated with 3-step LCAs with different retrofit measure as distal variables. The Lanza's method for categorical distal variables was used. (2) Standard errors are in parentheses. (3) *, **, and *** denote $p < 0.05$, $p < 0.01$, $p < 0.001$, respectively.

[7] An item probability graph for the 2-class model can be found in Section A, SI.

Table 6
The relationship between latent classes for motivations and household characteristics.

	Class 1 *Balanced motivation homeowners* (Reference)	Class 2 *Individual utility maximisers*	Class 3 *Immediate utility seekers*	Class 4 *Env. and immediate utility maximisers*	Class 5 *Env.-fin. sensitive majority*
	N = 270	N = 69	N = 149	N = 64	N = 459
Age (Baseline: 18–29)					
30-49		1.630 [0.436, 6.091]	**4.890 [1.074, 22.267]**	1.290 [0.340, 4.899]	1.805 [0.791, 4.120]
50-69	/	1.356 [0.368, 4.998]	**5.303 [1.180, 23.823]**	1.404 [0.382, 5.167]	**2.788 [1.247, 6.232]**
70 and above		1.950 [0.490, 7.759]	**5.433 [1.147, 25.744]**	1.811 [0.452, 7.260]	1.852 [0.768, 4.469]
Net household monthly income (Baseline: 2000 euros and below)					
2000–3000 euros		1.525 [0.591, 3.938]	1.507 [0.762, 2.980]	1.601 [0.585, 4.380]	1.304 [0.755, 2.254]
3000–4000 euros	/	2.077 [0.795, 5.428]	1.283 [0.617, 2.668]	2.059 [0.740, 5.734]	**2.017 [1.146, 3.552]**
4000–5000 euros		1.934 [0.701, 5.334]	1.308 [0.603, 2.837]	1.773 [0.594, 5.291]	1.656 [0.904, 3.034]
5000 euros and above		1.179 [0.387, 3.592]	1.881 [0.888, 3.981]	2.063 [0.698, 6.093]	1.573 [0.849, 2.913]
Education (Baseline: below secondary)					
Secondary		1.441 [0.717, 2.894]	0.973 [0.578, 1.639]	1.552 [0.695, 3.467]	1.045 [0.685, 1.595]
Bachelor's degree	/	1.666 [0.753, 3.689]	0.930 [0.494, 1.752]	**2.424 [1.025, 5.731]**	1.287 [0.783, 2.116]
Master's degree/PhD degree		1.095 [0.452, 2.651]	1.345 [0.736, 2.457]	**2.708 [1.151, 6.374]**	1.414 [0.856, 2.334]
Dwelling type (Reference: (semi-)detached house)					
Apartment		0.574 [0.202, 1.627]	**0.438 [0.199, 0.963]**	0.605 [0.192, 1.910]	**0.266 [0.133, 0.532]**
Terraced house	/	0.895 [0.504, 1.589]	**0.559 [0.356, 0.876]**	1.322 [0.726, 2.409]	0.750 [0.524, 1.074]
Other		0.905 [0.175, 4.689]	1.554 [0.537, 4.499]	0.596 [0.069, 5.176]	1.094 [0.409, 2.926]
Energy label (Baseline: Low (E/F/G))					
Medium (B/C/D)		1.246 [0.451, 3.438]	**2.575 [1.124, 5.898]**	3.115 [0.868, 11.177]	**2.320 [1.171, 4.596]**
High (A and above)	/	1.176 [0.371, 3.734]	1.568 [0.605, 4.065]	1.307 [0.285, 5.987]	**4.262 [2.035, 8.925]**
Unknown		1.451 [0.552, 3.814]	1.707 [0.752, 3.874]	2.646 [0.751, 9.320]	**2.522 [1.303, 4.881]**

Notes: (1) Results were estimated with multinomial logistic regressions using the 3-step LCA procedure with the socio-demographic and dwelling characteristics as covariates. The 3-step LCA was conducted separately for each socio-demographic and dwelling characteristic. (2) Estimates of odds ratios are presented. 95 % confidence intervals of odds ratios are in square brackets. (3) Bold text denotes $p < 0.05$.

the following, the characteristics of the three classes will be described according to the probabilities of each barrier item (Fig. 4), the probabilities of having implemented different retrofit measures (Table 8), and socio-demographic and dwelling characteristics (Table 9)[8].

Specifically, the majority of homeowners in our sample belongs to the *balanced financial and feasibility barriers class* (class 1). This class demonstrates balanced probabilities to indicate financial, practical, and external barriers. In particular, the probabilities of indicating financial affordability (0.336) and practical suitability (0.167) are relatively high compared to the other classes.

The *lack of demand* class (class 2) is characterised by a probability of 1 in reporting a lack of need to improve energy efficiency as one of the main barriers to implementing retrofit measures. Compared to the class with *balanced financial and feasibility barriers* (class 1), homeowners in the *lack of demand* class have a lower probability of having implemented glazing, but a higher probability of installing solar panels. Homeowners living in houses with a medium to high energy efficiency (energy label class D and above) are more likely to belong to the *lack of demand* class (class 2) than belonging to the *balanced financial and feasibility barriers* class (class 1).

Homeowners in class 3 demonstrate *prominent non-financial barriers*. In this class, the probabilities of transaction cost items are relatively high, with a probability of 0.233 for indicating the lack of time and 0.339 for the dislike of hassles and mess, respectively. Furthermore, this class is also prominent in indicating the lack of knowledge and skills as a major barrier with a probability of 0.787. Affordability and suitability are less of a concern for homeowners in this class with probabilities of 0. Compared to the class with *balanced financial and feasibility barriers* (class 1), the prominent non-financial barriers class has significantly lower probabilities of implementing several retrofitting measures, including insulation measures (including roof, floor, and window) and heat pump. The socio-demographic and dwelling characteristics of homeowners belonging to class 3 do not significantly differ from those of class 1.

[8] See Table C2, SI, for mean socio-demographic and dwelling characteristics per barrier latent class

[9] Item probabilities for barrier latent classes are summarised in Table B2, SI.

Table 7
Latent class models for energy retrofit barriers with fit indices.

K	Parameters	LL	AIC	BIC	CAIC	SABIC	VLMR-LRT	Entropy	Class sizes
1	8	−3154	6325	6364	6372	6339	/	/	100 %
2	17	−3108	6249	6333	6350	6279	p < 0.001	1.000	75 %/25 %
3	**26**	**−3089**	**6231**	**6359**	**6385**	**6276**	**p = 0.025**	**0.922**	72 %/24 %/3 %
4	35	−3076	6222	6394	6429	6283	p = 0.104	0.650	53 %/24 %/14 %/9 %
5	44	−3065	6218	6435	6479	6295	p = 0.093	0.680	62 %/24 %/7 %/4 %/3 %
6	53	−3056	6218	6479	6532	6311	p = 0.115	0.694	58 %/24 %/6 %/6 %/4 %/2 %
7	62	−3049	6222	6527	6589	6331	p = 0.110	0.818	50 %/21 %/7 %/7 %/6 %/6 %/3 %
8	71	−3044	6230	6579	6650	6353	p = 0.298	0.706	51 %/20 %/7 %/6 %/6 %/6 %/3 %/1 %

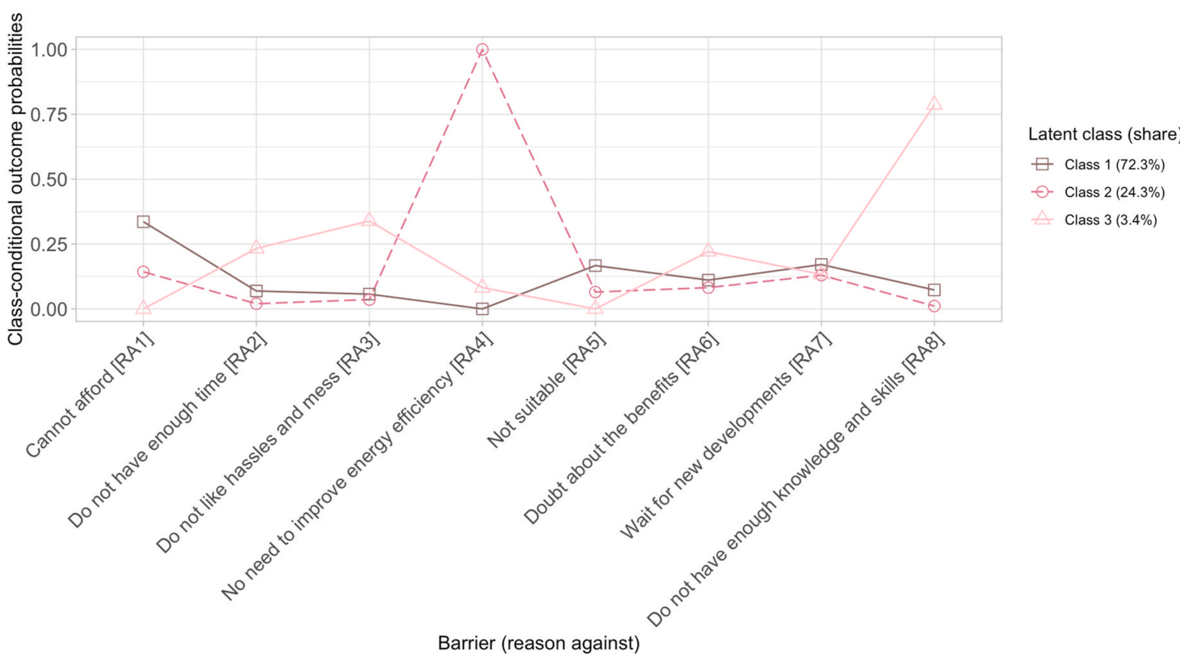

Fig. 4. Item probabilities for latent classes for energy retrofit barriers.[9]

Table 8
Probabilities of implementing retrofit measures by latent classes for energy retrofit barriers.

	Class 1 *Balanced fin. and feasibility barriers* (Reference)	Class 2 *Lack of demand*	Class 3 *Prominent non-fin. barriers*
	N = 731	N = 246	N = 34
Roof insulation	0.239	0.230	0.000***
	(0.016)	(0.027)	(0.000)
Floor insulation	0.254	0.233	0.087^{+}
	(0.018)	(0.027)	(0.090)
Cavity wall insulation	0.186	0.207	0.257
	(0.015)	(0.026)	(0.098)
External wall insulation	0.122	0.094	0.060
	(0.013)	(0.019)	(0.059)
Glazing	0.457	0.368*	0.266^{+}
	(0.020)	(0.031)	(0.091)
Heat pump	0.046	0.073	0.000***
	(0.008)	0.017	(0.000)
Solar panel	0.550	0.785***	0.668
	(0.020)	(0.026)	(0.101)
Solar heater	0.015	0.033	0.010
	(0.005)	(0.011)	(0.043)

Notes: (1) Results were estimated with 3-step LCAs with different retrofit measure as distal variables. The Lanza's method for categorical distal variables was used. (2) Standard errors are in parentheses. (3) $^{+}$, *, **, and *** denote $p < 0.1$, $p < 0.05$, $p < 0.01$, $p < 0.001$, respectively.

4.3. Linking latent classes for energy retrofit motivations and barriers

In Sections 4.1 and 4.2, we identified latent classes for homeowners' perceived motivations and barriers to undertaking home energy retrofit, respectively. Both segmentations for motivations and barriers show a high relative entropy above 0.9, indicating strong classification accuracy (Celeux and Soromenho, 1996; Weller et al., 2020). Additionally, both segmentation solutions provide meaningful substantive interpretations.

Our decision to perform LCA separately for perceived motivations and perceived barriers was based on the behavioural reasoning theory, which posits that reasons for and reasons against adopting innovative technologies influence individual decision-making in dissimilar ways (Claudy et al., 2015; Westaby, 2005; Yadav et al., 2022). Therefore, we assumed that individuals with the similar patterns of perceived motivations may exhibit different patterns of perceived barriers. To examine this assumption, we investigated the correlation of posterior probabilities for motivation and barrier latent classes. Model-based LCA allows us to calculate the probabilities of belonging to each latent class for every observation. Pearson's correlation tests were conducted based on the posterior probabilities, and the results are presented in Fig. 5.

Overall, the association between motivation and barrier segmentations is modest (X^2 (8, N = 1,011) = 21.616, p = 0.006, Cramer's V = 0.103). Motivations classes 2, 3, and 4 show no significant correlations with any barrier class. Yet, motivation class 1 (*balanced motivation homeowners*) is weakly positively correlated with barrier class 1 (*balanced financial and feasibility barriers class*) (r(1009) = 0.107, p <

Table 9
The relationship between latent classes for barriers and household characteristics.

	Class 1 *Balanced fin. and feasibility barriers* (Reference)	Class 2 *Lack of demand*	Class 3 *Prominent non-fin. barriers*
	N = 731	N = 246	N = 34
Age (Reference: 18–29)			
30-49		1.116 [0.477, 2.611]	0.184 [0.014, 2.363]
50-69	/	1.238 [0.539, 2.847]	0.880 [0.133, 5.812]
70 and above		1.309 [0.541, 3.169]	0.413 [0.040, 4.307]
Net household monthly income (Reference: 2000 euros and below)			
2000–3000 euros		0.914 [0.537, 1.555]	0.623 [0.101, 3.852]
3000–4000 euros	/	1.071 [0.629, 1.823]	0.747 [0.125, 4.447]
4000–5000 euros		1.407 [0.803, 2.465]	1.437 [0.261, 7.903]
5000 euros and above		**1.892 [1.079, 3.317]**	2.385 [0.470, 12.101]
Education (Reference: below secondary)			
Secondary		1.050 [0.713, 1.545]	3.041 [0.697, 13.279]
Bachelor's degree	/	1.073 [0.695, 1.657]	1.266 [0.191, 8.404]
Master's/PhD degree		1.205 [0.785, 1.848]	2.059 [0.385, 10.999]
Dwelling type (Reference: (semi-)detached house)			
Apartment		0.623 [0.321, 1.208]	0.000 [0.000, 0.000]
Terraced house	/	1.047 [0.769, 1.424]	1.771/ [0.664, 4.726]
Other		0.339 [0.116, 0.992]	0.660 [0.025, 17.160]
Energy label (Reference: Low (E/F/G))			
Medium (B/C/D)		**2.799 [1.143, 6.858]**	0.790 [0.067, 9.320]
High (A and above)	/	**11.084 [4.482, 27.410]**	1.516 [0.117, 19.699]
Unknown		2.391 [0.983, 5.817]	2.281 [0.251, 20.702]

Notes: (1) Results were estimated with multinomial logistic regressions using the 3-step LCA procedure with the socio-demographic and dwelling characteristics as covariates. The 3-step LCA was conducted separately for each socio-demographic and dwelling characteristic. (2) Estimates of odds ratios are presented. 95 % confidence intervals of odds ratios are in square brackets. (3) Bold text denotes $p < 0.05$.

0.001) and weakly negatively correlated with barrier class 2 (*lack of demand class*) ($r(1009) = -0.106$, $p < 0.001$). This suggests that homeowners with a balanced mix of financial, practical and external motivations tend to perceive a corresponding mix of barriers and are less likely to feel a lack of need to retrofit. In contrast, motivation class 5

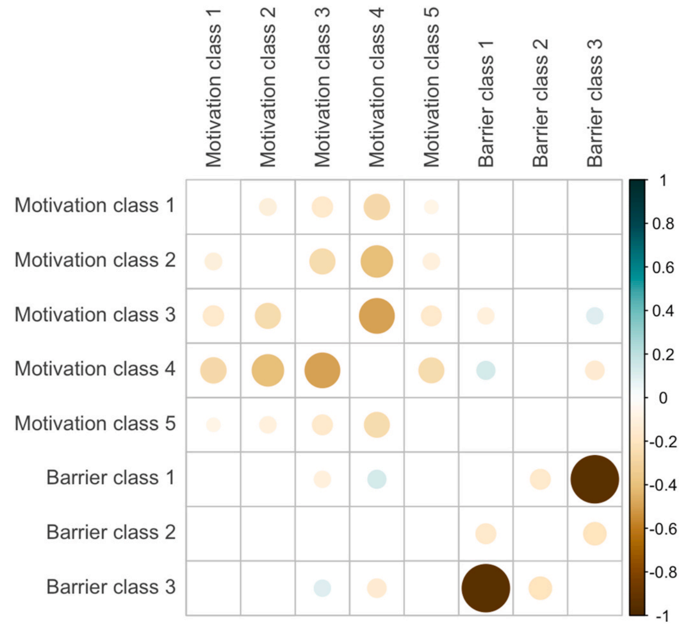

Fig. 5. Correlation of posterior probabilities for motivation and barrier latent classes.
(Notes: Blank cells indicate a statistically insignificant correlation. The areas of circles and the colour intensity are proportional to the correlation coefficients.)

(*environmental-financial sensitive majority*) is weakly negatively correlated with barrier class 1 (*balanced financial and feasibility barriers class*) ($r(1009) = -0.140$, $p < 0.001$) and weakly positively correlated with barrier class 2 (*lack of demand class*) ($r(1009) = 0.133$, $p < 0.001$). Given that these homeowners tend to own relatively energy-efficient homes (as shown in Table 6), they are more likely to indicate a lack of need rather than financial or feasibility concerns.

In sum, the marginal correlations between motivation and barrier class memberships are generally consistent with our theoretical expectation that these two dimensions capture complementary, largely independent aspects of homeowners' retrofit attitudes. To provide intuition, we cross-tabulated the membership of motivation latent classes and barrier latent classes (see Table 10). For example, 11.2 % of homeowners in our sample are motivated by saving energy costs and increasing home comfort (*immediate utility seekers*), while expressing concerns about financial affordability and practical suitability (*financial and feasible barriers* class).

5. Discussion

In Section 4, we identified five latent classes (balanced motivation homeowners, 26.7 %; individual utility maximisers, 6.8 %; immediate utility seekers, 14.7 %; environmental and immediate utility maximisers, 6.3 %; environmental-financial sensitive majority, 45.4 %) and three latent classes (balanced financial and feasibility barriers, 72.3 %; lack of demand, 24.3 %; prominent non-financial barriers, 3.4 %) for energy retrofit motivations and barriers, respectively. Similar to previous studies, saving energy costs is the most important motivation to invest in energy retrofit measures for certain consumer segments (Ghasemi et al., 2022; Tabi et al., 2014). Interestingly, we further found that this strong cost-saving motivation is often coupled with the motivation to increase home comfort, suggesting a preference for immediate individual utilities. Furthermore, for specific classes, the cost-saving motivation can also be coupled with increasing home value and saving the environment. In terms of barriers, the indication of individual barriers is consistent with findings of Wekhof and Houde (2023) that affordability and the lack of demand are major barriers, followed by various non-financial and behavioural barriers. Our analysis further

Table 10
Share of observations per cross-tabulated latent class.

	Class 1 *Balanced fin. and feasibility barriers*	Class 2 *Lack of demand*	Class 3 *Prominent non-fin. barriers*
Class 1 *Balanced motivation homeowners*	21.5 %	4.5 %	0.7 %
Class 2 *Individual utility maximisers*	4.9 %	1.6 %	0.3 %
Class 3 *Immediate utility seekers*	11.2 %	3.2 %	0.4 %
Class 4 *Env. and immediate utility maximisers*	4.9 %	1.2 %	0.2 %
Class 5 *Env. - financial sensitive majority*	29.8 %	13.8 %	1.8 %

suggests that the non-financial and behavioural barriers, including the lack of time, the dislike of hassles and mess, and the lack of knowledge and skills, are likely to jointly hinder energy retrofitting for a small but distinct class of homeowners.

5.1. Implications for targeted interventions

The energy efficiency gap, which describes the slower-than-optional diffusion of energy-efficient technologies (Gillingham and Palmery, 2014; Jaffe and Stavins, 1994), is a main focus of energy policies. Many market failures and behavioural biases contribute to the energy efficiency gap (Gillingham et al., 2009; Gillingham and Palmery, 2014), posing challenges for the implementation of the first-best policy portfolio (Fischer et al., 2021). For example, information disclosure on energy performance cannot fully address imperfect information when consumers are inattentive to energy efficiency. In such cases, policymakers, in a second-best world, can resort to adjusting an existing policy instrument to account for multiple market failures and behavioural biases (Fischer et al., 2021), or deploy multiple policy instruments to tackle a specific issue (Bennear and Stavins, 2007). By understanding homeowner segmentation in terms of motivations and barriers to energy retrofitting, we explore potential market and policy interventions to target specific homeowner segments, with the overall goal of enhancing the effectiveness and efficiency of demand-side interventions. Examples of potential interventions are provided in Table 11.

Table 11
Potential interventions targeting each homeowner segment.

Homeowner segment	Potential intervention
Balanced motivation homeowners	Provide a mixture of information on short-term and long-term, financial and non-financial benefits.
Individual utility maximisers	Provide clear information on expected energy cost savings, potential increase in house value, and comfort improvement; minimise emphasis on environmental information to avoid cognitive overload.
Immediate utility seekers	Target insulation measures; highlight immediate personal benefits such as cost savings and improved comfort
Environmental and immediate utility maximisers	Target solar panels; increase awareness of the financial and environmental benefits of insulation measures.
Environmental-financial sensitive majority	Provide salient cost-saving information combined with communication on the emission reduction potential of retrofit measures.
Balanced financial and feasibility barriers	Offer financial incentives (e.g., subsidies or loans); provide personalised information about the feasibility of retrofit measures.
Lack of demand	Provide information on the development of energy-efficient technologies and customised retrofit suggestions.
Prominent non-fin. barriers	Implement de-hassling interventions, such as one-stop shops and personal energy coaches, to reduce transaction costs and complexity.

The homeowner segmentation for energy retrofit motivations can primarily inform information programmes. All homeowners in our sample had experience with home energy retrofit, therefore, we assume that they were generally aware of the benefits of implementing retrofit measures and paid varying levels of attention to each potential benefit. For these homeowners who have formed awareness, information programmes can be designed to increase the salience of the benefits of interest. For example, for *individual utility maximisers*, providing salient information on expected energy cost savings, the potential increase in house value by upgrading the energy label, and the improvement of home comfort while reducing information on environmental benefits can be the most efficient information disclosure strategy. This targeted and salient information can effectively address potential market failure of imperfect information while avoiding cognitive overload (Frederiks et al., 2015). Furthermore, social marketing interventions can be designed to promote specific retrofit measures to a target segment. In our sample, among all segments, *environmental-financial sensitive homeowners* are most interested in installing solar panels. This may be due to a specific preference for generating domestic electricity or a lack of awareness of the financial and environmental benefits of insulation measures. Although potential causes remain speculative and require further investigation, the specific motivational pattern can be useful for policymakers and practitioners.

For potential adopters who are not yet familiar with home energy retrofit, results from the segmentation of experienced homeowners can inform a more effective structure of information provision to raise awareness of the benefits of implementing retrofit measures. Specifically, homeowners in three segments (*individual utility maximisers*, *immediate utility seekers*, and *environmental and immediate utility maximisers*), accounting for 27.3 % of the sample, indicated a motivation to increase immediate utilities, i.e., saving energy costs and increasing home comfort. In information programmes, highlighting these immediate utilities can efficiently capture attention. In addition, since two large segments of experienced homeowners are sensitive to environmental benefits, information on the emission reduction potential of retrofit measures can be a second piece of information to communicate. In addition, the mainstream segment is also motivated by investing in their homes. Therefore, next to the long-term social benefit of saving the environment, it is equally important to convey the long-term individual benefit of investing in home.

Furthermore, informed by the segmentation solution for energy retrofit barriers, the above information programmes can be complemented by providing additional information and introducing financial instruments. Homeowners in the segment with a *lack of demand* are overall more energy-efficient compared to the segment with *balanced financial and feasibility barriers*, but still a considerable share of homeowners of the former segment have a medium to low energy label (class B or lower, 29.6 %) or are unaware of their energy-efficiency class (32.5 %). Therefore, the perceived lack of demand may stem from imperfect information. For homeowners in this segment, information on the development of energy-efficient technologies and customised retrofit suggestions can complement motivation-triggering information programs.

Other market and policy interventions can support the remaining two segments for energy retrofit barriers. For homeowners with *prominent non-financial barriers*, de-hassling interventions, such as one-stop shops and personal energy coaches, can be most beneficial (De Vries et al., 2020). However, it should be noted that this segment only accounts for 3.4 % of homeowners in our sample. Therefore, although de-hassling interventions can benefit all consumers, it is possible that only a small consumer segment finds these interventions particularly useful and actively respond to them. For the majority of homeowners with *balanced financial and feasibility barriers*, a combination of financial incentives and personalised information about the feasibility of retrofit measures can be effective.

In summary, interventions targeting motivations and barriers to home energy retrofit can complement each other. Information programmes are particularly useful for triggering motivations. The identified segments for energy retrofit motivations can inform the design of these interventions, including both salient information provision targeting specific homeowner segment and awareness programme with structured information. Complementary to motivation-triggering information programmes, various interventions can support homeowners with different perceived barrier patterns. Specifically, personalised information, de-hassling interventions, and financial incentives can be provided individually or in combination to target specific barrier segments. Furthermore, policymakers should carefully account for the imbalance in share of these segments. By knowing the potential size of targeted population, policymakers can improve the precision of *ex ante* evaluations of interventions in terms of their energy saving potentials and cost-effectiveness.

5.2. Limitations and implications for future research

There are three limitations of this study that should be acknowledged.

First, the cross-sectional data does not allow causal inferences. In particular, the formation of perceived motivations and barriers was not captured in the survey. This is especially relevant for interpreting the probabilities of implementing retrofit measures by segments for perceived barriers. It is unclear whether the patterns of perceived barriers were formed by homeowners' previous experience with implementing retrofit measures, or whether pre-existing perceptions influenced their previous retrofitting decisions. Therefore, results should be interpreted with caution. Future research could investigate the formation of these perceptions, taking into account values and experiences, and to use identified segments to predict future energy-efficiency behaviours.

Second, all variables in the analysis are based on predefined survey items and self-reported measures. Response bias may lead to deviations between self-reported perceptions and true motivations and barriers. For instance, the indication of pro-environmental motivation may be subject to the social desirability bias (Vesely and Klöckner, 2020) and social motivations may be undervalued in self-reported measures (Nolan et al., 2008). Therefore, it should be noted that important motivation and barrier factors may be biased or omitted due to the limitation of predefined survey items and self-reported measures. Nevertheless, in the context of home energy retrofit, where many interventions are implemented through a personal approach involving intensive interpersonal interactions, the proposed targeted interventions are also largely based on stated perceptions of consumers and matching them with identified segments. Therefore, the self-reported data used in the LCAs align with the field information that will be addressed during the interventions. We believe the results based on the self-reported data are meaningful for the interventions discussed in Section 5.1. However, policy interventions that cannot be well-informed by perceived motivations and barriers such as those leveraging social norms (Nolan et al., 2008), fall beyond the scope of this segmentation study. Furthermore, it might be interesting for future research to empirically test the effectiveness of the proposed targeted interventions.

Third, we acknowledge limitations related to the analytical sample. The sample is not fully representative of the national homeowner population—particularly in terms of age distribution, with a higher proportion of respondents aged 50–69 and fewer aged 18–49 compared to national statistics. This may limit the generalisability of the findings to all homeowners. In addition, some segments identified in the LCA contain fewer than 100 observations, which may limit the statistical power to detect differences in retrofit behaviour probabilities between classes. Results related to these smaller classes should therefore be interpreted with caution. Future studies could increase the sample size and expand the scope to include homeowners without prior retrofit experience, allowing for comparisons across different experiential groups and enhancing the robustness of results.

6. Conclusion

This study aims to provide a nuanced understanding of homeowner segments in the context of home energy retrofitting to support the design of targeted interventions. By conducting latent class analyses based on a sample of 1,011 Dutch homeowners with real-world experiences in home energy retrofitting, we identified five segments for homeowners' energy retrofit motivations and three segments for homeowners' energy retrofit barriers. The identified segments for both motivations and barriers are highly differentiated and offer substantively meaningful insights.

Based on the segmentation solutions, potential policy interventions are proposed. Home energy retrofitting is a complex process that often involves several decision-making stages and intensive interactions with professionals. In such cases, information programmes can be designed to provide salient and targeted information, rather than broad, superficial information. Depending on the homeowner segment, interventions can choose to focus on salient information related to immediate utilities, long-term individual utilities, or environmental benefits. Additionally, to motivate homeowners who are not yet familiar with home energy retrofitting, the quantified segmentation results can help prioritise and structure information provision in awareness programmes, aiming to engage as many potential retrofitters as possible. Complementary to motivation-triggering interventions, we propose personalised information, de-hassling interventions, and a combination of financial incentives and tailored information to address the barriers faced by three distinctive segments of homeowners. Finally, the share of each segment can inform the potential audience size for different interventions, thus supporting *ex ante* evaluation of interventions.

CRediT authorship contribution statement

Shutong He: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Queena K. Qian:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Jarry T. Porsius:** Writing – review & editing, Methodology, Validation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Shutong He reports financial support was provided by Dutch Research Council. Queena K. Qian reports financial support was provided by Netherlands Enterprise Agency. 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

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2025.114699.

Data availability

Data will be made available on request.

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