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Examination of the Factors of Multidimensional Energy Poverty in a Hungarian Rural Settlement

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Abstract

Energy poverty is a multidimensional phenomenon that impairs access to basic energy services and threatens social well-being, particularly in disadvantaged rural communities. This study investigates the extent and drivers of household energy poverty in a Hungarian village through a survey-based analysis (N = 257) conducted in early 2025. The sample is not nationally representative, however, it reflects approximately 20% of the total village population (1331 inhabitants). This study aims to identify vulnerable household profiles, explore correlations between socio-economic and housing factors and perceived thermal comfort, and compare the effectiveness of multiple measurement indicators the 10% rule, low income high cost, 2M, and M/2. We employ descriptive statistics, Pearson correlation, Fuzzy C-Means clustering, and linear regression, revealing that over half of the sample is energy poor according to the 10% rule, while the LIHC method identifies 29%. Our regression results confirm that cluster membership significantly influences perceived comfort levels (R^2 = 0.063, p = 0.002). We conclude that single-indicator approaches are insufficient to capture the nuanced realities of rural energy poverty, therefore, we recommend the development of a rural energy poverty index. Such a tool could help identify affected households and support the formulation of context-sensitive, evidence-based energy and social policy interventions.

Keywords: energy poverty; fuel poverty; household energy poverty; Hungary

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1. Introduction

In recent decades, the phenomenon of energy poverty has become a central topic in social science and public policy discussions, attributable primarily to the interaction of low income, lack of energy efficiency, and energy price affordability [1–4]. Moreover, energy poverty is fundamentally connected to individual well-being [5,6], health status [7–9], housing conditions, and social inequalities, however, no universally accepted definition or standardized method exists for measuring it [10–13]. Past research [14] posited that "*a household is considered energy poor if it cannot afford the level of heating or other basic energy services necessary for a decent quality of life*". Conversely, most definitions consider households that spend more than a certain percentage of their income on energy to be energy poor [15]. Insufficient access to energy services directly affects health, the ability to study and work, and overall quality of life, thus, it cannot be captured by a single indicator [16,17].

1.1. The Difference Between Fuel Poverty and Energy Poverty

Energy poverty research often uses the terms fuel poverty and energy poverty interchangeably, although they originate from different contexts and do not entirely overlap [18]. Fuel poverty is primarily associated with the energy efficiency of housing stock, and it dominates Western European policy discourse. In Central and Eastern Europe, including Hungary, the concept of multidimensional energy poverty is gaining attention. This broader term considers household energy consumption patterns, adaptation strategies, and social vulnerability [19].

British scientific research [20] created the concept of fuel poverty. For a long time, it referred to households needing to spend more than 10% of their income on energy to achieve adequate thermal comfort. This cost-based approach defined energy poverty through the interplay of income, energy prices, and housing conditions [8,21,22]. To address the definitional challenges in the United Kingdom (UK), the "low income high cost" (LIHC) indicator was introduced [2], which considers energy needs, household income, and the available housing quality. From 2021 onward, the UK officially applied the "low income low energy efficiency" indicator. These measurement methods capture the existence of energy poverty as well as its depth and associated risk factors [23].

In contrast, the term energy poverty is more widely used by the European Union (EU) and international literature [18,24,25]. This includes heating and access to lighting, cooling, cooking, communication, IT, and other household energy services [26–28]. This definition is especially significant in the global South and Central and Eastern Europe, where formal indicators often overlook deprivation in energy use [29].

Recent studies have also highlighted the phenomenon of hidden energy poverty, where households deliberately under-consume energy (e.g., they do not heat their homes fully) to avoid high energy bills. Energy cost-based indicators do not capture this behavior [30,31].

In Hungary, the existence of energy poverty has been empirically confirmed [25,32], however, a consensus regarding the definition is still in progress. A specific feature of energy poverty in Hungary is its strong association with the quality of the housing stock, outdated heating systems, and the limited effectiveness of the social safety net. According to past research [33], hidden energy poverty is particularly prevalent in rural areas, among large families or older adults living alone, which statistical indicators might not reflect.

The consequences of energy poverty go beyond physical discomfort. According to the extant research [34], insufficient heating or cooling is directly associated with cardiovascular and respiratory diseases, as well as reduced mental health. Furthermore, financial stress, reduced housing comfort, and postponing basic expenditures (such as food and medicine) can lead to long-term destitution and social isolation [35,36].

1.2. The Concept and Role of Vulnerability

Energy poverty is a multidimensional socio-economic phenomenon that cannot be understood solely as a consequence of income poverty; instead, it must be interpreted within the interrelated context of household energy use, housing conditions, social status, and adaptive capacity [37]. Within this framework, vulnerability is a key concept that determines how much a given household is exposed to the occurrence, persistence, or worsening of energy poverty [18]. The notion of vulnerability originates from research on environmental, social, and economic fragility [38]. In the context of energy poverty, vulnerability refers to households that, for various reasons, are prone to falling into energy deprivation or are less able to adapt to changes in energy prices, income, or housing conditions.

Vulnerability can be understood through the following three main dimensions [23,39].

- "Exposure" is the extent to which the household is affected by external factors that may lead to energy poverty, e.g., high energy prices, poor energy efficiency of the home, and regional disadvantages.
- "Sensitivity" is the degree to which external factors influence the household's energy situation, e.g., low income, health status, and age.
- "Adaptive capacity" is the extent to which the household can adapt to or mitigate the risk of energy poverty, e.g., energy awareness, access to subsidies, and community support networks.

Vulnerability may not equate to the actual presence of energy poverty. A household may be highly vulnerable even if it is not yet experiencing energy poverty, however, a sudden drop in income, an increase in energy prices, or a deterioration of local infrastructure may quickly lead to energy poverty. This dynamic perspective enables the targeting of preventive policy interventions [39].

As stated, a crucial dimension of vulnerability is the phenomenon of hidden energy poverty, where households deliberately reduce their energy consumption (e.g., by not fully heating their home or postponing necessary maintenance) to avoid financial hardship. However, external indicators, such as energy bills, do not capture this situation [40,41].

Vulnerability should form the foundation of energy poverty prevention and intervention policies. The European Commission's strategies addressing energy poverty (e.g., the Just Transition Mechanism and Renovation Wave) emphasize the importance of identifying vulnerable consumers and providing targeted support. Moreover, analyzing vulnerability contributes to a deeper understanding of the structural causes of energy poverty and to incorporating the social dimensions of long-term sustainability into energy policy [13,42].

1.3. Measurement Approaches to Energy Poverty: Indicators, Methodological Differences, and Contexts of Application

Countries with varying levels of development apply different methodologies to measure energy poverty, which are closely related to the degree of household access to energy services and practical considerations of measurability and communicability. In many developing countries, binary access indicators (e.g., access to electricity or clean cooking fuels) have traditionally been used to identify energy poverty. However, in several emerging economies, such as Brazil, affordability and quality have become more pressing issues than access. The advantage of this approach lies in its simplicity, low cost of implementation, and ease of interpretation for political decision-makers [16,30].

In more developed countries, particularly in Europe, measurement approaches tend to rely on affordability-based indicators, which examine the ratio of energy costs to household income. These indicators include metrics such as the share of energy expenditure in total household spending (e.g., total payment ratio [TPR]), median-based indicators (e.g., 2M and M/2), and models applying income-based thresholds (e.g., after fuel cost poverty [AFCP], minimum standard income [MIS], and the LIHC indicator) [43,44]. For example, the 2M indicator identifies households that face disproportionately high energy expenditures. At the same time, the M/2 indicator focuses on households that likely under-consume energy, often involuntarily, as a manifestation of hidden energy poverty [45].

In continental Europe, the primary source for the statistical measurement of energy poverty is the Eurostat EU Statistics on Income and Living Conditions (EU-SILC) database. The EU-SILC records, among other things, the subjective experiences of households regarding their ability to keep the home adequately warm, postponed payment on utility bills, and the physical condition of the home and its surroundings [43]. These indicators provide important signals for social policy, however, they cannot capture the structural or hidden dimensions of energy poverty, such as excessive self-restriction or overconsumption due to poor housing quality [24].

To address these limitations, multidimensional approaches—most notably the multidimensional energy poverty index (MEPI)—have been developed. These approaches measure different aspects of energy deprivation through multiple variables, including access to energy sources, energy efficiency, household comfort, and income background. Such tools are particularly relevant in the global South and in Central and Eastern Europe, where structural factors (such as dependence on solid fuels, deficiencies in energy subsidy systems, or underdeveloped housing infrastructure) influence the prevalence of energy poverty [17,18,46].

According to a comprehensive literature review [45], the indicators used to measure energy poverty increasingly orient toward the integrated analysis of economic, social, and environmental dimensions. Empirical studies indicate that economic indicators (e.g., energy consumption, expenditure ratio, income) continue to dominate, however, social and environmental factors (e.g., perceived comfort, housing quality, access to renewable energy) are gaining prominence. Previous research [45] identified 34 energy poverty indices, which were categorized into those focusing on energy access, those measuring energy poverty, and those assessing vulnerability.

Energy poverty is a complex socio-economic phenomenon shaped by the combined effect of household-level and structural factors (Figure 1). Household energy use is primarily determined by income levels, housing quality (e.g., insulation), access to energy (e.g., utilities and solid fuels), and technical equipment (heating and cooling systems and the energy efficiency of household appliances). At the same time, the price of energy carriers, the regulatory and support environment, and weather conditions (particularly the number of heating days and extreme weather events) are external factors that can exacerbate or alleviate the extent of energy poverty. These factors highlight the need for a multidisciplinary and integrated approach in researching and managing this issue.

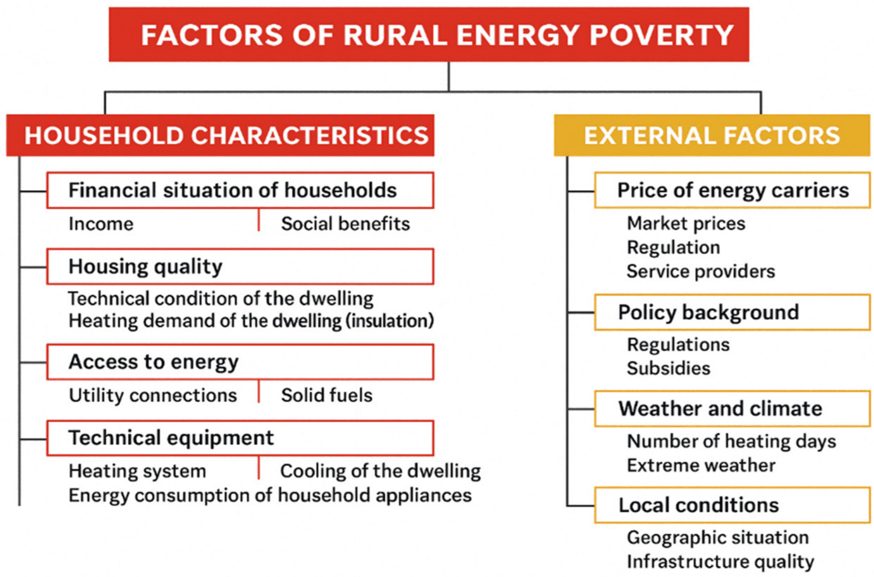

Figure 1. Factors of energy poverty (based on [47]).

Based on these considerations, this study surveys households in a Hungarian settlement to explore their energy poverty situation. We focus on housing conditions, energy use practices, financial burden, adaptive strategies, and vulnerability factors. This study makes three contributions. (1) We use fuzzy clustering to identify overlapping vulnerability profiles in a rural setting; this approach is rarely used in energy poverty research in Central and Eastern Europe. (2) We combine objective indicators, like income and energy costs, with subjective perceptions, such as thermal comfort, allowing for a more detailed analysis. (3) We propose a conceptual framework for a rural energy poverty index (RURAL EPI), designed for the specific needs of small settlements. These innovations aim to enrich the discussion on energy poverty, especially in often overlooked rural areas.

The following research questions are related to these objectives:

- RQ1: Are other essential expenditures (e.g., food, medicine) pushed into the background due to energy costs?
- RQ2: According to the 10% rule and the LIHC method, what proportion of households live in energy poverty in the examined settlement?
- RQ3: What is the relationship between household income and energy costs?
- RQ4: How do the energy characteristics of residential buildings (e.g., insulation and the condition of doors and windows) influence energy consumption and the degree of energy poverty?
- RQ5: What proportion of households implement energy-saving measures, and what is their effect on energy costs?
- RQ6: To what extent are signs of hidden energy poverty (e.g., reducing heating or sacrificing necessities) present in the surveyed households?

Based on these questions, we propose the following hypotheses:

H1. *Many households reduce essential expenditures (e.g., food and medicine) due to energy costs.*

H2. *A negative correlation exists between household income and the relative burden of energy expenditure.*

H3. *Poor housing conditions (e.g., insulation or outdated doors/windows) are associated with higher energy costs and lower thermal comfort.*

H4. *Hidden energy poverty (e.g., reducing heating or sacrificing necessities) exists in many households.*

2. Materials and Methods

Energy poverty is a complex, multifaceted socio-economic phenomenon, and exploring it requires the collection and interpretation of household-level data. This study employed a questionnaire-based survey method that included both closed-ended and open-ended questions, allowing for a systematic examination of income status, housing conditions, energy use habits, perceived comfort, and subjective experiences.

Data were collected in the first quarter of 2025, using self-administered questionnaires completed in person, distributed through targeted channels, and via civil society partners among rural households. This research was made in a small rural village, we adapted our sampling strategy to fit the local context. We used a combination of convenience and snowball sampling. The process began with a coded list of households provided by the municipality and the mayor. From this list, we randomly invited residents to participate in the study. Participation was entirely voluntary, only those who were willing and available took part. Participants were also encouraged to offer the survey with others in their community to reach as many diverse households as possible (snowball). This helped us include people who might otherwise be hard to reach, such as elderly residents, low-income families. While this approach does not guarantee full statistical representativeness, it allowed us to build trust, ensure ethical engagement and collect meaningful, locally grounded data in a way that made sense for the community. This approach could limit the generalizability of the findings, however, it is appropriate for exploratory, community-based research on energy poverty in marginalized contexts.

To ensure contextual relevance and clarity, three domain experts reviewed the draft survey, which was piloted with 15 households in a neighboring village before data collection. We made minor modifications based on the feedback (e.g., localizing heating terminology and adjusting income ranges).

Ethical approval for the study was obtained from the University Research Ethics Committee (Reference No. GTK-KB 001-2/2025). Participants were informed of this study's voluntary and anonymous nature and provided written consent before participation.

In total, 270 households completed the questionnaire; the dataset underwent preliminary cleaning (removal of missing responses and irrelevant data), leaving 257 evaluable responses. This sample represents approximately 20% of the total population of the studied village (1331 inhabitants), providing a robust basis for local-level analysis. This study uses snowball sampling, which introduces potential bias; the participants may reflect existing social networks and result in over- or under-representation of certain household types. Additionally, the sample size (N = 257) is statistically sufficient for the applied cluster and regression analyses, however, its modest scale calls for caution in generalizing the findings beyond the studied locality. Future studies should consider stratified random sampling and larger sample sizes to strengthen external validity.

All analyses were conducted using the JASP 0.19.3 statistical software package.

2.1. Descriptive and Correlation Analysis

The first step of the analysis used descriptive statistics to characterize the sample's socio-demographic structure (gender, age, education, and employment status), as well as background variables related to energy poverty. Pearson correlation analysis was then conducted to explore the direction and strength of linear relationships between perceived comfort and housing parameters (e.g., home size, income, and type of heating) [48]. The Pearson correlation coefficient (r) was calculated as follows:

$$r = \frac{\sum_{i=1}^{n} \left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{n} \left(X_i - \overline{X}\right)^2} * \sqrt{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2}} \quad (1)$$

where X and Y are the paired variables, and $\overline{X}$, $\overline{Y}$ are their respective means.

The central methodological element of the study was a fuzzy c-means (FCM) clustering algorithm [49], conducted using JASP. FCM allows for partial membership of each data point to multiple clusters based on similarity scores. The objective function minimized by FCM is

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} \mu_{ij}^{m} * \left\|x_i - c_j\right\|^2 \quad (2)$$

Here,

- n is the number of observations;
- c is the number of clusters;
- x_i is the i^{th} data point;
- c_j is the centroid of the j^{th} cluster;
- μ_{ij} is the membership degree of x_i in cluster j;
- m is the fuzziness coefficient ($m > 1$, here set to 2.0).

The clustering process included five background variables: monthly net household income, perceived comfort of the home during the winter period, number of persons living in the household, potential for energy-efficiency investments, and type of heating system. These clusters were selected based on Bayesian information criterion (BIC) minimization and the interpretability of social profiles. Although the silhouette score was low, the clusters revealed distinct vulnerability types relevant to energy poverty intervention. The clustering covered 100% of the respondents, and every participant was assigned to one of the groups.

Following the clustering, we developed a multiple linear regression model to test the association between cluster membership and perceived comfort level (dependent variable). The general form of the regression model is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \epsilon \quad (3)$$

Here,

- Y is the perceived thermal comfort score (1–5);
- β_0 is the intercept;
- β_k represents the coefficients for the predictor variables (X_k);
- ε is the error term.

In this model:

- X_1 = Cluster membership (categorical, dummy-coded);
- X_2 = Monthly household income;
- X_3 = Heating type (categorical).

Cluster 1 served as the reference group. Significance was tested using *t*-tests for each coefficient, and R^2, adjusted R^2, and the F-test were used to evaluate the model fit.

The newly created cluster membership variable was re-imported into the dataset from the JASP output and used as a nominal predictor. The regression model used cluster 1 as the reference category. Each cluster's effect on perceived comfort was evaluated based on standardized regression coefficients (β), significance levels (p), and 95% confidence intervals (CI). The coefficient of determination (R^2) and the F-test were used to assess model fit.

2.2. 2M and M/2 Indicators

2M and M/2 indicators essentially compare household energy consumption levels to the societal median, and their use is widespread in measuring energy poverty. These indicators are based on the principle that a household's energy consumption (or lack thereof) is assessed relative to the median level of energy consumption in the population. Such indicators can identify energy poverty stemming from either excessive or insufficient energy use, especially in cases where income-based approaches are insufficient [44].

- 2M Indicator: Under this indicator, a household is considered energy poor if its energy consumption exceeds twice the societal median (2 × M). M2 identifies households whose energy consumption is disproportionately high relative to their income level, often due to low-efficiency housing conditions. These households are referred to as "overburdened" [30].
- M/2 Indicator: This indicator classifies a household as energy poor if its energy consumption is less than half the societal median (M/2). The underlying cause is not inefficiency, but rather underconsumption, often due to enforced self-restriction. This phenomenon is one of the key manifestations of hidden energy poverty [30,31].

The following steps are followed to calculate both indicators:

- The annual energy consumption of each household is aggregated.
- The median energy consumption for the entire sample population is determined.
- Households are then compared to the median in two directions:
    - If consumption > 2 × M → excessive energy consumption (2M);
    - If consumption < M/2 → underconsumption (M/2).

2.3. Application of the LIHC Indicator

The LIHC indicator [50] offers a more complex, dual-criteria model than earlier one-dimensional approaches [23] for measuring energy poverty. Its application requires the following calculation steps.

1. Determine the income median based on the net per capita income data of the surveyed households.
2. Calculate the poverty threshold, defined as 60% of the median income [51].
3. Determine the median of energy costs based on the households' annual energy expenditure.
4. Compare energy expenditures with the median to assess whether the household's energy spending exceeds the societal median.
5. Calculate residual income, which is the annual energy cost subtracted from the household's income.
6. Evaluate the LIHC condition; if the household's energy expenditure exceeds the median energy cost and the residual income falls below the poverty threshold, the household is considered energy poor.

This method has the advantage of combining energy expenditure with income levels, thereby providing a more nuanced picture of energy poverty. This approach is especially relevant for marginal households, which cannot be reliably classified using a single indicator.

The questionnaire-based survey provides a detailed view of the energy poverty situation of the households, however, its limitations include response bias, inaccuracies in self-reporting, and non-representative sampling. Nevertheless, the analysis yields valuable qualitative and quantitative data, particularly for mapping hidden and structural forms of energy poverty.

3. Results

3.1. Sample Presentation

Analyzing the sample's socio-demographic composition is an essential prerequisite for understanding the levels and characteristics of energy poverty. Among the respondents, 75% were women and 25% men, indicating a significant skew toward female participants. Regarding employment status, more than half of the respondents (54.5%) were retired, while 36.9% were actively employed. The distribution of educational background revealed 47.5% of the participants had completed primary education, 46.3% had secondary education, and only 6.2% held a higher education degree. In terms of age, 37% were between 61 and 75 years old, and 19% were over 76 years of age (Table 1). These structural characteristics indicate that the sample might be particularly vulnerable to the effects of energy poverty. Previous studies also noted that low-income groups dominated by retirees exhibit the highest risk of energy poverty [13,52].

Table 1. Sample presentation (N = 257).

Characteristic	Division of the Sample	
	N	**%**
The number of respondents		
Total	257	100.0
Gender		
Male	64	24.9
Female	193	75.1
Age		
18–30	14	5.4
31–45	48	18.7

Table 1. *Cont.*

Characteristic	Division of the Sample	
	N	%
46–60	49	19.1
61–75	95	37.0
76 or above	51	19.8
Marital status		
Single	34	13.2
Married	134	52.1
Widow	68	26.5
Divorced	21	8.2
Education level		
Elementary	122	47.5
Intermediate	119	46.3
Higher	16	6.3
Employment status		
Full-time	95	36.9
Parental Leave Benefit (Hungarian)	9	3.5
Pension	140	54.5
Other	2	0.8
Unemployed	8	3.1
Part-time	3	1.2

Source: Author's calculation, 2025.

3.2. Results of Correlation Analysis

The statistical analyses included quantitative variables based on their theoretical relevance to energy poverty. Household monthly net income was measured on a five-point scale, similar to the categorization of the home's floor area. The number of persons living in the household was recorded as a numeric variable. The respondents evaluated perceived comfort on a five-point scale, while the intention to invest in energy efficiency and the type of heating were included as categorical variables. The average monthly net income of households was 3.64 (on a 1–5 scale, where 5 represents the highest category), with a standard deviation of 1.605. Income negatively correlated with perceived home comfort ($r = -0.354$, $p < 0.001$), supporting the notion that low-income households are less able to conduct adequate heating or energy-efficiency improvements. Home size (average 2.09 on a 0–3 scale) also showed a significant negative correlation with comfort level ($r = -0.404$, $p < 0.001$), indicating the energy-related challenges of larger but poorly insulated homes. Each of these variables captures a different aspect of energy poverty, be it income-related, infrastructural, or subjective.

The Pearson correlation analysis aimed to explore linear relationships between the variables. A positive, moderate-strength correlation was found between income and home size ($r = 0.291$, $p < 0.001$), suggesting that higher income is generally associated with larger housing. The correlation between income and household size was even stronger ($r = 0.460$, $p < 0.001$), likely because larger households may have more earners or sources of income. Perceived comfort negatively correlated with income ($r = -0.354$) and the floor area of the home ($r = -0.404$), which may initially seem paradoxical, however, this outcome can likely be explained by larger homes being more challenging to maintain and potentially providing lower thermal comfort. Moreover, residents of larger, inherited family homes frequently face outdated insulation systems and high heating costs [13]. The type of heating also showed a significant correlation with comfort ($r = 0.196$), reinforcing that the type of energy source can significantly influence residents' well-being.

According to the correlation matrix:

- A positive correlation can be observed between income and the floor area of the home (r = 0.291 ***).
- The correlation between household size and income is moderate (r = 0.460 ***).
- Home comfort level is negatively correlated with both income (r = −0.354 ***) and the floor area of the home (r = −0.404 ***) (Table 2).

Table 2. Correlation table among certain variables.

Variable		Pearson's Correlations						
		Household Income	**House Size**	**Household Size**	**Annual Cost**	**Comfort Level**	**Willingness to Invest**	**Heating System**
Household income	N	—						
	Pearson's r	—						
House size	N	257	—					
	Pearson's r	0.291 ***	—					
Household size	N	257	257	—				
	Pearson's r	0.460 ***	0.153 *	—				
Annual cost	N	257	257	257	—			
	Pearson's r	0.151 *	0.004	0.206 ***	—			
Comfort level	N	257	257	257	257	—		
	Pearson's r	−0.354 ***	−0.404 ***	−0.098	−0.059	—		
Willingness to invest	N	257	257	257	257	257	—	
	Pearson's r	0.055	0.089	−0.074	−0.139 *	−0.079	—	
Heating system	N	257	257	257	257	257	257	—
	Pearson's r	0.196 **	0.214 ***	0.010	−0.111	−0.284 ***	0.090	—

Source: Author's calculation, 2025. Note: * = $p < 0.05$, ** = $p < 0.01$, and *** = $p < 0.001$.

3.3. Results of Cluster Analysis

FCM clustering was applied based on objective background variables (income, home size, household size, type of heating, and potential for energy-efficiency investments) to explore the relationships further. The advantage of FCM lies in its ability to allow partial membership of observational units to multiple clusters, better reflecting the diversity of real-world social phenomena. The model was calculated using 257 observations, and the optimal number of clusters was determined based on the lowest BIC value and the relative silhouette score (BIC = 963.78; average silhouette = 0.130). The relatively low silhouette score indicates that the clusters are not fully separated, which is an expected and acceptable feature in FCM. As a result of the optimization, five clusters were identified.

- (C1) Large families with high income but investment-evading (N = 15): Members of this cluster live in larger households and have above-average income levels. Their perceived comfort during winter shows moderate variation, however, they demonstrate low willingness to invest in energy-efficiency measures. This situation may indicate that they already possess modernized solutions or do not perceive a need for further improvements.
- (C2) Low-income, adaptive households (N = 25): This cluster typically includes smaller households with low income who significantly adapt to the heating season, which is also reflected in their perceived comfort levels. Their low willingness to invest may be partly attributed to limited financial resources.
- (C3) Stable middle class, energy-conscious, and proactive (N = 55): This group could be one of the most relevant target groups for energy policy interventions. They have above-average income and medium household size; their comfort levels remain stable during winter, and they are open to energy-efficiency improvements. This cluster also tends to use more modern heating systems, indicating conscious energy consumption.

- (C4) Wealthy, comfort-sensitive but passive households (N = 38): Members of this cluster have favorable income levels and average household size, however, they are more sensitive to cold periods in terms of comfort and show little interest in energy-efficiency investments. This situation could reflect a lack of awareness or motivation regarding energy improvements.
- (C5) The largest group: disadvantaged households at risk of energy poverty (N = 124): Members of this cluster generally have low income, live in smaller households, experience a significant drop in comfort during the winter, and show limited willingness to invest in energy efficiency. This group is highly vulnerable to energy poverty and may be priority beneficiaries of targeted support and educational programs (Table 3).

Table 3. Result of the fuzzy c-means (FCM) cluster analysis.

Cluster	**Difference in Comfort Compared to Cluster 1 *p*-Value**	***p*-Value**	**Interpretation**		
2	+0.533	0.031	**Significantly higher comfort than cluster 1**		
3	+0.242	0.270	No significant difference		
4	+0.249	0.279	No significant difference		
5	+0.595	0.004	**Significantly higher comfort than cluster 1**		
Model Summary: FCM					
Clusters	N	R^2	AIC	BIC	Silhouette
5	257	0.444	875.060	963.780	0.130
Cluster Information					
Cluster		1	2	3	4	5
Size		15	25	55	38	124
Explained proportion within-cluster heterogeneity		0.053	0.063	0.291	0.116	0.477
Within the sum of squares		43.468	51.985	239.841	95.825	393.938
Silhouette score		0.063	0.383	−0.034	0.104	0.162

Source: Author's calculation, 2025. Note: The model is optimized concerning the BIC value. The optimum number of clusters is the maximum number of clusters, thus, the range of optimization might require adjustment.

Several household types with differing energy use patterns and income characteristics were identified based on FCM. Notably, C3 represents a potentially motivated, energy-conscious segment, while C5 is particularly vulnerable to energy poverty and calls for targeted policy intervention (Figure 2). This method provides an effective tool for mapping social energy profiles and can contribute to the development of efficient, target group-oriented energy policies.

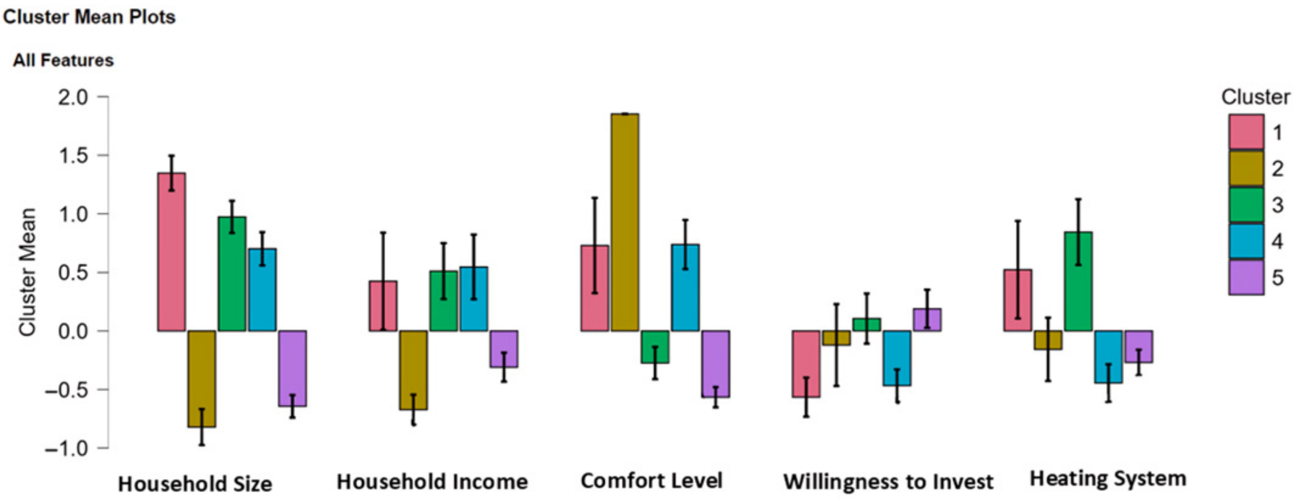

Figure 2. Visual representation of the clusters, Source: Author's calculation, 2025.

3.4. Results of the Regression Analysis

Linear regression analysis (Table 4) was employed to examine the effect of cluster membership on the general home comfort level. The dependent variable, respondents' self-reported general home comfort level, was explained using the cluster variable derived from the fuzzy clustering procedure. The coefficient of determination (R^2) was 0.063, indicating that cluster membership accounts for approximately 6.3% of the variance in perceived comfort. This outcome represents a moderate explanatory power. At the same time, the F-test (F = 4.230; p = 0.002) yielded a statistically significant result, suggesting that the model significantly differs from the null model and that the cluster variable is a meaningful predictor of perceived comfort.

Table 4. Result of the regression analysis.

Model Summary-Comfort Level									
Model	**R**	$\mathbf{R^2}$	**Adjusted** $\mathbf{R^2}$	**RMSE**	$\mathbf{R^2}$ **Change**	**F Change**	**df1**	**df2**	p
M_0	0.000	0.000	0.000	0.771	0.000		0	256	
M_1	0.251	0.063	0.048	0.752	0.063	4.230	4	252	0.002

Source: Author's calculation, 2025. Note: M_1 includes the "cluster variable".

A one-way analysis of variance (ANOVA) was conducted to assess model alignment. ANOVA enables us to determine the extent to which cluster membership as an independent variable explains the variation in general comfort levels. Table 5 shows that the four cluster variables included in the regression jointly accounted for 9.578 units of variance in comfort level. The residual variance (i.e., the portion not explained by the model) was 142.664 units, yielding a total variance of 152.241 in the sample. The F-test resulted in F(4; 252) = 4.230 with a significance level of p = 0.002, indicating that the overall effect of the cluster variables significantly improves the prediction of comfort level compared to the null model, which includes no predictors. The low p-value (<0.05) indicates that the null hypothesis (i.e., the cluster variables do not enhance the explanatory power of the model) can be rejected. The R^2 value of 0.063 implies that only 6.3% of the variance in comfort level is explained by the model, however, the statistically significant result confirms that cluster membership is a statistically relevant factor.

Table 5. Result of the ANOVA analysis.

ANOVA						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	p
M_1	Regression	9.578	4	2.394	4.230	0.002
	Residual	142.664	252	0.566		
	Total	152.241	256			

Source: Author's calculation, 2025. Note: M_1 includes "cluster variable". The intercept model is omitted, as no meaningful information can be shown.

The limited explanatory power of the regression model suggests that perceived comfort is likely shaped by additional factors, such as psychological resilience, cultural norms, or expectations not captured in our dataset. Future studies should incorporate qualitative or mixed-method approaches to understand these subjective dimensions.

The statistically significant effect of C2 suggests that its members experience higher-than-average comfort, likely due to active adaptation strategies and/or lower expectations regarding thermal comfort. The coefficients are not statistically significant for C3 and C4, indicating that their comfort levels do not differ significantly from those of C1. C5 members reported unexpectedly higher comfort levels, despite socio-economic disadvantages. This outcome may reflect subjective expectations or coping mechanisms, however, we emphasize that such interpretations remain hypothetical. Given the absence of qualitative or psychological data, we refrain from drawing firm conclusions and instead propose this as a direction for future research on behavioral adaptation and perceived comfort (Table 6).

Table 6. Interpretation of cluster effects (coefficients): detailed analysis.

Variable	B (Not Standardized)	SE	t	*p*	95% CI (Lower–Upper)	Interpretation
Cluster 1 (C1)	1.067	0.194	5.491	<0.001	0.684–1.449	The average comfort level of the reference group (C1) is 1.067.
Cluster 2 (C2)	0.533	0.246	2.170	0.031	0.049–1.017	Significant: Members of C2 report a comfort level that is 0.533 units higher on average.
Cluster 3 (C3)	0.242	0.219	1.106	0.270	−0.189–0.674	Non-significant difference between C3 and the reference.
Cluster 4 (C4)	0.249	0.229	1.086	0.279	−0.203–0.701	Non-significant.
Cluster 5 (C5)	0.595	0.206	2.891	0.004	0.190–1.000	Significant: Members of C5 report a comfort level that is 0.595 units higher than the reference.

Source: Author's calculation, 2025.

The results of the linear regression indicate that respondents' cluster membership has a statistically significant effect on their overall comfort levels. The most substantial positive effects are observed in C2 and C5, while the effects of clusters C3 and C4 are not statistically significant. This cluster-based approach helps identify and target specific social groups that influence energy-related comfort levels.

3.5. Analysis of the 10%, 2M, M/2, and LICH Indicators

Based on the various energy poverty indicators, substantial differences arise in the proportion of respondents classified as energy poor. The analysis employed four different indicators: LIHC, the 2M and M/2 indicators, and the traditional 10% income-to-expenditure ratio rule (Figure 3).

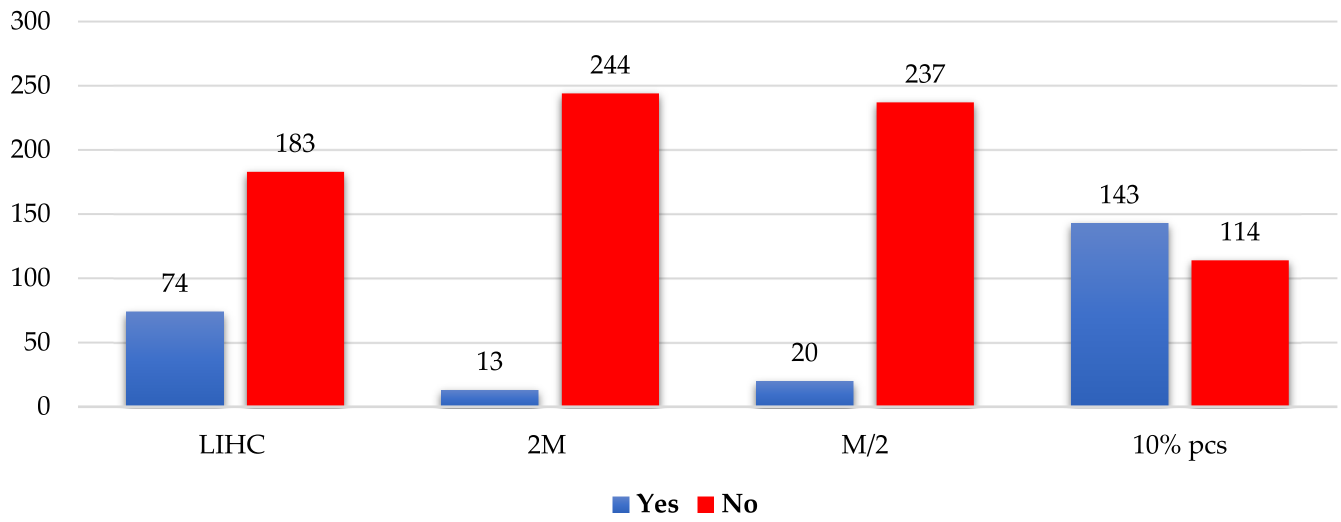

Figure 3. Comparison of energy poverty indicators for the respondents. Source: author's calculation, 2025.

According to the LIHC indicator, 74 respondents (approximately 29%) were classified as energy poor, while 183 were excluded. This moderately high proportion suggests that when considering both income level and energy expenditure, an identifiable social group affected by energy poverty becomes visible.

In contrast, the 2M and M/2 indicators apply much more restrictive definitions; the former identified only 13 individuals (5%) as energy poor, while the latter classified 20 individuals (7.8%). These indicators are likely based on comparisons to the median income or consumption and consider only those with extremely low values as energy poor, however, such a stringent approach may overlook the relative deprivation experienced by many households in practice.

The most pronounced difference occurred in the case of the 10% rule, which defines households as energy poor if they spend more than 10% of their income on energy bills. According to this criterion, 143 individuals (56%) were identified as energy poor, exceeding the 114 individuals categorized as not energy poor. This result suggests that income level alone may not be critical for all households, however, energy prices or energy demand place a significant burden on them.

These findings highlight that the measurement and interpretation of energy poverty depend significantly on the methodology applied. The different indicators emphasize various dimensions, such as objective income levels, the quantity of energy consumption, or the proportion of income spent on energy. This diversity indicates the need for multidimensional or composite indicator systems in policy planning to identify and effectively address real-world energy poverty.

4. Discussion

This study examines the relationship between household energy poverty and perceived comfort, based on a sample of 257 respondents, focusing on how various household profiles (clusters) influence comfort levels. Most respondents were elderly, retired women with primarily primary or secondary education. These social groups are particularly vulnerable to energy poverty and reduced thermal comfort.

Correlation analyses revealed a significant negative correlation between perceived comfort and home size ($r = -0.404$, $p < 0.001$), indicating that larger homes do not necessarily correspond to greater comfort. There was also a significant positive correlation between the type of heating and comfort ($r = 0.196$, $p < 0.01$), while the correlation between household income and comfort was weak but statistically significant ($r = 0.151$, $p < 0.05$). These findings confirm that perceived comfort is a multidimensional phenomenon, not determined solely by financial status.

Our FCM cluster analysis based on background variables (income, home size, household size, heating type, and potential for energy-efficiency investments) identified 5 distinct household types, covering 100% of the sample (N = 257). C1 included well-off, small households reporting the lowest levels of comfort. C2 comprised large, disadvantaged families who, surprisingly, reported significantly higher comfort levels. C3 included financially secure individuals living alone, while C4 represented balanced, average households. C5, the largest, consisted mainly of vulnerable pensioner households, who reported unexpectedly favorable comfort levels.

A linear regression model was used to assess the impact of cluster membership on perceived comfort. The results showed that cluster membership is a statistically significant predictor of comfort ($R^2 = 0.063$, $F [4; 252] = 4.230$, $p = 0.002$). Respondents in C2 reported significantly higher levels of comfort compared to those in C1 ($\beta = 0.533$, $p = 0.031$), as did those in C5 ($\beta = 0.595$, $p = 0.004$). C3 and C4 also showed positive coefficients, however, these differences were not statistically significant.

The study also paid particular attention to how much different energy poverty indicators yield varying classifications of households. The comparison highlighted that the definition used can significantly influence both the number and the social profile of those identified as energy poor. The traditional 10% rule (which classifies households as energy poor if they spend at least 10% of their income on energy) identified over half of the respondents as energy poor. In contrast, the stricter indicators based on median income or energy consumption thresholds (e.g., 2M and M/2) included only a small fraction of households. The LIHC approach offered a moderate middle ground by considering both low income and high energy expenditures, providing a more nuanced picture of the structure of energy poverty. These discrepancies confirm that energy poverty is not a one-dimensional phenomenon and that different indicators capture distinct social groups. Thus, the choice of measurement methodology is not merely a theoretical issue; it has direct implications for the identification of policy target groups. The results suggest that more accurate targeting requires composite indicators that integrate multiple dimensions, or the target groups identified by different indicators should be treated in parallel when designing intervention strategies.

The following presents responses to the research questions.

1. *Do energy costs sometimes result in other essential expenditures (e.g., food and medicine) being deprioritized?*

The applied energy poverty indicators and cluster analysis reveal that a significant portion of respondents experience hidden energy poverty. This situation is reflected in their reports of low thermal comfort and in questionnaire responses indicating a tendency to reduce heating or to forgo other necessities (e.g., food and medicine) due to the burden of energy-related payments.

2. *According to the 10% rule and the LIHC method, what proportion of households in the examined settlement live in energy poverty?*

According to the 10% income-expenditure rule, 22.6% of households have energy spending that exceeds 10% of their income, qualifying them as energy poor. According to the LIHC method, 11.7% of households are energy poor, based on the dual condition of low income and high energy expenditures.

3. *What relationship is observed between household income and energy expenditures?*

A weak but statistically significant negative correlation was observed; the higher a household's income, the smaller the proportion of income spent on energy. This correlation is especially pronounced among low-income households, where the share of energy expenditures can reach 20–25% relative to income.

4. *How do the energy-related characteristics of residential buildings (e.g., insulation and the condition of windows and doors) affect energy consumption and the extent of energy poverty?*

Poor-quality insulation and outdated windows and doors significantly increase energy costs, as inadequate heat retention requires households to consume more heating energy to maintain comfort. The cluster analysis shows that these problems are characteristic of the groups most affected by energy poverty.

5. *What proportion of households implement energy-saving measures, and how do these affect energy expenditures?*

Approximately 35% of households reported having implemented some energy-saving measure (e.g., LED lighting, thermostatic control, and energy-efficient appliances). Among these households, annual energy expenditures were generally 10–15% lower than those of households with similar income levels that did not adopt such measures.

6. *To what extent do signs of hidden energy poverty (e.g., reducing heating or forgoing basic needs) appear among the surveyed households?*

Of the respondents, 28% reported that they regularly reduce heating during the winter period to save on utility bills. Furthermore, around 20% stated that they deprioritize other essential expenses (e.g., food and medication) to cover energy costs; these are classic indicators of hidden energy poverty.

In addition to addressing the research questions, this study also tested four working hypotheses; the findings confirm all four. H1 proposed that a significant proportion of households reduce essential expenditures due to energy costs; our results show that 20% of respondents deprioritize food or medicine. H2 posited a negative relationship between household income and the relative burden of energy costs, which the observed inverse correlation between income and energy expenditure share supports. H3 linked poor housing conditions to higher energy costs and lower thermal comfort; correlation results and qualitative housing descriptions confirmed this hypothesis. Lastly, H4, addressing hidden energy poverty, was strongly supported, as 28% of respondents reported reducing heating, and 20% admitted sacrificing other necessities. These results underscore the multidimensional nature of energy poverty and the relevance of subjective and behavioral indicators in capturing its less visible forms.

Our results are consistent with more exhaustive research concerning energy poverty in Central and Eastern Europe. For example, several studies [17,31] emphasize the prevalent problem of hidden energy poverty, especially in rural regions with aging housing. This result is in line with our findings, which indicate that 28% of households minimize their heating and 20% prioritize other critical needs. The inverse relationship between income and energy comfort further corroborates [8], highlighting the increased susceptibility of low-income households with poor insulation. Additionally, the differences in energy poverty rates depending on the measurement approaches reflect trends identified by [24], who found that energy poverty's categorization can vary based on the chosen indicators. These associations imply that while this study centers on a particular area, our findings enhance the overall understanding of the structural and behavioral dimensions of rural energy poverty.

Overall, our analysis confirms that the combined effect of multiple factors determines the relationship between energy poverty and perceived thermal comfort. The combined use of the cluster-based approach and the comparison of various indicators can significantly contribute to a more accurate identification of target groups for intervention, thereby enabling the development of more targeted energy policy and social support programs.

Limitations

This study employed the snowball sampling method, which does not provide a full statistical representation. This approach was chosen because no local household registries exist, and there is a need to reach underrepresented and vulnerable groups. One of the co-authors is the village mayor, and he has strong, trust-based relationships with the local population. His commitment to combating energy poverty and his direct involvement in community support provided ethical and practical access to households that might otherwise be overlooked. Using snowball sampling in this context created a more inclusive and context-aware dataset than traditional random sampling. Participation was entirely voluntary, anonymous, and based on informed consent. While the results cannot be generalized to all of Hungary, the sample broadly represents the social and housing conditions of the studied village. This village shares many structural similarities with other rural settlements in Hungary, therefore, the findings can provide valuable insights into familiar patterns and challenges in similar contexts. Nonetheless, this sampling method may introduce some biases, so caution is necessary when extending conclusions beyond the studied area. Future studies could combine this approach with stratified or random sampling to improve external validity.

The average silhouette score (0.130) indicates a relatively low level of cluster separation, however, this outcome is not unusual in the case of the FCM method, particularly when applied to small, socially homogeneous datasets. Unlike complex clustering algorithms, FCM is designed to model partial membership and overlapping group boundaries, which naturally provides lower silhouette values. This study did not aim to generate sharply separated groups, but rather to capture the nuanced, fuzzy nature of vulnerability profiles. This approach may limit generalizability, however, the identified clusters remain analytically sound, as supported by their statistically significant associations with perceived comfort in the regression analysis.

5. Conclusions

The study aimed to provide a comprehensive picture of energy poverty as an existing social and economic problem. After reviewing the conceptual framework, various known and applied measurement methods were presented, revealing that a uniform measurement or indicator system could not be used to identify the affected target groups. The primary was conducted in a small Hungarian settlement (under 5000 inhabitants), confirming that energy poverty is statistically detectable and an existing phenomenon that significantly burdens affected households. The survey also identified causal factors described in the literature, such as low income, properties with poor energy performance, and high energy expenditure levels. The different measurement indicators used in the research showed a significant variance in the number of families affected by energy poverty, meaning that the "univariate" indicators show very different results, which hinders the identification of the most vulnerable households.

There are several possible proposals for addressing and alleviating energy poverty, however, no uniformly accepted measurement system or uniform definition exists in Hungary. In protected areas in Hungary, especially in settlements with less than 5000 inhabitants, defining an officially accepted, precise definition of energy poverty could provide a clear basis for developing the necessary measures. In parallel, a complex, multi-aspect indicator system should be developed to serve specifically for the objective and comparable measurement of energy poverty in rural settlements. We tentatively propose a rural EPI as a conceptual tool for future development. While not tested in this study, a rural EPI could integrate both objective and subjective dimensions of energy poverty in rural contexts. Further methodological work is required to operationalize and validate such a framework; thus, we provide several practical recommendations based on our findings.

First, identifying different vulnerability profiles shows the need for varied policy responses. Low-income households with limited adaptation ability (C5) need targeted subsidies or voucher-based support. In contrast, proactive, energy-savvy groups (C3) might benefit more from incentives for small-scale efficiency investments. Second, hidden energy poverty indicates that energy-related struggles often go unnoticed by traditional income-based measures. We suggest policymakers use subjective and behavioral data in energy poverty monitoring systems, such as perceived comfort and coping strategies. Third, local pilot programs should be created in rural areas to combine energy audits, financial counseling, and community awareness campaigns. These programs could address both technical and social aspects of energy vulnerability. Finally, improving rural housing through easy-access renovation grants could lead to long-term cost savings and ease the burden on vulnerable households.

Unfortunately, the energy condition of households suffering from energy poverty is often extremely unfavorable. The long-term goal of developing these buildings is to renovate uninsulated houses, modernize heating systems, replace windows and doors, or install renewable energy sources (e.g., solar panels). In addition to providing the necessary resources, such developments also require serious professional, energy-related knowledge transfer and sharing.

In Hungary, creating energy communities is in its initial phase, and public initiatives can be said to be almost negligible, however, in the long term, energy communities can play a critical role in strengthening energy independence and developing decentralized energy production. This approach can create a more transparent, even socially just, system where energy communities can take meaningful steps toward alleviating and managing energy poverty, however, energy communities must continually be developed by the given social environment. In this way, they can achieve positive results in a targeted manner, with the broad involvement of social actors [53,54].

In Hungary, there have been advances in the fight against energy poverty, but complex programs organized explicitly from the bottom up are not noticeable. Therefore, it would be worthwhile to launch pilot programs specifically at the settlement level, where the results could be adaptable. Based on existing and newly developed experiences, a fully tested, controlled, and feedback-based project should be implemented, where broad social and professional participation must be ensured.

The impact of measures to alleviate energy poverty must be continuously examined, and their effectiveness should be analyzed. An essential condition for this is the introduction of a smart metering system, especially in small settlements. Smart metering systems can provide real-time data, thereby enabling those in need.

While not directly examined in this study, technologies like smart metering or community-based energy initiatives can be potential tools to reduce energy vulnerability. We note these possibilities as possible directions for future exploration, particularly in rural areas. However, these recommendations exceed our current data and should be considered preliminary considerations, not evidence-based prescriptions.

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Abbreviations

The following abbreviations are used in this manuscript:

ANOVA	Analysis of variance
BIC	Bayesian information criterion
CI	Confidence intervals

EU	European Union
FCM	Fuzzy c-means
LIHC	Low-income, high cost
UK	United Kingdom

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