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Original research article

Beyond one-size-fits-all: Data-driven tenants personas for targeted intervention strategies in social housing renovation

Stefanie Horian [a,*], Queena K. Qian [a], Henk Visscher [a]

[a] Department Management in the Built Environment, Faculty of Architecture and the Built Environment, Delft University of Technology, Netherlands

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ABSTRACT

The need to decarbonize the built environment has increased policy and research attention on large-scale energy-efficient renovations (EER) in the residential sector, particularly social housing. While technical pathways for such renovations are increasingly well-defined, successful implementation depends on an often underestimated factor: the human dimension. In practice, success depends not only on technical solutions but also on tenant consent and participation. In the Netherlands, social housing associations (HAs) are required to obtain consent from at least 70% of affected tenants before proceeding with impactful EER projects. Yet, current practice often relies on uniform consent and communication strategies, implicitly treating tenants as homogeneous despite wide variation in behavioural determinants, perceptions, and personal characteristics.

Drawing on behavioural insights and a tailored survey among Dutch social housing tenants, this study develops a data-driven persona framework using Latent Class Analysis (LCA). The analysis identifies five benefit-based classes and seven barrier-based classes that capture systematic heterogeneity in comfort expectations, trust, perceptions of financial risk, transaction costs, and decision preferences. These probabilistic classes are translated into actionable personas that reflect tenants' differential receptiveness to information and engagement modes, thereby enabling practitioners and policymakers to better anticipate where non-agreement risks may emerge and to design targeted intervention strategies.

The studies' main contribution lies in operationalizing behavioural heterogeneity as an implementation tool for consent-based governance. It provides a scalable method for designing differentiated, targeted intervention strategies, anticipating consent dynamics, and supporting more just and effective implementation of EER projects in social housing.

1. Introduction

In recent years, energy-efficient renovation (EER) of residential buildings has been widely promoted as a key strategy to reduce energy consumption and greenhouse gas emissions by improving energy and resource efficiency [1]. In the social housing sector, such EER projects are particularly pressing, as they aim to improve the energy performance of dwellings through measures such as insulation, efficient building systems, and renewable energy technologies, while also addressing the needs of low-income and vulnerable households [2,3]. More specifically, EER encompasses measures and interventions aimed at reducing energy consumption, enhancing the energy efficiency of building systems, and supporting the use of electricity from renewable sources, such as solar energy [4–6]. The recent developments in European policy in the light of the housing crisis strongly promote the upgrade of social housing dwellings through EER, to ensure affordability for tenants and address energy poverty [1,7]. European policy frameworks and initiatives, such as the Renovation Wave or Affordable Housing Initiative, emphasize not only technical improvements but also the importance of a socially inclusive renovation process to empower citizens, including vulnerable groups [1]. In addition, the revised Energy Performance and Building Directive (EPBD) stipulates that financial incentives should prioritize vulnerable households, those affected by energy poverty, and residents of social housing [6]. EER is regarded as among the most cost-effective ways to alleviate energy poverty in the residential sector [4]. This makes EER a promising, but complex and multifaceted endeavor, situated at the intersection of technical, social, and justice-related concerns.

Accordingly, social housing plays a pivotal role in the energy transition because it combines scale, public mandate, and concentrated responsibility for low-income groups [8]. In the Netherlands, social

* Corresponding author.
E-mail address: s.horian@tudelft.nl (S. Horian).

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housing associations (HA) are strongly encouraged, under national performance agreements, to phase out natural gas and to improve low-performing dwellings with E-F-G energy labels [9]. However, implementation remains challenging in social housing due to the legal requirement that at least 70% of tenants must provide consent before an EER project can proceed [10]. Although this rule protects tenants' rights, it also creates a major bottleneck, as HA frequently reports that securing tenant agreement is among the largest obstacles to timely and effective EER delivery [11]. This is particularly consequential because tenant support is shaped by perceived benefits, disruption, and the extent to which renovation proposals align with residents' needs and preferences [2]. A major point in making EER equitable is a fair inclusion and empowerment of residents, recognizing the variety of their needs, by placing them at the center of the EER process [12,13]. It is crucial to identify residents' diversity in EER decision-making, rather than promoting one-size-fits-all approaches [15]. A more just and effective energy transition, therefore, requires better insight into tenant heterogeneity, so that engagement strategies can be aligned with different profiles rather than assuming a homogeneous tenant population.

The bottleneck of tenants' inclusion is not merely administrative. Despite being central stakeholders, tenants are often treated as passive recipients of top-down EER plans, which limit their ability to engage meaningfully in the process and to accept the renovation outcomes. Prior studies emphasize the importance of early tenant engagement for fostering acceptance and ensuring proper use of post-renovation technologies [14–16]. Their integration as expert stakeholders can contribute to retrofit processes in social housing [17]. At the same time, vulnerable tenants may particularly experience barriers such as a lack of trust, limited understanding of environmental benefits, perceived costs, uncertainty, or fear of disruptions [18–20]. In contrast, participation in EER projects is associated with anticipated benefits such as lower total housing costs, improved living comfort, upgrades to in-home amenities (new bathroom, kitchen, toilet), and improvements to the neighborhood environment [2]. These findings suggest that tenant responses to renovation are not uniform but shaped by behavioural heterogeneity in residents' perceptions of EER. Recognizing these behavioural differences is essential for designing pre-renovation intervention strategies that are responsive to distinct tenant profiles and more effective in supporting equitable engagement in EER.

A key policy tension follows: the consent regulatory requirement is uniform, but tenants' motivations, constraints, and decision preferences are not. If HAs and policymakers aim to meet consent thresholds while maintaining fairness and inclusion, they require tools that translate heterogeneity into actionable guidance for targeted support and communication. Targeting refers to the deliberate allocation of benefits to those most in need, aiming to reduce inequality and enhance the efficient use of resources [21]. This can be advantageous for the future formulation of funds and initiatives to provide targeted interventions for tenants in social housing.

Achieving such targeted allocation requires a nuanced understanding of population heterogeneity. Identifying relevant behavioural factors with the aim of accelerating EER of residential buildings is a promising practice [22]. The behavioural insights perspective offers a valuable lens for understanding behavioural determinants that can hinder or promote decisions to agree and adhere to proposed EER-plans. The application of behavioural insights is suitable to address and analyze practical issues in real-world settings by acting as an integrative transition layer [23,24]. Research working with behavioural insight can contribute to the formulation of interventions, and empowers governments to design policies that align with the way people think, behave, and make decisions [25,26]. Together, these perspectives imply that improving consent-based governance for EER requires a systematic way to anticipate variation in tenant receptiveness to information and engagement options. Despite growing recognition that tailored messages, nudges, co-creation strategies, and targeted support mechanisms can bridge the gap between technical plans and user acceptance [15,27,28]. Existing evidence is often not translated into empirically grounded segmentation that enables housing providers to anticipate where non-agreement risks are likely to arise. While studies document a range of barriers and benefits [14,29,30], they less frequently provide a scalable approach that links these perceptions to differentiated consent and engagement strategies, particularly in contexts where consent thresholds are legally binding. Carley underscores the necessity of incorporating the "human dimension" into the energy transition, with a particular focus on including vulnerable and traditionally disadvantaged groups [27].

This study addresses this gap through data-driven personas, an empirically grounded approach that represents tenants' heterogeneity in perception of EER. Drawing on latent class analysis (LCA), the study identifies latent tenant segments based on their perceived benefits and barriers to EER and translates the resulting latent classes into actionable personas that integrate behavioural perceptions with socio-demographic, household, and housing characteristics, alongside preferences for information and engagement. In contrast to narrative personas derived primarily from interviews, these data-driven personas are grounded in probabilistic response patterns and systematically related to contextual variables and intervention preferences. This enables a stronger methodological link between empirical segmentation and practically relevant tenant profiles that can inform more targeted communication and engagement strategies.

Our central research question is: *How can social housing tenants be segmented based on their perceived benefits and barriers to EER, what are their key predictors, and how can these segments inform targeted intervention strategies?* To answer this research question, a representative sample of 1068 tenants in the Dutch social housing sector was analyzed. Distinct latent classes were identified, and predictors such as age, income, household type, and building characteristics were examined. The tenants' data-driven personas are then defined as a composite based on statistically significant class predictors, enabling the translation of behavioural heterogeneity into decision-relevant profiles for practice.

This article operationalizes behavioural heterogeneity as an implementation tool for consent-based EER governance by developing empirically grounded personas that link tenant benefit–barrier profiles to differentiated information, engagement, and support strategies. Our findings offer practical guidance for HAs and policymakers to move toward targeted, evidence-based interventions that align with tenant realities. In doing so, the study aims to support a more inclusive and efficient energy transition in the built environment.

The remainder of the article is organized as follows: **Section 2** positions the study within relevant renovation, behavioural, and segmentation literature; **Section 3** outlines the study design and analytical approach; **Section 4** presents the empirical results; **Sections 5 and 6** discuss implications and translate findings into potential targeted intervention strategies.

2. Literature review

2.1. Governance challenge in Dutch social housing energy-efficient renovation (EER)

The governance challenge of EER in Dutch social housing arises from the sector's strategic importance and its tightly structured institutional constraints. In the Netherlands, the social housing[1] constitutes 28,3% of the total residential housing stock, positioning the sector as critical for achieving national climate objectives [31]. From this share, approximately 142,900 dwellings (6,2%) were registered in 2025 with a low

[1] Total residential housing stock in the Netherlands (2024) 100% = 8,204,049, of which 28.3% = 2,321,421 are managed by housing associations (CBS 2024).

energy label (E/F/G) and are expected to be upgraded to at least label D before 2028 under the National Performance Agreements [32]. At the same time that national policy places explicit pressure on the sector to accelerate the upgrading of poorly performing dwellings, Dutch HA are mission-driven organizations with a regulated public task, acting as non-profit organizations [33]. Their primary role is to provide affordable housing to lower-income households, with annual rent increases capped and monthly rent limited [34–36]. In practice, this constrains the extent to which capital-intensive renovation costs can be recovered through rental income, particularly where HA seek to protect tenants from rising housing costs and are not allowed to pass on rent increases for insulation measures [32].

Financial support for Dutch HA remains limited. Although HA can access relatively favorable financing through the guarantee system, which enables borrowing at a lower cost, this does not remove the need to absorb substantial upfront investment within a tightly regulated non-profit model [37]. Public support is available only through applications at specific times, such as subsidies for natural-gas-free homes [38]. However, those public subsidies are limited and claimed almost immediately [38]. Moreover, subsidies for tenants, in conjunction with engagement, are not available, except for the tenants' consent to regulatory requirements.

A distinctive governance mechanism shaping EER-projects in Dutch social housing is the 70% agreement rule.[2] For renovation proposals affecting complexes with often or more dwellings, a consent of at least 70% of affected tenants is required before the project can proceed [10]. This rule reflects an important protective logic; it seeks to safeguard tenants against intrusive or burdensome interventions, particularly where renovation requires access to dwellings, temporary relocation, or changes in housing costs. In this sense, the rule is especially relevant in social housing, where precautionary protections for low-income and potentially energy-poor households are institutionally prioritized [39,40].

These protections matter because social housing tenants differ in crucial ways from homeowners and private-market tenants. In the Netherlands, access to social housing is income-regulated, meaning the sector is primarily targeted at lower-income households; in 2026, the main income thresholds are €51,537 for one-person households and €56,910 for multi-person households [41]. In the European context, non-profit social housing is characterized by its public-interest mission of affordability and its focus on households with lower socio-economic status or particular vulnerabilities [5]. This indicates that social housing tenants might be disproportionately concentrated among the lowest-income groups and that affordability pressures often coincide with wider social vulnerabilities.

This socio-economic profile has direct implications for how tenants perceive and respond to renovation. Studies on Dutch social housing tenants show that willingness to participate in retrofit programs is not determined by technical attributes alone, but also by concerns about affordability, disturbance, and trust [2,14]. The split incentive is predominantly present, infusing that tenants are constrained in their capacity to improve dwelling performance themselves, making them more dependent on landlords and more sensitive to disruptions, uncertainty, and cost-related risks [3,42]. It is the social housing providers' role to alleviate energy poverty, which supports the idea that vulnerable tenants often rely on providers rather than acting independently [40]. In the Dutch context, around 75% of energy-poor households live in social housing, underlining the sector's relevance for both climate policy and social protection [3]. Taken together, these findings suggest that tenants in social housing should not be treated as a generic resident category, but as a population whose lower incomes, constrained agency, and greater exposure to energy vulnerability strongly condition responsiveness to EER strategies. A crucial factor for housing associations, policies have to take into account to ensure adequate engagement, implying procedural justice.

2.2. Behavioural barriers, transaction costs, and benefits in tenants' decision-making

Tenant decision-making is shaped by individual characteristics and by the environment in which choices are made. Behavioural insights offer a realistic understanding of human behavior and decision-making by accounting for contextual factors and socio-technical influences that shape individual preferences and choices [43]. Behavioural determinants and biases are commonly operationalized by identifying relevant mechanisms and translating them into survey measures that reflect realistic decision situations [44]. Accordingly, behavioural determinants are understood here as context-dependent factors that shape the judgements, interactions, and choices of actors involved in renovation processes. Examples include perceived disturbances, perceived effort, and lack of knowledge [20,45]. Behavioural biases are then seen as broader patterns of distorted or suboptimal decision-making that can emerge when several determinants accumulate and reinforce one another over time. In social housing renovation settings, cognitive biases such as myopic tendencies, loss aversion, and status quo bias have been discussed as plausible influences on tenants' evaluation of renovation proposals [44]. Building on this approach, the present study derives benefit and barrier statements from the EER literature, identifies practical perceived barriers and drivers from a behavioural insights perspective, and translates them into survey items (Table A2-A5). The guiding assumption is that perceived benefits and perceived barriers shape tenants' willingness to agree to EER plans, and that these perceptions vary across tenants. The following summarises the perceived benefits and barriers identified in the literature as potentially relevant to tenant decision-making in EER.

2.2.1. Perceived benefits

Agreement with EER proposals is more likely when expected improvements are tangible, directly experienced, and framed as enhancing one's own well-being and quality of life, e.g. increased security and safety [18]. In social housing, perceived benefits often include improved aesthetics, enhanced living comfort, environmental friendliness, cost reductions, and upgraded appliances [14]. Further, thermal comfort, benefits for health [46], and reduced energy consumption, hence reducing the energy bill, which can be salient for low-income households [47]. Tenants may also value non-energy improvements such as enhanced security and safety, outdoor environment, or upgraded facilities (e.g., kitchen, bathroom, toilet) [2,18], or the relevance of neighborhood improvements [48]. Health-related benefits refer to perceived improvements in the physical indoor living environment, such as fewer draughts and reduced humidity [46], whereas well-being refers to broader subjective improvements in comfort and overall quality of life at home or in the neighborhood [48]. Nevertheless, some tenants remain unaware of these potential advantages, and climate change is seldom the primary motivator for supporting EER [19].

2.2.2. Perceived barriers

Barriers to agreement are multi-dimensional, reflecting the hypothetical yet realistic decision-making context that tenants encounter during EER planning processes. Attitudinal factors matter because tenants may support EER only when they perceive a need for change based on discomfort or suboptimal housing conditions [19,49]. Trust and power dynamics also play a central role in landlord–tenant contexts. The split-incentive dilemma is frequently discussed as a source of skepticism because landlords initiate decisions while tenants experience disruption and, at times, financial consequences [50,51]. Evidence from the Dutch context indicates that tenants may view HAs as responsible for improving housing quality, yet skepticism can emerge when tenants

[2] Tenants' Rights in Dutch Law / Huurrecht Artikel 220 Burgerlijk Wetboek Boek 7

doubt whether their interests are represented [51]. Information can be conveyed by HAs or by intermediaries such as energy ambassadors and coaches, potentially shaping how tenants interpret EER proposals [39]. Communication quality and consistency are associated with tenants' ability to make informed decisions under uncertainty [52]. However, trust is fragile, often undermined when engagement is perceived as tokenistic [53]. Personal constraints further influence agreement as some tenants face limited time, interest, or physical capacity, which can restrict participation and reduce willingness to engage with complex renovation information [16,48]. A complementary lens is transaction costs, which captures non-financial burdens associated with uncertainty and information asymmetry. In renovation contexts, transaction costs include lack of knowledge, limited time to acquire knowledge, and perceived effort to search for and process information [45,54,55]. Transaction cost concepts have been applied to explain hidden burdens in retrofit decision-making. In addition, tenants report process-related concerns, including nuisance, uncertainty about timelines, fear of strangers entering the home, and dissatisfaction with overdue renovations [14]. Financial barriers remain salient, including worries about rent increases, unclear financial returns, and mistrust in promised energy savings [48,51], as well as additional costs [14].

2.3. From segmentation to data-driven personas

Segmentation studies provide an important starting point for representing heterogeneity relevant to energy and housing policy. In housing and retrofit research, segmentation has been used to identify heterogeneity in energy poverty among tenants [56], perception of energy retrofit [57], adoption of photovoltaic [58], energy efficiency gap [59], acceptance of retrofit [29] willingness to participate [2], or energy performance gap [60]. Collectively, these studies demonstrate that households and tenants are not a homogeneous population and that policy and intervention design can benefit from recognizing meaningful subgroup differences.

At the same time, segmentation in housing and retrofit research often remains primarily descriptive. Many studies identify resident groups based on socio-demographic characteristics, attitudes, routines, or stated preferences, but do not always translate these segments into operational profiles that can inform tailored communication or intervention design. This limitation is particularly visible in studies that distinguish clusters of residents with different behavioural orientations but stop short of converting these analytical patterns into more interpretable user representations. For example, Liu et al. [2] identified latent groups with different preferences for natural gas-free heating options of social housing tenants. Their findings indicate that tenants can be motivated by the potential to reduce total housing costs, improve living comfort, upgrade individual amenities such as bathrooms, kitchens, and toilets, and enhance the neighborhood environment. Similarly, Balest and Vettorato [29] differentiated households according to life stage, daily routines, and socio-demographics. While such studies clearly reveal heterogeneity, their outputs often remain limited to static cluster descriptions. As a result, they provide only limited guidance for how segmentation findings can be translated into practical communication strategies, engagement approaches, or policy instruments.

One way to address this limitation is by enhancing segmentation studies through persona modelling [61]. Personas are socially constructed representations that translate individuals' behavioural statements into recognizable roles within a market context, and are used in marketing strategies [62]. They typically reflect the traits of specific customer segments, referred to as personas [63,64]. Personas are commonly described as fictional yet evidence-based archetypes or detailed user models that represent distinct patterns of behavior, goals, and motivations observed during research [65]. They have also been defined as archetypal user models developed through systematic analysis of real user data [66]. In marketing and design research, personas are used to translate complex empirical data into recognizable profiles that support communication, product development, and strategic decision-making [67,68]. Rather than merely identifying statistical groups, persona approaches aim to personify those groups in ways that are meaningful to decision-makers and easier to use in practice.

In the energy and housing domain, persona-based approaches have shown promise, but remain relatively limited and often rely on qualitative or mixed-method design [28,53,69]. Haines and Mitchel [69], for instance, developed retrofit-related personas based on households' attitudes, motivations, and behaviors, demonstrating how persona thinking can make variation in retrofit decision-making more tangible. Palm et al. [53] identified tenant types related to interests and attitudes toward EER and highlighted that tenants may perceive meaningful influence as requiring more effort than they can commit. Likewise, Sokol et al. [28] identified a large set of personas for lighting behavior using mixed methods, combining interviews, workshops, and survey data. While these studies provide valuable interpretive insights, they offer less statistical grounding and a limited ability to link profiles to contextual characteristics or intervention preferences.

Against this background, data-driven personas provide a stronger methodological bridge between empirical segmentation and actionable intervention design. Data-driven personas are persona profiles that are constructed from observed quantitative data using analytical methods rather than being derived primarily from qualitative interpretation alone [70,71]. Common quantitative methods applied to data-driven persona development include k-means clustering, factor analysis, hierarchical clustering, and latent class analysis [68,72–74]. Their added value lies in combining empirical rigor with interpretability: they retain the analytical strength of segmentation while presenting the results in a more accessible, practical form. In this sense, personas do not replace segmentation but extend it by transforming statistical groupings into richer behavioural profiles that can support targeted policy and engagement strategies.

In the present study, this bridge is established through latent class analysis (LCA). LCA is a person-centered statistical approach that identifies unobserved subgroups of individuals who share similar response patterns, making it particularly suitable for contexts in which heterogeneity is expected but not directly observable (Weller et al., 2020). In energy research, latent class methods are increasingly used to uncover hidden subgroups in areas such as energy poverty [56], retrofit motivations and barriers [57], and tenant participation in social housing renovation [2]. The three-step LCA applied in this study enables the probabilistic identification of tenant segments whose benefit perceptions, barrier perceptions, and contextual characteristics systematically co-vary with different preferences for information provision and engagement formats. Building on these latent segments, the study develops interpretable tenant personas. In this way, the LCA results are not treated as an end in themselves, but as the empirical basis for constructing behaviourally meaningful profiles. This approach makes it possible to move beyond static segmentation toward profiles that are both statistically grounded and practically interpretable. The novelty of the approach, therefore, lies not simply in identifying tenant segments but in converting latent class structures into data-driven personas that can inform more targeted communication and engagement strategies in the context of EER.

3. Methodology

3.1. Survey and sample of Dutch social housing tenants

Data were collected through an online questionnaire administered to tenants in the Dutch social housing sector, through a professional research agency that recruits respondents from its own online panel and conducts fieldwork in accordance with predefined sampling requirements. To align the sample with the Dutch social housing tenant population, fieldwork quotas followed the age distribution reported in the national WoON 2021 dataset. Appendix Table A1 provides a frequency comparison between WoON 2021 and the study sample. Data collection closed at the end of July 2024. A total of 1659 social housing tenants clicked the survey link distributed by the company; of these, 587 respondents have not completed the questionnaire or passed the attention check and were removed as invalid responses. An attention-check item was included mid-survey to identify careless responding; only respondents who passed the attention check and completed the whole survey were retained [75]. After data cleaning, 1072 responses remained. Four cases with gender recorded as "other" were excluded to retain a two-category gender variable for analysis, yielding a final analytic sample of 1068 tenants.

The survey was developed by the authors and reviewed in consultation with project consortium members with practical field experience to ensure the items' clarity and relevance to the renovation decision context. It was administered and supervised using the online platform Qualtrics. The survey items were informed by the literature review outlined in Section 2.2, while full item wording and response options are provided in Appendix Tables A2–A5. Although some conceptual proximity between individual survey items may remain, the items were designed to be as distinguishable as possible by grounding them in literature and refining them through practitioners' feedback. The analysis draws on five variable blocks: (a) perceived benefit of EER, (b) perceived barriers to agreeing to EER, (c) preferred engagement modes, (d) preferred information channels, and (e) contextual characteristics such as socio-demographic, household, and housing variables. Perceived benefits were measured with nine indicators denoted as [BE1] to [BE9], to capture the extent to which respondents care about various benefits associated with EER, shown in Fig. 1. Respondents rated each item on a five-point Likert scale (5 = I care a lot; 4 = I care; 3 = Neutral; 2 = I don't care; 1 = I don't care at all). In Fig. 1 it is visible that most of the benefit statements were indicated with "*I care a lot*" and "*I care*". The most strongly valued benefits are reducing consumption [BE6], comfort [BE1], and health [BE2]. The Likert-Scale response distribution are reported in Appendix Fig. A6-A7.

Perceived barriers were measured using 14 indicators, denoted [BA1] to [BA14], to capture the extent to which specific concerns would prevent respondents' agreement with an EER plan, as shown in Fig. 2. Respondents rated each item on a six-point scale that included an explicit uncertainty category (0 = I don't know, 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree). For the barrier indicators, "I don't know" was treated as a valid substantive category rather than missing data or a neutral midpoint, reflecting uncertainty or an unformed evaluation [76,77]. In Fig. 2 it is visible that the most commonly agreed-upon barrier, the rent increase [BA12], would discourage their support. Similarly, moving out temporarily [BA7] and increased service charges [BA14] were perceived as major obstacles.

Engagement preferences were measured using six items, denoted [E1] to [E6], that asked whether respondents preferred a specific engagement mode. Items were recorded on a five-point agreement scale (1 = *Strongly disagree* to 5 = *Strongly agree*) and re-coded to binary outcomes for distal-outcome analyses: *Agree/Strongly agree* = 1 and all other categories = 0. The vast majority of respondents expressed a strong desire to be involved through information [E2] about the renovation, and wish to actively vote [E1] on the chosen renovation plan proposed by their HA (Table 1). Information preferences were measured using six binary items, denoted [I1] to [I6]. Respondents were asked how they would prefer to be approached with information regarding EER. Items were recorded as binary yes/no outcomes. The most favored communication channels were letter by mail [I1] and email [I2]. Context variables included age, gender, household characteristics, and housing characteristics (Appendix Table A8).

3.2. From latent class analysis to persona profiling

Given the identified need for empirically grounded, policy-relevant segmentation (Section 2), a three-step Latent Class Analysis (LCA) is applied. LCA is a well-established person-centered approach for identifying latent subgroups within heterogeneous populations based on shared response patterns and is therefore well suited to empirically deriving meaningful tenant profiles for persona modelling [78]. The three-step specification further allows external covariates and outcomes to be related to class membership [79,80].

The three-step LCA was performed using the professional software LatentGOLD 6.1, following the three-step procedure [81–83]. Local independence was assessed by inspecting bivariate residuals for all indicator pairs; results are reported in Appendix Tables A11–A12 [83]. Where bivariate residuals suggested elevated local dependence, this information was taken into account when interpreting the final class profiles. For the plot visualizations and further correlation calculations, R was used. The statistically significant predictors are used for the persona profiling of each latent class. All the data-driven results from the three-step LCA are combined to define the persona profile of social housing tenants.

Two LCAs were estimated: one for benefit indicators (BE1–BE9) and one for barrier indicators (BA1–BA14). This separation reflects prior evidence that groups with similar retrofit motivations may nonetheless exhibit heterogeneous barrier configurations, warranting distinct benefit- and barrier-based class solutions [57], and confirmed in correlation analysis (Section 4.3). For both the benefit and barrier LCAs, the selection of the optimal number of latent classes was based on a combined evaluation of statistical model fit, classification quality, and substantive interpretability. Statistical model fit was evaluated using the log-likelihood value (LL), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), consistent AIC (CAIC), sample-size-adjusted BIC (SABIC), and the Vuong-Lo-Mendell-Rubin Test (VLMR) with its associated *p*-value [78,84,85]. In line with common practice, penalized fit indices, particularly BIC and CAIC, were given greater weight because they balance model fit against model complexity and thereby reduce the risk of overfitting. Entropy was additionally examined to assess classification quality, with values above 0.80 generally indicating relatively clear class separation [78]. To ensure numerical stability, the latent class models were estimated to use multiple random starting values. The final solutions were retained when the best log-likelihood was replicated across runs. Given the aim of deriving interpretable, policy-relevant personas, classification precision was considered an important complementary criterion. Finally, the selected solution was required to show a meaningful and reasonable class distribution, including sufficiently large and substantively interpretable classes.

After identifying unconditional class solutions, the association between class membership and contextual characteristics (e.g., age, gender, household, and housing variables) was examined, using the three-step (Step-3) multinomial logistic regression framework that corrects for classification error [82,83]. Prior to covariate modelling, predictors were screened for multicollinearity. The estimate (log-odds), the standard error**,** the z-value, and the ***p***-value to test statistical significance are reported. The threshold is $|z| \geq 1.96$, which indicates that $p < 0.05$ and corresponds to a 95% confidence interval. To relate latent classes to distal outcomes, namely tenants' engagement preferences and information channels, the Block–Croon–Hagenaars (BCH[3]) method was applied. This approach uses class-specific weights to obtain bias-corrected estimates of distal outcome means across classes while preserving the measurement model [81]. Differential item functioning or measurement non-invariance across key covariates, such as age or gender, was not formally tested. Accordingly, the measurement model was assumed to be invariant across these groups.

LCA is a model-based clustering approach that identifies unobserved

[3] BCH method developed by Block, Croon, and Hagenaars (2004) was integrated and discussed for the three-step LCA in Vermunt (2010).

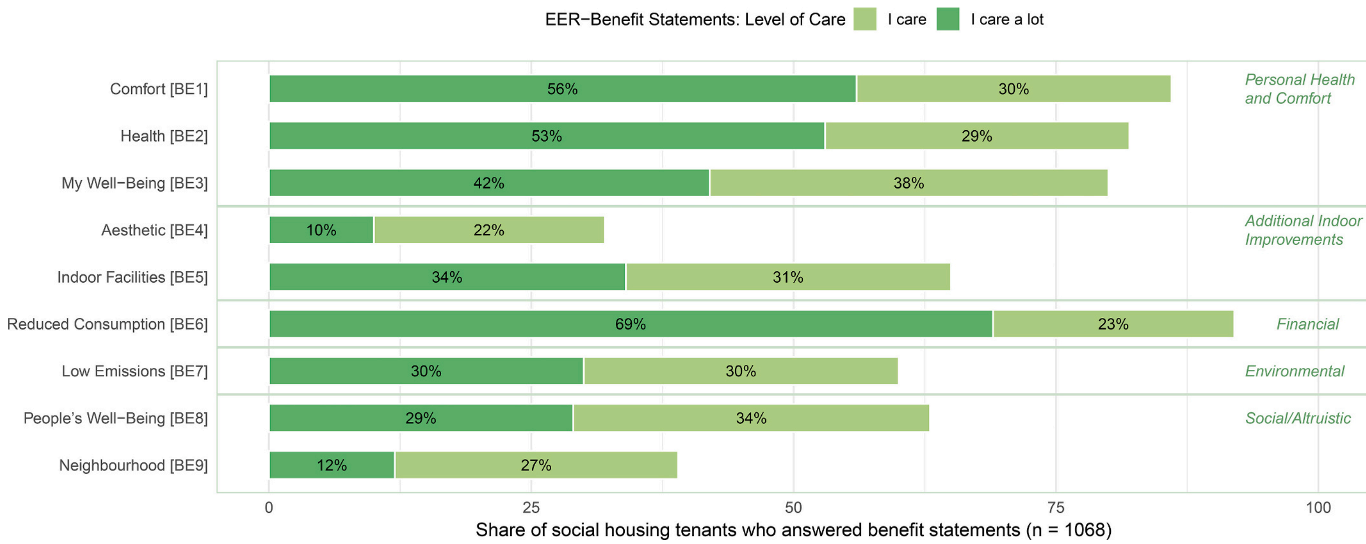

Fig. 1. Percentage of tenants perceived care for EER benefits by benefit item.

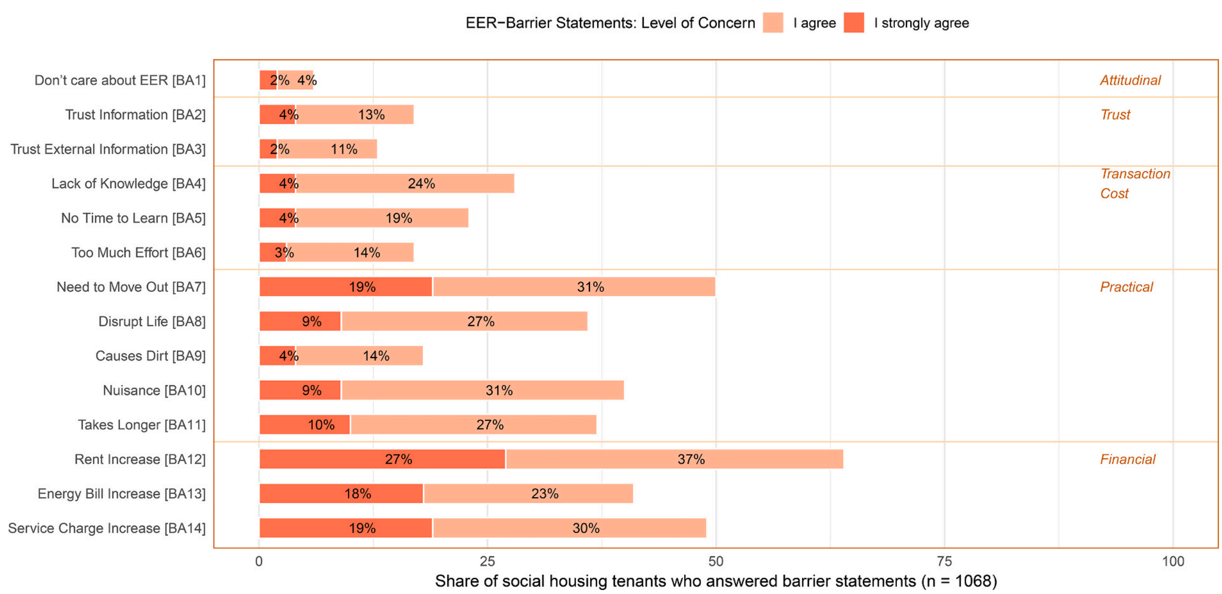

Fig. 2. Percentage of tenants' perceived concern for EER barriers by barrier item.

Table 1
Summary of percentage of Items for each engagement and information preference answered with Yes [$N = 1068$].

Engagement Preference		Information Preference	
Items	YES	Items	YES
[E1] Voting for renovation plans	74%	[I1] Letter by mail	81%
[E2] Receiving renovation information	92%	[I2] *E*-Mail	81%
[E3] Observing one discussion event	49%	[I3] Phone message	16%
[E4] One-time discussion participation	36%	[I4] Home visit	38%
[E5] Repeated active involvement	41%	[I5] Information event	66%
[E6] No involvement	9%	[I6] Group discussion session	43%

Note: Full survey questions in Appendix A4 and A5.

subgroups from response patterns and estimates probabilistic class membership. Building on this foundation, data-driven personas are operationalized by linking each latent class to statistically significant contextual predictors and to class-specific information and engagement preferences. This moves beyond purely descriptive profiling[4] and yields personas that are both interpretable for decision-makers and empirically anchored in covariate and distal-outcome associations.

4. Results

4.1. *Persona profiling of EER-benefit statements*

The latent class models were estimated to be 2 to 8 classes across nine EER-benefit statements (BE1-BE9). Class selection was based on a combined assessment of penalized fit indices, classification quality, and substantive interpretability (Table 2). Among the estimated models, the 5-class solution showed the lowest BIC, indicating the most favorable balance between model fit and parsimony. Although the 4-class solution yielded the highest entropy (0.8495), the difference in entropy relative

[4] Descriptive profile summaries of LCA in Appendix A9 and 10

Table 2
Goodness of fit statistics for latent classes of EER-benefit statements.

Class	Npar	LL	BIC	AIC	CAIC	SABIC	VLMR	Entropy	Class distribution (rounded in %)
2	73	-10538	21585	21222	21658	21353	2157***	0.8468	50 / 50
3	110	-10125	21017	20470	21127	20668	825***	0.8471	43 / 37 / 20
4	147	-9962	20950	20219	21097	20483	325***	0.8495	40 / 37 / 16 / 7
5	184	-9816	20916	20001	21100	20332	291***	0.8465	37 / 20 / 20 / 16 / 7
6	221	-9715	20971	19872	21192	20269	202***	0.8330	27 / 23 / 16 / 15 / 12 / 7
7	258	-9633	21065	19782	21323	20245	164***	0.8512	23 / 18 / 14 / 14 / 13 / 12 / 6
8	295	-9564	21184	19717	21479	20247	138**	0.8375	19 / 19 / 15 / 12 / 12 / 10 / 8 / 6

Notes: Log-likelihood values, Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), consistent AIC (CAIC), sample-size-adjusted BIC (SABIC), Vuong-Lo-Mendell-Rubin Test (VLMR) and its p-value (*$p < 0.001$***; $p < 0.01$***), Entropy, and class distribution are presented for models 2–8 classes, rounded. The selected classification is highlighted. Model diagnostics for the selected 5-class solution: APP range = 0.86–0.93; overall classification error = 0.09; minimum class size = 7.2% ($n = 77$).

to the 5-class solution (0.8465) was marginal, while the 5-class model provided improved fit and greater substantive differentiation between classes. The selected 5-class solution showed acceptable classification diagnostics and retained a meaningful minimum class size. Taken together, the statistical indicators and substantive interpretability supported the 5-class solution for the subsequent analyses.

The optimal grouping of tenants living in social housing is **five latent classes**. The distribution is based on the most likely class membership, the second step in the three-step LCA. The distribution for five latent classes for [$n = 1068$] is 37.36% [$n = 399$] / 20.29% [$n = 217$] / 19.58% [$n = 209$] / 15.47% [$n = 165$] / 7.30% [$n = 78$].[5] According to the results of the LCA and item probabilities that are also used for the interpretation of the individual classes, the five classes can be named as class 1: *Immediate Utility Seekers*, class 2: *Personal Comfort Seekers, class 3: Balanced Benefit Idealists, class 4: Indifferent Responders,* and class 5: *Pessimists.* The latent classes are described using the conditional response probabilities based on the likelihood that members of each class gave a certain response (from "*I don't care at all*" to "*I care a lot*") to each benefit statement. High probabilities (typically above 0.40) are considered dominant in defining the class profile. Each EER-Benefit class is described and named based on dominant response probabilities across multiple benefit items (Fig. 3),[6] relationship to covariates and relevant predictor variables (Table 3), and probabilities of engagement and information preference (Table 4 and Table 5).

By integrating all the results, the personas according to the five class solution of EER-Benefit, can be described as follows: *The Immediate Utility Seekers*, (Class 1–37.36%) compromises the largest share of the sample and report high probabilities of caring about comfort (0.4868 "*I care*", 0.4613 "*I care a lot*"), health (0.4894, 0.4300), reducing energy consumption (0.3518, 0.6311), indoor improvements (0.4989, 0.2462) and personal well-being the highest (0.8252 "I care"). In contrast, they care less about aesthetics or collective aspects like neighborhood benefits. This group serves as the reference class for subsequent comparisons.

The Personal Comfort Seeker (Class 2–20.3%), is characterized by high concern (*"I care a lot")* for comfort (0.8723), health (0.8490), low emission (0.5452), individual and collective wellbeing (0.9466 and 0.6252, respectively), while showing low probabilities of caring about aesthetics (0.0007) or neighborhood improvements (0.0561). This class is positively associated with older tenants aged 55–74 (z = 2.53, 2.03) and female gender (z = 2.13), suggesting older women are more likely to belong. A mid-income level of €40 k–50 k is negatively associated (z = −2.23), indicating that this class skews lower-income. Respondents who occupied buildings from 1946 to 1970 (z = −2.43) are less likely to be in class 2 than in class 1. Respondents in this class are more likely to engage in an on-time discussion event (z = 2.5777); the same applies for class 3 (z = 1.9960).

The Balanced Benefit Idealist (Class 3–19.6%) exhibits a highly engaged and benefit-driven profile, with high probabilities across nearly all statements. Responses are particularly strong ("*I care a lot*") for comfort (0.8527), health (0.9216), reducing energy consumption (0.9645), and personal well-being (0.9263), indoor improvements (0.7861) and people's well-being (0.7097). Older age (65–74 years; z = 2.17) and heat pump use (z = 2.35) predict membership, suggesting familiarity with renewable technologies. Compared to class 1, class 3 shows a high positive significance for the information preference of contact via Phone, home visits, events, and Group discussion, indicating a high openness to collective and interactive engagement formats.

The Indifferent Responders (Class 4–15.5%) display low levels of care across most benefit categories. The probability of responding "*neutral*" is high for aesthetics (0.7241), neighborhood improvement (0.8283), and people's well-being (0.8980), indicating general ambivalence toward the listed benefits. Few respondents report strong care ("*I care a lot*"), for any benefit, with only reducing energy consumption (0.3202) and comfort (0.4037) approaching moderate concern. No socio-demographic, household, or housing predictors significantly differentiate this group from Class 1. However, they prefer information via phone and are less likely to respond to email or event-based outreach.

The Pessimists (Class 5–7.2%), are defined by widespread indifference or ambivalence, this group shows high "*I don't care*" to "*neutral*" responses across most benefits: they *don't care* about aesthetics (0.3811; 0.3847), neighborhood improvements (0.3550; 0.3974), indoor improvement (0.3097), and low emission (0.3300); and high *neutral* responses on health, my well-being. Only one benefit, for reducing energy consumption (0.3343, "*I care a lot*"), exceeds the modest care level. *Pessimists* are significantly more likely to be female (z = −3.68), live as couples without children (z = −3.16), and use a hybrid energy system that includes natural gas, district heating, heat pumps, or solar panels (z = 2.35). They are significantly less likely to prefer information through e-mail or events. (−2.74; −3,40). Finally, across all EER-Benefit classes, no significant associations were found with education level, employment status, property type, or energy label.

4.2. Persona profiling of EER-barrier statements

The latent class models were estimated with 2 to 10 classes across

[5] Class distribution 2-Step LCA has an average deviation of 0.7%, which is acknowledged in further calculations of 3-Step LCA. For clarity, class distribution is displayed as in the Step 1-LCA analysis.

[6] See Figure A11 in the Appendix, showing response probability profiles per EER-Benefit item across EER-Benefit latent class response items.

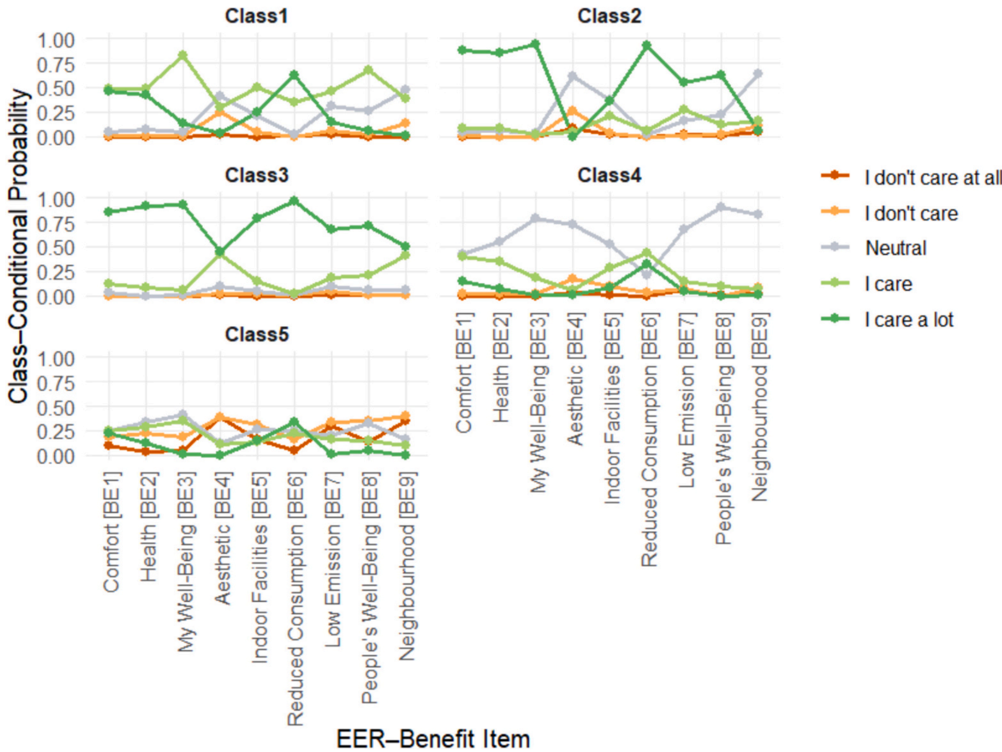

Fig. 3. Response probability profiles per EER-benefit item within each EER-benefit latent class – per latent class.

nine EER-barrier statements (BA1-BA14). Class selection was based on the same criteria as for the benefit model: penalized fit indices, classification quality, and substantive interpretability (Table 6). The BIC continued to improve up to the 8-class solution, whereas the CAIC reached its lowest value at the 7-class solution, favoring a more parsimonious specification. Although the 8-class model showed a marginally lower BIC and slightly higher entropy, these improvements were limited, while the 7-class solution offered a clearer balance between fit, parsimony, and interpretability. The selected 7-class model also demonstrated strong classification quality and retained an acceptable minimum class size of 5.1% (n = 54). Given the study's objective of deriving interpretable, policy-relevant personas, the 7-class solution was retained for subsequent analyses.

The optimal grouping of tenants living in social housing, based on the barrier statements, yields seven latent classes. The distribution for seven latent classes for [n = 1068] is 26.54% [n = 283] / 23.08% [n = 247] / 13.26% [n = 142] / 12.87% [n = 137] / 11.67% [n = 125] / 7.44% [n = 79] / 5.14% [n = 55][3]. According to the results of the LCA and item probabilities that are also used for interpretation of the individual classes, the seven classes can be named as class 1: *Financial Sensitive*; class 2: *Practical and Financial Concerned;* class 3: *The Ambivalent Observer;* class 4: *The Self-Reliant but Unconvinced;* class 5: *The Financially Alarmed*; class 6: *The Confident Acceptors;* class 7: *The Uncertain*. The latent classes are described using the conditional response probabilities, based on the likelihood that members of each class indicated a certain response to each barrier statement. High probabilities (typically above 0.40) are considered dominant in defining the class profile. Each EER-Barrier class is interpreted based on dominant response probabilities across multiple barrier items (Fig. 4), relationship to covariates (Table 7), and probabilities of information (Table 8) and engagement preference (Table 9).

By integrating all the results, the personas according to the seven class solutions of EER-Barriers can be described as follows: *The Financial Sensitive (Class 1–26.5%)* is the largest segment and consistently disagrees with most barrier statements. While they strongly care about EER, they reject having key transaction cost barriers, such as lack of knowledge ("*I disagree*" - 0.4417), no time to learn (0.5217), and too much effort (0.4962). On the practical side, they disagree that EER causes nuisance (0.4035), dirt (0.5021), or disrupts life (0.4443), but agree on the hassle of moving out temporarily (0.3402). They are likely to be positively predisposed to EER but remain sensitive to perceived financial burdens as they agree that rent increases (0.4841) and service charge increases (0.3785). This class served as a reference class for further analysis.

The Practical and Financial Concerned (Class 2–23.1%) is defined by practical and financial concerns, accompanied by agreement with transaction cost barriers, including lack of knowledge (0.4530) and no time to learn (0.3940), indicating a sense of informational overload. They care about EER, with high agreement on renovation-related disruptions such as moving out (0.5681), life disruption (0.6584), nuisance (0.7275), and extended duration (0.6777). Financial concerns are pronounced, with increases in rent (0.5339), energy bill (0.4765), and service charge (0.5744), indicating they are financially risk-averse. Despite these practical and financial concerns, they tend to trust the information provided by both their housing association (0.4908) and external sources (0.3535). Class membership is significantly associated with dwellings built between 1986 and 2000 or before 1970, and less likely to have a lower or unknown energy label. No information or engagement preference has been detected as significant.

The Ambivalent Observers (Class 3–13.3%) is characterized by a widespread pattern of neutral response probabilities across nearly all barrier items, illustrating that this class is marked by uncertainty and disengagement, potentially reflecting low awareness or cognitive overload. No significant predictors were identified in the covariate calculation. Respondents are unlikely to engage and unlikely to prefer events (z = −2.05).

The Self-Reliant but Unconvinced (Class 4–12.9%) is characterized by a high concentration of "*I don't know*" responses, particularly across practical and financial barrier items: Practical disruptions are frequently met with uncertainty: "takes longer" (0.7782), "causes dirt" (0.6927), and "nuisance" (0.5173) all show high "*I don't know*" probabilities. Similarly, financial concerns: rent (0.5224), energy bill (0.6612), and

Table 3
Relationship between EER-benefit latent classes and covariate items.

Covariates	Class 1 37.36% [n = 399]	Class 2 20.29% [n = 217]	Class 3 19.58% [n = 209]	Class 4 15.47% [n = 165]	Class 5 7.30% [n = 78]
Age in years					
18–24 *(reference)*	–	–	–	–	–
25–34	/	0.1331 [0.6210; 0.2143]	0.5774 [0.5661; 1.0199]	0.4177 [0.6991; 0.5975]	0.0224 [0.6921; 0.0324]
35–44	/	0.5299 [0.6156; 0.8608]	1.0941 [0.5824; 1.8787]	0.8642 [0.6842; 1.2630]	0.2194 [0.6983; 0.3141]
45–54	/	0.6807 [0.5949; 1.1442]	0.7249 [0.5847; 1.2398]	0.2935 [0.6966; 0.4213]	−0.9120 [0.7918; −1.1518]
55–64	/	**1.5103 [0.5972; 2.5291]**	1.0892 [0.5994; 1.8172]	0.4833 [0.7235; 0.6681]	−0.6359 [0.7704; −0.8255]
65–74	/	**1.6293 [0.8044; 2.0255]**	**1.6444 [0.7599; 2.1640]**	0.3258 [0.8254; 0.3948]	−1.0727 [0.9898; −1.0838]
< 75 years	/	1.4502 [0.8540; 1.6981]	0.9772 [0.8299; 1.1774]	0.6751 [0.8811; 0.7662]	−1.8524 [1.0766; −1.7206]
Gender					
Male *(ref.)*	/	–	–	–	–
Female	/	**0.5341 [0.2511; 2.1270]**	0.3726 [0.2528; 1.4739]	−0.4606 [0.2750; −1.6747]	**−1.3122 [0.3565; −3.6805]**
Household Income					
Less than €10.000 - €20.000 *(ref.)*	/	–	–	–	–
€20.000 - €30.000	/	0.0141 [0.3013; 0.0468]	−0.1196 [0.3075; −0.3890]	0.1737 [0.3514; 0.4943]	−0.4045 [0.4290; −0.9430]
€30.000 - €40.000	/	−0.5562 [0.3179; −1.7495]	−0.5628 [0.3178; −1.7706]	−0.0403 [0.3449; −0.1169]	−0.6338 [0.4325; −1.4655]
€40.000 - €50.000	/	**−0.8552 [0.3840; −2.2269]**	−0.5243 [0.3739; −1.4023]	0.0737 [0.3931; 0.1875]	0.0200 [0.4563; 0.0437]
More than €50.000	/	−0.6314 [0.3453; −1.8285]	−0.2775 [0.3418; −0.8119]	−0.5558 [0.4283; −1.2975]	−0.7868 [0.5223; −1.5065]
Prefer not to say	/	−0.2547 [0.3297; −0.7726]	−0.3070 [0.3300; −0.9301]	0.0203 [0.3668; 0.0553]	−1.0060 [0.5342; −1.8833]
Household Composition					
One Person Household *(ref.)*	/	–	–	–	–
Single Parent	/	−0.5389 [0.4017; −1.3416]	0.1427 [0.3249; 0.4392]	−0.4884 [0.4201; −1.1626]	−1.3029 [0.7005; −1.8599]
Couples without Children	/	0.3265 [0.2284; 1.4294]	−0.3039 [0.2591; −1.1728]	−0.1656 [0.2716; −0.6097]	**−1.5036 [0.4756; −3.1614]**
Couples with Children	/	−0.0536 [0.2993; −0.1790]	−0.1350 [0.2964; −0.4556]	−0.0472 [0.3059. -0.1543]	−0.7774 [0.4760; −1.6334]
Building Year					
From 2001 *(ref.)*	/	–	–	–	–
2000 to 1986	/	−0.2453 [0.3505; −0.6999]	0.2653 [0.4149; 0.6394]	−0.0131 [0.4058; −0.0323]	0.2457 [0.6598; 0.3724]
1985 to 1971	/	−0.3535 [0.3115; −1.1348]	0.6018 [0.3677; 1.6364]	0.1516 [0.3669; 0.4132]	0.7655 [0.6245; 1.2256]
1970 to 1946	/	**−0.8560 [0.3518; −2.4332]**	0.0872 [0.3894; 0.2240]	−0.1368 [0.3740; −0.3658]	0.1792 [0.6995; 0.2562]
Older than 1945	/	−0.4138 [0.4351; −0.9509]	0.6234 [0.4597; 1.3562]	−0.3412 [0.5497; −0.6208]	−0.2293 [0.9296; −0.2467]
I don't know	/	0.2831 [0.4535; 0.6243]	0.8045 [0.5319; 1.5126]	0.4849 [0.5250; 0.9236]	1.0587 [0.7386; 1.4334]
Heating Type					
Natural Gas *(ref.)*	/	–	–	–	–
DH	/	−0.4911 [0.3257; −1.5077]	−0.3094 [0.3578; −0.8648]	−0.3549 [0.3457; −1.0265]	0.0546 [0.4408; 0.1239]
HP	/	−0.3871 [0.5024; −0.7706]	**0.9323 [0.3961; 2.3538]**	0.5524 [0.4661; 1.1851]	0.9669 [0.6594; 1.4663]
Combination & Other	/	0.3389 [0.6179; 0.5485]	0.7073 [0.6071; 1.1652]	0.9847 [0.5772; 1.7061]	**1.4255 [0.6061; 2.3519]**
I don't know	/	−0.8992 [0.4695; −1.9153]	−1.4158 [0.7536; −1.8788]	−0.6997 [0.5203; −1.3448]	0.2475 [0.6079; 0.4071]

Notes: (1) Results were estimated with multinominal logistic regression using the Step3 approach in LatentGOLD with external variables classified as covariates. The Step3 approach was calculated separately for each block of covariates (2) Log-odds coefficient, S.E. and z-values are presented in the table. (3) The threshold $|z| \geq 1.96$, then $p < 0.05$ is used, marked bold. Prediction based on 95% confidence intervals. (4) Only items with significant predictors are shown; the full results for all items are provided in Appendix A15.

Table 4
Probabilities of information preferences by EER-benefit latent classes.

Information Preference	Class 1 37.36% [n = 399]	Class 2 20.29% [n = 217]	Class 3 19.58% [n = 209]	Class 4 15.47% [n = 165]	Class 5 7.30% [n = 78]
Letter by mail	/	0.0821 [0.2444; 0.3362]	−0.0294 [0.2436; −0.1208]	−0.1313 [0.2535; −0.5178]	−0.1060 [0.3297; −0.3215]
Email	/	−0.2639 [0.2445; −1.0882]	0.3404 [0.2943; 1.1567]	**−0.5004 [0.2501; −2.0009]**	**−0.8219 [0.2999; −2.7403]**
Phone message	/	−0.0035 [0.2890; −0.0121]	**1.0524 [0.2387; 4.4085]**	**0.5768 [0.2717; 2.1232]**	−0.0223 [0.4098; −0.0544]
Home visit	/	0.3490 [0.1909; 1.8279]	**0.6396 [0.1936; 3.3038]**	−0.0872 [0.2153; −0.4051]	−0.6062 [0.3213; −1.8867]
Information event	/	0.2164 [0.2051; 1.0550]	**0.6036 [0.2278; 2.6496]**	**−0.6119 [0.2083; −2.9382]**	**−0.9329 [0.2736; −3.4097]**
Group discussion session	/	0.1116 [0.1881; 0.5934]	**0.8187 [0.1957; 4.1832]**	−0.3578 [0.2155; −1.6604]	−0.4573 [0.2899; −1.5776]

Notes: (1) Results were estimated with 3-Step LCA with information preferences items as distal outcomes, using BCH according to Bakk and Vermunt 2016 (2) display of log-odds of indicating "yes", standard errors and z-value in parentheses (3) bold displays significance $p < 0.05$, threshold is $|z| \geq 1.96$.

Table 5
Probabilities of engagement preferences by EER-benefit latent classes.

Engagement Preference	Class 1 37.36% [n = 399]	Class 2 20.29% [n = 217]	Class 3 19.58% [n = 209]	Class 4 15.47% [n = 165]	Class 5 7.30% [n = 78]
Voting for renovation plans	/	−0.3086 [0.2035; −1.5167]	0.3245 [−0.2295; 1.4138]	0.0557 [0.2380; 0.2342]	0.3502 [0.3368; 1.0397]
Receiving renovation information	/	−0.3522 [0.3337; −1.0555]	0.1010 [0.3722; 0.0273]	−0.3962 [0.3648; −1.0860]	0.6073 [0.7021; 0.8650]
Observing one discussion event	/	0.1299 [0.1861; 0.6980]	0.1339 [0.1906; 0.7024]	−0.0332 [0.2036; −0.1629]	0.0777 [0.2690; 0.2889]
One-time discussion participation	/	**0.5017 [0.1946; 2.5777]**	**0.4008 [0.2008; 1.9960]**	0.2993 [0.2161; 1.3847]	0.5194 [0.2772; 1.8739]
Repeated active involvement	/	−0.2346 [0.1923; −1.2202]	−0.0277 [0.1937; −0.1433]	0.2292 [0.2041; 1.1230]	−0.0034 [0.2722; −0.0126]
No involvement	/	0.1978 [0.3310; 0.5974]	0.2017 [0.3470; 0.5813]	0.6272 [0.3346; 1.8742]	0.2179 [0.4903; 0.4445]

Notes: (1) Results were estimated with 3-Step LCA with engagement preferences items as distal outcomes, using BCH according to Bakk and Vermunt 2016 (2) display of log-odds of indicating "yes", standard errors and z-value in parentheses (3) bold displays significance p < 0.05, threshold is |z| ≥ 1.96.

Table 6
Goodness of fit statistics for latent classes of EER-barrier statements.

Class	Npar	LL	BIC	AIC	CAIC	SABIC	VLMR	Entropy	Class distribution (rounded in %)
2	141	-22589	46160	45459	46301	45712	3562***	0.9233	73 / 27
3	212	-21596	44670	43615	44882	43996	1986***	0.9042	52 / 29 / 19
4	283	-20833	43640	42233	43923	42741	1525***	0.9128	41 / 23 / 20 / 16
5	254	-20405	43278	41517	43632	42153	857***	0.9160	27 / 27 / 19 / 16 / 11
6	425	-20044	43051	40938	43476	41702	722***	0.9255	29 / 23 / 16 / 13 / 12 / 7
7	496	-19751	42962	40495	43458	41386	585***	0.9218	27 / 23 / 13 / 13 / 12 / 7 / 5
8	567	-19498	42949	40129	43516	41148	507***	0.9327	27 / 17 / 15 / 13 / 11 / 8 / 6 / 3
9	638	-19262	42974	39801	43612	40947	471***	0.9313	18 / 16 / 15 / 14 / 12 / 11 / 6 / 5 / 3
10	709	-19114	43174	39647	43883	40922	295***	0.9326	17 / 16 / 15 / 14 / 10 / 8 / 6 / 5 / 5 / 4

Notes: Log-likelihood values, Bayesian Information Criterium (BIC), Akaike Information Criterium (AIC), consistent AIC (CAIC), sample-size-adjusted BIC (SABIC), Vuong-Lo-Mendell-Rubin Test (VLMR) and its *p*-value (*p < 0.001**; p < 0.01**),* Entropy and class distribution are presented for models 2–10 classes, rounded. The selected classification is highlighted. Model diagnostics for the selected 7-class solution: APP range = 0.82–0.91; overall classification error = 0.11; minimum class size = 5.1% (n = 54).

service charge increase (0.6411), are also dominated by indecision. This combination indicates an ambivalent yet highly uncertain class. Self-reliant as they don't recognize TC [BA4-BA6] as an individual barrier. Significant predictor variables from the covariate section include the household composition; couples without children are less likely to be in this class (z = −2.35). They prefer home-visits for receiving information about EER (z = 2.32).

The Financially Alarmed (Class 5–11.7%) is sharply defined by extreme concern over financial consequences of EER. The majority of respondents in this class *strongly agree* that rent increases (0.9362), energy bill increases (0.7751), and service charge increases (0.8528) would act as barriers. This class expresses the highest level of financial concern in the entire segmentation. They also report intense concerns over practical disruption, with high probabilities of strong agreement for relocation (0.6561), life disruption (0.4974), and delays (0.4872). In contrast, trust and TC-related items show mostly neutral responses, indicating that those are not central barriers for this group. Although they support EER in principle, financial risk dominates. Significant predictors for this class are that this group is most likely to live in a building older than 1945 (z = 1.99). And that people indicating "other" in employment, who are mostly students or self-employed (z = −2.06), are not likely to be in this class.

The Confident Acceptors (Class 6–7.4%) reject all listed barriers and exemplify the ideal EER adopter: trusting, feeling informed, tolerant of inconvenience, and unconcerned about cost. Unemployed (z = −6.36) and retired respondents (z = −2.11) are less likely to belong to this class. Heat pump (z = 2.36) and combination/other systems (z = 2.42) predict higher likelihood, indicating preference for or familiarity with non-traditional heating. For Class 6 and Class 7, all age items (25–34 to <75) show a strong positive association. They do not prefer observation as an engagement method (z = −2.39).

The Uncertain (Class 7–5.1%), is dominated by "*I don't know*" responses across all barrier items, illustrating widespread indecision, and information asymmetry, requiring intensive informational support and individualized guidance to participate in the EER process. As with Class 5, people indicating "other" for employment are unlikely to be in this class as well. Single parents are significantly less likely to belong (z = −11.61) as well as Maisonette being the property type (z = −3.43). They prefer home visits as an information preference.

4.3. Overview of all persona profiles

Table 10 and Table 11 provide an overview of all variables used for persona profiling, including dominant response probabilities across multiple items as a key indicator for the latent class, the relevant predictor variables in the covariate sections, and statistically significant probabilities to information and engagement preferences. The summary helps to translate the persona profiles into tangible and practical targeted intervention strategies (see Table 12 and Table 13).

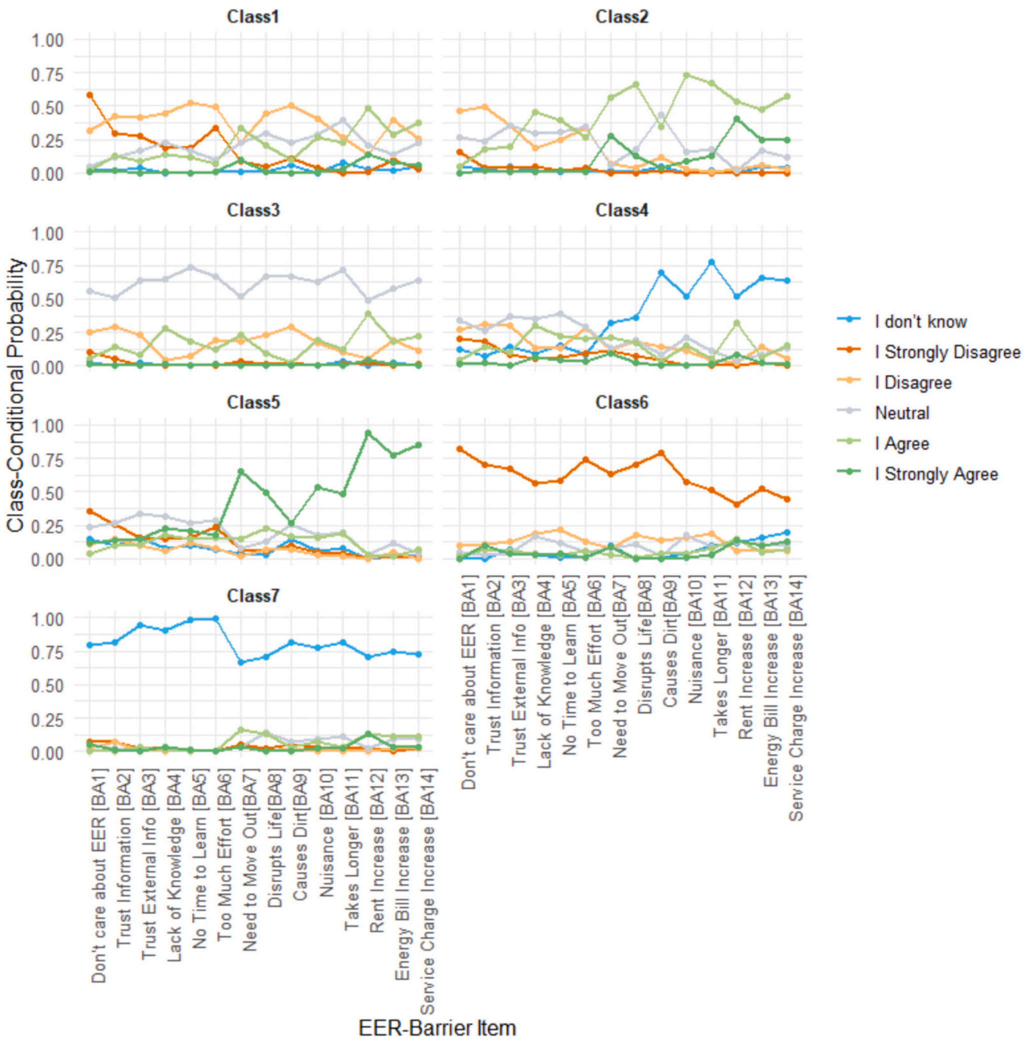

Fig. 4. Response probability profiles per EER-barrier item within each EER-barrier latent class – per latent class.

Table 7
Relationship between EER-barrier latent classes and covariate items.

Covariates	Class 1 26.54% [*n* = 283]	Class 2 23.08% [*n* = 247]	Class 3 13.26% [n = 142]	Class 4 12.87% [n = 137]	Class 5 11.67% [n = 125]	Class 6 7.44% [*n* = 79]	Class 7 5.14% [*n* = 55]
Age in years							
18–24 *(reference)*	–	–	–	–	–	–	–
25–34	/	0.6140 [0.5284; 1.1621]	0.3120 [0.5475; 0.5698]	−0.0072 [0.6711; −0.0107]	0.0396 [0.5791; 0.0683]	**5.6357 [0.7503; 7.5110]**	**5.2095 [0.7706; 6.7607]**
35–44	/	0.4779 [0.5308; 0.9002]	0.7172 [0.5552; 1.2917]	0.4049 [0.6477; 0.6251]	−0.0825 [0.6218; −0.1327]	**6.0147 [0.7933; 7.5816]**	**5.8128 [0.7705; 7.5439]**
45–54	/	1.1418 [0.5182; 0.2736]	−0.0814 [0.5519; −0.1474]	0.0411 [0.6432; 0.0639]	−0.3175 [0.5942; −0.5343]	**5.3511 [0.7505; 7.1297]**	**4.5835 [0.8555; 5.3576]**
55–64	/	0.4737 [0.5354; 0.8847]	0.0800 [0.5758; 0.1390]	0.3213 [0.6328; 0.5077]	−0.1351 [0.6403; −0.2110]	**5.8569 [0.7325; 7.9958]**	**5.1105 [0.8455; 6.0446]**
65–74	/	0.3852 [0.6835; 0.5636]	0.2318 [0.7019; 0.3302]	0.3387 [0.9000; 0.3764]	0.0340 [0.7894; 0.431]	**6.5253 [0.9017; 7.2368]**	**5.6470 [1.2624; 4.4733]**
< 75 years	/	0.2969 [0.7461; 0.3979]	0.6893 [0.7836; 0.8796]	0.3327 [0.9727; 0.3420]	0.3662 [0.8754; 0.4183]	**6.8878 [0.9883; 6.9692]**	**6.2878 [1.3735; 4.5778]**
Employment							
Full-time *(ref.)*	/	–	–	–	–	–	–
Part-time	/	0.3350 [0.3217; 1.0416]	0.0116 [0.3470; 0.0335]	−0.6380 [0.4010; −1.5910]	−0.1029 [0.3432; −0.2998]	−0.5851 [0.4537; −1.2898]	−0.4446 [0.5357; −0.8300]
Unemployed	/	−1.1145 [0.7561; −1.4740]	−0.1263 [0.5262; −0.2400]	−0.5958 [0.6031; −0.9880]	−0.7385 [0.6034; −1.2240]	**−5.8138 [0.9140; −6.3605]**	−0.0843 [0.8014; −0.1051]
Retired	/	0.2115 [0.5410; 0.3909]	−0.4800 [0.5570; −0.8619]	−0.4238 [0.7178; −0.5904]	−0.4764 [0.6455; −0.7380]	**−1.4331 [0.6780; −2.1136]**	−0.1839 [1.0858; −0.1694]
House Carer	/	0.0650 [0.5554; 0.1170]	−0.4199 [0.6127; −0.6853]	−0.3034 [0.5484; −0.5532]	−0.2547 [0.6289; −0.4049]	−1.2104 [0.8224; −1.4717]	−0.1726 [0.8343; −0.2069]
Unable to Work	/	0.1344 [0.3892; 0.3452]	−0.4470 [0.4503; −0.9925]	−0.1536 [0.3995; −0.3844]	−0.1997 [0.4305; −0.4639]	−0.0152 [0.4224; −0.0360]	−0.3696 [0.6509; −0.5678]
Other. e.g. Students. ZZP	/	−0.2997 [0.5016; −0.5975]	0.0486 [0.4964; 0.0980]	−0.9413 [0.6739; −1.3968]	**−1.8300 [0.8871; −2.0630]**	−1.2310 [0.8723; −1.4113]	**−5.0108 [0.6427; −7.7964]**
Household Composition							
One Person Household *(ref.)*	/	–	–	–	–	–	–
Single Parent	/	−0.0395 [0.3495; −0.1131]	−0.0299 [0.4057; −0.0736]	−0.0507 [0.3880; −0.1306]	−0.0630 [0.4336; −0.1452]	−0.0904 [0.5131; −0.1761]	**−5.2313 [0.4504; −11.6145]**
Couples without Children	/	−0.1721 [0.2366; −0.7273]	0.1227 [0.2717; 0.4518]	**−0.6949 [0.2957; −2.3499]**	−0.1576 [0.2957; −0.5330]	−0.0533 [0.3385; −0.1574]	−0.4855 [0.4048; −1.1993]
Couples with Children	/	−0.1078 [0.3005; −0.3586]	0.3616 [0.3213; 1.1255]	−0.2020 [0.3309; −0.6107]	0.2337 [0.3361; 0.6954]	−0.0377 [0.4131; −0.0912]	−0.3155 [0.4723; −0.6680]
Property							
Apartment *(ref.)*	/	–	–	–	–	–	–
Maisonette	/	−2.0427 [1.2483; −1.6364]	−0.7270 [0.8462; −0.8592]	−0.2079 [0.7011; −0.2966]	−0.1030 [0.6113; −0.1685]	1.1283 [0.5844; 1.9309]	**−4.6159 [0.6881; −6.7084]**
Terraced House	/	0.1279 [0.2302; 0.5558]	0.0693 [0.2501; 0.2769]	−0.2830 [0.2690; −1.0523]	−0.1552 [0.2689; −0.5773]	0.3583 [0.3089; 1.1599]	0.0410 [0.3543; 0.1156]
Corner House	/	−0.1967 [0.3095; −0.6355]	−0.1700 [0.3261; −0.5215]	−0.4110 [0.3433; −1.1972]	−0.3393 [0.3563; −0.9523]	−0.4555 [0.4881; −0.9331]	−0.5524 [0.5333; −1.0357]
Semi-detached or detached House	/	−0.0097 [0.5000; −0.0194]	−0.7418 [0.6840; −1.0845]	0.0805 [0.5530; 0.1456]	0.0846 [0.5759; 0.1470]	0.0212 [0.7082; 0.0299]	1.0372 [0.5939; 1.7463]
Building Year							

(*continued on next page*)

Table 7 (*continued*)

Covariates	Class 1 26.54% [n = 283]	Class 2 23.08% [n = 247]	Class 3 13.26% [n = 142]	Class 4 12.87% [n = 137]	Class 5 11.67% [n = 125]	Class 6 7.44% [n = 79]	Class 7 5.14% [n = 55]
From 2001 *(ref.)*	/	–	–	–	–	–	–
2000 to 1986	/	**0.7699 [0.3618; 2.1281]**	0.4658 [0.4142; 1.1246]	0.2713 [0.4619; 0.5874]	0.5941 [0.4354; 1.3644]	0.0630 [0.5132; 0.1227]	−0.0630 [0.5308; −0.1188]
1985 to 1971	/	0.5984 [0.3365; 1.7782]	0.1929 [0.3738; 0.5159]	0.5586 [0.3998; 1.3972]	0.3373 [0.3963; 0.8510]	0.1065 [0.4276; 0.2490]	−0.3981 [0.5157; −0.7719]
1970 to 1946	/	**1.0512 [0.3529; 2.9787]**	0.4716 [0.4019; 1.1735]	0.8591 [0.4206; 2.0427]	0.6334 [0.4337; 1.4603]	0.7606 [0.4361; 1.7438]	−0.5830 [0.5769; −1.0105]
Older than 1945	/	**0.9386 [0.4537; 2.0689]**	0.5135 [0.5163; 0.9946]	0.3668 [0.5730; 0.6401]	**1.0247 [0.5124; 1.9998]**	0.4605 [0.6490; 0.7096]	−1.5125 [1.1225; −1.3474]
I don't know	/	**0.8973 [0.4528; 1.9817]**	0.4025 [0.5083; 0.7918]	0.2275 [0.5958; 0.3819]	0.3486 [0.5538; 0.6294]	−0.3302 [0.6842; −0.4826]	−0.2973 [0.7338; −0.4052]
Energy Label							
High (A. A+ or better)	/	–	–	–			
Middle (B. C. D)	/	**−1.0553 [0.3029; −3.4837]**	0.0797 [0.3621; 0.2201]	−0.0651 [0.4098; −0.1588]	−0.7573 [0.3994; −1.8962]	−0.5128 [0.4391; −1.1679]	−0.4309 [0.5068; −0.8504]
Low (E. F. G)	/	**−1.0782 [0.4846; −2.2250]**	−0.0810 [0.5781; −0.1401]	−0.1510 [0.6061; −0.2491]	0.0268 [0.5055; 0.0531]	−0.5656 [0.7050; −0.8022]	−1.3101 [0.9851; −1.3298]
I don't know	/	**−0.8558 [0.2716; −3.1510]**	0.0671 [0.3491; 0.1923]	0.2058 [0.3850; 0.5345]	−0.1966 [0.3427; −0.5737]	0.0972 [0.3973; 0.2446]	−0.1872 [0.4640; −0.4034]
Heating Type							
Natural Gas *(ref.)*	/	–	–	–	–	–	–
DH	/	−0.0341 [0.3106; −0.1099]	−0.0739 [0.3413; −0.2166]	−0.2259 [0.3872; −0.5835]	0.0740 [0.3551; 0.2084]	0.4585 [0.3952; 1.1603]	−0.8696 [0.6293; −1.3820]
HP	/	0.0959 [0.3892; 0.2465]	0.4339 [0.4545; 0.9547]	0.2614 [0.5380; 0.4859]	0.1326 [0.4891; 0.2711]	**1.1750 [0.4989; 2.3551]**	−1.0044 [0.8626; −1.1644]
Combination & Other	/	0.0796 [0.5262; 0.1513]	0.1008 [0.5815; 0.1733]	0.5851 [0.5443; 1.0751]	−0.7449 [0.9031; −0.8248]	**1.3205 [0.5457; 2.4196]**	−0.9324 [0.9320; −1.0004]
I don't know	/	−0.4942 [0.5366; −0.9211]	−0.1353 [0.5289; −0.2559]	0.0057 [0.4957; 0.0115]	0.1353 [0.5186; 0.2608]	−0.3648 [0.6857; −0.5321]	−1.1916 [1.0304; −1.1564]

Notes: (1) Results were estimated with multinominal logistic regression using the Step3 approach in LatentGOLD with external variables classified as covariates. The Step3 approach was calculated separately for each block of covariates (2) Log-odds coefficient. S.E. and z-values are presented in the table. (3) The threshold $|z| \geq 1.96$. then $p < 0.05$ is used, marked bold. Prediction based on 95% confidence intervals. (4) Only items with significant predictors are shown; the full results for all items are provided in Appendix A16.

Table 8
Probabilities of information preferences by EER-barrier latent classes.

Information Preference	Class 1 26.54% [n = 283]	Class 2 23.08% [n = 247]	Class 3 13.26% [n = 142]	Class 4 12.87% [n = 137]	Class 5 11.67% [n = 125]	Class 6 7.44% [n = 79]	Class 7 5.14% [n = 55]
Letter by mail	/	−0.1189 [0.2439; −0.4877]	−0.1001 [0.2752; −0.3639]	−0.4209 [0.2627; −1.6025]	0.0898 [0.3007; 0.2986]	0.1848 [0.3639; 0.5077]	0.1317 [0.4190; 0.3142]
Email	/	0.1029 [0.2536; 0.4058]	−0.1488 [0.2750; −0.5409]	−0.0273 [0.2857; −0.0957]	−0.4745 [0.2708; −1.7518]	0.3822 [0.3895; 0.9814]	−0.6187 [0.3543; −1.7462]
Phone message	/	−0.2057 [0.2482; −0.8287]	−0.1446 [0.2830; −0.5110]	0.0972 [0.2710; 0.3586]	−0.5993 [0.3324; −1.8030]	−0.2808 [0.3682; −0.7625]	−0.7560 [0.4982; −1.5174]
Home visit	/	0.0196 [0.1963; 0.0998]	−0.0402 [0.2261; −0.1777]	**0.5114 [0.2205; 2.3189]**	0.2163 [0.2313; 0.9354]	0.3713 [0.2688; 1.3815]	**0.6052 [0.3093; 1.9569]**
Information event	/	−0.1164 [0.2044; −0.5693]	**−0.5294 [0.2228; −2.3764]**	−0.1920 [0.2327; −0.8254]	−0.1656 [0.2406; −0.6883]	−0.0800 [0.2846; −0.2810]	−0.2371 [0.3241; −0.7314]
Group discussion session	/	0.0731 [0.1888; 0.3873]	-0.2635 [0.2186; −1.2052]	−0.0113 [0.2185; −0.0518]	−0.2095 [0.2281; −0.9183]	−0.1759 [0.2682; −0.6556]	−0.2264 [0.3132; −0.7229]

Notes: (1) Results were estimated with 3-Step LCA with information preferences items as distal outcomes, using BCH according to Bakk and Vermunt 2016 (2) display of log-odds of indicating "yes", standard errors and z-value in parentheses (3) bold displays significance $p < 0.05$, threshold is $|z| \geq 1.96$.

Table 9
Probabilities of engagement preferences by EER-barrier latent classes.

Engagement Preference	Class 1 26.54% [n = 283]	Class 2 23.08% [n = 247]	Class 3 13.26% [n = 142]	Class 4 12.87% [n = 137]	Class 5 11.67% [n = 125]	Class 6 7.44% [n = 79]	Class 7 5.14% [n = 55]
Voting for renovation plans	/	−0.2223 [0.2208; −1.0067]	−0.3549 [0.3549; 0.2430]	−0.4512 [0.2458; −1.8359]	−0.3367 [0.2543; −1.3243]	−0.1042 [0.3101; −0.3359]	0.0046 [0.3726; 0.0125]
Receiving renovation information	/	−0.3393 [0.3757; −0.9030]	-0.1696 [0.4323; −0.3922]	−0.6834 [0.3934; −1.7371]	−0.0537 [0.4704; −0.1141]	−0.1240 [0.5185; −0.2391]	−0.5431 [0.5405; −1.0048]
Observing one discussion event	/	−0.1426 [0.1883; −0.7572]	−0.1177 [0.2137; −0.5506]	−0.0547 [0.2173; −0.2514]	−0.3691 [0.2260; −1.6332]	**−0.6514 [0.2726; −2.3893]**	−0.1236 [0.3069; −0.4026]
One-time discussion participation	/	0.2566 [0.1937; 1.3247]	−0.2371 [0.2298; −1.0316]	0.2789 [0.2232; 1.2494]	−0.0199 [0.2364; −0.0841]	−0.0507 [0.2803; −0.1807]	0.2359 [0.3153; 0.7483]
Repeated active involvement	/	−0.1664 [0.1908; −0.8723]	0.0477 [0.2146; 0.2221]	−0.2460 [0.2218; −1.1092]	−0.2193 [0.2283; −0.9606]	−0.3675 [0.2744; −1.3392]	−0.4685 [0.3228; −1.4514]
No involvement	/	0.5887 [0.3297; 1.7856]	**0.8714 [0.3529; 2.4690]**	−0.4153 [0.5183; −0.8013]	0.6182 [0.3865; 1.5996]	−0.7695 [0.6250; −1.2312]	0.1875 [0.5792; 0.3238]

Notes: (1) Results were estimated with 3-Step LCA with engagement preferences items as distal outcomes, using BCH according to Bakk and Vermunt 2016 (2) display of log-odds of indicating "yes", standard errors and z-value in parentheses (3) bold displays significance p < 0.05, threshold is $|z| \geq 1.96$.

Table 10
Overview of persona profiles of EER-benefit classes with codes.

Persona Name	Key Indicator	Summary of Predictor	Information Preference	Engagement Preference
Class 1: Immediate Utility Seeker (37,4%)	Caring for Comfort [BE1], Health [BE2], My-Well-Being [BE3], Indoor Facilities [BE5], Reduced Energy Consumption [BE6], Peoples Wellbeing [BE8]	*Reference*	*Reference*	*Reference*
Class 2: Personal Comfort Seekers (20,3%)	Caring for Comfort [BE1], Health [BE2], My Wellbeing [BE3], Low Emission [BE6], Peoples Wellbeing [BE8]	Likely: 55–64; 65–74 years; female, Not likely: 40 k–50 k Euro; building year 1970–1946;	–	Prefers: One-time discussion participation [E4]
Class 3: Balanced Benefit Idealist (19,6%)	Caring for all items [BE1-BE9]	Likely: 65–74 years; heat pump	Prefer: Phone message [I3], Home visit [I4], Information event [I5], Group discussion session [I6]	Prefer: One-time discussion participation [E4]
Class 4: Indifferent Respondents (15,5%)	Neutral for most BE; Caring for Comfort [BE1]; Reduced Consumption [BE6]	–	Not preferred: *E*-Mail [I2], Information event [I5] Prefer: Phone massage [I3]	
Class 5: Pessimists (7,2%)	Caring for Reduce Consumption [BE6]; Not Caring for Aesthetics [BE4]; Indoor Facilities [BE5], Low Emission [BE7], Neighborhood [BE9]	Likely: Combination & other Not likely: female, couples without children	Not preferred: E-Mail [I2], Information event [I5]	–

Table 11
Overview of persona profiles of EER-barrier classes with codes.

Persona Name	Key Indicator	Summary of Predictor	Information Preference	Engagement Preference
Class 1: Financial Sensitive (26,5%)	Barrier[1]: Need to Move out [BA7]; Rent Increase [BA12]; Service Charge Increase [BA14]	*Reference*	*Reference*	*Reference*
Class 2: Practical and Financial Concerned (23,1%)	Barriers: Lack of Knowledge [BA4]; No Time to Learn [BA5]; Need to Move Out [BA7]; Disrupt Life [BA8]; Causes Dirt [BA9]; Nuisance [BA10]; Takes Longer [BA11]; Rent Increase [BA12]; Energy Bill Increase [BA13]; Service Charge Increase [BA14]	Not likely: energy label B-G; I don't know Likely: building year 1986–2000; 1970-older than 1945; I don't know	–	–
Class 3: Ambivalent Observer (13,3%)	Barriers rated as "Neutral" for all Items [BA1-BA14]	–	Not preferred: Information event [I5]	Prefer: No involvement [E6]
Class 4: Self-Reliant but Unconvinced; (12,9%)	Barrier rated as "I don't know" for practical [BA7-BA11] and financial [BA12-BA14] statements	Not Likely: couples without children	Prefer: Home visit [I4]	–
Class 5: Financially Alarmed; (11,7%)	Barrier: practical are Need to Move Out [BA7], Disrupt Life [BA8], Nuisance [BA10], Takes Longer [BA11], and financial are increase of Rent, Energy Bill, and Service Charge [BA12-BA14]	Likely: employment other, e.g., student or ZZP; property building year older than 1945;	–	–
Class 6: Confident Acceptors; (7,4%)	No Barrier, as all items [BA1-BA14] were rated with "I strongly disagree."	Likely: all age groups; heating type is HP; combination or other Not likely: employment: unemployed; retired	–	Not preferred: Observing one discussion event [E3]
Class 7: The Uncertain. (5,1%)	Barrier rated as "I don't know" for all items [BA1-BA14]	Likely: all age groups; Not likely: employment other, e.g., student or ZZP; household: single parent; property: maisonette;	Prefer: Home visit [I4]	–

[1] Items are recognized as a barrier when respondents indicated "I agree" or "I strongly agree". That means that the barrier would prevent them from agreeing to an EER plan, see Table 1. If barrier items are answered with neutral, disagree or I don't know, it is mentioned additionally.

Table 12
Empirically informed targeted intervention strategies for each EER-benefit data-driven persona profile.

Persona (Benefit)	*Potential targeted intervention strategy*
Immediate Utility Seeker	Target this group with clear, practical communication emphasizing immediate household-level gains, particularly comfort, health, indoor improvements, and reduced energy consumption.
Personal Comfort Seeker	Use comfort-, health-, and well-being-oriented messaging, combined with a one-time discussion-based engagement format that allows tenants to actively explore the renovation's implications.
Balanced Benefit Idealist	Engage this group through broad benefit framing with slight emphasis on comfort, health, reduced energy consumption, and well-being, and pursue interactive participation formats, such as phone messages, home visits, events, and group discussions.
Indifferent Respondents	Approach this group with simple, personalized, low-effort communication through App or SMS, focused on a small number of directly relevant benefits, and low-effort gains (e.g., "warmer home for lower cost").
Pessimists	Use minimal, practical communication on energy-saving benefits through direct non-digital channels, with optional one-to-one support and relatable peer examples.

Notes: The proposed potential targeted intervention strategies are derived from the key indicators, information, and engagement preferences of EER-Benefits data-driven persona profiles in Table 10 in Section 4.3.

Table 13
Empirically informed targeted intervention strategies for each EER-Barrier persona profile.

Persona (Barrier)	*Potential targeted intervention strategy*
Financial Sensitive	Emphasize financial transparency, particularly regarding rent and service charge increases, while reducing relocation concerns, through clear, simplified procedural planning that minimizes perceived transaction costs.
Practical and Financial Concerned	Combine practical reassurance with financial clarity by offering stepwise guidance on renovation logistics, expected disruptions, and cost consequences. Communicate directly by the HA in a clear manner to reduce perceived transaction costs.
Ambivalent Observer	Use low-threshold, highly accessible communication that gradually builds awareness, rather than relying on active participation or event-based outreach. Deliver short, personalized messages by offering passive involvement.
Self-Reliant but Unconvinced	Provide personalized home-based communication that clarifies practical and financial uncertainties while respecting their preference for receiving information in a direct but non-demanding format.
Financially Alarmed	Prioritize strong financial reassurance through explicit information on rent, energy bills, and service charges before emphasizing renovation benefits. Provide comprehensive information to this group, as they don't perceive transaction costs as a barrier.
Confident Acceptors	Maintain straightforward, efficient communication, as this group appears broadly accepting and requires little persuasion. Think of engaging them as peer leaders in the community and EER-project.
The Uncertain.	Offer individualized support through home visits aimed at reducing uncertainty, clarifying information, and building confidence in the EER project.

Notes: The proposed potential targeted intervention strategies are derived from the key indicators, information, and engagement preferences of EER-Barrier data-driven persona profiles in Table 11 in Section 4.3.

4.4. Linking EER-benefit and EER-barrier latent classes

In Sections 4.1 and 4.2, latent classes were identified among social housing tenants regarding their perceived benefits and barriers to EER. To develop a more holistic profile of tenant heterogeneity, potential overlap between these latent class structures is examined. Specifically, the analysis assesses whether tenants with a higher likelihood of belonging to a particular EER-benefit class are also more likely to belong to a specific EER-barrier class, thereby indicating shared patterns of perception. Identifying such associations may support the design of more targeted interventions. The linkage between the two latent class structures is analyzed in two ways: first, through correlations between the posterior probabilities of EER-benefit and EER-barrier class membership (see Fig. 5), and second, through cross-tabulations of relative frequencies between the EER-benefit and EER-barrier latent classes (see Fig. 6).

Fig. 5 presents the Pearson correlation matrix between posterior probabilities of class membership for the EER-Benefit and EER-Barrier latent class solutions. The size and colour intensity of each circle indicate the strength of statistically significant correlations ($p < 0.05$), while insignificant associations are left blank for clarity. Within-construct correlations, strong negative correlations are visible within the EER-Benefit class block, particularly between: Benefit class 1 and classes 2, 3, and 4 ($r \approx -0.39$ to -0.31), and EER-Benefit class 2 and classes 3, 4, and 5 ($r \approx -0.39$ to -0.17). This reflects the mutual exclusivity of class assignments in latent class analysis: a higher probability of belonging to one class naturally reduces the likelihood of membership in competing classes. A similar, though more moderate, pattern is observed within the EER-Barrier class block, with weak-to-moderate negative correlations ($r \approx -0.31$ to -0.15) between several barrier classes, most notably: EER-Barrier class 1 and class 2 ($r = -0.31$), EER-Barrier class 1 and classes 3–5 ($r = -0.24$). These patterns again reflect mutual exclusivity. The matrix confirms the expected inverse structure within EER-Benefit and EER-Barrier classes, while also revealing slight associations between class memberships across the two domains.

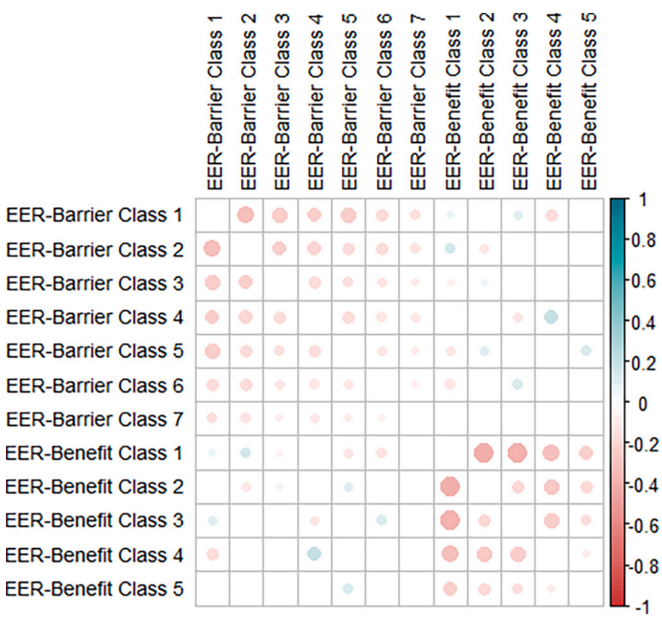

Fig. 5. Correlation of posterior probabilities for EER-benefit and EER-barrier latent classes

Notes: (1) Pearson Correlation (2) Intensity of correlation according to the correlation coefficient is displayed in circle size and colour intensity (3) blank cells indicate statistical insignificant correlations.

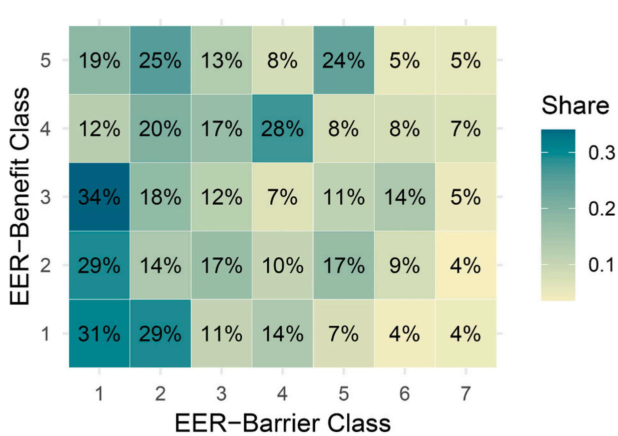

Fig. 6. Heatmap of cross-tabulated counts and relative frequencies between EER-benefit and EER-barrier latent classes

Note: (1) values are row-normalized (2) sum to 100% across each EER-Benefit Classes (row). (3) colouring reflects this percentage, with darker green indicating higher proportions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The heatmap in Fig. 6 presents the relative frequency distribution of EER-Benefit latent classes membership within each EER-Barrier latent class. The heatmap shows that EER-Barrier classes are not uniformly distributed across EER-Benefit Classes. Instead, different EER-Benefit segments are associated with distinct EER-Barrier profiles. However, overlap patterns above 24% were selected to illustrate how multiple EER-benefit and EER-barrier classes may be interpreted together as broader composite tenant personas (Appendix A17).

Notably, the *Financial Sensitive* persona (EER-Barrier Class 1) is relatively strongly represented with the *Immediate Utility Seekers* persona (EER-Benefit Class 1, 31%), with the *Personal Comfort Seekers* persona (EER-Benefit Class 2, 29%), and the *Balanced Benefit Idealist* persona (EER-Benefit Class 3, 34%). This pattern indicates that tenants who recognize the clear benefits of EER, particularly comfort, health, energy reduction, and well-being, while simultaneously expressing concerns about financial implications, such as rent, service charges, or the need to relocate. In other words, a positive evaluation of EER benefits does not necessarily preclude the presence of strong financial concerns.

The *Practical and Financial Concerned* persona (EER-Barrier Class 2) is most strongly associated with the *Immediate Utility Seekers* persona (EER-Benefit Class 1, 29%) and the *Pessimists* persona (EER-Benefit Class 5, 25%). This may indicate that respondents with practical and financial concerns tend to care for immediate, tangible benefits, such as reduced consumption, and do not care for aesthetic, indoor facilities, emissions, and neighborhoods. This pattern also suggests internal heterogeneity within this barrier profile: some tenants still value direct, tangible outcomes, whereas others remain broadly unconvinced. This implies that even within a shared barrier structure, the motivational basis for agreement with EER may differ substantially.

The *Self-Reliant but Unconvinced* persona (EER-Barrier Class 4) shows its strongest overlap with the *Indifferent Respondents* persona (EER-Benefit Class 4, 28%), suggesting a more disengaged profile in which both personas have majorly answered "*I don't care*" for practical and financial barriers and "*neutral*" for most benefit items. Suggest that if a respondent is indifferent, it most likely applies to both barrier and benefit categories. These tenants do not appear strongly opposed, but neither do they perceive substantial value in EER.

The *Financially Alarmed* persona (EER-Barrier Class 5) is most strongly represented among *the Pessimists persona (EER-Benefit Class 5, 24%),* indicating that strong financial concerns may co-occur with weak perceived benefit of EER. An overview of the mentioned representations is illustrated in Appendix A17 in addition to Fig. 6. Together, these illustrative combinations show that several EER-Benefit classes are distributed across multiple EER-Barrier classes, indicating substantial heterogeneity in how tenants combine perceived benefits and barriers. Overall, the findings underline that benefit-oriented and barrier-oriented profiles do not map neatly onto one another. This has practical implications for intervention design, as tenants with similar benefit perceptions may still differ markedly in the barriers they perceive, and vice versa.

5. Discussion

This study examined behavioural heterogeneity among tenants in

Dutch HAs regarding EER and assessed how such heterogeneity can be operationalized to support consent-oriented implementation. Using LCA, five benefit-based and seven barrier-based latent classes were identified and translated into persona profiles by linking class membership to significant contextual predictors, as well as to information and engagement preferences. The results show that tenants' evaluations of EER are highly differentiated; therefore, "average-tenant" approaches are unlikely to be effective under consent-based governance.

Across the five EER-Benefit persona profiles, namely *Immediate Utility Seekers*, *Personal Comfort Seekers*, *Balanced Benefit Idealists*, *Indifferent Responders*, and *Pessimists* demonstrate how tenants prioritize personal, tangible gains over collective or aesthetic improvements. Conditional response probabilities consistently indicate a strong concern for comfort, health, personal well-being, reduced consumption and energy bills, low emissions, and overall people's well-being. Less emphasis was placed on possible benefits, such as aesthetic value, indoor facilities, or neighborhood development. This pattern is consistent with prior evidence that social housing tenants emphasize comfort and financial benefits [2,53]. Substantively, most respondents belonged to EER-Benefit classes 1 to 3, indicating that most social housing tenants care about multiple EER benefit items. A minority of respondents were classified as *Indifferent* (class 4, 15.5%) or *Pessimists* (class 5, 7.2%), indicating that a few tenants do not recognize the benefits of EER. Overall, the results suggest that tenants place greater value on direct, personal, and tangible benefits such as comfort, health, and financial savings. In contrast, collective or abstract benefits (e.g., aesthetics, improved neighborhood, or indoor facilities) receive comparatively less prioritization.

The seven EER-Barrier persona profiles, namely *Financial Sensitive, Practical, Financially Concerned, Ambivalent Observer, Self-Reliant but Unconvinced, Financially Alarmed, Confident Acceptors,* and *Uncertain*, reveal a clear pattern of financial constraints and practical disruptions as the most salient obstacles. This includes concerns about potential rent increases, energy bills, and service charges. This is evident, as financial barriers are perceived at varying intensities, for example, in classes 1 and 5. This finding aligns with other research, that frames financial concerns as a crucial barrier [14,53]. Practical disruptions such as having to move out temporarily [BA7], disruption of daily life, dirt, and renovation taking longer than expected were also commonly perceived as burdensome. In contrast, attitudinal barriers (e.g., "I don't care about EER") and trust-related barriers (e.g., mistrust in the housing association or external information) were less frequently endorsed, indicating that most tenants care about EER and generally trust the information they receive. Overall, the results indicate that financial and practical considerations are the primary perceived barriers to EER for tenants, while ideological resistance or distrust is relatively rare. A significant portion of tenants show uncertainty or require tailored support, underscoring the need for personalized, transparent communication strategies.

Taken together, these findings suggest that tenant heterogeneity in decision-making regarding EER is driven less by a fundamental resistance to renovation and more by differences in how they weigh expected benefits against anticipated barriers. This is an important sociological insight. From this perspective, tenants' responses to EER should not be reduced to individual preference alone but understood as embedded in broader questions of distributive, procedural, and recognitional justice [13]. Recent scholarship on just renovation argues that socially sustainable renovation depends not only on energy performance outcomes, but also on whose needs are recognized, how burdens and benefits are distributed, and whether residents are meaningfully included in decision-making [12,13,86]. This is part of the recognitional justice discussions. Ricci's recent review shows that justice-oriented renovation scholarship increasingly foregrounds resident inclusion, lived experience, and vulnerable housing contexts, including disadvantaged households [13]. Justice research in social housing similarly emphasizes how situated justice claims from residents are key dimensions of a fair renovation process [87]. In this light, the benefit and barrier personas identified here can be understood as different configurations of perceived justice: some tenants primarily assess renovation based on expected improvements in comfort, health, and affordability, whereas others are more strongly oriented toward cost exposure, disruption, or uncertainty throughout implementation.

The prominence of practical and financial barriers also highlights the importance of everyday-life disruption as a mechanism shaping renovation acceptance [88]. Concerns about temporary relocation, dirt, delays, and interruption of routines should not be interpreted as superficial reluctance. Rather, they reflect the lived consequences of renovation for households with limited capacity to absorb practical or financial shocks. Recent work on social housing renovation similarly shows that standardized renovation approaches can overlook how residents adapt and use their homes, thereby generating justice claims when interventions disrupt established practices of comfort, care, and daily organization [87]. This interpretation is highly relevant in the present case: practical disruption is not a secondary inconvenience but a central element in the social perception of renovation. In this regard, it cannot be assumed that simply accelerating EER is inherently just because it contributes to climate goals. For disadvantaged tenants' households, they may have limited capacity to absorb additional costs or disruptions. The legitimacy of EER depends on whether EER generates tangible benefits for them, such as improved comfort, health, and affordability, without disproportionately shifting financial or practical burdens onto those least able to bear them.

This perspective can also be situated within the broader split incentive debate in rental housing. In its classic formulation, the split incentive arises because landlords are responsible for investing in dwelling performance, while tenants often bear part of the consequences through altered charges, disruption, and uncertainty about whether promised savings or comfort gains will materialize. Recent evidence confirms that rental housing remains a key domain in which owner-renter misalignment complicates energy-efficiency investments [42]. However, the present results suggest that the split-incentive framework alone does not fully explain tenant-side variation. Many tenants in this study did not express strong ideological opposition to EER, nor did they distrust the dominant pattern. Instead, concerns clustered around affordability and disruption. The implementation challenge is therefore not only one of misaligned economic incentives, but also one of perceived risk, burden distribution, and procedural reassurance. In social housing, the legitimacy of renovation depends not simply on whether the landlord invests, but on whether tenants believe that the process protects their daily life and material security while delivering credible benefits. This underlines the need to develop adequate engagement strategies and information provision for social housing tenants that are suited to diverse heterogeneous profiles.

Another notable finding of the LCA is that contextual variables do not appear to determine tenants' perception in a simple or uniform way. While previous literature points to the sociological relevance of contextual variables such as education, age, and income, [2,51,89], the present analysis did not reveal a straightforward pattern in which particular socio-demographic groups consistently aligned with the personas. Instead, the results suggest that perceptions of EER cut across conventional socio-demographic categories. This is substantively important because it indicates that behavioural heterogeneity in renovation decision-making is better understood through how tenants interpret and evaluate perceived barriers and benefits than through objective characteristics alone. In this respect, the persona-centered approach offers clear value, as it captures meaningful variation in support needs and evaluative orientations that may be hidden in conventional demographic profiling or classic linear analytical approaches.

Methodologically, this study contributes to the growing application of data-driven persona-centered frameworks in energy-transition research by moving beyond narrative approaches and purely descriptive segmentation. Rather than constructing tenant "types" heuristically, the study derives personas from probabilistic latent class solutions and systematically connects these to information and engagement preferences. This is in alignment with prior segmentation studies [2,29,69], with the aim of enhancing interpretability, actionable guidance for tailoring engagement and support, and policy usability. The contribution, therefore, lies not in the persona label itself but in translating statistically observed heterogeneity into an operationally usable format for implementation design. In the following, an evidence-based operational synthesis of the EER-Benefit and EER-Barrier persona profiles is presented to outline potential implications for targeted intervention strategies (see Table 12 and Table 13).

5.1. Implications for targeted intervention strategies

From an implementation and governance perspective, the central challenge is to achieve sufficient tenant agreement under binding consent requirements while using limited engagement capacity efficiently and fairly. The findings suggest that persona-informed implementation can support this task by helping HAs differentiate between tenants who primarily require benefit-oriented communication, those who require barrier reduction and procedural reassurance, and those who need more intensive clarification or intensified engagement. The practical value of the personas, therefore, lies not in labeling residents, but in improving the fit between intervention design and perception. In practical terms, persona-based targeting can integrate four intervention dimensions: (a) communication framing, (b) participation formats, (c) administrative burden reduction, and (d) financial protections and supports. Targeting refers to the deliberate allocation of program benefits to those most in need, aiming to reduce inequality and enhance the efficient use of resources [21].

The relevance of these findings extends to policymakers, HA, contractors, municipalities, tenants' organizations, and NGOs. HA remain the primary actors in organizing communication, sequencing participation, and ensuring affordability protections, but implementation can also be strengthened by contractors, municipalities, tenants associations, NGOs, or the umbrella organization Aedes [34]. Contractors are especially relevant where disruption management, realistic planning, and trust in delivery are central concerns. Tenant associations and local intermediaries can improve legitimacy by translating technical plans into resident-centered language and by offering peer-based reassurance. Municipalities and national governments shape the regulatory and financial conditions that determine whether communication standards, tenant protection measures, and support infrastructures can be embedded in the renovation process. Persona-informed targeting should therefore be understood as a multi-actor governance strategy rather than solely as a communication tool for HAs.

In this sense, the findings in this article can serve as inspiration for implications for EU and national support design. Current EU policy increasingly recognizes that building renovation requires more than investment in physical measures alone. EU initiatives such as the Renovation Wave, REPowerEU, and the Affordable Housing Initiative, together with the recast Energy Performance of Buildings Directive – including practical guidance on establishing one-stop shops for renovation assistance - signal a broader policy shift toward the necessary combination of capital investment with implementation support [6,90,91].

In the Dutch social housing sector, this discussion must be situated within a distinctive institutional context. Unlike many other forms of public or affordable housing in Europe, Dutch social housing is provided by non-profit HAs operating within a nationally coordinated system, in which sectoral targets are shaped through national performance agreements involving government and Aedes [11,34]. The abolition of the landlord tax increases the sector's investment capacity and was tied to binding national agreements on affordability, construction, and sustainability [92]. These agreements also strengthen affordability protections, including rent moderation, to provide affordable rent for eligible tenants under private-market conditions, and the principle of no rent increase for insulation measures [93]. This supports personas like *Financial Sensitive, Practical and Financially Concerned, and Financially Alarmed*, which reflect increasing concern about financial statements. Against this background, the present finding suggests that the acceleration of EER in social housing cannot depend solely on capital finance. In consent-based renovation processes, tenant-facing support structures are equally important, including financial transparency, protection against perceived cost burdens, low-threshold clarification, and practical assistance in navigating the renovation process. A social-housing-adapted support platform, inspired by the one-stop-shop principle but tailored to tenants' needs rather than homeowners' needs, could centralize information on timelines, expected disruption, rent and service-charge implications, tenant rights during renovation, available support, and channels for complaints or clarification. The concept of a one-stop shop is to provide a central information point, with the underlying principle of reducing fragmentation across various information channels [90,94]. Such an inclusive mechanism would be particularly valuable for *the Financially Alarmed*, *the Practically Concerned*, or *the Uncertain* persona profiles, because it reduces administrative and cognitive burdens while increasing transparency and procedural clarity. A key implication for both EU and national policy is therefore that renovation finance should be complemented by engagement finance, for example through dedicated resources for tenant communication, local support desks, housing-association-based engagement teams, or independent advisory services that help residents understand renovation in practice.

To synthesize these empirical implications for applied audiences, such as HAs and other actors mentioned as involved in renovation governance, Tables 12 and 13 present empirically informed intervention strategies tailored to the identified benefit-based and barrier-based persona profiles. The proposed implications translate the class-specific key indicators and the information and engagement preferences presented in Tables 10 and 11 into differentiated approaches that may support HAs and other stakeholders in designing more targeted tenant outreach. While these intervention strategies remain speculative and require further investigation and empirical validation, they can still be useful for policymakers and practitioners. More broadly, the data-driven tenant personas show how segmentation can inform communication and engagement strategies in social housing renovation, as differences in key indicators and preferences suggest that outreach can be better aligned with the factors most relevant to each segment.

In this respect, Table 12 links the dominant benefit key indicators and associated information and engagement preferences of the EER-Benefit personas to targeted intervention strategies. The findings suggest that for *Immediate Utility Seekers* and *Personal Comfort Seekers*, the most suitable strategy is likely to emphasize direct, tangible household-level gains, such as improved comfort, health, and reduced energy consumption, while placing less emphasis on broader collective or aesthetic outcomes. Similarly, *Balanced Benefit Idealists* appear more receptive to broader benefit framing and more interactive forms of engagement and participatory formats. By contrast, for more ambivalent personas, such as *Indifferent Responders and Pessimists*, simpler, more selective communication, such as one-to-one clarification, is likely to resonate more than information-rich or intensive engagement approaches. In summary, the findings show that comfort, health, and personal well-being benefits [BE1-BE3], financial benefits [BE6], and environmental benefits [BE7] should be prioritized in targeted communication, as these emerged as the most prominent and widely recognized benefit dimensions.

The same procedure applies to the EER-Barrier personas. Table 13 shows potential targeted intervention strategies derived from the empirical results in Table 11. The findings suggest that the *Financial Sensitive* and *Practical and Financial Concerned* personas require financial transparency and clarity about practical disruptions. As both personas seem to perceive high individual transaction costs, the communication process and EER-project presentation should be as clear and simple as possible. In contrast, the *Financially Alarmed* express stronger perceived financial concerns but lower individual transaction cost burdens and lower trust in HAs, suggesting that providing comprehensive information to this group could be a suitable strategy. *The Self-Reliant but Unconvinced* and *the Uncertain* represent distinct governance challenges, as their dominant "*I don't know*" response patterns point to informational ambiguity, bounded rationality, or limited confidence in decision-making; since both personas prefer home visits, personalized communication may help as they are willing to seek clarity. By contrast, the *Ambivalent Observer* appears more detached and less inclusive toward participation, making those personas the most challenging to engage. Lastly, the *Confident Acceptors* appear broadly supportive of EER and could function as informal peer ambassadors within the EER project.

This interpretation is consistent with previous research showing that households vary substantially in their renovation preference and that tailored, more differentiated intervention approaches, rather than uniform communication strategies, can improve the fit between policy instrument and user motivation [2,57]. It also aligns with the wider evidence on health effects in renovation, that clear communication, practical support, and appropriately calibrated resident involvement can reduce renovation-related stress and strengthen acceptance in social housing settings [95].

Implementation should treat benefit communication and barrier reduction as complementary but separable strategies. EER project success is unlikely if it relies solely on promoting benefits while leaving financial and practical frictions unaddressed. This aligns with the evidence that intervention needs vary by segment in terms of motivations and barriers [57], and that tenants' willingness to agree depends on the type of information provided [47]. Persona-informed targeting can therefore guide subsidy design and governance requirements (e.g., standardized financial disclosure and minimum inclusion procedures), aligning policy instruments with heterogeneous tenant perception. This is particularly relevant in social housing systems where affordability is shaped by state oversight and support mechanisms, including favorable financing and housing allowances [8,96], and where more stringent policy designs can be used to steer energy-related behavior [97]. This research supports the growing recognition that heterogeneity must be acknowledged in order to design tailored support for energy-efficiency projects, moving beyond one-size-fits-all approaches and contributing to a more just energy transition [15,98]. Persona-based targeting may support a more just renovation process by recognizing tenant heterogeneity rather than applying uniform pressure across diverse groups.

5.2. Limitations and directions for future research

Several limitations should be acknowledged. First, the analysis relies on self-reported survey measures, which can be affected by response bias and may not fully align with respondents' perceptions or actual experiences of benefits or barriers. While the personas are data-driven and empirically grounded, the analysis does not observe actual consent decisions or post-renovation behavior. The personas, therefore, do not predict outcomes directly, but rather represent differing patterns of sensitivity and receptiveness to interventions at the pre-decision stage. Future research could link these personas to observed consent rates or renovation outcomes to further validate their predictive performance. This limitation is evident in the underreporting of transaction cost-related barriers. Previous qualitative research suggests that tenants often lack the knowledge to fully comprehend the complexities of EER, yet still perceive themselves as competent decision-makers in the process [16,53]. Second, the Likert-scale design, while suitable for LCA and persona profiling [67], may induce acquiescence or social desirability bias [99–101]. Third, the study is situated in Dutch social housing, which limits contextual variation and may constrain generalizability to private rental or owner-occupied sectors. Transferability is most plausible in contexts where tenants depend on landlords for renovation decisions and where consent thresholds shape implementation Fourth, even with quota-based representativeness, the sample may underrepresent the least engaged tenants. In practice, non-participation can impede implementation even in the absence of strong opposition [102]. Although quota-based sampling was used to improve alignment with the target population, panel-based recruitment may introduce selection bias, as participation is limited to individuals registered with the panel and willing to complete surveys. This may affect representativeness; the final sample may still underrepresent harder-to-reach groups and over-represent respondents who are more accustomed to survey participation. Fifth, socio-demographic and housing variables showed only a limited significant influence on class membership, indicating that tenants' perceptions of EER are shaped predominantly by behavioural and perceptual factors rather than by background characteristics. Sixth, this study is based on a hypothetical scenario of a potential EER project; future research would therefore require a design that includes both consenting and non-consenting tenants. Finally, although LCA is well-suited to identifying unobserved heterogeneity, it represents social complexity through a finite number of discrete classes and does not fully capture dynamic or interaction-based decision processes. Moreover, because the analysis identifies distinct configurations of perceived benefits and information preferences rather than estimating causal intervention effects, the proposed targeted intervention strategies should be interpreted as evidence-informed implementation implications that require further investigation and validation. Future Research could also explore this persona classification further toward predictive persona evaluation [70] or other LLM or AI persona generation and validation approaches [71,103].

6. Conclusion

This study provides an empirically grounded understanding of tenant heterogeneity in the context of EER in Dutch social housing, with the explicit aim of supporting consent-oriented implementation. Using a three-step LCA on a representative sample of 1068 Dutch social housing tenants, the study identified five benefit segments and seven barrier segments. These class structures were highly differentiated and substantively meaningful, demonstrating that social housing tenants do not perceive EER as a homogenous population. The findings therefore challenge one-size-fits-all implementation approaches and show that effective renovation governance requires greater sensitivity to behavioural heterogeneity.

Building on these empirical patterns, the study translated statistically derived classes into data-driven persona profiles by linking class membership to significant contextual predictors as well as tenants'information and engagement preferences. This makes it possible to move beyond descriptive segmentation toward a more practice-oriented understanding of how different tenant groups may interpret and respond to EER statements. In this sense, the study contributes not only an analytical framework for identifying heterogeneity but also a practical basis for tailoring information and engagement strategies to different tenant persona profiles.

Overall, the study shows that tenant heterogeneity is not a peripheral issue but a central implementation condition in social housing renovation. Recognizing variation in perceived benefits, perceived barriers, and preferred information and engagement formats can help HAs, practitioners, and policymakers design interventions that are more equitable and operationally effective. Rather than distributing generic information, HAs can align communication framing, participation formats, and support mechanisms with persona-specific configurations. The study offers a replicable framework for designing targeted, equity-relevant interventions by providing potential intervention strategies for each persona, helping practitioners and policymakers anticipate the likely audience for different potential targeted intervention strategies. The findings therefore support the broader shift toward tailored engagement support in energy-efficiency policy and practice, contributing to a more just and effective energy transition in the social housing sector.

CRediT authorship contribution statement

Stefanie Horian: 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. **Henk Visscher:** Writing – review & editing, Supervision.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.erss.2026.104784.

Data availability

Data will be made available on request.

References

[1] EC, 01 2026 | A European Green Deal | Renovation Wave Initiative in the Buildings Sector [Online]. Available: https://www.europarl.europa.eu/legislative-train/carriage/renovation-wave/report?sid=9901, 2026.

[2] X. Liu, D. Yang, T. Arentze, T. Wielders, The willingness of social housing tenants to participate in natural gas-free heating systems project: Insights from a stated choice experiment in the Netherlands, Appl. Energy 350 (2023) 121706, https://doi.org/10.1016/j.apenergy.2023.121706.

[3] P. Mulder, F. Dalla Longa, K. Straver, Energy poverty in the Netherlands at the national and local level: a multi-dimensional spatial analysis, *Energy Res.* Soc. Sci. 96 (2023) 102892. Feb. https://doi.org/10.1016/j.erss.2022.102892.

[4] J. Dolšak, Determinants of energy efficient retrofits in residential sector: A comprehensive analysis, Energ. Buildings 282 (2023) 112801. Mar. https://doi.org/10.1016/j.enbuild.2023.112801.

[5] F. Filippidou, N. Nieboer, H. Visscher, Are we moving fast enough? The energy renovation rate of the Dutch non-profit housing using the national energy labelling database, Energy Policy 109 (2017) 488–498. Oct. https://doi.org/10.1016/j.enpol.2017.07.025.

[6] EC, Energy Performance of Buildings Directive [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L_202401275&pk_keyhttps://energy.ec.europa.eu/topics/energy-efficiency/energy-performance-buildings/energy-performance-buildings-directive_enword=Energy&pk_content=Directive, 2024.

[7] EC, The European Affordable Housing Plan, European Commission, SWD(2025), 2025, 1053 final. [Online]. Available: https://housing.ec.europa.eu/document/download/756915b5-d1b1-4bde-ac82-03532d2d3d90_en?filename=0.pdf.

[8] J. Hoekstra, Reregulation and Residualization in Dutch Social Housing: A Critical Evaluation of New Policies, Crit. Hous. Anal. 4 (1) (2017) 31–39. Jun. 10.13060/23362839.2017.4.1.322.

[9] Aedes, Hoe zit het met … woningen met E-, F—en G-labels, Accessed: Dec. 12 (2024) [Online]. Available: https://aedes.nl/verduurzaming/hoe-zit-het-met-woningen-met-e-f-en-g-labels.

[10] Aedes, De 70 procent-regeling, Accessed Dec. 12 (2024) [Online]. Available: https://aedes.nl/verduurzaming/de-70-procent-regeling.

[11] S. Horian, Q.K. Qian, J.S.C.M. Hoekstra, Henk J. Visscher, Towards understanding the barriers in the decision- making process of EER projects in Dutch housing associations: a conceptual framework, Sustain. Built Environ. Conf. 2025 (2025).

[12] W. Broers, R. Kemp, V. Vasseur, N. Abujidi, Z. Vroon, Justice in social housing: Towards a people-centred energy renovation process, Energy Res. Soc. Sci. 88 (2022) 102527. Jun. https://doi.org/10.1016/j.erss.2022.102527.

[13] D. Ricci, T. Konstantinou, H. Visscher, Making energy renovations equitable: A literature review of decision-making criteria for a just energy transition in residential buildings, Energy Res. Soc. Sci. 122 (2025) 104016. Apr. https://doi.org/10.1016/j.erss.2025.104016.

[14] M. Bal, F.M. Stok, C. Van Hemel, J.B.F. De Wit, Including Social Housing Residents in the Energy Transition: A Mixed-Method Case Study on Residents' Beliefs, Attitudes, and Motivation Toward Sustainable Energy Use in a Zero-Energy Building Renovation in the Netherlands, Front. Sustain. Cities 3 (2021) 656781. May, https://doi.org/10.3389/frsc.2021.656781.

[15] V. Gianfrate, C. Piccardo, D. Longo, A. Giachetta, Rethinking social housing: Behavioural patterns and technological innovations, Sustain. Cities Soc. 33 (2017) 102–112. Aug. https://doi.org/10.1016/j.scs.2017.05.015.

[16] W. Swan, R. Fitton, P. Brown, Managing Behavioral Risks in Large- Scale Social Housing Sustainable Retrofit Projects in the UK, ECEEE Summer Study Proc., 2013, pp. 661–669.

[17] S. Furman, K. Hadjri, Wasted expertise: Why retrofit should include residents, Energy Res. Soc. Sci. 119 (2025) 103894. Jan. https://doi.org/10.1016/j.erss.2024.103894.

[18] Å. Blomsterberg, E. Pedersen, Tenants Acceptance or Rejection of Major Energy Renovation of Block of Flats – IEA Annex 56, Energy Procedia 78 (2015) 2346–2351. Nov. https://doi.org/10.1016/j.egypro.2015.11.396.

[19] S. Chahal, W. Swan, P. Brown, Tenant Perceptions and Experiences of Retrofit, 2011.

[20] P. Femenias, K. Granath, M. Buser, J. Widmark, Uncertainties and anticipated disturbances as drivers of tenant relocation in Swedish housing renovation, Energy Res. Soc. Sci. 133 (2026) 104556. Mar. https://doi.org/10.1016/j.erss.2026.104556.

[21] P. Simshauser, The 2022 energy crisis: Fuel poverty and the impact of policy interventions in Australia's National Electricity Market, Energy Econ. 121 (2023) 106660, https://doi.org/10.1016/j.eneco.2023.106660.

[22] EEA, Accelerating the energy efficiency renovation of residential buildings — a behavioral approach, European Environment Agency (EEA) (2023) [Online]. Available: https://www.eea.europa.eu/publications/accelerating-the-energy-efficiency.

[23] M. Hallswort, M. Egan, J. Rutter, J. McCrae, Behavioural Government. Using behaviourak science to improvide how governments make decisions, The Bheavioural Insights Team, 2018.

[24] M. Hallsworth, A manifesto for applying behavioural science, Nat. Hum. Behav. 7 (3) (2023) 310–322. Mar. https://doi.org/10.1038/s41562-023-01555-3.

[25] M. Dupoux, et al., Unlocking the full potential of behavioural insights for policy: from influencing the individual to shaping the system, European Commission. Joint Research Centre. (2025), https://doi.org/10.2760/7367599.

[26] OECD, Behavioural Insights [Online]. Available: https://www.oecd.org/gov/regulatory-policy/behavioural-insights.htm, 2025.

[27] S. Carley, Specialty grand challenge: Energy transitions, human dimensions, and society, Front. Sustain. Energy Policy 1 (2022) 1063207. Dec. https://doi.org/10.3389/fsuep.2022.1063207.

[28] N. Sokol, et al., 'Personas for lighting'. Three methods to develop personas for the indoor lighting environment, Energ. Buildings 278 (2023) 112580. Jan. https://doi.org/10.1016/j.enbuild.2022.112580.

[29] J. Balest, D. Vettorato, Social Acceptance of Energy Retrofit in Social Housing: Beyond the Technological Viewpoint, in: A. Bisello, D. Vettorato, P. Laconte, S. Costa (Eds.), Smart and Sustainable Planning for Cities and Regions, Springer International Publishing, 2018, pp. 167–178.

[30] M. Pellegrino, C. Wernert, A. Chartier, Social housing net-zero energy renovations with energy performance contract: incorporating occupants' behaviour, Urban Plan. 7 (2) (2022), https://doi.org/10.17645/up.v7i2.5029 no. 2, Art.. Apr.

[31] CBS, Housing Stock; Ownership, Landlord Type, Occupancy, Region [Online]. Available: https://opendata.cbs.nl/statline/#/CBS/nl/dataset/82900NED/table?dl=2AA82, 2025.

[32] M. Verlinden, Homes with EFG Labels - What Next [Online]. Available: https://aedes.nl/verduurzaming/woningen-met-efg-labels-hoe-verder, 2025.

[33] H. van Deursen, The people's housing: woningcorporaties and the Dutch social housing system - Part 1: the history, Jt. Cent. Hous. Stdies Harv. Univ. (2023).

[34] Aedes, Nationale Prestatieafspraken [Online]. Available: https://aedes.nl/media/document/volledige-tekst-nationale-prestatieafspraken, 2022. (Accessed 12 December 2024).

[35] Rijksoverheid, What Rules Apply to A Rent Increase [Online]. Available: https://www.rijksoverheid.nl/onderwerpen/woning-huren/vraag-en-antwoord/welke-regels-gelden-er-voor-een-huurverhoging, 2025.

[36] Rijksoverheid, Woningwet*: regels voor woningcorporaties* [Online]. Available: https://www.rijksoverheid.nl/onderwerpen/woning-verhuren/woningwet-regels-voor-woningcorporaties, 2015.

[37] WSW, Social Housing Guarantee Fund. Wie Zijn Wij [Online]. Available: https://www.wsw.nl/over-wsw/over-ons/wie-zijn-wij, 2025.

[38] Rijksdienst voor Ondernemend Nederland, Incentive Scheme For Natural Gas-Free Rental Homes [Online]. Available: https://www.rvo.nl/subsidies-financiering/sah, 2026.

[39] T.M. Croon, et al., Energy coaching and 'fix team' retrofitting to mitigate energy poverty: An ex-post analysis of treatment and interaction effects, Energy Res. Soc. Sci. 119 (2025) 103807. Jan. https://doi.org/10.1016/j.erss.2024.103807.

[40] T.M. Croon, J.S.C.M. Hoekstra, U. Dubois, Energy poverty alleviation by social housing providers: A qualitative investigation of targeted interventions in France, England, and the Netherlands, Energy Policy 192 (2024) 114247. Sep. https://doi.org/10.1016/j.enpol.2024.114247.

[41] Rijksoverheid, Kom ik in aanmerking voor een sociale huurwoning van een woningcorporatie? [Online]. Available: https://www.rijksoverheid.nl/onderwerpen/huurwoning-zoeken/vraag-en-antwoord/wanneer-kom-ik-in-aanmerking-voor-een-sociale-huurwoning, 2026.

[42] P. Singhal, S. Sommer, K. Kaestner, M. Pahle, Split-incentives in energy efficiency investments? Evidence from rental housing, Resour. Energy Econ. 82 (2025) 101488. May, https://doi.org/10.1016/j.reseneeco.2025.101488.

[43] L. Mundaca, X. Zhu, M. Hackenfort, Behavioural insights for sustainable energy use, Energy Policy 171 (2022) 113292. Dec. https://doi.org/10.1016/j.enpol.2022.113292.
[44] N. DellaValle, A. Bisello, J. Balest, In search of behavioural and social levers for effective social housing retrofit programs, Energ. Buildings 172 (2018) 517–524. Aug. https://doi.org/10.1016/j.enbuild.2018.05.002.
[45] B. Kiss, Exploring transaction costs in passive house-oriented retrofitting, J. Clean. Prod. 123 (2016) 65–76, https://doi.org/10.1016/j.jclepro.2015.09.035.
[46] C.S. Monteiro, F. Causone, S. Cunha, A. Pina, S. Erba, Addressing the challenges of public housing retrofits, Energy Procedia 134 (2017) 442–451. Oct. https://doi.org/10.1016/j.egypro.2017.09.600.
[47] I.V. Ossokina, S. Kerperien, T.A. Arentze, Does information encourage or discourage tenants to accept energy retrofitting of homes? Energy Econ. 103 (2021) 105534. Nov. https://doi.org/10.1016/j.eneco.2021.105534.
[48] S. Breukers, R.M. Mourik, L.F.M. Van Summeren, G.P.J. Verbong, Institutional 'lock-out' towards local self-governance? Environmental justice and sustainable transformations in Dutch social housing neighbourhoods, Energy Res. Soc. Sci. 23 (2017) 148–158. Jan. https://doi.org/10.1016/j.erss.2016.10.007.
[49] N. DellaValle, People's decisions matter: understanding and addressing energy poverty with behavioral economics, Energ. Buildings 204 (2019) 109515. Dec. https://doi.org/10.1016/j.enbuild.2019.109515.
[50] B. Bengtsson, H. Bohman, Tenant voice – as strong as it gets. Exit, voice and loyalty in housing renovation, Hous. Theory Soc. 38 (3) (2021), https://doi.org/10.1080/14036096.2020.1766558 no. 3, Art. no.. May.
[51] S.R. Jansma, J.F. Gosselt, M.D.T. De Jong, Kissing natural gas goodbye? Homeowner versus tenant perceptions of the transition towards sustainable heat in the Netherlands, Energy Res. Soc. Sci. 69 (2020) 101694. Nov. https://doi.org/10.1016/j.erss.2020.101694.
[52] F. Sanders, M. Overtoom, Unlocking grey scientific data on resident behaviour to increase the climate impact of Dutch sustainable housing, Urban Plan. 7 (2) (2022), https://doi.org/10.17645/up.v7i2.4865 no. 2, Art. no. Apr.
[53] J. Palm, K. Reindl, A. Ambrose, Understanding tenants' responses to energy efficiency renovations in public housing in Sweden: From the resigned to the demanding, Energy Rep. 6 (2020) 2619–2626. Nov. https://doi.org/10.1016/j.egyr.2020.09.020.
[54] S. Ebrahimigharehbaghi, Q.K. Qian, F.M. Meijer, H.J. Visscher, Transaction costs as a barrier in the renovation decision-making process: A study of homeowners in the Netherlands, Energ. Buildings 215 (2020) 109849. May, https://doi.org/10.1016/j.enbuild.2020.109849.
[55] L. Mundaca, M. Mansoz, L. Neij, G.R. Timilsina, Transaction costs analysis of low-carbon technologies, Clim. Pol. 13 (4) (2013), https://doi.org/10.1080/14693062.2013.781452. Art. no. 4, Jul.
[56] R. Bardazzi, D. Charlier, B. Legendre, M.G. Pazienza, Energy vulnerability in Mediterranean countries: A latent class analysis approach, Energy Econ. 126 (2023) 106883. Oct. https://doi.org/10.1016/j.eneco.2023.106883.
[57] S. He, Q.K. Qian, J.T. Porsius, Trigger my motivations and remove my barriers: Latent class analyses of homeowners' perception about home energy retrofit, Energy Policy 205 (2025) 114699. Oct. https://doi.org/10.1016/j.enpol.2025.114699.
[58] W. Broers, V. Vasseur, R. Kemp, N. Abujidi, Z. Vroon, Not all homeowners are alike: a segmentation model based on a quantitative analysis of Dutch adopters of residential photovoltaics, Energ. Effic. 14 (3) (2021), https://doi.org/10.1007/s12053-021-09937-0. Mar.
[59] M.J. Pelenur, H.J. Cruickshank, Closing the Energy Efficiency Gap: A study linking demographics with barriers to adopting energy efficiency measures in the home, Energy 47, no. 1, Art. no. 1 (2012), https://doi.org/10.1016/j.energy.2012.09.058. Nov.
[60] D. Charlier, Explaining the energy performance gap in buildings with a latent profile analysis, Energy Policy 156 (2021) 112480. Sep. https://doi.org/10.1016/j.enpol.2021.112480.
[61] H. Syrjälä, C.D. Ruiz, H. Leipämaa-Leskinen, H.T. Luomala, From consumers to consumption: The socio-technical assemblage of the persona in market segmentation, J. Bus. Res. 194 (2025) 115387. May, https://doi.org/10.1016/j.jbusres.2025.115387.
[62] D. Zwick, N. Dholakia, Whose identity is it anyway? consumer representation in the age of database marketing, J. Macromark. 24 (1) (2004) 31–43, https://doi.org/10.1177/0276146704263920.
[63] I. Aimé, F. Berger-Remy, M.E. Laporte, The brand, the persona, and the algorithm: How datafication is reconfiguring marketing work, J. Bus. Res. 145 (2022) 814–827, https://doi.org/10.1016/j.jbusres.2022.03.047.
[64] A. Revella, Buyer personas: How to gain insights into your customer's expectations, align your marketing strategies, and win more business, Wley, 2015.
[65] S. Calde, K. Goodwin, R. Reimann, SHS Orcas: the first integrated information system for long-term healthcare facility management, in: Case Studies of the CHI2002|AIGA Experience Design FORUM, ACM, Minneapolis Minnesota, 2002, pp. 2–16, https://doi.org/10.1145/507752.507753. Apr.
[66] N. Tu, X. Dong, P.-L.P. Rau, T. Zhang, Using Cluster Analysis in Persona Development, 2010.
[67] P.-F. Hsu, Y.-H. Lu, S.-C. Chen, P.P.-Y. Kuo, Creating and validating predictive personas for target marketing, Int. J. Hum.-Comput. Stud. 181 (2024) 103147, https://doi.org/10.1016/j.ijhcs.2023.103147.
[68] J. (Jen) McGinn, N. Kotamraju, Data-driven persona development, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, Florence Italy, 2008, pp. 1521–1524, https://doi.org/10.1145/1357054.1357292. Apr.
[69] V. Haines, V. Mitchell, A persona-based approach to domestic energy retrofit, Build. Res. Inf. 42 (4) (2014) 462–476, https://doi.org/10.1080/09613218.2014.893161.
[70] B. Jansen, J. Salminen, S.-G. Jung, K. Guan, Data-Driven Personas, Springer Nature, 2021, https://doi.org/10.1007/978-3-031-02231-9.
[71] S.-G. Jung, J. Salminen, K.K. Aldous, B.J. Jansen, PersonaCraft: Leveraging language models for data-driven persona development, Int. J. Hum.-Comput. Stud. 197 (2025) 103445, https://doi.org/10.1016/j.ijhcs.2025.103445.
[72] L. Al-Dabbas, H. Al-Tarawneh, T.A. Al-Rawashdeh, Customer Personality Segmentation Using K-Means Clustering, in: in *2023 International Conference on Information Technology (ICIT)*, IEEE, Amman, Jordan, Aug. 2023, pp. 537–543, https://doi.org/10.1109/ICIT58056.2023.10225996.
[73] S.M.H. Anik, X. Gao, N. Meng, Towards automated occupant profile creation in smart buildings: A machine learning-enabled approach for user persona generation, Energ. Buildings 297 (2023) 113485. Oct. https://doi.org/10.1016/j.enbuild.2023.113485.
[74] E. Ditton, A. Swinbourne, T. Myers, Selecting a clustering algorithm: A semi-automated hyperparameter tuning framework for effective persona development, Array 14 (2022) 100186. Jul. https://doi.org/10.1016/j.array.2022.100186.
[75] F.Y.H. Kung, N. Kwok, D.J. Brown, Are Attention Check Questions a Threat to Scale Validity? Appl. Psychol. 67 (2) (2018) 264–283. Apr. https://doi.org/10.1111/apps.12108.
[76] C. Dassa, J. Lambert, R. Blais, D. Potvin, N. Gauthier, Effects of a Neutral Answer Choice on the Reliability and Validity of Attitude and Opinion Items, Can. J. Program Eval. 12 (2) (1997) 61–80. Sep. https://doi.org/10.3138/cjpe.12.004.
[77] L.T. Mariano, A. Phillips, K. Estes, R. Kilburn, Should Survey Likert Scales Include Neutral Response Categories? Evidence from a Randomized School Climate Survey, RAND Corporation (2024), https://doi.org/10.7249/WRA3135-2.
[78] B.E. Weller, N.K. Bowen, S.J. Faubert, Latent Class Analysis: A Guide to Best Practice, J. Black Psychol. 46 (4) (2020) 287–311. May, https://doi.org/10.1177/0095798420930932.
[79] Z. Bakk, D.L. Oberski, J.K. Vermunt, Relating latent class assignments to external variables: standard errors for correct inference, Polit. Anal. 2 (4) (2017), https://doi.org/10.1093/pan/mpu003.
[80] Z. Bakk, J.K. Vermunt, Step-3 models with covariates, distal outcomes, and multiple latent variables., 2013.
[81] Z. Bakk, J.K. Vermunt, Robustness of Stepwise Latent Class Modeling With Continuous Distal Outcomes, Struct. Equ. Model. Multidiscip. J. 23 (1) (2015) 20–31, https://doi.org/10.1080/10705511.2014.955104.
[82] J.K. Vermunt, Latent Class Modeling with Covariates: Two Improved Three-Step Approaches, Polit. Anal. 18 (4) (2010) 450–469, https://doi.org/10.1093/pan/mpq025.
[83] J.K. Vermunt, J. Magidson, How to Perform Three-Step Latent Class Analysis in the Presence of Measurement Non-Invariance or Differential Item Functioning, Struct. Equ. Model. Multidiscip. J. 28 (3) (2021) 356–364, https://doi.org/10.1080/10705511.2020.1818084.
[84] Y. Lo, N.R. Mendell, D.B. Rubin, Testing the number of components in a normal mixture, Biometrika 88 (3) (2001) 767–778.
[85] Q.H. Vuong, Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses, Econometrica 57 (2) (1989) 307, https://doi.org/10.2307/1912557.
[86] D. Ricci, C. Leiwakabessy, S. Van Wieringen, P. De Koning, T. Konstantinou, Co-creating justice in housing energy transitions through energy living labs, Build. Cities 6 (1) (2025) 747–766, https://doi.org/10.5334/bc.591.
[87] S. Van Wieringen, P. De Koning, M. Kaufmann, E. Jansen, S. Veenman, M. Wiering, Heating and cooling places: Justice claims on energy behind the front door, Energy Res. Soc. Sci. 126 (2025) 104148, https://doi.org/10.1016/j.erss.2025.104148.
[88] S. Seebauer, How to make building renovation work for low-income renters: Preferences for distributional principles and procedural options in Austria, Energy Res. Soc. Sci. 82 (2021) 102270, https://doi.org/10.1016/j.erss.2021.102270.
[89] S. Ebrahimigharehbaghi, Q.K. Qian, F.M. Meijer, H.J. Visscher, Unravelling Dutch homeowners' behaviour towards energy efficiency renovations: What drives and hinders their decision-making? Energy Policy 129 (2019) 546–561, https://doi.org/10.1016/j.enpol.2019.02.046.
[90] P. Bertoldi, B. Boza-Kiss, N. Della Valle, M. Economidou, The role of one-stop shops in energy renovation - a comparative analysis of OSSs cases in Europe, Energ. Buildings 250 (2021) 111273, https://doi.org/10.1016/j.enbuild.2021.111273.
[91] EC, Financing Building Renovations [Online]. Available: https://energy.ec.europa.eu/topics/energy-efficiency/financing/financing-building-renovations_en?, 2026.
[92] Aedes, Rijksbegroting 2023: de belangrijkste plannen voor woningcorporaties [Online]. Available: https://aedes.nl/politiek/rijksbegroting-2023-de-belangrijkste-plannen-voor-woningcorporaties, 2022.
[93] Volkshuisvestingnederland, Affortable Rent Act, Ministerie van Volkshuisvesting en Ruimtelijke Ordening (2024) [Online]. Available: https://www.volkshuisvestingnederland.nl/onderwerpen/wet-betaalbare-huur.
[94] B. Boza-Kiss, P. Bertoldi, N. Della Valle, M. Economidou, One-stop shops for residential building energy renovation in the EU: analysis & policy recommendations, European Commission, JRC Science for Policy Report, 2021, https://doi.org/10.2760/245015. Accessed: Dec. 13, 2024. [Online]. Available:.
[95] H.E. Koops-Van Hoffen, Y.M.R. Vendrig-De Punder, F.J. Van Lenthe, F. Borlée, M. Jambroes, C.B.M. Kamphuis, Health effects of holistic housing renovation in a

disadvantaged neighbourhood in the Netherlands: a qualitative exploration among residents and professionals, BMC Public Health 24 (1) (2024) 1056. Apr. https://doi.org/10.1186/s12889-024-18500-2.
[96] D. Czischke, G. Van Bortel, An exploration of concepts and polices on ‘affordable housing’ in England, Italy, Poland and The Netherlands, J. Housing Built Environ. 38 (1) (2018) 283–303, https://doi.org/10.1007/s10901-018-9598-1.
[97] M. Van Middelkoop, K. Vringer, H. Visser, Are Dutch residents ready for a more stringent policy to enhance the energy performance of their homes? Energy Policy 105 (2017) 269–282. Jun. https://doi.org/10.1016/j.enpol.2017.02.050.
[98] I. Loche, C. Recart, L. Kuijer, R. Loonen, Integrating residents’ heating practices into energy retrofit decision-making: a sufficiency-oriented approach, J. Build. Eng. 112 (2025) 113781, https://doi.org/10.1016/j.jobe.2025.113781.
[99] D.L. Paulhus, Measurement and Control of Response Bias, in: Measures of Personality and Social Psychological Attitudes, Elsevier, 1991, pp. 17–59, https://doi.org/10.1016/B978-0-12-590241-0.50006-X.
[100] Q. Tran-Nam, Social Desirability Bias in Likert Scale Design: Concerns and Suggestions, Proceedings of the International Symposium on Management 22 (2025) 521–526.
[101] S. Vesely, C.A. Klöckner, Social Desirability in Environmental Psychology Research: Three Meta-Analyses, Front. Psychol. 11 (2020) 1395. Jul. https://doi.org/10.3389/fpsyg.2020.01395.
[102] D. Noy, Nieuwe 70% regel verhoogt tempo verduurzaming, Atriensis. [Online]. Available: https://atriensis.nl/nieuwe-70-regel-verhoogt-tempo-verduurzaming/, 2024.
[103] J. Salminen, S.-G. Jung, S. Chowdhury, D.R. Robillos, B. Jansen, The ability of personas: An empirical evaluation of altering incorrect preconceptions about users, Int. J. Hum.-Comput. Stud. 153 (2021) 102645, https://doi.org/10.1016/j.ijhcs.2021.102645.