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Mapping multidimensional energy deprivation: Socio-spatial inequalities and policy implications in Great Britain

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ABSTRACT

This work provides a thorough Energy Deprivation Segmentation (EDS) for Great Britain, which aims to address the complex and varied aspects of energy poverty in different small regions. By proposing a reproducible analytical framework, we combine many data sources to provide a comprehensive segmentation that encompasses various dimensions such as energy efficiency, accessibility, demand and supply, housing conditions, and financial vulnerability. The results indicate notable disparities in energy deprivation based on social and spatial factors. We observed higher degrees of deprivation in the peripheral areas of major cities and suburbs in the northern regions of England, southern regions of Wales, and central regions of Scotland. The created EDS identifies six top-level Supergroups and 14 finer Groups and was validated internally and externally to confirm its robustness and applicability. This segmentation offers a more comprehensive insights into the characteristics and distribution of energy-deprived neighbourhoods than traditional measures. This research facilitates policymakers to design targeted strategies and resource allocation to combat specific vulnerabilities within communities and foster sustainable and equitable urban growth. Additionally, a practical tool is provided for monitoring and evaluating the effectiveness of policies aimed at reducing energy poverty.

1. Introduction

The global energy market faced significant shortages in 2021 as a result of the rapid post-pandemic economic rebound and the energy supply-demand imbalance (IEA, 2021). These pressures were further intensified following the Russo-Ukrainian War in February 2022 and instantly expanded to a global energy crisis. Due to its historical dependence on Russian gas exports, Europe exhibited particular vulnerability (IEA, 2022). In the UK, energy prices surged dramatically, exacerbating inflationary pressures and causing an unprecedented rise in the cost of living, thereby posing severe challenges for households. As of April 2023, approximately 7.5 million households in the UK were identified as fuel-poor (National Energy Action, 2023).

The UK government has launched a series of policies to support households in order to address the energy crisis, including immediate financial aid to directly lower high energy bills (e.g., Energy Price Guarantee 2022–23), and long-term initiatives aimed at improving energy efficiency to eventually lower energy bills (e.g., the Energy Company Obligation) (Miller, Landzaat, Johnson, & Duke, 2023). Nevertheless, as growing energy costs are only one of the several influencing factors, both short-term and long-term initiatives can only marginally reduce household energy poverty (Atkins, 2023). Furthermore, information on who faces more barriers to energy services and infrastructure and where these populations are located, remains underdeveloped (Miller et al., 2023; Robinson, Bouzarovski, & Lindley, 2018; Robinson, Lindley, & Bouzarovski, 2019). Therefore, an accurate, up-to-date and geographically detailed map that captures the multidimensional energy deprivation and reveals socio-spatial inequalities is urgently required. Mapping energy deprivation can not only support targeted policy interventions but also help achieve the European Green Deal goal (European Commission, 2023) and the UK's Fuel Poverty Target (BEIS, 2021), which aims for 'no person or place left behind by 2050' and a minimum energy efficiency rating of Band C for fuel poor homes by 2030.

Fuel poverty has long been a concern in policy and practice across Great Britain (GB). It traditionally refers to the inability of households to afford the essential energy needed for heating, particularly among those with low incomes and unaffordable warmth (Li, Lloyd, Liang, & Wei,

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2014; Walker & Day, 2012). More widely across Europe, the concept has developed into energy poverty, which comprises wider elements beyond the affordability of heating fuels but includes the accessibility of all essential energy services to meet household basic needs, such as heating, cooling, lighting, and cooking (Bouzarovski & Petrova, 2015; González-Eguino, 2015; Khan, 2019; Reddy et al., 2000). A further extension of energy poverty is energy deprivation, which emphasises the systemic barriers to accessing modern energy-related infrastructure and services (Bouzarovski & Petrova, 2015). Compared with energy poverty, energy deprivation incorporates multifaceted factors at both social and environmental levels, such as reliance on non-renewable energy, inefficiencies in energy consumption, and the interplay between household needs and social norms. Our research finds great benefit from the more broad conceptualisation of energy deprivation since it highlights the complex and multiple character of the issue.

Energy deprivation can lead to negative consequences in health issues and environmental problems due to inadequate, unreliable, or dangerous heating or cooling. It also restricts access to nutritious foods due to limited cooking and refrigeration facilities (Bouzarovski & Robinson, 2022; Liddell & Morris, 2010). Therefore, understanding energy deprivation at a fine geographical scale is essential for locating hidden pockets of vulnerability and creating efficient treatments.

The overarching aim of this paper is to provide greater insight into the differentiation of energy deprivation at a small-area level across GB. To achieve the aim, three objectives are proposed. First, we develop a reproducible conceptual and methodological framework to understand neighbourhood energy deprivation. Second, we identify vulnerable population groups that require targeted interventions due to their exposure to multiple but distinct energy deprivation aspects. Finally, we produce a new dataset and tool to assist policymakers and researchers in analysing energy poverty across GB. Complementing a theoretical framework, this study defines areas of energy deprivation including energy efficiency, energy access, energy demand and supply, housing conditions, and financial vulnerability by combining a range of factors measured at small spatial units. By means of a geodemographic technique (Openshaw & Blake, 1995; Singleton & Longley, 2009; Singleton & Spielman, 2014), a countrywide segmentation is generated and validated, thereby offering a localised typology of residential neighbourhoods experiencing different degrees of energy deprivation across GB.

This study contributes to energy poverty research and policy in several aspects. First, unlike conventional measurements that sometimes concentrate on single criterion such income or energy efficiency, our approach illustrates how multiple variables combine to form complex patterns of energy deprivation at a granular spatial scale. Second, the suggested methodology provides a deeper and more sophisticated understanding of socio-spatial inequalities, especially in disadvantaged sub-communities ignored in research employing coarser geographical units at the national or regional level. Third, it delivers practical and policy-relevant insights to facilitate evidence-based interventions. These might be infrastructural upgrades for places with inadequate housing or financial aid for economically disadvantaged communities. Lastly, our energy deprivation segmentation, including the identified domains, variables, and methodological framework, is highly adaptable and can be replicated in other contexts beyond GB for energy deprivation assessments, provided the necessary data is available.

2. Literature review

Fuel poverty has been a policy concern in the UK for decades. Assessments of fuel poverty and energy poverty have gained significant attention from both government bodies and academic researchers. Income-based indicators have traditionally been used in governmental assessments of fuel poverty. The 10 % threshold first identified a household as fuel poor if it spent more than 10 % of its income on adequate heating. This was later refined into the Low-Income High-Cost (LIHC) indicator, which identifies households as fuel poor if their energy costs are high and residual income falls below the poverty line. More recently, the Low-Income Low-Energy Efficiency (LILEE) indicator was established later to link fuel poverty to both household income and energy efficiency. However, many academic studies have demonstrated that energy poverty is a complex phenomenon that encompasses more than affordability and energy efficiency. Important elements should also be the frequency of prepayment meters, large household sizes, household-specific vulnerabilities, housing characteristics, and socio-demographic aspects including ethnicity and population age (Boardman, 2013; Bouzarovski, 2014; Butler & Sherriff, 2017; Middlemiss, 2022; Robinson et al., 2018, 2019).

Studies on more general ideas of energy poverty and energy deprivation have been conducted outside the UK. In many European countries, energy poverty has been assessed through arrears on utility bills, the inability to maintain adequate indoor temperatures, and housing conditions (Bouzarovski & Petrova, 2015; González-Eguino, 2015). In regions where housing stock varies significantly in terms of energy efficiency and tenure type, access to modern energy services and reliable infrastructure has been identified as a critical component of energy poverty assessments (George, Graham, & Lennard, 2013; Wright, 2004). Research in the Global South highlights problems with infrastructure shortages and energy access. Studies have indicated that rural areas often lack grid connections, forcing households to rely on inefficient or hazardous energy sources such as biomass and kerosene for cooking and heating (Pachauri et al., 2013; Reddy et al., 2000). This limited access is worsened by financial constraints, poor housing quality, and inconsistent energy supply, leading to negative health and economic results for vulnerable communities.

The spatial disparity of energy poverty and deprivation illustrates even more its complexity since some areas and groups are disproportionately impacted (Middlemiss, 2022). Localised studies of spatial inequalities are absolutely vital if we are to create sensible policies and treatments giving the most vulnerable communities first priority. Studies in the Global North have demonstrated that under the impacts of concentrated disadvantage, poor housing conditions, and demographic differences, energy poverty can vary significantly even within the same city or region (Chen, Feng, Luke, Kuo, & Fu, 2022; Mashhoodi, Stead, & van Timmeren, 2019; Reames, 2016; Riva, Kingunza Makasi, Dufresne, O'Sullivan, & Toth, 2021). For instance, older housing stock with poor energy efficiency, low-income households, and areas with high proportions of ethnic minorities or the elderly frequently exhibit greater levels of energy poverty (Robinson et al., 2019). These localised variations highlight the need for fine-grained, spatially disaggregated analyses to capture the full complexity of energy poverty.

Studies have revealed that although energy poverty shows regional variations and is driven by numerous factors, it obviously exposes disparities. Conventional UK methods, including LILEE indicator, largely focus on income and energy efficiency, thereby ignoring other very crucial elements of energy deprivation. Furthermore, existing studies mostly rely on broad national or regional level due to limited fine-grained spatial data (Chen et al., 2022; Mashhoodi et al., 2019; Middlemiss, 2022; Reames, 2016; Riva et al., 2021), which obscure the understanding of intra-regional disparities of energy poverty. This makes it more difficult for legislators to concentrate their efforts since it is difficult for them to locate and satisfy the particular demands of underprivileged groups (Miller et al., 2023; Robinson et al., 2018). We need to develop multidimensional, geographically disaggregated models using many different data sources to fill up these gaps. These kinds of tools would enable legislators to identify hidden weaknesses and make wise, location-based adjustments.

3. Data and methods

3.1. Data sources

The data utilised in this study are all open and were traced from various data sources in GB. Detailed information on the data is reported in Table 1, including spatiotemporal granularities and brief descriptions of these measures, and their data sources. All datasets were collated in their latest available form to ensure timeliness and representation of a bespoke segmentation. Since the National Records for Scotland (NRS) have postponed the 2022 Census outputs until May 2024, the 2011 Scotland's Census outputs were utilised as replacements to estimate socioeconomic features. The stability of the Scottish Census in certain societal aspects since 2011, such as housing structure and education level, has been justified (Wyszomierski, Longley, Singleton, Gale, & O'Brien, 2023). For dynamic conditions, such as the age groups of residents in established neighbourhoods, the latest Scottish Mid-2021 Population Estimates were utilised.

Originally presented in 2007 and extensively used in policymaking, EPCs in the UK provide information about the energy efficiency of properties and various relevant attributes (Pasichnyi, Wallin, Levihn, Shahrokni, & Kordas, 2019). EPCs have been appended to unique identifiers for each addressable place since 2021, offering detailed information about the attributes of housing. Although EPCs have been criticised for aspects like incomplete data coverage, minor mismatches in address allocation, and potentially divergent assessment outcomes by multiple assessors for a single property (Boswarva, 2022; DLUHC, 2023; Jenkins, Simpson, & Peacock, 2017), they still offer valuable insights into property attributes that would have been challenging to achieve through other publicly available data in GB (Buyuklieva, Oléron-Evans, Bailey, & Dennett, 2024). Furthermore, these potential biases can be mitigated using geographic aggregation that produces estimations at the neighbourhood scale.

3.2. Variable measures

Based on a systematic literature review (see Table 2), five domains encompassing energy efficiency, energy access, energy demand and supplies, housing conditions, and financial vulnerability were summarised and developed in our study. We collated and measured 40 variables to understand socio-spatial inequality of energy deprivation in GB. These domains take inspiration from a variety of research providing frameworks and justifications to aid understanding of energy poverty, vulnerability and precarity (e.g. Castaño-Rosa, Solís-Guzmán, & Marrero, 2020; Gouveia, Palma, & Simoes, 2019; Nussbaumer, Bazilian, & Modi, 2012; Petrova, 2018).

These variables were measured at different levels, such as populations, households, and properties. To effectively integrate these variables and mitigate data bias stemming from inconsistencies, most variables were transformed into percentages relative to their corresponding respondent units, which excluded the variables of energy consumption and household income. Through the processing steps of aggregation, averaging, ratioing, joining, and reweighting, each variable was unified across 42,648 small areas to ensure neighbourhood consistency and comparability. The geographic units used are the 35,672 Lower Layer Output Areas (LSOAs) for the devolved nations of England and Wales and 6976 Data Zones (DZs) for Scotland, accommodating populations ranging from 400 to 1200 households and 1000 to 3000 individuals across GB. This commonly used zonal geography was chosen to be aggregated enough to maximise the availability of input data and produce reliable estimates, while also being granular enough to observe local variations in energy deprivation.

3.3. Data preprocessing

Exploratory data analysis was implemented to examine the distribution, ranges, and variability of each variable (see Table 3). This provided a deeper understanding of the data and addressed potential data quality issues, such as missingness, inconsistency and outliers, which can influence clustering results. The variable 'renewable only' was excluded as it had large amounts of missing data compared with other variables.

For the remaining 39 variables, we implemented a Box-Cox transformation and *Z*-score standardisation to transform skewed data into a normalised distribution and identical scales. These two methods have been commonly employed prior to a machine learning algorithm (Liu, Singleton, Arribas-bel, & Chen, 2021; Singleton, Dolega, Riddlesden, & Longley, 2016) that allows for the equal contribution of each measure to the outcome of the cluster analysis. Correlation analysis was then performed to identify highly correlated variables for removal, as these redundancies can bias the outcome of the clustering process towards particular characteristics. Through pairwise correlations between variables, a subset of variables was selected based on their correlation strength. (see Fig. 1). The green and pink colours representing positive and negative relationships, and the darker the colour (i.e., absolute values close to 1 or -1), the higher the correlation values. Correlation greater than the absolute value of 0.75 is identified as extremely strong correlation. Six variables, including property's annual carbon dioxide emissions, properties with prepayment electricity meters, population with retired people, households with under occupancy, properties with outright ownership, and households receiving universal credit, were excluded due to their extremely strong associations with one or more variables.

3.4. Energy deprivation segmentation

Since this study emphasises the identification of shared

Table 1
Data information in space, time, descriptions, and sources.

Datasets	Temporal Scale	Spatial Scale	Descriptions	Data Sources
Energy Performance Certificates (EPCs)	01/10/2013–30/09/2023	Property level	EPCs are evaluations carried out when the properties are built, sold or rented, providing detailed information about energy performance of properties (from most efficient band A to least efficient band G). Available since October 2008, EPC are valid for ten years. This study uses domestic EPCs for GB	Department for Levelling Up, Housing & Communities (DLUHC) & Scottish Government
Census	2021 2011	2021 LSOAs, 2011 DZs	Census is updated for each decade relating to population, society and the labour market	Office for National Statistics (ONS) & National Records for Scotland (NRS)
Mid-year Population Estimates	2021	2011 DZs	Small Area Population Estimates (SAPE) for Scotland	NRS
Gas and Electricity Statistics	2021	2011 LSOAs/DZs	Annual statistics related to energy consumption (i.e., gas and electricity), prepayment electricity meters, and gas grid connection	Department for Business, Energy & Industrial Strategy (BEIS)
Gross Disposable Household Income (GDHI)	2021	2011 LSOAs/DZs	GDHI refers to the funds remaining for spending or saving by individuals in the household sector after tax payments, indirect taxes, and direct benefits are accounted for. These estimates pertain to the total funds available to individuals within each LSOA, rather than to average household or family units	ONS
Benefit Statistics	2021	2011 LSOAs/DZs	Statistics related to benefits, pensions, and employment of residents, updated monthly and quarterly	Department for Work and Pensions (DWP)

Table 2
Five domains and 40 measures of energy deprivation0F0F.

Domains	Dimensions	Variables/Measures	Reference
Energy Efficiency	Energy efficiency	Properties rated as A and B	(Boardman, 2013; Office for National Statistics, 2022a; Walker, 2008; Yohanis, Mondol, Wright, & Norton, 2008)
		Properties rated as E, F and G	
	Fuel types	Properties with fossil fuels dependency (fossil fuels are all types of gas, oils, and coals)	
	CO_2 emissions	Properties total annual emissions based on calculated energy demand*	
	Property age	Properties built before 1930	
		Properties built since 2003	
	Gas consumption	Properties average domestic gas consumption KWh per meter	
	Electricity consumption	Properties average domestic electricity consumption KWh per meter	
Energy Access	Central heating	Properties with no access to central heating	(Boardman, 2013; Office for National Statistics, 2022b; Robinson et al., 2019; Wright, 2004)
		Properties with renewable energy access only*	
		Properties with electricity access only	
		Properties not connected to the gas grid	
		Properties with pre-payment electricity meters*	
Energy Demands & Services	Young and old	Households with young children aged 4 and below	(George et al., 2013; Healy & Clinch, 2004; O'Sullivan, Telfar Barnard, Viggers, & Howden-Chapman, 2016; Robinson et al., 2019; Snell, Bevan, & Thomson, 2015; Walker & Day, 2012; Wright, 2004; Yohanis et al., 2008)
		Households with older persons aged 75 years and over	
	Children dependency	Households with lone parent with dependent children	
	Large household size	Households with large household size (more than five people)	
	Occupancy	Households with under-occupancy (i.e., room occupancy rating of positive 1 and more)*	
	Retirement	Persons that are retired*	
	Illness and disability	Persons with long-term illness or disability	
	Family care	Persons with family or caring responsibility	
	Language	Persons that cannot speak English	
Housing Type	Accommodation type	Property detached	(Butler & Sherriff, 2017; Middlemiss & Gillard, 2015; Robinson et al., 2019; Walker & Day, 2012)
		Property semi-detached	
		Property terraced	
		Property flat	
		Property shared houses	
	Tenure type	Property is owned outright*	
		Property is socially rented	
		Property is privately rented	
Financial Vulnerability	Loan/Shared Ownership	Households with mortgage or loan or shared ownership	(Bouzarovski, 2014; Butler & Sherriff, 2017; George et al., 2013; Healy & Clinch, 2004; Middlemiss & Gillard, 2015; Norman & Purdam, 2013; Robinson et al., 2019; Snell et al., 2015; Wright, 2004)
	Income	Households' gross disposable income	
	Benefit	Households receiving universal credit*	
	Occupation	Persons with elementary occupation	
	Unpaid care	Persons with unpaid care more than 20 h	
	Employment	Persons unemployed	
		Persons in part-time employment	
	Student	Persons that are full-time student	
	Ethnicity	Persons that are ethnic minorities (i.e., ethnic minorities (excluding white minorities))	
	Education	Persons with entry-level qualifications or below	

The symbol '*' indicates measures that are not included in the classification but were used to interpret the results for characterisation of small areas.

characteristics of energy deprivation at neighbourhoods rather than the spatial dependency, a non-spatial cluster method, K-means clustering, was chosen due to its widespread applications in small area contextualisation (Gale, Singleton, Bates, & Longley, 2016; Singleton, Alexiou, & Savani, 2020). Furthermore, this approach offers intuitive interpretations that support targeted policy interventions and computational efficiency for handling large and multidimensional datasets. Before implementing k-means clustering on the remaining 33 variables, the number of clusters (k) needed to be determined. To do this, we applied a visual method called Clustergram (Fleischmann, 2023; Schonlau, 2002), which plotted a series of potential k values ranging from two to ten, along with the weighted average of their first principal component, to identify the most appropriate k value. The principal component is a part of Principle Component Analysis (PCA) that captures the most variance in the data. This method highlights clusters that are well split across the y axis and might represent a sensible number of clusters given the input data. From Fig. 2, $k = 6$ generates robust and reasonable clusters after tens of thousands of iterations, given the nature of the cluster centres and the spatial patterns of clusters when mapped. Hence, six cluster values were assigned to 42,648 neighbourhoods after clustering analysis.

For better interpretation of results, we computed index scores (i.e., $x/\bar{x}$ *100 where $\bar{x}$ refers to the average value of the observations) for the initial 40 variables, aiming to reflect the representation of how each variable compares to the average value (i.e., an index score of 100). A score of 50 would indicate a rate half the average, while 200 would signify double. These scores enable the depiction of detailed socio-spatial profiles of energy deprivation in GB.

Table 3
Variable distributions and descriptions.

Variables	Count	Mean	Std	Min	25 %	50 %	75 %	Max
Efficiency A-B	40,615	11.0	15.3	0.0	2.0	5.3	13.5	100.0
Efficiency *E*-G	42,288	15.9	11.4	0.0	8.3	13.6	20.3	86.5
Gas consumption	41,078	10,154.5	2775.8	507.6	8396.8	9719.6	11,368.2	52,924.8
Electricity consumption	42,641	2545.1	522.8	1075.6	2225.8	2449.9	2735.9	8177.0
Fossil fuels dependency	42,626	82.8	17.3	0.0	75.1	88.5	95.7	100.0
Co2 emissions	42,645	4.0	1.4	0.0	3.1	3.7	4.5	18.9
Old property: before 1930	37,983	22.8	22.5	0.0	5.0	15.5	34.3	100.0
New property: since 2003	37,857	9.2	12.0	0.0	1.9	5.4	11.9	99.2
Without gas grid	41,078	11.8	17.8	0.0	1.3	5.1	14.0	99.6
Prepay electricity	42,648	11.2	9.8	0.0	3.5	8.3	16.9	69.5
No central heating	42,648	1.6	1.4	0.0	0.7	1.2	2.0	23.4
Renewable only	35,672	0.4	0.9	0.0	0.0	0.1	0.3	13.9
Electricity only	42,648	8.8	10.1	0.0	2.9	5.4	10.7	90.6
Age 0–4	42,645	5.2	1.8	0.1	4.0	5.0	6.3	18.8
Age 75+	42,645	8.9	4.7	0.0	5.3	8.3	11.7	41.5
Lone parent	42,648	6.3	4.0	0.0	3.4	5.4	8.4	36.9
Large household size	42,648	2.3	3.0	0.0	0.9	1.5	2.5	46.1
Under occupancy	42,648	69.4	16.9	8.4	58.5	72.7	83.2	98.6
Retired	42,648	20.9	9.5	0.0	13.7	20.1	27.4	70.0
Disability and long-term illness	42,648	4.4	3.0	0.0	2.2	3.6	5.9	24.3
Family care	42,648	4.6	2.4	0.0	3.0	4.0	5.5	27.7
Non-English speaking	42,648	4.4	5.7	0.0	0.8	2.1	5.3	52.0
Detached	42,648	23.5	22.5	0.0	4.7	14.5	38.8	98.9
Semi-detached	42,648	30.9	19.2	0.0	16.7	28.5	42.4	98.1
Terraced	42,648	22.7	18.2	0.0	8.4	18.0	32.7	96.1
Flat	42,648	18.3	22.0	0.0	2.8	9.8	24.6	99.6
Shared house	42,648	3.0	6.7	0.0	0.3	0.8	2.3	70.6
Owns outright	42,648	32.5	14.6	0.2	20.9	32.3	43.9	79.9
Social rented	42,648	17.9	17.0	0.0	4.6	12.2	26.9	98.4
Private rented	42,648	18.3	12.8	0.0	9.5	14.3	23.3	93.0
Mortgage and shared	42,648	30.8	11.0	0.7	23.7	30.8	37.3	85.9
Income	42,648	21,459.6	7771.2	0.0	17,320.4	21,114.7	24,828.8	533,068.9
Universal credit	42,639	9.1	5.5	0.3	4.7	7.7	12.5	69.0
Elementary occupation	42,648	11.0	5.6	0.2	6.8	9.8	14.1	49.2
Unpaid care	42,648	4.5	1.6	0.1	3.4	4.4	5.5	13.7
Unemployment	42,648	4.4	3.8	0.3	2.3	3.3	5.2	41.6
Part-time employment	42,648	16.5	2.8	0.8	14.9	16.7	18.3	47.6
Student	42,648	5.2	5.4	0.0	3.1	3.9	5.4	79.6
Ethnic minority	42,648	15.0	19.3	0.0	2.7	6.2	19.2	99.2
Entry-level qualification	42,648	31.8	13.5	1.0	22.6	29.7	38.4	84.7

To capture finer-scale energy deprivation disparities within each cluster, neighbourhoods were further divided into smaller partitions following an identical framework. Fig. 3 illustrates the varying numbers of k determined for the six initial clusters. The number of k for Supergroup from A to F is three, two, two, two, three and two, highlighted by yellow rectangles. As a result, 14 clusters (referred to as Groups) at a lower level of the hierarchy with relevant index scores were derived from the six initial clusters (referred to as Supergroups). A name or labelling with description was given to each Supergroup and Group following the naming criteria of consistency, accuracy, neutrality, and distinctiveness (Brunsdon, Charlton, & Rigby, 2018), as well as actual spatial distribution and index scores. These contextual details are crucial to maximise the usefulness of a segmentation and offer end users a clear understanding of the primary characteristics of each cluster (Singleton et al., 2020).

3.5. Segmentation validation

To assess the robustness and reliability of the EDS, both internal and external validations were performed. The Internal validation assesses the accuracy of the cluster results, while the external validation demonstrates a pragmatic use of the EDS utilising external data that was not integrated into the segmentation.

For internal validation, the Within-Cluster Sum of Squares (WCSS) was conducted to evaluate the clustering results by calculating the sum of squared Euclidean distances between each data point and its corresponding centroid. It measures the variance within each cluster, with the aim of having clusters that are as compact as possible. A lower WCSS indicates a tighter grouping of data points within the clusters, which generally signifies a better clustering solution.

External validation was completed using two official indicator datasets. Firstly, the LILEE indicator, a fuel poverty statistic in England estimated for 2021 LSOAs. This official statistic is predominately modelled from the English Housing Survey, which is a nationwide survey consisting of an average of 13,300 household interviews and 6200 physical inspections of a subset of dwellings, gathering information about resident's housing circumstances, housing condition, and energy efficiency. A household is considered fuel poor if it exhibits both low energy efficiency of band D or below, and low income, where their residual household income would fall below the official poverty line considering their modelled energy costs. The energy efficiency rating in LILEE is not equivalent to that of EPCs which have been used as variable measures in our segmentation, where the former is adjusted based on the impact of policy interventions and is only estimated from 6200 dwellings.

The LILEE indicator is not available for Wales and Scotland. Therefore, another external IMD dataset was used for validation. IMD are localised assessments of relative deprivation spanning the UK's constituent nations, each comprising small areas delineated by 2011 LSOAs or DZs. These areas are ranked based on their level of deprivation, from the most deprived to the least deprived. Each nation has slight variations in measurement methodologies. Nonetheless, common themes are encompassed in the assessment: income, employment, education, health, crime rates, housing and service accessibility barriers, and the overall living environment.

The validation process for both was similar, appending the latest

Fig. 1. Correlation matrix to select variables for segmentation.

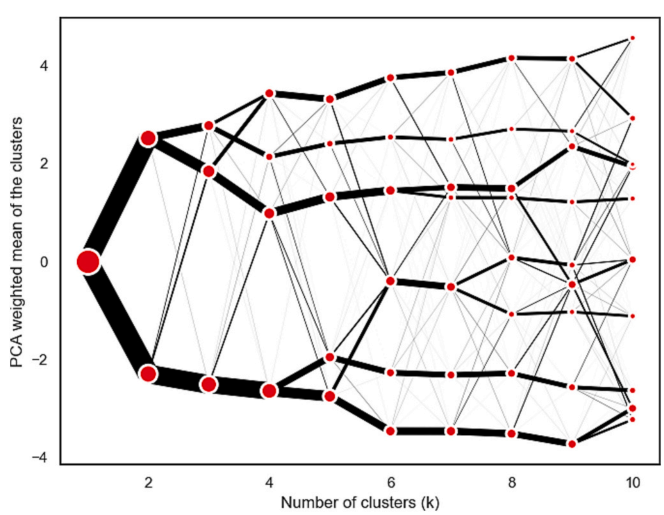

Fig. 2. A visual Clustergram to select appropriate cluster numbers for Kmeans clustering method.

2021 LILEE, 2019 English IMD, 2019 Welsh IMD and 2020 Scottish IMD to the EDS. To ensure consistency in the validation comparison across England, Wales, and Scotland, the IMD scores were standardized into percentiles. This was necessary because the scores varied considerably among these three devolved nations of Great Britain. We then measured and compared the percentages of fuel poor households and relative deprivation within the six Supergroups identified in the segmentation. This comparison aimed to determine whether areas classified as experiencing the highest levels of energy deprivation also exhibited a greater number of households experiencing fuel poverty and were characterized by heightened multiple deprivation.

4. Results

4.1. Energy deprivation segmentation

Each small area in GB is organised into six top-level Supergroup clusters and further divided into 14 Groups. The top-level six Supergroups across GB are depicted in Fig. 4, alongside the enlarged distribution of Greater London, Cardiff, and Edinburgh, which are the capital cities of England, Wales, and Scotland. The Supergroups are presented broadly in the order of their relative deprivation of adequate energy services (from least deprived to most), such as heating, cooling, lighting, and cooking. Hence, the typology is referred to as the Energy Deprivation Segmentation (EDS).

The cluster labels were formulated through an iterative process and in collaboration with an Advisory Group (a list of organisations is shown in Supplementary Note 1) comprising end-users from local governments, charities, industries, and academia. Table 4 depicts the naming and statistical attributes of Supergroups and Groups. Supergroup A, 'Energy Efficient Suburbs', and Supergroup B, 'Energy Secure Fringes', are the largest in GB, implying that 40.3 % small areas have access to relatively better energy services than others. Supergroup C, 'Energy Isolated Urbanities' (10.3 %), and Group 2, 'Electricity Intense Renters' (3.80 %), located at urban cores (Fig. 4), own the least shares across GB. Supergroup E, 'Energy Vulnerable Communities', and Supergroup F, 'Energy Deprived Periphery', represents the most energy deprived neighbourhoods that require the most attention, accounting for appropriately one-third of GB.

Fig. 5 displays the computed index scores of all variables aacross the six Supergroups of EDS. A value of 100 represents a propensity for the characteristics that matches the national average/. A higher value (in wheat hue) indicates a stronger presence of that characteristic within

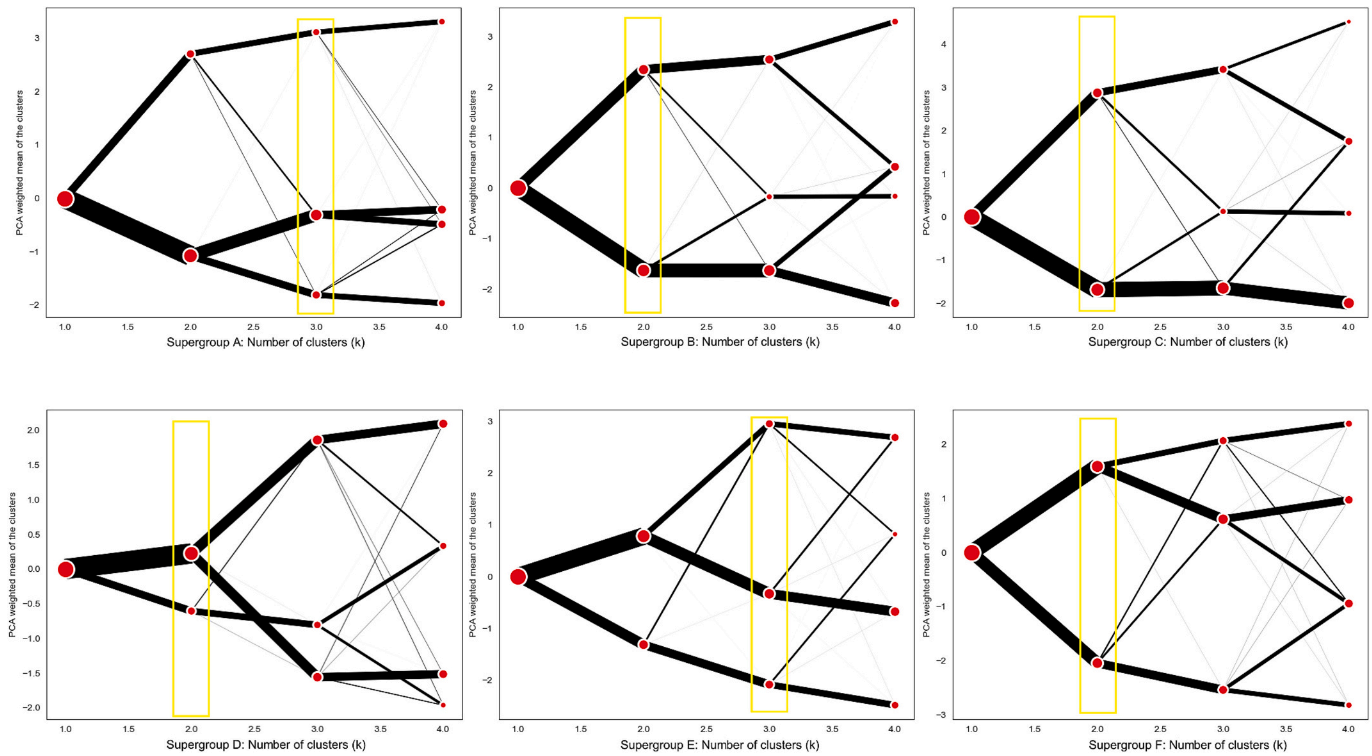

Fig. 3. Clustergrams for the determination of varying k within each Supergroup at finer Group level.

the Supergroup, whereas a lower value (in cyan hue) signifies a weaker presence. A detailed contextual analysis of EDS is obtained from index scores in Fig. 5 alongside its spatial distribution in Fig. 4.

Residents of Supergroup A, 'Energy Efficient Suburbs,' typically live in new houses built from 2003 onwards with the highest energy efficiency (i.e., A or B) compared to other Supergroups. They tend to own their homes through a mortgage, loan, or shared ownership scheme. Properties in this Supergroup are typically semi-detached or terraced and well-connected to the mains gas grid. A higher proportion of families have very young children below four years old. This Supergroup is found throughout suburban areas in GB, especially in the south of England, indicating a relatively low risk of energy deprivation.

Supergroup B, 'Energy Secure Fringes,' is characterized by residents with higher incomes who own their detached or semi-detached properties, either outright, with a mortgage, or through shared ownership. Properties in this group are typically well-supplied with energy infrastructure, including central heating and a well-connected mains gas. However, these properties tend to be under-occupied, and higher gas consumption is common as many residents are of retirement age, directing potential energy wastage compared to younger residents in smaller homes. This Supergroup is pervasive in urban outskirts and towns close to cities.

Many residents within Supergroup C, 'Energy Isolated Urbanites,' are economically inactive full-time students and ethnic minorities, many of whom face English barriers. They are concentrated in high-density neighbourhoods, either in privately rented newer flats with higher energy efficiency (i.e., A or B) or in older shared houses. These households often rely heavily on electricity for heating, cooking, and lighting, as they often lack access to the mains gas grid and central heating. The overall limited English proficiency, dependence on electricity, and high-density living conditions reflect significant energy isolation of this Supergroup, which is predominantly concentrated in city centres across GB.

Areas classified in Supergroup D, 'Rural Energy Inefficiency,' are predominantly located in rural parts of GB. Residents are typically aging, retired, and of white ethnic group, and they tend to live in detached houses owned outright. These properties were typically built before 1930 and lack gas grid connections due to their rurality. Most properties have low energy efficiency ratings (i.e., E, F, or G) and produce higher carbon emissions per capita annually. Despite a higher use of renewable energy, this Supergroup continues to face persistent energy challenges.

Residents in Supergroup E, 'Energy Vulnerable Communities,' typically experience imbalances between energy demands and supplies, predominantly located in the urban edges and suburbs of northern England, southern Wales, and central Scotland. Properties within these areas typically consist of rented flats or terraced social housing. A greater number of residents rely on government welfare to cover their essential living costs and employ costly prepayment electricity meters to manage their energy expenditures. The prevalence of lone parents, individuals with long-term illnesses or disabilities, and unpaid carers further exacerbates their energy vulnerability, illustrating significant socio-spatial disparities in energy supply and demand.

Supergroup F, 'Energy Deprived Periphery,' is prevalent in peripheral parts of urban areas across GB and particularly evident in Greater London, where households face the most severe energy deprivation challenges. Neighbourhoods within this Supergroup have a mixture of rented terraced houses, flats, and older shared occupancy properties, coupled with constrained access to energy infrastructure, including no central heating and a dependence on expensive prepayment electricity meters. This Supergroup includes a high proportion of low-income and overcrowded households, full-time students, ethnic minorities, family carers, lone parent families, and young children below four years old. These populations experience energy deprivation across multiple domains and require urgent policy intervention.

Further details on finer Group level classifications, including spatial distributions, index scores, labels, and descriptions, are provided in the Supplementary Fig. 1, Supplementary Table 1, and Supplementary Note 2. A publicly data tool (https://data.geods.ac.uk/dataset/energy-deprivation-classification) has also been developed, enabling stakeholders to explore areas of interest through an interactive mapping tool and allowing researchers to conduct further studies.

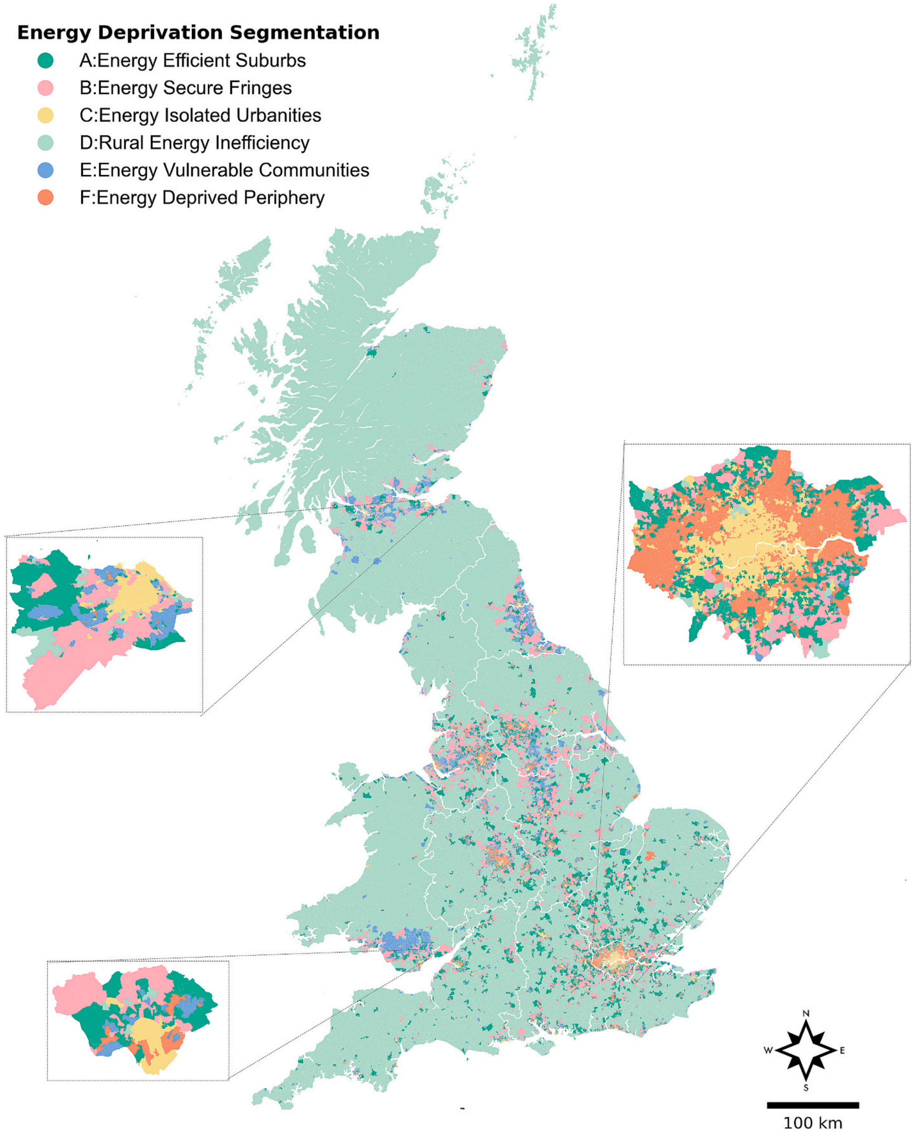

Fig. 4. Spatial distribution of energy deprivation segmentation for LSOAs/DZs across Great Britain, and the enlarged distribution of Greater London, Cardiff, and Edinburgh, which are the capital cities of England, Wales, and Scotland.

4.2. Segmentation reliability validation

The quality of internal clustering results was assessed by calculating the WCSS for each cluster, comprehensively examining whether the cluster fit had spatial bias and potential reliability issues (see Fig. 6). No apparent spatial bias is detected in the clusters (Fig. 6a), with the fit values distributed reasonably and randomly across both urban and rural areas. Rural areas in England exhibit slightly higher cluster accuracy compared to those in Wales and Scotland. An exception is observed in London, where areas with poorer cluster fit are primarily concentrated, reflecting London's uniqueness relative to the rest of GB. Among the three devolved nations of GB, EDS cluster results perform better in Wales and worse in Scotland based on the mean and median measures of the errors (Fig. 6b).

We further examined the EDS fit to compare disparities between and within the six Supergroups (Fig. 6c). Neighbourhoods classified as Energy Efficient Suburbs, Energy Secure Fringes, Rural Energy Insecurity, and Energy Vulnerable Communities (i.e., Supergroups A, B, D and E, respectively) tend to exhibit a better cluster fit as most neighbourhoods in each Supergroup fall into the fit ranges from 200 to 400, where the density of the shades is the most prominent. Areas within the Energy Isolated Urbanities (i.e., Supergroup C) show the poorest cluster fit, followed by the Energy Deprived Periphery (i.e., Supergroup F), given that the fit values for these Supergroups are higher and more sparsely distributed. Within the Supergroups, areas identified as Terraced Communities, Semi-Detached Owner-Occupiers, and Energy Burdened (i.e., Groups A1, B1 and E1) rank as the top three with the best cluster fit among the 14 finer Groups.

External validation appended the Low-Income Low-Energy Efficiency (LILEE) fuel poverty indicator for England (2021) and Index of Multiple Deprivation (IMD) from England (2019), Wales (2019), and Scotland (2020) to the EDS. The rates for these different measures, segmented by the EDS Supergroup clusters, are presented in Fig. 7. The relationships broadly conform our hypothesis: the segmentation identifies areas as Energy Vulnerable Communities and Energy Deprived Periphery (i.e., Supergroup E and F), where a larger share of household experience fuel poverty based on the LILEE and are more likely to be measured as deprived according to the IMD percentiles. Conversely, areas classified as Energy Secure Fringes (i.e., Supergroup B) align with lower instances of fuel poor households (Fig. 7a) and are typically situated in more affluent areas (Fig. 7b). The overall distribution between the external data and the EDS consistently represents a general gradient

Table 4
Segmentation names and summary statistics.

Supergroups (S)	Groups (G)	LSOA/DZ count	LSOA/DZ percentage (S)	LSOA/DZ percentage (G)
A: Energy Efficient Suburbs	A1: Terraced Communities	4452	20.6 %	10.4 %
	A2: Family Nest-Builders	1878		4.4 %
	A3: Ethnic Minority Workers	2459		5.8 %
B: Energy Secure Fringes	B1: Semi-Detached Owner-Occupiers	4945	19.7 %	11.6 %
	B2: Detached Networked Profligates	3441		8.1 %
C: Energy Isolated Urbanities	C1: Old-Shared & Multi-Occupancy Renters	2762	10.3 %	6.5 %
	C2: Electricity Intense Renters	1619		3.8 %
D: Rural Energy Inefficiency	D1: Aging Gas-Scarce Profligates	1775	15.4 %	4.2 %
	D2: Rural Energy Security	4786		11.2 %
E: Energy Vulnerable Communities	E1: Energy Burdened	2509	19.2 %	5.9 %
	E2: Semi-Detached Strivers	3481		8.2 %
	E3: Hard-pressed Young Families	2163		5.1 %
F: Energy Deprived Periphery	F1: Overcrowded Energy Precarity	2791	15.0 %	6.6 %
	F2: Energy Strapped Enclaves	3587		8.4 %

of decreasing energy deprivation from Energy Efficient Suburbs (i.e., Supergroup A) to Energy Deprived Periphery (i.e., Supergroup F). In the IMD validations (Fig. 7b), Supergroups in Wales perform marginally better than those in England and Scotland.

5. Discussion

The findings indicate multiple facets of energy deprivation in GB as well as important contextual and spatial variations in energy efficiency, accessibility, supply, security, and affordability among various neighbourhood areas and demographic groups. Energy deprivation is a challenging issue for England and Wales since their number of neighbourhoods classified as Supergroup E (Energy Vulnerable Communities) and F (Energy Deprived Periphery) is higher than those of Scotland. These two Supergroups, predominantly located in the peripheral parts of major cities and suburbs of northern England, southern Wales, and central Scotland, are generally characterized by numerous lone parents, individuals with long-term illnesses or disabilities, socially rented flats or terraces, low-income households, and unemployed residents. These results align with current research pointing out these demographic groups as especially vulnerable to energy poverty (Middlemiss & Gillard, 2015; Robinson et al., 2019). Furthermore, our results allow a comprehensive spatial awareness of the concentration of these vulnerable groups over GB, therefore highlighting the importance of these places in urban planning and development policies. Conversely, Supergroups A (Energy Efficient Suburbs) and B (Energy Secure Fringes), which collectively account for 40.3 % of small areas in GB, experience relatively better energy services. They usually have a large number of newly built and energy-efficient properties, or they have a higher socioeconomic position with reliable and well-connected energy supplies. The findings correspond with earlier studies highlighting the advantages of contemporary architecture and stable socioeconomic level in

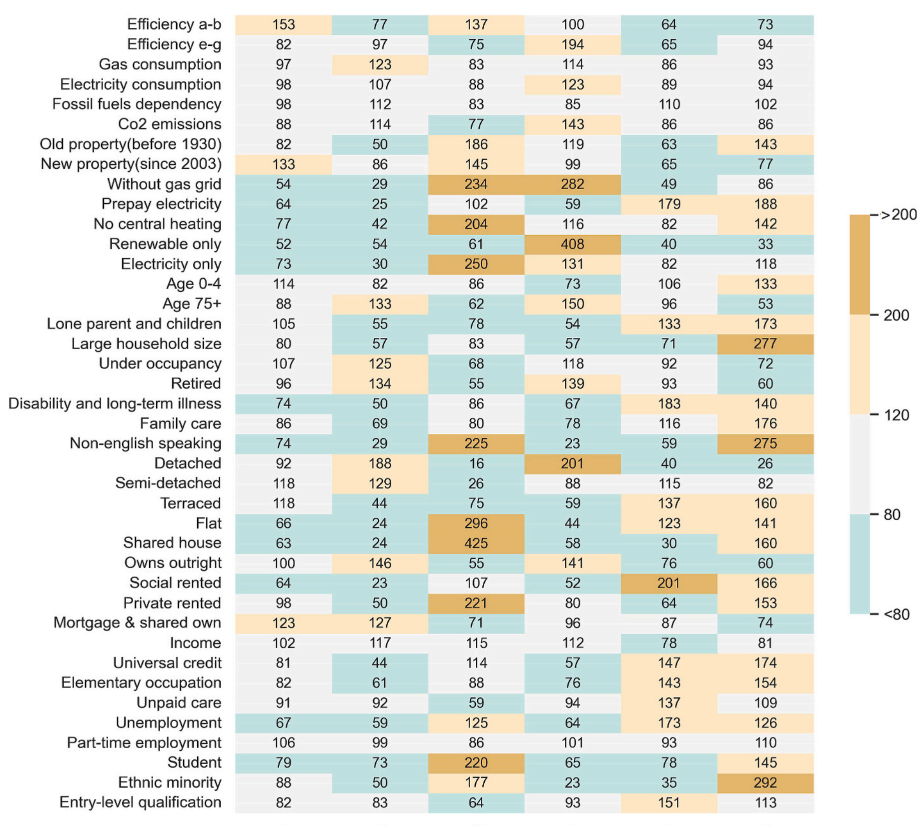

Fig. 5. Index scores for energy deprivation segmentation. A value of 100 represents a propensity for the characteristics that matches the national average, a score of 200 would be twice the national average, and 50 a rate of half.

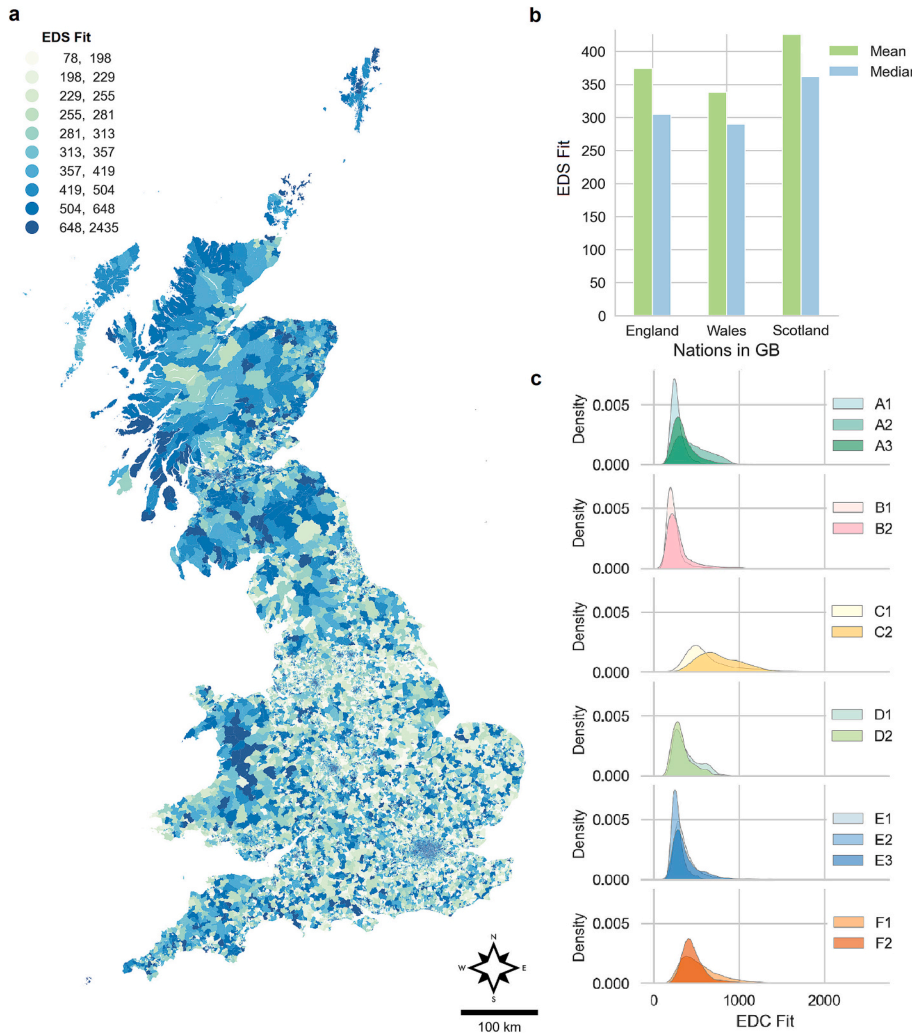

Fig. 6. Internal validation for cluster fit by Euclidean distance metric. a, Spatial distribution of EDS fit across neighbourhoods in GB, where lighter colour indicates better cluster fit. b, Mean and median values of EDS fit for England, Wales, and Scotland. c, Kernel density disparities of EDS fit between and within the six Supergroups. A higher value of EDS fit indicates an area with worse cluster quality.

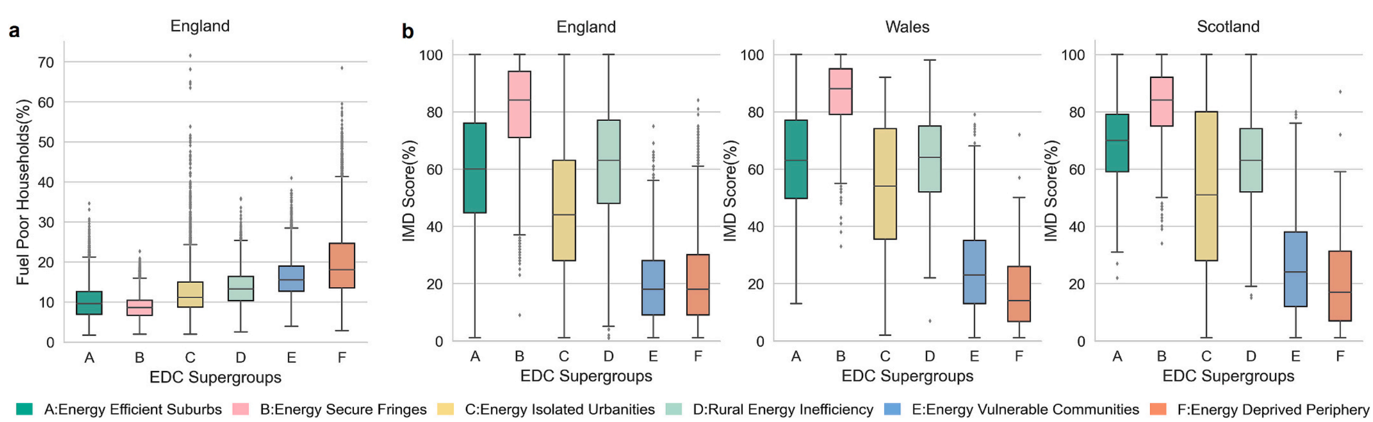

Fig. 7. External validation of energy deprivation segmentation. a, Validation using external LILEE indicator for England only. b, Validation using external IMD at percentiles for devolved nations England, Wales and Scotland.

reducing energy poverty (Boardman, 2013; Bouzarovski & Petrova, 2015). Contemporary dwellings are usually associated with better insulation and more efficient heating systems, which performed together contribute to reduce energy costs (Boardman, 2013). Households that have higher income levels and lower unemployment rates can not only afford sufficient energy services but also have the capacity to invest in improvements to their homes, securing stable and reliable access to energy (Bouzarovski & Petrova, 2015; Snell et al., 2015; Walker & Day, 2012).

The findings' robustness and reliability are validated by both internal and external validation, with no obvious geographical bias between urban and rural areas and good alignment with two external indicators: LILEE and IMD. These validations support the value and efficiency of segmentation in offering a complex knowledge of energy deprivation, which is necessary for planning focused effective treatments (Reames, 2016; Walker & Day, 2012). Unlike the LILEE and IMD indicators, the EDS clearly has one advantage: it can capture a wide spectrum of contextual neighbourhood-specific traits while still focussing on features of energy poverty.

The EDS presents a complex picture for UK legislators on how to create policies addressing both systematic, long-term structural changes and urgent alleviation of energy poverty. Short-term interventions should prioritise tackling acute vulnerabilities. Households within Supergroup F (Energy Deprived Periphery), characterized by overcrowding and reliance on prepayment meters, require urgent financial assistance, such as energy bill subsidies, prepayment cost grants, and temporary discounted energy tariffs. Residents in Supergroup E (Energy Vulnerable Communities), which comprise large numbers of single parents and disabled individuals, demand localised outreach initiatives to facilitate their awareness and access to current support schemes, such as the Warm Home Discount. For Long-term structural reforms, actions should focus on addressing systemic inequities. Supergroup D (Rural Energy Inefficiency), defined by aging, off-grid properties with poor energy efficiency, indicates the need of retrofitting grants and investments in rural renewable energy infrastructure to reduce dependence on fossil fuels. Likewise, with high private renting rates and limited gas grid access, urban neighbourhoods in Supergroup C (Energy Isolated Urbanities) and F (Energy Deprived Periphery) require more rigorous application of Minimum Energy Efficiency Standards (MEES) and incentives for landlords to improve housing stock. These steps guarantee actions are both transformative in addressing root causes and sensitive to current emergencies, therefore complementing the UK's 2030 Fuel Poverty Target and Net Zero Strategy and help to prevent the escalation of socio-spatial inequalities during the climate transitions.

Apart from policy responds, the EDS could function as a monitoring and evaluating tool. This allows users to assess policy impacts and adjust strategies as need. While long-term success might be measured by better EPC ratings in renovated areas, short-term progress could be tracked by declining prepayment meter use in Supergroups E or F. Collaboration across local authorities, energy suppliers, Non-Governmental Organisations (NGOs), and researchers is encouraged through our segmentation to enhance the effectiveness of policy interventions of local energy needs. Examples of this are partnerships with NGOs to involve non-English speaking residents in Energy Isolated Urbanities and with utilities to prototype time-limited rates in Energy Deprived Periphery areas. Segmentation insights allow policymakers to maximise the design and execution of initiatives meant to reduce energy poverty and progress global Sustainable Development Goals 1 (No Poverty), 7 (Affordable and Clean Energy), 10 (Reduced Inequalities), and 11 (Sustainable Cities and Communities). These initiatives not only address immediate energy demands but also reinforce the long-term resilience and sustainability of urban environments.

6. Conclusion

In response to the growing energy crisis since 2022, this study creates a multidimensional and nationwide EDS in GB to enable the swift identification of the contextual characteristics of energy-deprived areas. We conducted a systematic literature analysis on the subject of energy poverty and vulnerability, evaluating the factors that influence whether people have access to necessary energy services. We gathered multiple datasets from diverse sources and integrated them into the 2021 LSOAs for England and Wales and 2011 DZs for Scotland. By doing so, we identified and analysed various dimensions of energy deprivation, including energy efficiency, energy access, energy demands and supplies, housing conditions and financial vulnerability. Through a well-developed framework, a new effective segmentation that categorizes neighbourhoods by their multidimensional characteristics of energy deprivation is produced for GB.

Our segmentation addresses the critical difficulty of identifying locations where households have energy deprivation and require targeted assistance (Miller et al., 2023; National Energy Action, 2023; Office for National Statistics, 2022a). Second, the developed segmentation effectively reveals the socio-spatial inequality of energy deprivation across five diverse domains at finer-grained communities on a national scale, allowing for more compatibility and a better understanding of energy deprivation. This fills a research gap that only highlights areas experiencing energy poverty due to the difficulty of data availability (Petrova, 2018; Robinson et al., 2018, 2019). Finally, our study disseminates these new insights through a new dataset and mapping platform that are accessible to governments, charities, energy suppliers, and researchers, enabling them to delve into the intricate details of energy deprivation and contribute to policy development, such as the transition to net zero.

Although the segmentation offers thorough investigation of regional variations in energy deprivation over small areas, it is important to identify the limitations in order to increase the efficiency and use of the EDS in next investigations. One drawback is the great reliance on the coverage, timeliness, and granularity of the accessible data sources. For instance, the most recent prepayment electricity meter data is only accessible in 2017, and the 2011 Scottish Census is employed as a substitute due to the 2022 Scottish Census at small areas is not yet available. Improving data collection methods and expanding energy-related data sources would enable a more comprehensive and up-to-date understanding of energy deprivation. Furthermore, the present segmentation ignores significant qualitative elements such cultural and behavioural dimensions, so failing to completely depict the complexity of energy poverty. Household heating choices or community-level trust in energy providers could be part of cultural standards and affect susceptibility or energy usage patterns. Behavioural elements can include energy-saving behaviours and resistance to apply retrofits meant to further stratify deprivation risks. Future studies could combine quantitative geodemographic segmentation with qualitative analysis such as household surveys. Through collaborating with local advisory groups, this mixed method could further refine the segmentation and ensure culturally sensitive policy recommendations. At last, even if the framework is replicable and flexible, the six segments found in this study could vary if the suggested technique framework is used in other countries or cities because of variations in different attributes and spatial granularity. Future research should give much thought to this so that the approach fairly depicts local patterns of energy scarcity.

CRediT authorship contribution statement

Meixu Chen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Caitlin Robinson:** Supervision, Resources, Conceptualization, Writing – review & editing. **Alex Singleton:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2025.102324.

Data availability

The developed new data are available at Geographic Data Service (https://data.geods.ac.uk/dataset/energy-deprivation-classification) through data application.

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