

## DISAGGREGATED CONSUMPTION INFORMATION AND THE NEIGHBOR CONSUMPTION INDEX IN HOUSEHOLD ELECTRICITY USE

### INFORMAÇÃO DESAGREGADA SOBRE O CONSUMO E O ÍNDICE DE CONSUMO DOS VIZINHOS NO USO DOMÉSTICO DE ELETRICIDADE

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The authors declare that there is no conflict of interest

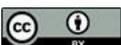
#### Abstract

Enhancing the efficiency of electricity consumption is an important step in mitigating environmental degradation, as the reliance on fossil fuels in energy production remains one of the primary contributors to carbon emissions and ecological harm. The objective of this study was to develop the Neighbor Consumption Index (NCI), a tool designed to explore differences in household electricity usage and to compare two groups of households with and without access to a service providing detailed information about electricity consumption. The central motivation of our research lies in comparing electricity consumption among geographically proximate households with similar usage patterns. We applied K-means clustering to group households and statistical tests to examine differences in consumption between households with and without access to disaggregation technology. The NCI was then calculated as a relative measure with the potential to provide households with a benchmark relative to their neighbors, thereby supporting reflection on their own consumption behavior. For the empirical analysis, we utilized data processed by the software company Bidgely.

**Keywords:** Disaggregation. Consumer Behavior. Household Electricity Consumption. Neighbor Clusters.

#### Resumo

*Aumentar a eficiência do consumo de eletricidade é um passo importante para mitigar a degradação ambiental, uma vez que a dependência dos combustíveis fósseis na produção de energia continua a ser um dos principais fatores que contribuem para as emissões de carbono e os danos ecológicos. O objetivo deste estudo foi desenvolver o Índice de Consumo dos Vizinhos (NCI), uma ferramenta concebida para explorar as diferenças no consumo de eletricidade das famílias e comparar dois grupos de famílias com e sem acesso a um serviço que fornece informações detalhadas sobre o consumo de eletricidade. A motivação central de nossa pesquisa reside na comparação do consumo de eletricidade entre residências geograficamente próximas com padrões de uso semelhantes. Aplicamos o agrupamento K-means para agrupar as residências e testes estatísticos para examinar as diferenças no consumo entre residências com e sem acesso à tecnologia de desagregação. O NCI foi então calculado como uma medida relativa com o potencial de fornecer às famílias uma referência em relação aos seus vizinhos, apoiando assim a reflexão sobre o seu próprio comportamento de consumo. Para a análise empírica, utilizamos dados processados pela empresa de software Bidgely.*



*Palavras-chave:* Desagregação. Comportamento do Consumidor. Consumo Doméstico de Eletricidade. Grupos de Vizinhos.

## 1 INTRODUCTION

Electricity consumption plays a central role in contemporary economic activity and household welfare, yet it remains one of the key drivers of environmental degradation due to the persistent reliance on fossil fuels in energy production. Despite substantial investments in renewable energy technologies, fossil fuels continue to account for a significant share of global electricity generation, contributing to greenhouse gas emissions and climate-related externalities. From an economic perspective, improving energy efficiency on the demand side is increasingly recognized as a cost-effective complement to supply-side decarbonization policies, particularly in the residential sector, where individual consumption decisions aggregate into substantial system-wide impacts (Mundaca et al., 2018).

Traditional economic approaches explain household electricity consumption primarily through prices, income, and technological efficiency. However, a growing body of literature in behavioral economics and energy economics demonstrates that consumers frequently deviate from fully rational behavior. Information asymmetries, limited attention, habits, and social norms often lead to persistent inefficiencies in energy use, even when financially beneficial savings opportunities are available (Allcott & Kessler, 2019). These behavioral frictions help explain why households may underinvest in energy efficiency or fail to adjust consumption despite rising energy prices and increasing environmental awareness.

Recent research emphasizes that behavioral interventions, particularly those leveraging feedback and social comparison, can play a significant role in shaping household energy behavior. Studies show that providing consumers with timely, comprehensible information about their electricity use can reduce consumption by making energy use more salient and actionable (Karlin et al., 2015; Delmas et al., 2013). Moreover, peer-based comparisons, in which households receive information about how their consumption compares with that of similar neighbors, have been found to activate

social norms and motivate voluntary reductions in energy use (Allcott, 2011; Andor et al., 2020). Such mechanisms are especially relevant in residential settings, where consumption is often invisible and abstract.

In parallel, advances in data analytics and smart metering technologies have enabled the development of electricity consumption disaggregation techniques, which break down total household electricity use into appliance-level or activity-based components. Disaggregated feedback has been shown to improve consumer understanding of energy consumption patterns and enhance perceived control over energy-saving actions (Kelly & Knottenbelt, 2015; Himeur et al., 2021). From a behavioral standpoint, this type of information reduces cognitive barriers and supports more informed decision-making, while from an economic perspective it enhances the effectiveness of non-price interventions by lowering information costs.

Despite these advances, the literature highlights that feedback alone may not be sufficient to sustain long-term behavioral change. Combining disaggregated consumption data with social benchmarks has been identified as a promising approach to reinforce motivation and persistence of energy-saving behavior (Schultz et al., 2007; Mi et al., 2021). However, empirical evidence on how such combined tools perform over extended periods and across comparable household clusters remains limited.

This study aims to examine whether access to detailed and disaggregated information on household electricity consumption is associated with differences in electricity use between consumers. Rather than assuming a direct behavioral effect, the analysis focuses on identifying whether measurable differences exist between households with and without access to such information across comparable groups. To support this analysis, the study introduces the Neighbor Consumption Index (NCI) as a pilot metric designed to express household electricity consumption relative to geographically and contextually similar households. The index is intended as a comparative reference rather than a performance measure and serves as an exploratory tool for assessing relative consumption patterns.

Using household-level electricity consumption data processed by Bidgely, the study empirically evaluates differences in consumption across user groups and consumption segments. By doing so, it contributes to the literature on informational and

behavioral approaches to energy consumption by providing empirical evidence on the scope and limitations of data-driven comparison tools in the residential electricity context.

This paper is structured as follows: **Section 1**, “*Literature review*”, reviews key findings related to sustainable behavioral changes in consumption habits. It also briefly outlines the Bidgely technology, which represents one of the leading disaggregation approaches currently in use, and serves as the source of the data analyzed in this study. **Section 2**, “*Data description and Methodology*”, outlines the dataset and the methodological framework applied to the analysis of electricity consumption. **Section 3**, “*Results*”, presents the empirical results concerning energy efficiency–related behavior. **Section 4**, “*Discussion*”, discusses the main findings, potential pathways for their practical implementation as well as limitations and possible future research directions. The last section, “*Conclusion*” summarizes the study and its main idea.

## 2 LITERATURE REVIEW

The residential sector has become an increasingly important focus of energy economics and sustainability research, as household electricity consumption constitutes a substantial and growing share of total energy demand (Wolske et al., 2020). While technological progress has improved the energy efficiency of appliances and buildings, aggregate electricity consumption continues to rise, driven by increasing electrification, digitalization, and lifestyle changes (Prasanna et al., 2018). This divergence between technological potential and actual consumption outcomes has directed scholarly attention toward the behavioral and economic determinants of household energy use.

From a traditional economic perspective, electricity consumption is primarily modeled as a function of prices, income, and technological efficiency. Price-based instruments such as tariffs and taxes are assumed to incentivize consumers to adjust their consumption rationally in response to cost signals. However, empirical evidence suggests that price elasticity of residential electricity demand is relatively low in the short run, limiting the effectiveness of purely price-driven policies (Ito, 2014; Alberini et al., 2020). Moreover, households often fail to exploit cost-effective energy-saving opportunities, a phenomenon commonly referred to as the “energy efficiency gap” (Gillingham & Palmer, 2014).

Behavioral economics offers complementary explanations for these persistent inefficiencies by highlighting the role of cognitive limitations, habits, and social influences. Consumers frequently face information asymmetries regarding their electricity use, as energy consumption is largely invisible and abstract in everyday life (Sintov and Schultz, 2015). Limited attention, status quo bias, and present bias further reduce the likelihood that households will actively monitor or optimize their consumption, even when financial incentives exist (DellaVigna, 2009). As a result, informational and behavioral interventions have gained prominence as cost-effective tools to influence energy-related decision-making without restricting consumer choice.

A substantial body of literature demonstrates that feedback mechanisms can significantly affect household electricity consumption. Providing consumers with frequent, clear, and personalized information about their energy use increases awareness and enables more informed decisions. Compared to traditional monthly billing, real-time or near-real-time feedback has been shown to improve the salience of consumption and support short-term reductions in electricity use (Andor et al., 2020, Buchanan et al., 2015). However, the magnitude and persistence of these effects vary considerably across households and contexts.

One of the interesting findings in the literature relates to the effectiveness of social comparison and peer benchmarking. Social norm–based interventions inform households how their electricity consumption compares with that of similar peers, typically neighbors or households with comparable characteristics. Such comparisons activate descriptive social norms and have been found to induce statistically significant and economically meaningful reductions in electricity consumption (Agarwal et al., 2023). Importantly, these effects have been observed across different countries and institutional settings, suggesting a high degree of external validity. Nevertheless, concerns remain regarding potential rebound effects and the risk that low-consuming households may increase consumption when informed that they are below average, highlighting the need for carefully designed benchmarks (Schultz et al., 2019).

In recent years, advances in smart metering and data analytics have enabled the development of electricity consumption disaggregation techniques, which decompose aggregate household electricity use into appliance-level or activity-based components. Non-intrusive load monitoring (NILM) technologies allow utilities and service providers

to infer detailed usage patterns without additional hardware installation (Zoha et al., 2012). Recent empirical studies suggest that disaggregated feedback improves consumers' understanding of where and how electricity is consumed, thereby increasing perceived behavioral control and facilitating targeted energy-saving actions (Gerstser et al., 2025; Herrmann et al., 2021). However, the literature also points to a lack of long-term empirical evidence on how such approaches perform over extended periods and across comparable household groups. Many existing studies rely on short intervention windows or experimental settings, limiting their ability to capture sustained behavioral change.

Against this background, technologies such as those developed by Bidgely represent an important advancement in the application of data-driven behavioral tools in the energy sector. By enabling large-scale disaggregation of household electricity consumption, these technologies provide a foundation for personalized feedback and peer-based comparisons. The current study builds on this body of research by examining how socially contextualized, disaggregated consumption information, operationalized through the Neighbor Consumption Index, can contribute to more efficient and sustainable electricity use in residential settings.

### 3 DATA DESCRIPTION AND METHODOLOGY

#### 3.1 Data description and sample of datasets

The study examines two datasets of electricity consumption data from consumers required by legislation to install smart meters in Slovakia since 2014. Datasets consist of demographical data of consumers and monthly electricity usage during the same period of three years (2020 – 2022) and containing the electricity consumption data of more than 20 000 consumers within the household segment in Slovakia. The first one, named *OM\_data* includes more than 25 000 rows, which contain information related to consumers (*Group* - with/without access to disaggregation; *OV* – consumer identification No.; *Age*; *EIC* (unique identification code of a particular place of consumption - household), *OM\_locations* (postal code and town/municipality, where the household is

located) and other columns that have not been included for the purpose of this study. A sample of the dataset is shown in Table 1.

**Table 1**

*Sample of dataset OM\_data*

Group	OV	AGE	EIC	OM_location
GroupA	5000085058	70	24ZVS0000224131O	065 12   Jakubany
GroupA	5000481811	60	24ZVS00001638387	048 01   Rudná
GroupA	5000968028	59	24ZVS0000515508K	077 01   Kráľovský Chlmec
GroupA	5001005061	31	24ZVS0000632845Z	044 45   Bačkovík
GroupA	5000363224	37	24ZVS00006133301	044 02   Turňa nad Bodvou
GroupA	5000932158	33	24ZVS0000560427F	040 14   Košice - Košická Nová Ves
GroupA	5000120807	61	24ZVS00005693297	040 17   Košice - Barca
GroupA	5000243205	89	24ZVS0000475580K	053 71   Nižné Repaše
GroupA	5000055563	78	24ZVS0000585049L	040 11   Košice - Západ
GroupA	5000170300	41	24ZVS00004997849	040 01   Košice - Vyšné Opátske

The second dataset, *Usage\_data* consists of more than 3 720 000 rows and contains information about the monthly electricity usage of consumers included in the study within the period from 1.1.2020 to 31.12.2022. A sample of the dataset is shown in Table 2. The dataset contained five columns (*OM\_Id* – identification No. of the place of electricity consumption, *EIC*, *Start\_date* - related to period of consumption volume in the column Usage, *End date* – again related to consumption volume in the column Usage and column *Usage* – volume of electricity consumed in kWh).

Each household is assigned an *EIC* (Unique Electricity Identification Code of Consumer Residence), which serves as a unique identifier of electricity consumption at the residential level. *EIC* is primary key of datasets and was used for join of described datasets in R-Studio, which was used in following work with the datasets. Unnecessary columns were deleted from both datasets.

**Table 2**

*Sample of dataset Usage\_data*

OM_Id	EIC	Start date	End date	Usage (kWh)
0000166263	24ZVS0000139675Y	1.1.2020	1.2.2020	364,690
0000166263	24ZVS0000139675Y	1.2.2020	1.3.2020	273,783
0000166263	24ZVS0000139675Y	1.3.2020	1.4.2020	257,575
0000166263	24ZVS0000139675Y	1.4.2020	1.5.2020	172,278
0000166263	24ZVS0000139675Y	1.5.2020	1.6.2020	236,993
0000166263	24ZVS0000139675Y	1.6.2020	1.7.2020	332,798

0000166263	24ZVS0000139675Y	1.7.2020	1.8.2020	329,332
0000166263	24ZVS0000139675Y	1.8.2020	1.9.2020	348,086
0000166263	24ZVS0000139675Y	1.9.2020	1.10.2020	255,027
0000166263	24ZVS0000139675Y	1.10.2020	1.11.2020	330,103

The first step involved preprocessing the data. We grouped data by unique EIC in dataset Usage\_data and we counted monthly average of electricity usage for each consumer (EIC). Monthly electricity consumption records are available for each consumer, resulting in a balanced or near-balanced panel with a minimum of 24 monthly observations per household after data cleaning. Only consumers with sufficiently complete consumption histories were retained in the final sample to ensure robustness and comparability across time. Each observation includes monthly electricity usage, postal code (ZIP code), and consumer age. Although household size is not observed, actual electricity consumption is assumed to implicitly capture differences in household composition and usage intensity, which is a common assumption in applied energy consumption studies.

### 3.2 Methodology of research

#### 3.2.1 Geographic and environmental augmentation

Postal codes were used to enrich the dataset with geographic information. Specifically, each consumer was assigned geographic coordinates (longitude and latitude) corresponding to their place of residence. Based on these coordinates, elevation above sea level (altitude) was calculated using publicly available geospatial data sources. Elevation was included as an environmental proxy variable reflecting climatic and heating-related conditions that may systematically influence electricity consumption patterns. Compared to administrative identifiers alone, altitude provides a more continuous and physically meaningful measure for grouping households exposed to similar environmental conditions.

### 3.2.2 Consumption-based segmentation

To account for structural heterogeneity in electricity usage, consumers were first divided into two primary segments based on their average annual electricity consumption. A threshold of 8,000 kWh per year (corresponding to an average monthly consumption of over 660 kWh) was applied to distinguish between lower- and higher-consumption households. This classification is grounded in the assumption that households using electricity for heating typically exhibit annual electricity consumption exceeding 8,000 kWh and consequently incur higher energy-related costs (Héjjová & Bucko, 2023). To ensure comparability among households with similar electricity usage profiles, consumers were therefore initially categorized into these two distinct groups. This segmentation allows for separate analyses of fundamentally different consumption regimes and reduces within-group variance in subsequent clustering procedures.

### 3.2.3 Regional segmentation

Within each consumption segment, consumers were further manually classified according to their geographic location based on the geopolitical division of Slovakia into three broader regions: Eastern, Central, and Western Slovakia. This regional classification reflects differences in infrastructure and climatic conditions and enables the implementation of region-specific clustering and comparative analyses.

### 3.2.4 Clustering procedure

For each region and consumption segment, clusters of consumers were identified using the *k-means clustering algorithm*. Clustering was performed based on two standardized variables:

1. *Mean monthly electricity consumption (Mean\_usage)*, calculated as the average of monthly usage over the observation period, and
2. *Altitude*, representing elevation above sea level.

The number of clusters was determined using standard validation techniques (elbow method and silhouette analysis) to balance interpretability and within-cluster

homogeneity. This approach allows households with similar consumption intensity and comparable environmental conditions to be grouped together in a data-driven manner.

### 3.2.5 Calculation of the Neighbor Consumption Index (NCI)

The Neighbor Consumption Index (NCI) for consumer  $i$  assigned to cluster  $c$  is defined as:

$$NCI_i = \frac{\bar{E}_i}{\bar{E}_c} \quad (1)$$

where:

$\bar{E}_i$  denotes the average electricity consumption of consumer  $i$  over the observed period,  
 $\bar{E}_c$  represents the centroid value of cluster  $c$ , calculated as the average electricity consumption of all consumers belonging to that cluster.

Values of  $NCI_i > 1$  indicate that the consumer's electricity consumption exceeds the cluster reference level, while values of  $NCI_i < 1$  indicate consumption below the cluster average. Values around 1, which is treated as the reference consumption level, reflect consumption similar to the average cluster value.

### 3.2.6 Group comparison within clusters

Within each cluster and region, consumers from Group A (with the service to see detailed monthly consumption) and Group B (without the service) were identified. This within-cluster comparison ensures that users are matched on both consumption characteristics and environmental conditions, thereby reducing confounding effects unrelated to service usage.

Statistical tests were applied to assess whether differences in electricity consumption between Group A and Group B within the same cluster are statistically significant. Differences in average electricity consumption between user groups were analysed using Welch's two-sample t-test. Designed by Welch (1951), it is a method to

test the equality of two populations means, reliable when the two samples have unequal variances and sample sizes (Ruxton, 2006). To verify the robustness of the results, the non-parametric Mann–Whitney U test was also applied (Fay and Proschan, 2010).

Based on the assumptions mentioned earlier these tests were used to examine a hypothesis:

*Hypothesis 1:* The monthly average electricity consumption of consumers from Groups A and B is not statistically significantly different for each cluster.

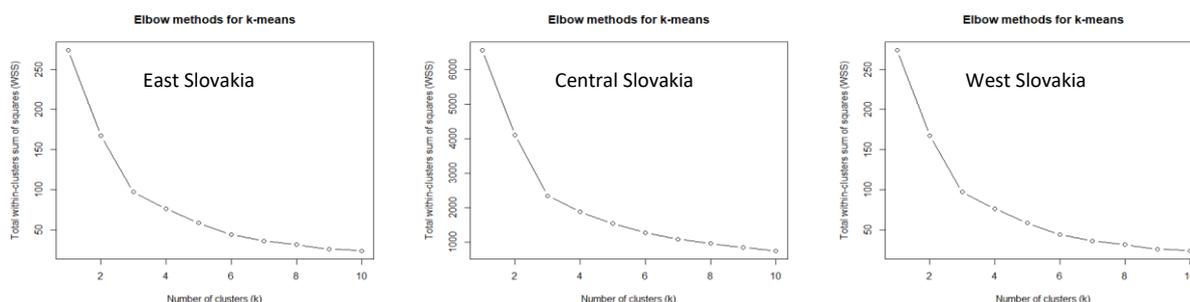
Additionally, depending on the results of Hypothesis 1 we also ask one research question: Is the NCI of Group A lower than NCI of Group B for each cluster?

## **4 RESULTS**

After dividing all households into three major regions of Slovakia (East, Central, and West), the analysis first focused on households with an average annual electricity consumption exceeding 8,000 kWh, corresponding to an average monthly consumption above 666 kWh. All computations were performed in the R programming environment.

### **4.1 Results of cluster algorithm above 8000kWh**

Within each regional subset, a K-means clustering algorithm was applied using two input variables: average monthly electricity consumption and residential elevation. The optimal number of clusters was determined separately for each region using the elbow method.

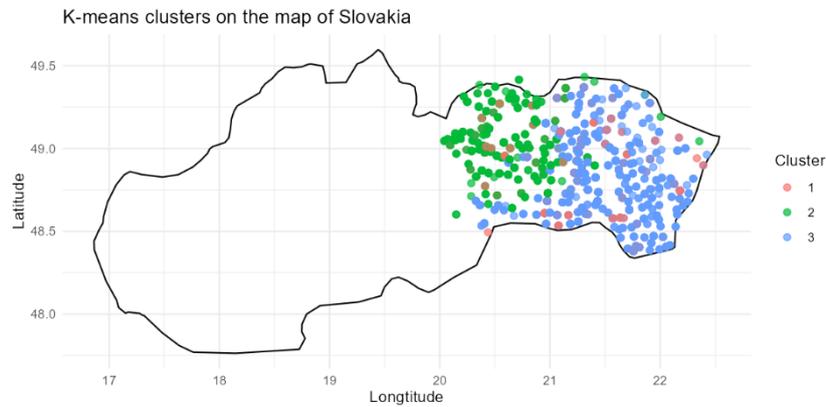
**Figure 1***Elbow method for each sub dataset above 8000kWh*

In all three regions, the elbow criterion consistently indicated three clusters as the most appropriate solution, as can be seen in Fig. 1.

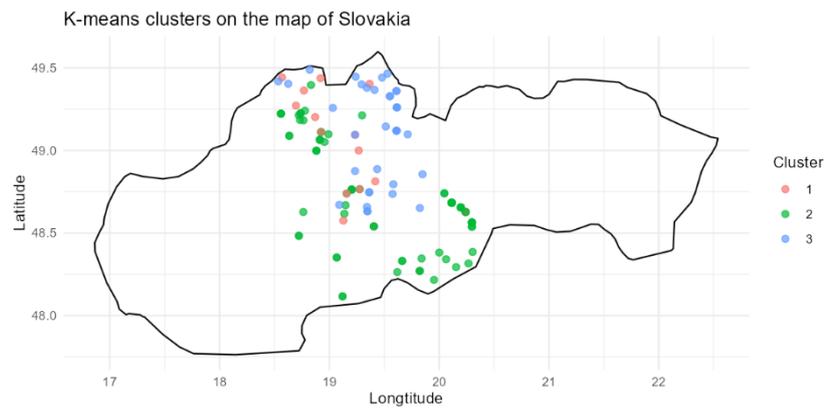
**Table 3***The value of cluster centroids for households with yearly consumption - above 8000kWh*

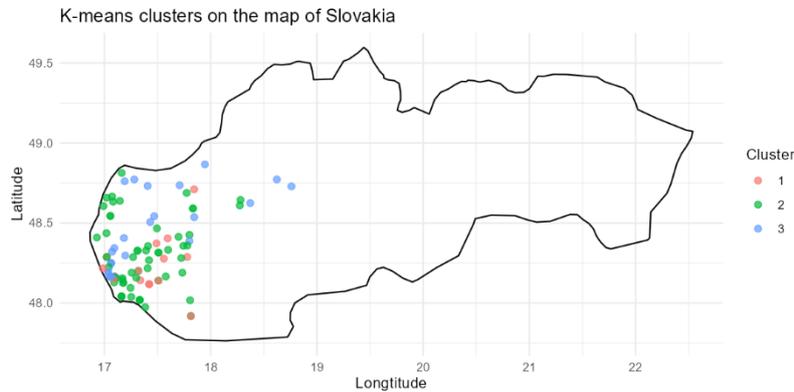
Cluster	<i>Eastern Slovakia</i>			<i>Central Slovakia</i>			<i>Western Slovakia</i>		
	Mean	Elev.	N	Mean	Elev.	N	Mean	Elev.	N
<b>1</b>	1785,649	237.21	396	2016,019	507,64	17	1503,460	149,86	15
<b>2</b>	920,981	640.00	911	885,011	347,8	85	847,877	150,07	57
<b>3</b>	868,547	262.26	1973	948,303	687,69	36	934,822	261,82	28

Table 3 summarizes the characteristics of the K-means clusters for households with annual electricity consumption above 8,000 kWh across the three Slovak regions. Across all regions, one cluster is consistently characterized by noticeably higher average electricity consumption than the remaining clusters. The other clusters show lower and relatively similar consumption levels, while differing mainly in average elevation.

**Figure 2***K-means clusters of East Slovakia - above 8000kWh*

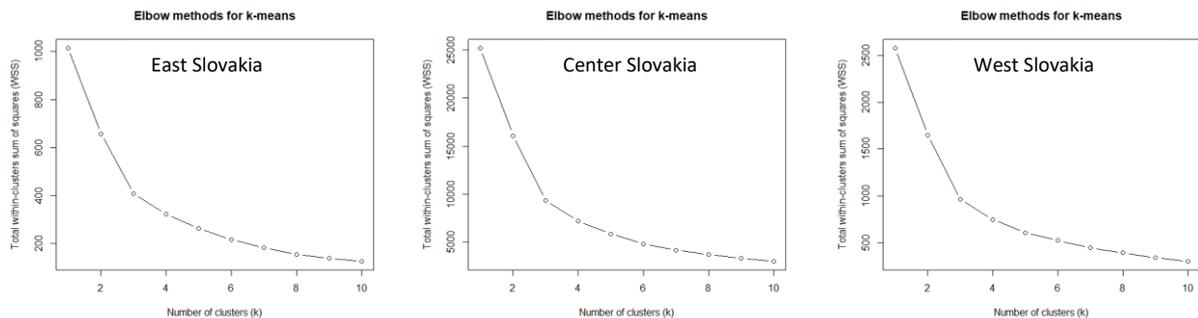
Geographical distribution of households in the clusters can be seen in Fig 2-4. Cluster sizes vary substantially between regions, with the eastern region comprising the largest share of observations. This clustering procedure primarily serves to group households with comparable consumption and elevation characteristics within each region, for further analysis.

**Figure 3***K-means clusters of Center Slovakia - above 8000kWh*

**Figure 4***K-means clusters of West Slovakia - above 8000kWh*

## 4.2 Results of cluster algorithm below 8000kWh

Following the analysis of households with higher electricity consumption, the same clustering procedure was applied to households with an average annual electricity consumption below 8,000 kWh (i.e., below 666 kWh per month).

**Figure 5***Elbow method for each sub dataset below 8000kWh*

As in the previous case, households were first divided into eastern, central, and western regions of Slovakia. Within each region, K-means clustering was performed using average monthly electricity consumption and residential elevation as input variables. The elbow method again indicated three clusters as the most appropriate solution in all regions (Fig. 5).

**Table 4**

*The value of cluster centroids for households with yearly consumption - below 8000kWh*

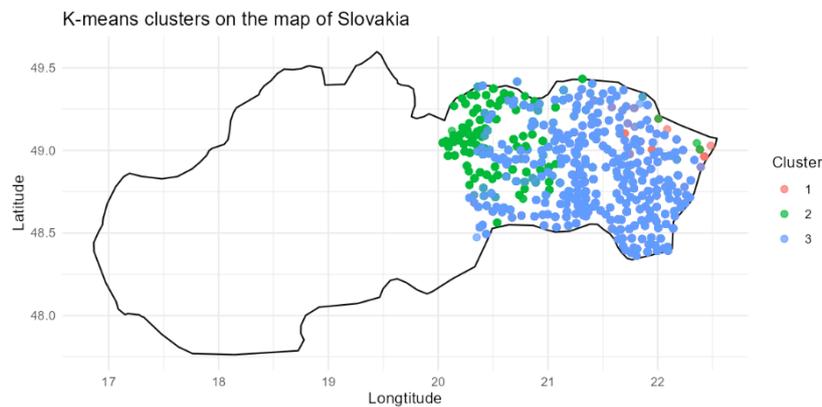
Cluster	Eastern Slovakia			Central Slovakia			Western Slovakia		
	Mean	Elev.	N	Mean	Elev.	N	Mean	Elev.	N
<b>1</b>	401.84	237.21	5388	446.07	666.75	125	392.06	316.46	164
<b>2</b>	456.85	640.00	3224	561.40	372.51	164	348.24	151.22	756
<b>3</b>	566.35	262.26	3993	397.78	339.93	219	534.57	153.09	370

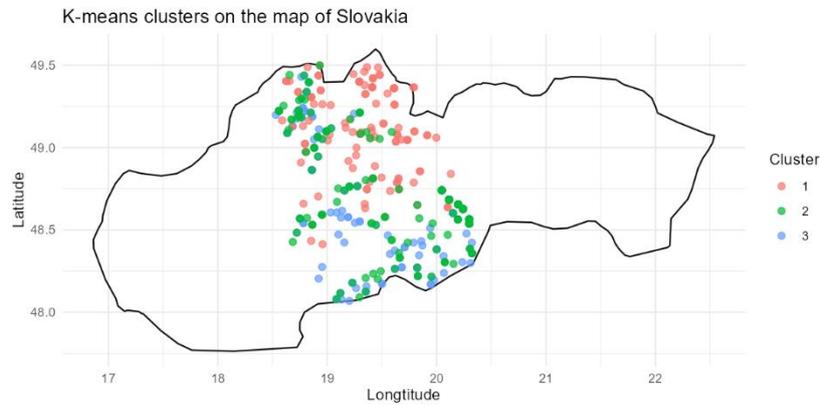
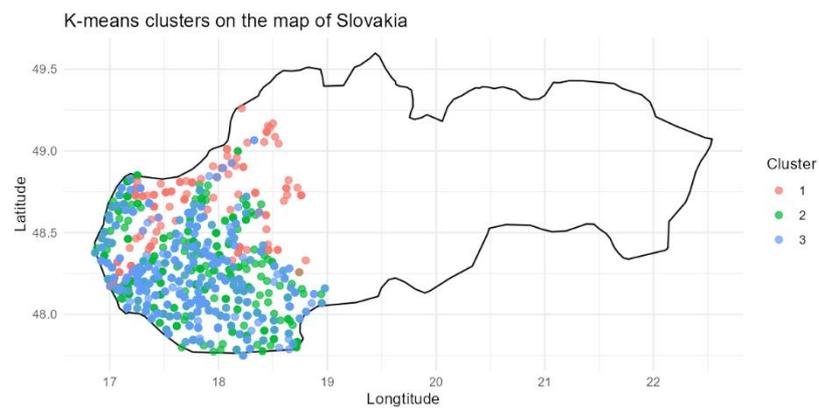
Table 4 presents the cluster characteristics for households with lower electricity consumption across the three regions. Compared to the higher-consumption group, this category includes a substantially larger number of households, particularly in the eastern region.

This distribution is consistent with the assumption that only a subset of households relies primarily on electricity for space heating, while the majority falls into lower-consumption categories. As in the higher-consumption segment, the clustering serves to define region-specific comparison groups for subsequent analysis rather than to imply distinct behavioral categories.

**Figure 6**

*K-means clusters of East Slovakia – below 8000kWh*



**Figure 7***K-means clusters of Center Slovakia – below 8000kWh***Figure 8***K-means clusters of West Slovakia – below 8000kWh*

### 4.3 Results of groups comparison above 8000kWh

To examine whether households with access to the service differ in electricity consumption from those without it, statistical comparisons were conducted within each cluster. By testing group differences inside clusters rather than across the full sample, the analysis accounts for heterogeneity in location, consumption levels and elevation identified in the previous section.

**Table 5***Results of Welch's two-sample t-test and Mann–Whitney U test – above 8000kWh*

<i>Eastern Slovakia</i>				
<b>cluster</b>	<b>n_GroupA</b>	<b>n_GroupB</b>	<b>welch_p</b>	<b>mw_p</b>
1	252	144	0,587	0,502
2	545	366	0,003	0,003
3	1327	646	1,513E-08	9,9431E-09
<i>Central Slovakia</i>				
<b>cluster</b>	<b>n_GroupA</b>	<b>n_GroupB</b>	<b>welch_p</b>	<b>mw_p</b>
1	5	12	0,073	0,140
2	28	57	0,340	0,242
3	2	34	0,425	1
<i>Western Slovakia</i>				
<b>cluster</b>	<b>n_GroupA</b>	<b>n_GroupB</b>	<b>welch_p</b>	<b>mw_p</b>
1	0	15	NA	NA
2	1	56	NA	NA
3	1	27	NA	NA

Table 5 reports the results of the Welch two-sample t-test and the Mann–Whitney U test comparing electricity consumption between Group A and Group B across clusters and regions for households with annual consumption above 8,000 kWh.

In Eastern Slovakia, statistically significant differences between the two groups were observed in clusters 2 and 3. In both clusters, the results are consistent across the Welch and Mann–Whitney tests, and the corresponding 95% confidence intervals do not include zero after applying the Benjamini–Hochberg correction for multiple testing, as seen in Fig. 9. No statistically significant difference was detected in cluster 1.

In Central Slovakia, no statistically significant differences in mean electricity consumption were detected between the two groups in any of the clusters. In each cluster, the 95% confidence intervals overlap with zero, suggesting that the observed mean differences may be attributable to random variation rather than systematic group effects (Fig 10).

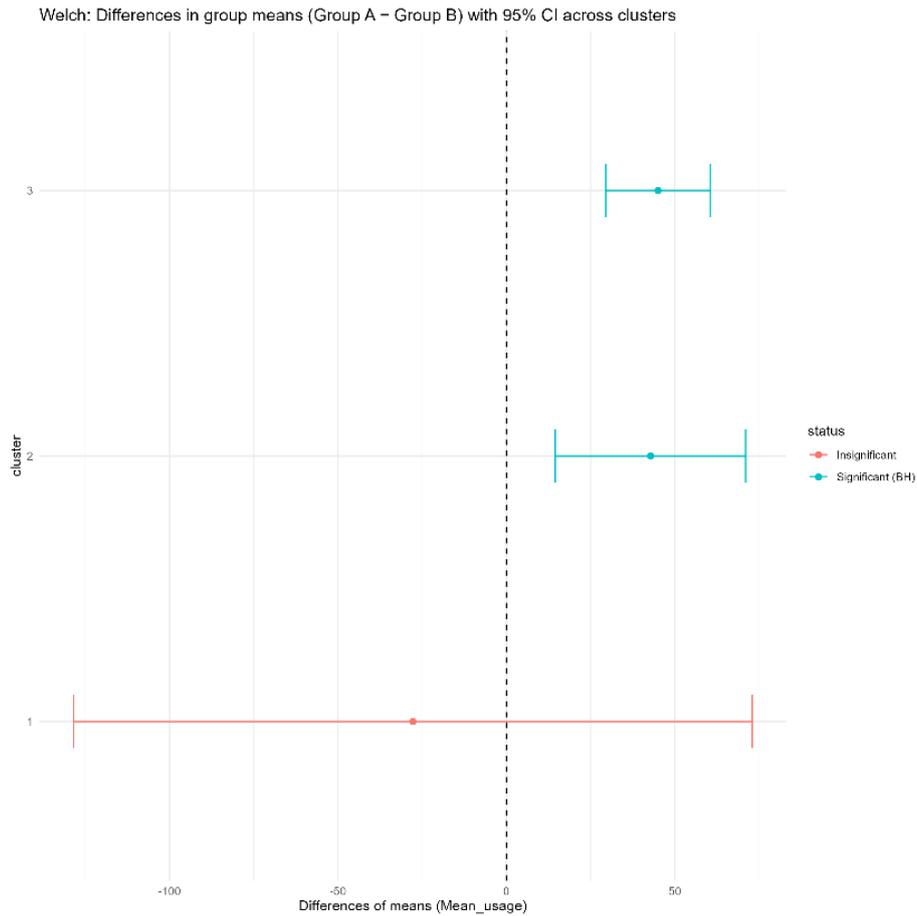
In Western Slovakia, statistical testing was limited by very small group sizes in several clusters, which prevented reliable estimation of group differences. As a result, no statistically significant differences were identified in this region.

With respect to Hypothesis 1, the results for households with annual electricity consumption above 8,000 kWh provide mixed evidence. The null hypothesis of no difference between Group A and Group B cannot be rejected in most clusters and regions.

However, statistically significant differences are observed in Clusters 2 and 3 in East Slovakia, leading to a rejection of Hypothesis 1 for these specific clusters.

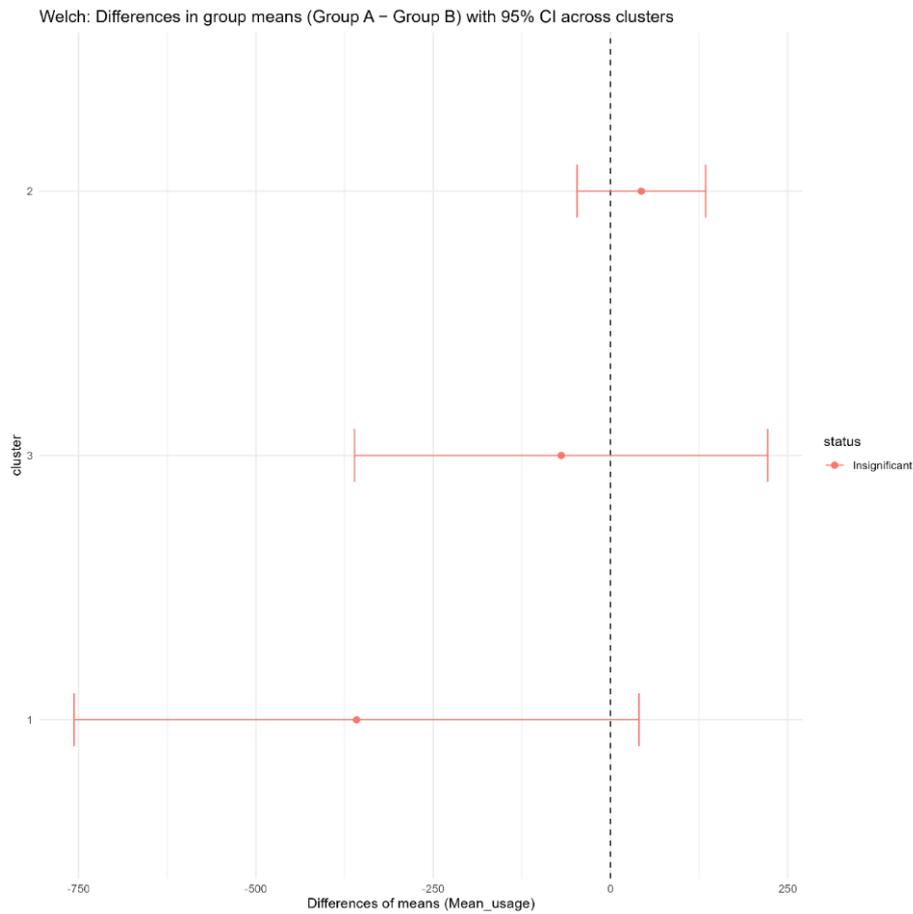
### Figure 9

*Differences in group A and Group B of East Slovakia - above 8000kWh*



**Figure 10**

*Differences in group A and Group B of Center Slovakia - above 8000kWh*



**4.4 Results of groups comparison below 8000kWh**

The same group comparison procedure was subsequently applied to households with an average annual electricity consumption below 8,000 kWh.

**Table 6**

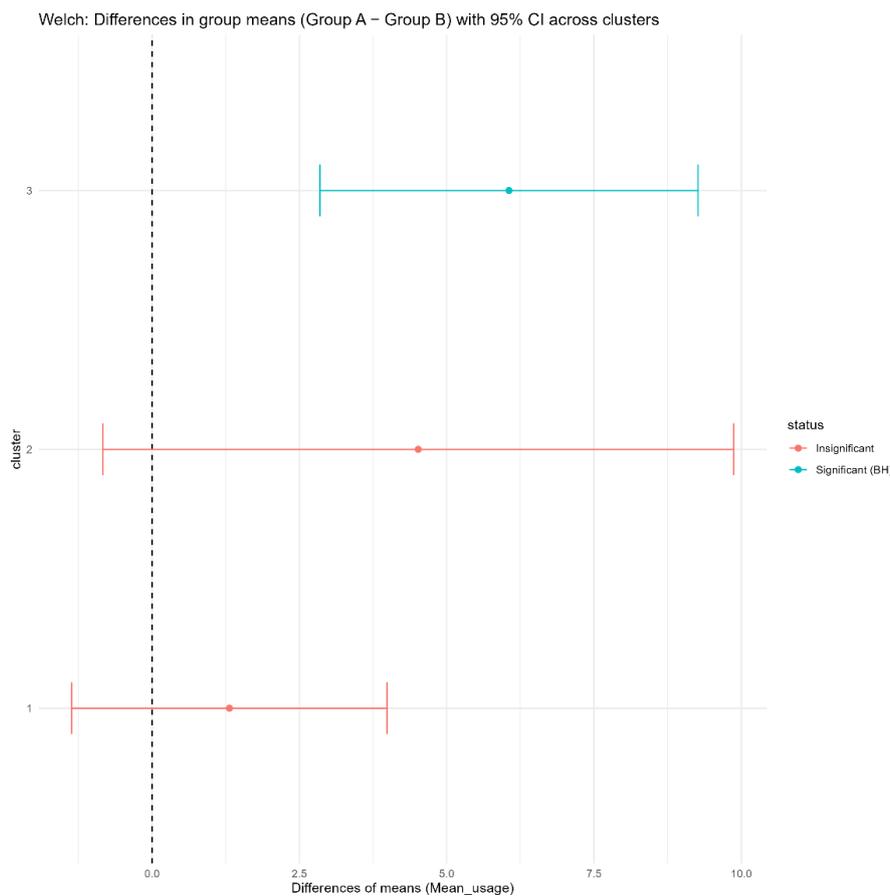
*Results of Welch’s two-sample t-test and Mann–Whitney U test – below 8000kWh*

<i>Eastern Slovakia</i>				
cluster	n_GroupA	n_GroupB	welch_p	mw_p
1	2591	2797	0,336	0,145
2	1617	1607	0,098	0,044
3	2298	1695	<0,001	<0,001
<i>Central Slovakia</i>				
cluster	n_GroupA	n_GroupB	welch_p	mw_p
1	14	111	0,544	0,562

2	40	124	0,009	0,014
3	40	179	0,261	0,350
<i>Western Slovakia</i>				
cluster	n_GroupA	n_GroupB	welch_p	mw_p
1	3	161	0,105	0,036
2	0	756	NA	NA
3	2	368	0,268	0,159

**Figure 11**

*Differences in group A and Group B of East Slovakia - below 8000kWh*



In East Slovakia, a statistically significant difference between the two groups is observed in Cluster 3. The result is consistent across both tests and remains significant after adjustment for multiple comparisons. In Clusters 1 and 2, no statistically significant differences are detected, as the corresponding confidence intervals include zero, as can be seen in Fig 11.

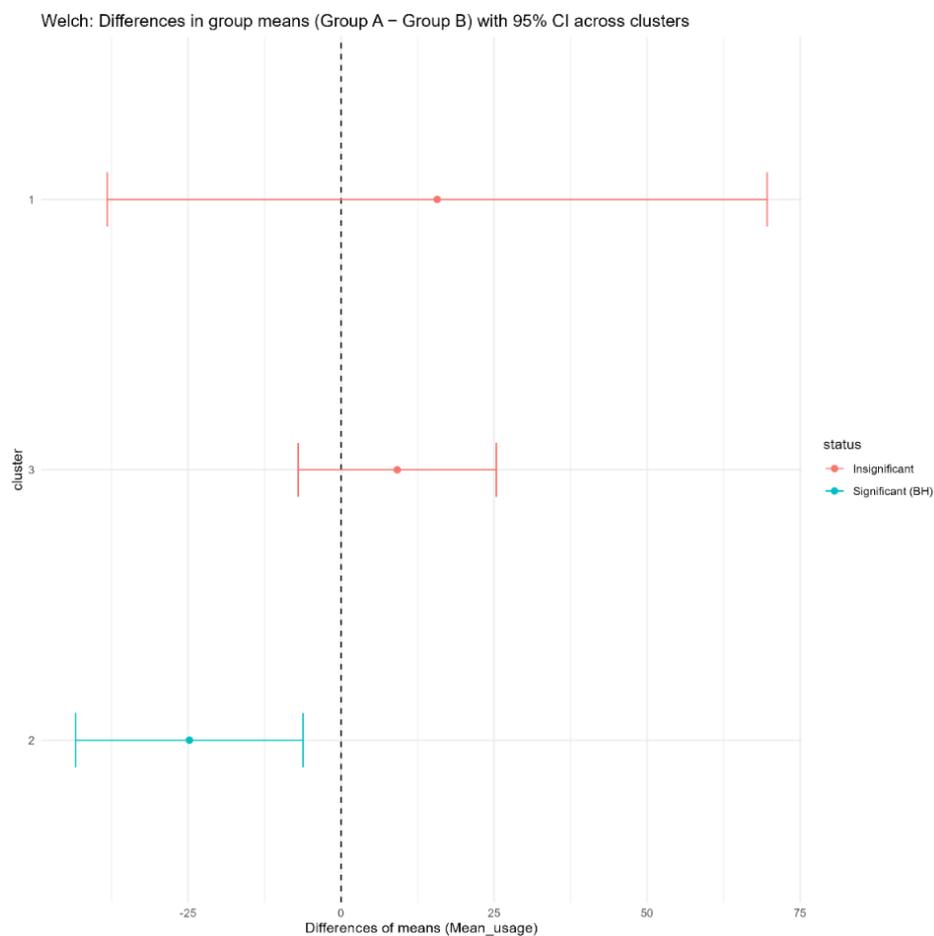
In Central Slovakia, a statistically significant difference between Group A and Group B is identified in Cluster 2, while no significant differences are found in Clusters

1 and 3. As in the eastern region, the observed group differences are therefore limited to a specific cluster rather than being present across the entire lower-consumption segment.

In West Slovakia, statistical inference is again constrained by very small group sizes in the clusters. Although point estimates vary, the Welch test does not indicate statistically significant differences between the groups in any cluster, and no robust conclusions can be drawn for this region because of the sample size.

## Figure 12

### *Differences in group A and Group B of Center Slovakia – below 8000kWh*



For households with annual electricity consumption below 8,000 kWh, the results similarly indicate limited support for systematic differences between Group A and Group B. Hypothesis 1 cannot be rejected in most clusters across regions. Statistically significant differences are detected only in specific clusters in East and Central Slovakia, leading to a rejection of the hypothesis in these isolated cases.

#### 4.5 Summary of the results comparing NCI Group A and Group B

In addition to comparing absolute electricity consumption between Group A and Group B, a relative measure of consumption was constructed in the form of the Neighbor Consumption Index which is defined as the ratio between a household's average monthly electricity consumption and the average consumption of the cluster to which the household belongs. The purpose of the NCI is not to measure absolute differences in consumption, but to capture households' relative position within a group of comparable households defined by similar consumption levels and elevation. In this section, average NCI values are compared between Group A and Group B within each cluster.

**Table 7**

*The summary of results comparing NCI - above 8000kWh*

<i>Eastern Slovakia</i>						
<b>cluster</b>	<b>mean_usage_A</b>	<b>n_A</b>	<b>mean_NCI_A</b>	<b>mean_usage_B</b>	<b>n_B</b>	<b>mean_NCI_B</b>
1	1775,548	252	0,994	1803,326	144	1,009
2	938,154	545	1,018	895,409	366	0,972
3	883,268	1327	1,016	838,307	646	0,965
<i>Central Slovakia</i>						
<b>cluster</b>	<b>mean_usage_A</b>	<b>n_A</b>	<b>mean_NCI_A</b>	<b>mean_usage_B</b>	<b>n_B</b>	<b>mean_NCI_B</b>
1	1763,282	5	0,874	2121,326	12	1,0522
2	914,154	28	1,032	870,696	57	0,983
3	882,665	2	0,930	952,164	34	1,004
<i>Western Slovakia</i>						
<b>cluster</b>	<b>mean_usage_A</b>	<b>n_A</b>	<b>mean_NCI_A</b>	<b>mean_usage_B</b>	<b>n_B</b>	<b>mean_NCI_B</b>
1	NA	0	NA	1503,460	15	1
2	753,461	1	0,888	849,563	56	1,001
3	1211,419	1	1,295	924,577	27	0,989

In Table 7 one can see that in most clusters and regions, Group A exhibits equal or higher average NCI values compared to Group B, indicating higher relative consumption within the respective clusters. A notably lower average NCI for Group A is observed only Cluster 1 in East Slovakia and Clusters 1 and 3 in West Slovakia. However, in clusters where statistically significant differences in absolute electricity consumption between Group A and Group B were identified in the previous section (Clusters 2 and 3 in East Slovakia), Group A displays higher average NCI values than Group B.

For the group below 8000kwh, average NCI values for Group A and Group B are generally very close to one, meaning relatively small differences in consumption within clusters. A lower average NCI for Group A is observed only in Cluster 2 in Central Slovakia. In all other clusters, Group A displays equal or slightly higher average NCI values than Group B. As in the higher-consumption group, clusters in which statistically significant differences in absolute consumption were detected do not correspond to lower relative NCI among households in Group A

**Table 8**

*The summary of results comparing NCI - below 8000kWh*

<i>Eastern Slovakia</i>						
<b>cluster</b>	<b>mean_usage_A</b>	<b>n_A</b>	<b>mean_NCI_A</b>	<b>mean_usage_B</b>	<b>n_B</b>	<b>mean_NCI_B</b>
1	402,523	2591	1,001	401,211	2797	0,998
2	459,103	1617	1,004	454,586	1607	0,995
3	568,920	2298	1,004	562,864	1695	0,993
<i>Central Slovakia</i>						
<b>cluster</b>	<b>mean_usage_A</b>	<b>n_A</b>	<b>mean_NCI_A</b>	<b>mean_usage_B</b>	<b>n_B</b>	<b>mean_NCI_B</b>
1	460,007	14	1,031254508	444,307	111	0,996
2	542,657	40	0,96661487	567,445	124	1,010
3	405,277	40	1,018855629	396,100	179	0,995
<i>Western Slovakia</i>						
<b>cluster</b>	<b>mean_usage_A</b>	<b>n_A</b>	<b>mean_NCI_A</b>	<b>mean_usage_B</b>	<b>n_B</b>	<b>mean_NCI_B</b>
1	507,9539	3	1,295	389,898	161	0,994
2	NA	0	NA	348,244	756	1
3	477,790	2	0,893	534,878	368	1

These findings suggest that access to detailed consumption information alone is not sufficient to ensure lower absolute or relative electricity consumption and that observed differences are context-specific rather than systematic.

## 5 DISCUSSION

One possible explanation for the limited and inconsistent differences observed between households with and without access to the service is that access to information alone may not be sufficient to induce meaningful changes in electricity consumption. While detailed feedback can increase awareness, it does not necessarily lead to behavioral change, particularly in the absence of financial incentives, constraints, or targeted recommendations. Prior research in the field of energy consumption has repeatedly shown

that informational interventions tend to produce modest and highly heterogeneous effects. Allcott (2011) and Allcott and Rogers (2014) demonstrate that feedback based on social norms or peer comparisons can influence energy use, but the magnitude and persistence of these effects vary substantially across households. A thorough understanding of these varying factors, including appliance ownership, energy-saving habits, and attitudes toward consumption, is necessary for the effective design of tariffs and the equitable distribution of energy resources (Andersen et al., 2021)

One of the more notable findings of this study is that in clusters where statistically significant differences in electricity consumption between Group A and Group B are observed, households in Group A tend to exhibit higher rather than lower values of the Neighbor Consumption Index. This pattern runs counter to the initial expectation that access to detailed consumption information would be associated with lower relative electricity use. A first possible explanation relates to self-selection effects (Davis et al., 2013). Households that actively opt into services providing detailed consumption feedback may differ systematically from those that do not. Prior research suggests that users of energy-monitoring technologies are often more technologically engaged and more aware of their energy use, but not necessarily lower consumers of electricity (Ferraro & Price, 2013; Jessoe & Rapson, 2014). In this context, it is possible that households with higher baseline electricity consumption are more likely to adopt such services because their consumption levels are higher, which results in elevated NCI even when compared to similar households within the same cluster. Alternatively, it might be possible that further savings for these households are more difficult to achieve as they already tried to take measures to save energy (Tiefenbeck et al., 2016)

A second explanation is linked to moral licensing and rebound effects. Access to detailed consumption data may increase users' perceived sense of control over their energy use, which can, paradoxically, weaken incentives to actively reduce consumption. When individuals feel that they are already behaving responsibly, by monitoring or understanding their consumption, they may become less motivated to pursue additional reductions (Webb et al., 2014). This mechanism has been documented in the context of energy feedback systems, where increased salience does not always translate into sustained conservation behavior (Tiefenbeck et al., 2013; Gillingham et al., 2013). In such cases, information may alter perceptions without producing proportional behavioral

change. This psychological phenomenon suggests that the mere act of engaging with energy-saving tools can lead to a compensatory increase in consumption behaviors (Schleich et al., 2023). Such rebound effects can manifest in various ways, including increased usage of energy-intensive appliances or a reduced propensity to adopt further energy-saving measures, thereby undermining the intended benefits of smart meter deployments and feedback mechanisms (Buckley, 2019). Furthermore, some users, upon realizing that their electricity consumption was already low, reported a decreased motivation to continue energy-saving behaviors, sometimes even leading to increased consumption, a phenomenon dubbed the "boomerang effect" (Li & Cao, 2021). This suggests that while feedback is crucial, its design and delivery must be carefully considered to avoid unintended consequences, potentially requiring complementary measures such as personalized recommendations and supportive technologies to maximize effectiveness (Schrammel et al., 2023).

We feel important to note that our idea with the NCI is that it should not be interpreted as a direct indicator of energy savings or behavioral improvement. Rather, the index should be viewed as a diagnostic and informational tool that captures a household's relative position within a group of comparable households. The conceptual motivation behind the Neighbor Consumption Index builds on the idea that individuals evaluate their own behavior not in isolation, but relative to others they consider as comparable. Behavioral research suggests that social comparison is most relevant when the reference group shares similar conditions, such as location or living environment, rather than when it is based on abstract averages or distant populations (Festinger, 1954; Goethals & Darley, 1977).

From this perspective, relative consumption measures grounded in local similarity may be more informative than absolute indicators alone. Seeing that comparable households use less electricity—and therefore potentially pay lower energy costs—can encourage individuals to reflect on their own consumption. Similar effects of locally framed peer comparisons have been documented not only in energy use, but also in areas such as household finance, water consumption, and pro-environmental behavior (Goldstein et al., 2008; Gerber & Rogers, 2009).

In this sense the NCI is intended as a contextual comparison tool that helps households place their consumption within a locally relevant peer group and may prompt behavioral adjustment even in the absence of explicit incentives.

### **5.1 Limitations and future work**

This study is subject to several limitations. Most importantly, the analysis is based on a limited set of household-level variables, as no detailed demographic or structural information about households was available. Factors such as household size, dwelling characteristics, income, or heating technology could substantially affect electricity consumption and may alter the observed patterns. In addition, the levels of energy consumption and efficiency are complex topics influenced by a group of factors. We focused on the impact of an individual tool based on behavioral principles. Its impact can be intensified when combined, for example, with campaigns by state authorities

In terms of examining sustainable behavioral changes, consumers do not tend to stay and live under unchanged circumstances, especially when the period examined reaches years. Applied to the consumers included in this study, they could have, for example, increased the number of devices in their household, which led to an increase in the absolute volume of electricity consumption but not necessarily a decrease in energy effectiveness. Finally, the clustering approach represents a methodological simplification. While clustering based on consumption levels and elevation allowed for the construction of comparable peer groups, alternative segmentation methods or clustering variables could yield different group structures and potentially different results.

Future research could extend this work by incorporating richer household-level data to enable more refined segmentation and deeper analysis. In particular, longitudinal or experimental designs examining consumption patterns before and after the introduction of peer-based feedback mechanisms, such as the Neighbor Consumption Index, would help assess their behavioral impact more directly. Further studies could also explore the effectiveness of combining informational feedback with targeted recommendations or incentives.

## 6 CONCLUSION

This study examined whether access to detailed information on monthly electricity consumption is associated with differences in electricity use between households. Using observational data from Slovakia, households were segmented into comparable groups, and statistical tests were applied to compare electricity consumption between users with and without access to the service.

The results provide limited evidence of systematic differences between the two groups, with statistically significant effects observed only in a small number of contexts. To complement the analysis of absolute consumption, the Neighbor Consumption Index was introduced as a pilot metric capturing households' relative consumption within comparable peer groups.

Although the NCI does not indicate consistently lower relative consumption among households with access to detailed information, it represents a potential framework for peer-based feedback and further behavioral interventions. Overall, the findings suggest that informational tools alone are unlikely to produce uniform reductions in electricity consumption but may serve as a useful component of broader energy-efficiency strategies.

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## ETHICAL CONSIDERATIONS

Not applicable.

## DECLARATION OF CONFLICTING INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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## DATA AVAILABILITY STATEMENT

The full datasets collected and analysed for this study are not publicly available due to confidentiality agreements with the involved parties. Upon reasonable request and subject to signing non-disclosure agreement with the data provider, datasets may be provided. All inquiries should be directed to the corresponding author.

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### Authors' Contribution

All authors contributed equally to the development of this article.

### Data availability

All datasets relevant to this study's findings are fully available within the article.

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