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An empirical critique of the low income low energy efficiency approach to measuring fuel poverty

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ABSTRACT

Fuel poverty is a complex socioenvironmental issue of increasing global significance. In England, fuel poverty is assessed via the Low Income Low Energy Efficiency (LILEE) indicator, yet concerns exist regarding the efficacy of this metric given its omission of households based on Energy Performance Certificate (EPC) ratings, rather than the ability of occupants to afford energy. To assess the potential shortcomings of the LILEE metric, we perform quantitative analyses of fuel poverty and energy security in London, UK. A spatial analysis of London exposes discrepancies between deprivation and expected fuel poverty incidence, demonstrating that a significant proportion of households are currently classed as “not fuel poor” (4.4% of the city’s stock, around 171,091 households) but remain likely to be energy insecure. Subsequently, we analyse primary survey data (n = 2886) collected in London using a Random Parameters Ordered Probit modelling framework. 28.2% of respondents were energy insecure, which is 145% higher than the LILEE estimate for London. Surprisingly, no significant variation in energy insecurity rates was found between the most and least efficient homes surveyed. Model estimation results reveal the key characteristics of respondents impacting energy security in the London. Our results can be used to inform a new or amended approach to measuring fuel poverty in England.

1. Introduction

Domestic energy consumption is responsible for 17.0% of UK carbon dioxide emissions. The majority of this consumption is attributable to heating, with cooking or other gas/electricity fuelled appliances accounting for the remainder (BEIS, 2022). Despite the necessity of such consumption, research has found that an inability to adequately warm one’s home (commonly referred to as *fuel poverty*, *energy poverty* or *energy insecurity*) not only contributes to excess winter mortality (E3G, 2018; Teller-Elsberg, et al., 2016) but can have far-reaching negative effects on mental and physical health (Hernandez, 2016). Fuel poverty is influenced by a range of factors, including energy costs, sociodemographics and building characteristics, including the fuel types used for heating and building fabrics (e.g., insulation, glazing, floor type etc.). With the ongoing cost of living and energy crises generating downward pressures on disposable household incomes, the inevitable result is more households becoming fuel poor. In such a setting it is vital that fuel poverty metrics are able to take all relevant contributory factors into account, yet there are concerns that the current fuel poverty metric used in England, the Low Income Low Energy Efficiency (LILEE) indicator, fails to do this.

Fuel poverty, also commonly referred to as energy poverty, is a multidimensional social issue affecting a significant proportion of UK households. The most recent data from the Department for Business, Energy and Industrial Strategy (BEIS) indicate that 13.2% of English households are currently fuel poor according to the LILEE indicator (BEIS, 2023). However, while these figures were released in 2023, they were estimated from data generated in 2021. This delay in publication of fuel poverty statistics is cited as one of the main obstacles to introducing responsive energy policies (Boardman, 2009). The true rate of fuel poverty in 2023 is likely higher than that reported, further exacerbated by intervening events such as COVID-19 and the cost of living crisis, characterised by wage stagnation, rapid inflation (ONS, 2022a) and escalating energy prices (UK Government, 2022a). The Joseph Rowntree

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Foundation (2023) reported that, during November 2022, around 40% of low-income families were spending less on food for their children, while around 60% were heating their home less often and around 50% were engaging in other energy conserving behaviours. The Consumer Prices Index (CPI), which is an inflation metric used by the Office for National Statistics (ONS), was often in excess of 10% throughout 2022 (ONS, 2022a), further increasing pressure on low-income households. Wholesale gas prices increased significantly during 2022 due to an unfavourable coalescence of geopolitical and economic issues. In response, the energy price cap set by Ofgem, the UK's energy market regulator, has progressively increased resulting in an unpreceded rise in consumer energy prices (UK Government, 2022a). Further remedial action was introduced in the form of the Energy Price Guarantee, which provides consumers with some protection against unpredictable wholesale prices, with the typical household energy bill now estimated at £2500 per year (UK Government, 2022b).

Myriad studies have analysed the sociodemographic, built environment and regional characteristics affecting fuel poverty and energy insecurity (Belaïd, 2018; Boardman, 2009; Hernandez, 2016; Jones, 2022; ONS, 2023; Robinson et al., 2018), however, most precede the recent economic downturn. Belaïd (2018) found that a wide variety of variables, including household composition, tenure status, socioeconomic status, ethnicity, building fabrics and dimensions significantly affected fuel poverty risk (Belaïd, 2018). Burlinson et al. (2018) went further showing that these issues generated three distinct types of fuel poverty: "income-poverty-high-cost", "housing-cost-induced-poverty--high-cost" and "fuel-cost-induced-poverty-high-cost". The study's findings emphasise the multidimensional nature of fuel poverty and the need for interventions that protect financially vulnerable households from volatile energy prices, as opposed to focusing solely on housing upgrades. This was echoed in a recent UK-wide study analysing energy insecurity in the winter of 2022 (ONS, 2023), which showed the likelihood of energy insecurity was exacerbated by various sociodemographic characteristics: being below the age of 65; belonging to an ethnic minority background (excluding white minorities); having a disability (mental or physical); displaying depressive symptoms; personal income below £40,000 per year; and living in a rented property.

There is a distinct challenge in comparing studies of fuel poverty, especially at international level. There is little standardisation of its measurement and significant variation in the metrics adopted across the world, with varying metric adoption having a stark effect on fuel poverty rates (Moore, 2012; Robinson et al., 2018). In England alone, there have been three fuel poverty metrics active within a single decade. The UK Government, aiming to simultaneously address social vulnerability and housing quality, recently introduced policy that defined the new LILEE fuel poverty metric, replacing the transient Low Income High Costs (LIHC) indicator, as well as setting ambitious targets to upgrade the Energy Performance Certificate (EPC) ratings of the English housing stock (UK Government, 2021). EPC ratings are now an essential criterion of the LILEE fuel poverty metric, which is defined as follows: "*a household is considered to be fuel poor if residual household income is below the poverty line (following energy expenses) and the home has an EPC rating of D–G*" (UK Government, 2021). The immediate concern with the LILEE approach is that EPC A–C rated households (which are generally considered to be "efficient housing" and constitute 41.9% of the entire English housing stock (UK Government, 2023a)) cannot, *by definition of the metric*, be considered fuel poor, regardless of household income, household composition or energy prices. Specifically, the UK Government's policy paper *"Sustainable Warmth"* states that:

> *"Whilst we recognise that there are households living in energy efficiency Band A, B or C homes who are unable to afford sufficient energy to keep warm, due to a very low income, most will not significantly benefit from energy efficiency measures […] As such, households in homes that have been improved to B and C or above, will not be considered as being in our measure of fuel poverty" (UK Government, 2021).*

This statement contradicts the previous consensus on fuel poverty, that household income, energy prices and the proportion of income required for sufficient energy use are crucial factors (Boardman, 2009; Middlemiss, 2017), and places greater emphasis on energy efficiency. Furthermore, both LILEE, and the LIHC indicator which preceded it, are relative metrics. LIHC for example considered a household to be fuel poor if its income dropped below the poverty line (before or after the cost of energy) and the property had "higher than typical energy costs" (i.e., relative to median household energy costs). This relativeness, which effectively caps the proportion of households that can be defined as experiencing fuel poverty, stands in sharp contrast to the absolute nature of the 10% indicator, which is still adopted by most European countries (European Commission, 2021). The 10% metric considers a household to be fuel poor if the occupant(s) spend more than 10% of household income on energy to maintain "an adequate level of warmth" (European Commission, 2021). There are yet further concerns with LILEE given that: (i) it is generally accepted that EPC assessments are prone to human and measurement error (Nagarajah and Davis, 2019), whilst it has also been found that *a priori* energy consumption per EPC band is often an underestimate of empirical consumption (Coyne and Denny, 2021), which increases the risk of misclassifying both properties and poverty levels; (ii) there is no clause protecting those with known vulnerabilities to fuel poverty in EPC A–C properties, for example, those with heath conditions, single-parent or single-pensioner households, or those with a prepayment meter; and (iii) the LILEE indicator effectively neglects the impact of increased energy prices on occupants of EPC A–C rated properties altogether. Middlemiss (2017) criticises LILEE's predecessor, LIHC, for many of the same reasons, most notably, an unjust focus on energy efficiency improvements and an inability to account for changing energy costs. All of these concerns relate to what is arguably a conflation of two issues: energy efficiency characteristics and demographic poverty characteristics. Despite the conspicuousness of LILEE's shortcomings, it is not definitively inferior to LIHC or the 10% indicator, the latter of which can tend to overestimate and underestimate fuel poverty depending on regional characteristics (Liddell, et al., 2012).

The definition of energy security differs slightly from fuel poverty, such that energy security focuses primarily on a household or person's ability to afford energy while not sacrificing other necessities, such as food or medicine. A recent study by Harker Steele and Bergstrom (2021) compares several frameworks to identify energy insecure households. The validity of each is tested by analysing responses to the 2015 Residential Energy Consumption Survey (RECS), which is administered by the US Energy Information Administration on a triennial basis. Unlike the LILEE metric, the RECS focuses on person-centric aspects of energy use and affordability, including trade-offs with other essential expenses, subjective assessment of household temperature, affordability of the household's main heat source and illnesses linked to inadequate temperature. Typically, energy security scales do not consider household energy efficiency. Energy vulnerability and precarity are two further denominations that appear frequently in the literature and describe related conditions (Gatto and Busato, 2020; Middlemiss and Gillard, 2015; Petrova, 2018). Energy vulnerability considers fuel poverty in terms of three contributory characteristics: exposure, sensitivity and adaptive capacity (Middlemiss and Gillard, 2015; Petrova, 2018), whereas energy precarity describes the normalisation of fuel poverty via politically and structurally induced insecurities, with a particular focus on the energy market mechanisms used to govern vulnerable populations (Petrova, 2018). It is worth noting, however, that the nomenclature of fuel poverty tends to vary by country and many of the aforementioned terms appear to be, erroneously, used interchangeably. In this study we aim to investigate the potential discrepancy between fuel poverty (according to the LILEE definition) and energy security (self-reported ability to afford sufficient energy according to the RECS scale).

To achieve this, we deploy two analytical methods. In our first analysis (Stage 1), fuel poverty, employment, deprivation and EPC data are used to estimate the number of financially vulnerable households currently omitted from LILEE fuel poverty statistics in the case study city of London, UK. It should be noted, that when referring to London as the study area, reference is being made to Greater London, which includes the City of London and surrounding boroughs. London is a highly suitable case study, with a high-density urban population, characterised by some of the most affluent and most deprived neighbourhoods in England. The focus on the urban setting is also reinforced by previous research (Roberts, et al., 2015), suggesting that fuel poverty is more persistent among urban dwellers. In some cases, however, the urban versus rural experience of fuel poverty is muddied by a host of covariates, including the agricultural character of an area (Cyrek and Cyrek, 2022), energy supply logistics and tenure status (Roberts, et al., 2015). Nevertheless, London is deemed a suitable case study to gauge the urban experience of fuel poverty and energy security. In the second part of our analysis (Stage 2), we use primary survey data, collected in London during winter 2022, to model the sociodemographic, behavioural and perceptual characteristics associated with energy insecurity. Here we deploy the RECS question scale, as previously described. Following both analyses, the findings are critically examined in terms of policy implications, with a view to informing the measurement criteria for future fuel poverty and energy security metrics.

2. Methodological approach

2.1. Data & sampling strategy

The completion of the Stage 1 analysis requires the integration of publicly accessible datasets for LILEE fuel poverty (BEIS, 2023), employment status (UK Government, 2023b), Index of Multiple Deprivation (IMD) (UK Government, 2020) and EPC ratings (UK Government, 2023a). For Stage 2, primary survey data gauging food and energy insecurity in London are analysed using a discrete outcome modelling framework (described further in *Stage 2: Methods*). The survey was disseminated among London-based users of OLIO (a popular mobile app where users share food and household items) and was active from November 22, 2022–December 05, 2022. As well as recording food and energy security scores (via RECS) of the respondents during the winter 2022 period, the survey collected sociodemographic (e.g., age, gender, household income and household characteristics), behavioural (e.g., food and energy consumption habits, and reliance on family, friends or charities) and perceptual characteristics (e.g., life satisfaction and financial anxiety). As discussed in the literature (Dutwin and Buskirk, 2023; Chambers et al., 2022), the deployment of the survey via a mobile app could lead to certain demographics being excluded. Chambers et al. (2022) explore the potential digital exclusion of certain individuals or households given the growing digitalisation of the energy market (e.g., smart meters and other internet-dependent services). It is possible that households with no internet access, or simply those who are late adopters of digital technologies, were not able to be reached in our survey. In any case, the survey sample was highly representative of London in terms of socioeconomic status, as discussed in the following paragraph, so the degree of digital exclusion related to affordability is at least partially controlled for in the survey sample.

In total, there were 2886 respondents, however the number of complete observations (those that could be used in the statistical analysis) was 2170. The survey sampling strategy involved the application of quota restraints for socioeconomic status (informed by the IMD score of respondents' home area, according to Lower Super Output Areas (LSOAs)). Fig. 1 shows the distribution of LSOA IMD deciles for the survey sample versus the City of London, indicating the highly representative nature of the survey in terms of LSOA IMD deciles. It is worth commenting on the slight right skew present in the survey sample and across London, with the exception of the first decile. The high proportion (>10%) of London LSOAs in the second, third and fourth decile, suggests that many London residents live in LSOAs with higher-than-average IMD scores; however, the significant underrepresentation of decile one shows that, despite this, London residents rarely live in LSOAs that are in the most deprived 10% of English LSOAs. This reiterates the socioeconomic heterogeneity that London is known for.

2.2. Stage 1: methods

A bivariate spatial analysis of fuel poverty prevalence and the level of deprivation (based on IMD rank) expected within Greater London's LSOAs is conducted, allowing potential discrepancies between the two variables to be examined. Previous research (Marchand, et al., 2019) has

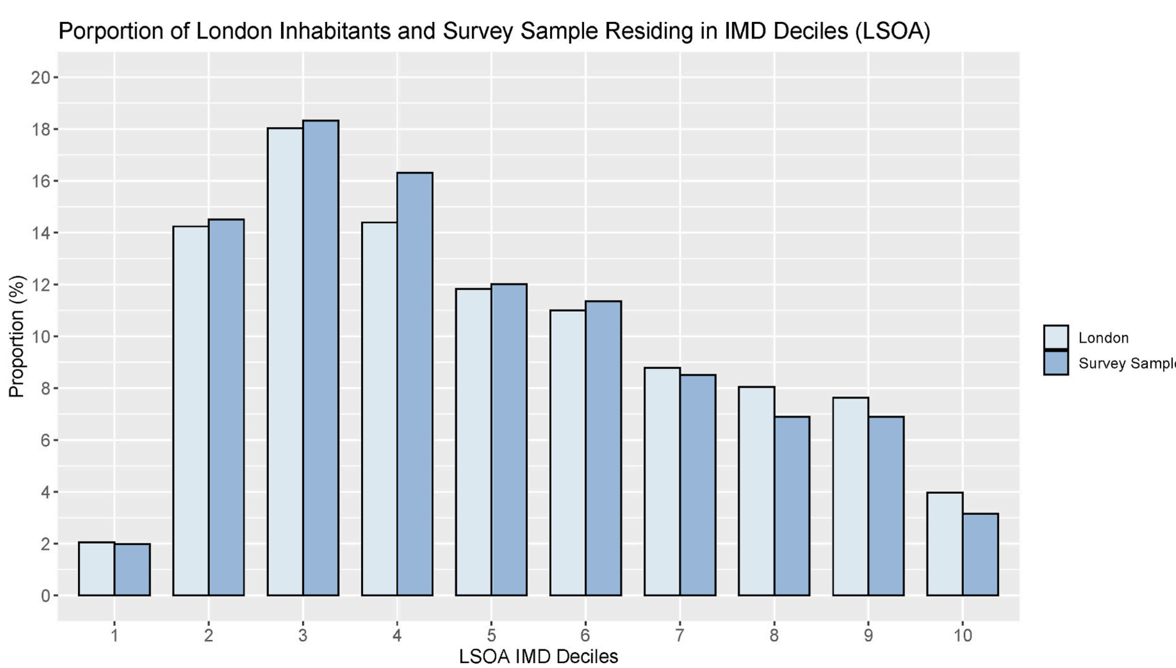

Fig. 1. Proportion of London and survey sample respondents' LSOA IMD deciles (where 1 = most deprived decile & 10 = most affluent) (n = 2886).

analysed the relationship between IMD and fuel poverty across England, according to the previously adopted 10% fuel poverty definition. The ONS (2021b) define LSOAs as areas with between 400 and 1200 households and resident populations of 1000–3000; the average number of households per LSOA in London is 725. Following the spatial analysis, the number of financially vulnerable London households that are omitted from LILEE fuel poverty statistics is estimated via the integration of EPC and employment datasets.

2.3. Stage 2: methods

In order to complete Stage 2, a discrete outcome modelling framework is adopted to investigate the factors influencing energy security in London. Discrete outcome models are used in the case of a discrete dependent variable (Washington, et al., 2020). In this case, the dependent variable (Y) has four discrete, ordered outcomes: (Y = 1) very low energy security; (Y = 2) low energy security; (Y = 3) marginal energy security; and (Y = 4) high energy security. For ordinal dependent variables, the Fixed Parameters Ordered Probit (FPOP) framework was deemed most appropriate. Random parameters, which allow for the potential effects of unobserved heterogeneity (i.e., unobserved characteristics of the respondents not recorded in the survey) within independent variables to be accounted for, are also trialled in the modelling framework. As such the modelling framework is referred to as the Random Parameters Ordered Probit (RPOP) from hereon. Previous studies have shown that accounting for unobserved heterogeneity in discrete outcome models can achieve significantly higher explanatory power than fixed parameters approaches (Mannering, et al., 2016). The modelling framework we employ echoes the approach in Washington et al. (2020). An ordered probit model is derived by defining a latent variable (z), typically specified as a linear function per observation (z_n) as follows:

$$z_n = \boldsymbol{\beta}\mathbf{X}_n + \varepsilon \tag{1}$$

where $\boldsymbol{\beta}$ is a vector of estimable parameters, $\mathbf{X}$ denotes a vector of independent variables dictating the discrete ordering per observation, n, and ε is random disturbance, which is assumed to be normally distributed across observations (with mean = 0 and variance = 1). The ordered outcomes, y, for each observation are defined as:

$$y = 1 \text{ if } z \le \boldsymbol{\mu}_0$$

$$y = 2 \text{ if } \boldsymbol{\mu}_0 < z \le \boldsymbol{\mu}_1$$

$$y = \text{"..."}$$

$$y = I \text{ if } z \ge \boldsymbol{\mu}_{I-1} \tag{2}$$

where $\boldsymbol{\mu}_I$ are estimable parameters (i.e., thresholds) that explain y, which correspond to levels of the ordered dependent variable (i.e., energy security outcomes). The thresholds, $\boldsymbol{\mu}_I$, are estimated in conjunction with model parameters, $\boldsymbol{\beta}$. The main objective of model estimation then becomes determining the probability of I for each observation, n. Given the previously assumed distribution of ε, and that $\boldsymbol{\Phi}$ denotes the cumulative normal distribution, the resulting ordered selection probabilities are as follows:

$$P(y = 1) = \boldsymbol{\Phi}(-\boldsymbol{\beta}\mathbf{X})$$

$$P(y = 2) = \boldsymbol{\Phi}(\boldsymbol{\mu}_1 - \boldsymbol{\beta}\mathbf{X}) - \boldsymbol{\Phi}(-\boldsymbol{\beta}\mathbf{X})$$

$$P(y = 3) = \boldsymbol{\Phi}(\boldsymbol{\mu}_2 - \boldsymbol{\beta}\mathbf{X}) - \boldsymbol{\Phi}(\boldsymbol{\mu}_1 - \boldsymbol{\beta}\mathbf{X})$$

$$P(y = 4) = 1 - \boldsymbol{\Phi}(\boldsymbol{\mu}_2 - \boldsymbol{\beta}\mathbf{X}) \tag{3}$$

To allow for random parameters within the ordered probit framework, the estimable parameters are written as follows:

$$\boldsymbol{\beta}_n = \boldsymbol{\beta} + \boldsymbol{\omega}_n \tag{4}$$

Where, $\boldsymbol{\beta}_n$ is a vector of estimable parameters that may vary across observations, n, $\boldsymbol{\beta}$ is the vector of mean parameter estimates across the dataset and $\boldsymbol{\omega}_n$ is a vector of randomly distributed terms (normally distributed with mean = 0 and variance = σ^2). Due to the complexity of calculating the ordered selection probabilities (equation (3)) a simulation-based maximum likelihood is used for model estimation (Washington, et al., 2020). Halton draws are often considered a more effective alternative to random draws (Halton, 1960) and are thus employed here. Selection of independent variables in the final model is justified via the Akaike Information Criterion (AIC) and following the RPOP model estimation, average marginal effects are calculated for each independent variable.

3. Stage 1 analysis: results & discussion

3.1. Spatial analysis of LILEE fuel poverty in London

The average rate of LILEE fuel poverty across London is estimated to be 11.9% (BEIS, 2023). Fig. 2 displays a bivariate choropleth map of Greater London where the two plotted variables are fuel poverty (according to LILEE) and IMD, which is a metric developed by the UK's ONS that accounts for various aspects of deprivation. Each of the areas in Fig. 2 represents an LSOA (neighbourhood) in London, showing considerable variation between levels of LILEE fuel poverty and IMD (see Table 1 for numerical interpretation of Fig. 2 legend). There are a total of 4835 LSOAs across the Greater London area. Surprisingly, 220 of these LSOAs (around 4.7%) have IMD scores that rank them amongst the most deprived in London, but lower than average rates of fuel poverty. Given that IMD utilises a ranking system, i.e., LSOAs are ranked from most to least deprived, the LSOAs analysed here were also ranked in terms of fuel poverty prevalence.

In order to help interpret the bivariate legend, consider cell A3 (dark pink) in Fig. 2: LSOAs of this colour have a fuel poverty rate higher than the London average (fuel poverty index[1] = 1.34–2.00, i.e., these LSOAs are in top ~33% of fuel poor areas in London), however, the corresponding IMD index[2] is 0.00–0.67, which means the LSOA is in the least deprived ~33% of areas in London. These statistics refer to variation between London LSOAs only, as per footnotes 1 and 2. This is a particularly important point, as London is a distinctive UK city with the largest municipal population and area, while median household income also tends to be higher than other regions (ONS, 2022b). LSOAs with black fill indicate missing estimates of LILEE fuel poverty. In total, this applies to 176 LSOAs (around 3.6%). It is unclear why LILEE estimates are not available for these LSOAs; a more detailed investigation of missing data LSOAs may reveal whether this is a further shortcoming of the LILEE methodology. However, an initial characterisation of missing data LSOAs reveals that they are, on average, more deprived than all other LSOAs across London, which is further cause for concern given the LILEE metric's other known deficiencies.

Fig. 3 shows LSOA IMD index plotted against LSOA fuel poverty index. The R^2 value of 0.27 shows that there is a moderately positive relationship between IMD and fuel poverty. However, there are a considerable number of outlying LSOAs, which can be seen in the top left and bottom right sections of Fig. 3 (highlighted by red polygons), corresponding to cells A3 and C1 of the bivariate legend, respectively. It is likely that the LILEE metric's omission of households with EPC ratings of A–C is the cause of many outlying LSOAs. It may be informative to further characterise the outlying LSOAs, for example, by examining

[1] Calculation of FP index: $i_{FP} = {}^{\text{LSOA FP rank}}/_{\text{Median London FP rate (\%)}}$

[2] Calculation of IMD index: $i_{IMD} = {}^{\text{LSOA IMD rank}}/_{\text{Median London LSOA rank}}$

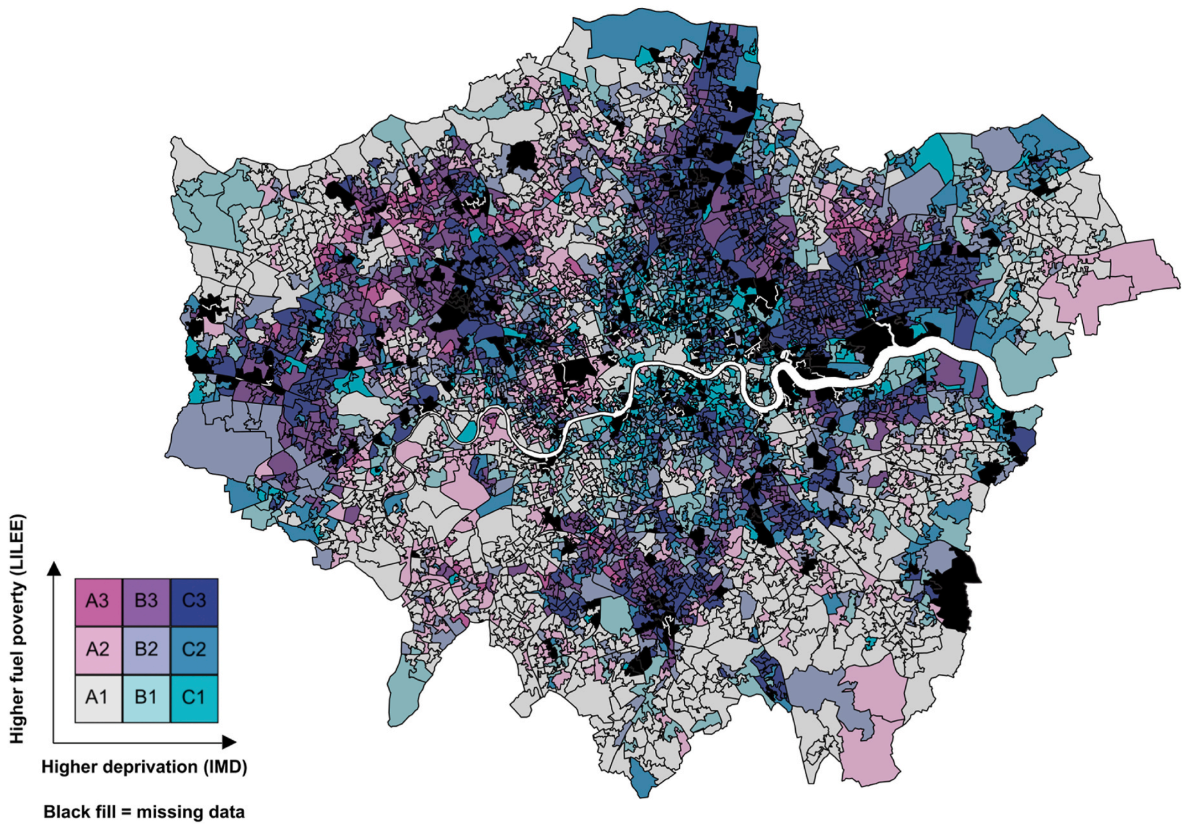

Fig. 2. Bivariate choropleth map of Greater London: fuel poverty (LILEE) and IMD per LSOA.

Table 1
Corresponding A, B & C legend codes for fuel poverty and IMD.

Legend code	Fuel poverty index (i_{FP})	IMD index (i_{IMD})
A1	0.00–0.67	0.00–0.67
A2	>0.67 & <1.34	0.00–0.67
A3	1.34–2.00	0.00–0.67
B1	0.00–0.67	>0.67 & <1.34
B2	>0.67 & <1.34	>0.67 & <1.34
B3	1.34–2.00	>0.67 & <1.34
C1	0.00–0.67	1.34–2.00
C2	>0.67 & <1.34	1.34–2.00
C3	1.34–2.00	1.34–2.00

geographical trends in housing quality or demographic composition, but this is out of scope for this paper. It is worth noting, however, that in the context of the 10% fuel poverty indicator, Marchand et al. (2019) also comment on the surprisingly disparate distribution of fuel poverty and IMD in English LSOAs, suggesting that this may in fact be a common trend between various fuel poverty metrics and IMD.

3.2. Estimation of vulnerable households omitted from LILEE statistics in London

According to the LILEE metric, the fuel poverty rate in London is 11.9%, which is slightly lower than the average across the UK (13.2%) (BEIS, 2023). Given that the LILEE metric defines EPC A–C rated properties as "not fuel poor" by default, in this section we estimate the proportion of financially vulnerable, EPC A–C rated homes in London. This estimation process is based on tenure status and the economic activity of the household reference person (HRP), defined as the highest earner within the household (UK Government, 2023b). First, the number of EPC A–C rated properties in London was calculated. There is a total of 3,864,247 lodged EPCs in London, with 1,819,012 (47.1%) having an EPC rating of A–C and therefore considered "not fuel poor" by default under LILEE. Second, the proportion of EPC A–C rated properties that are socially or privately rented was calculated (see Table 2), these homes typically having lower incomes (ONS, 2022c) and are more likely to experience energy insecurity than other tenures (ONS, 2023). Interestingly, the proportion of EPC A–C rated homes that are socially rented (20.2%) was considerably higher than among EPC D–G properties (15.6%). This highlights a further potential oversight of the LILEE approach, as those living in socially rented properties are known to be at increased fuel poverty risk (Boardman, 2009).

The third step of the estimation references the English Housing Survey (UK Government, 2023b) to determine the typical economic activity of HRPs in socially and privately rented properties (see Table 3). We focus on households where HRPs are unemployed or economically inactive,[3] as many of these households are likely to be heavily dependent on benefits as their main source of income (ONS, 2022d). *Economically inactive* is defined as "*people not in employment who have not been seeking work within the last 4 weeks and/or are unable to start work within the next 2 weeks*". This distinction versus being *unemployed* (i.e., not employed but actively seeking work) is important, as a significant proportion of those who are economically inactive have a disability or long-term illness preventing them from working, a risk factor which has also been associated with fuel poverty and energy insecurity (Boardman, 2009; Hernandez, 2016; Snell et al., 2015).

[3] In reality, a proportion of those belonging to each economic status category in Table 3 are likely to be in receipt of some form of benefits, however, a lack of granular income data makes these proportions hard to calculate. As a result, we do not focus on those who work part/full-time, are retired or are in full-time education.

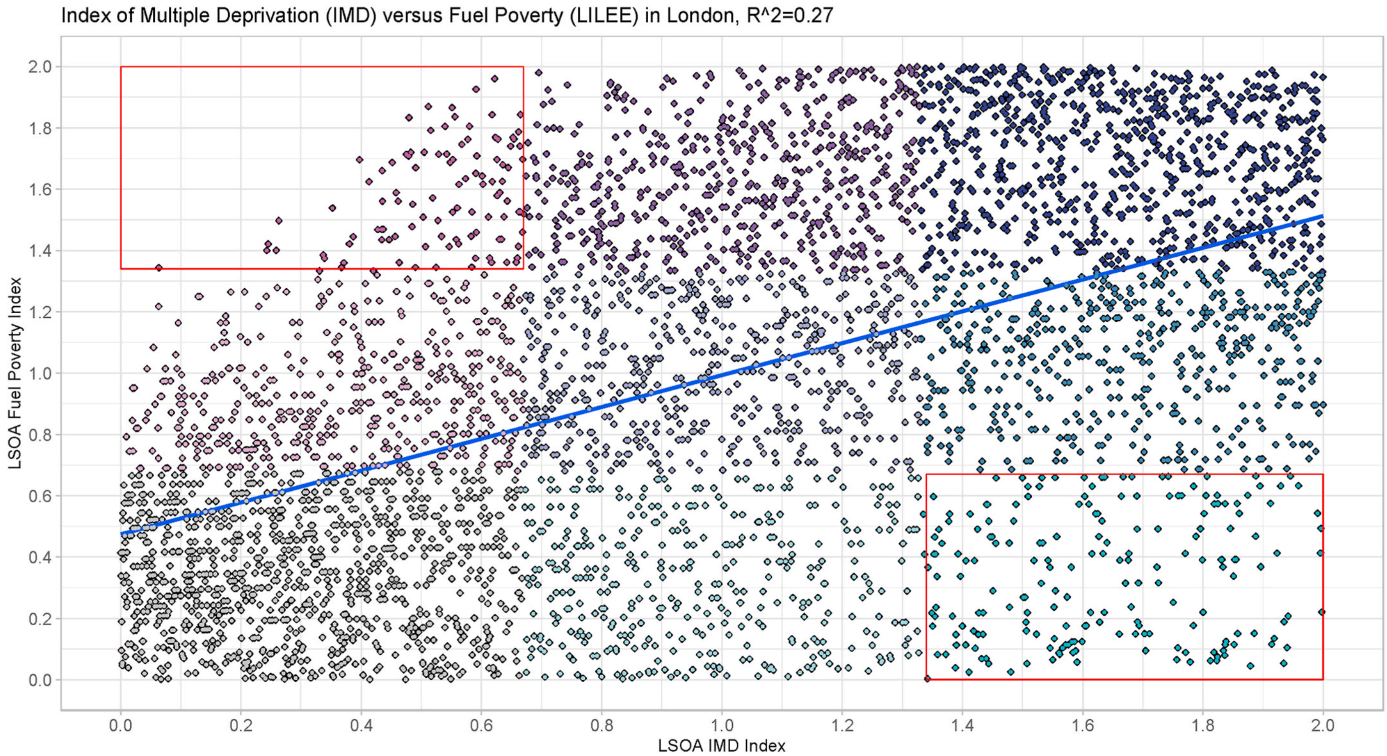

Fig. 3. IMD plotted against fuel poverty (LILEE) per LSOA in Greater London (n = 4659 LSOAs).

Table 2
Tenure status among EPC A–C rated London properties (UK Government, 2023a).

Tenure	Frequency (% in parentheses)
Owner-occupied	494,394 (27.2%)
Privately rented	516,731 (28.4%)
Socially rented	367,786 (20.2%)
Unknown	440,101 (24.2%)

Table 3
Economic status of HRP per tenure type (UK Government, 2023b).

Economic status of HRP	Proportion of tenure type (%)	
	Socially rented	Privately rented
Full-time work	28.5%	66.1%
Part-time work	14.8%	11.4%
Retired	25.5%	6.8%
Unemployed	7.9%	3.6%
Full-time education	1.3%	3.8%
Economically inactive	21.9%	8.3%

Based on Tables 2 and 3, there are an estimated 29,055 HRPs[4] who were unemployed and a further 80,545 who were economically inactive in EPC A–C rated social homes in London. Among the privately rented properties, 18,602 HRPs were unemployed and 42,889 were inactive. Collectively, 171,091 households in London have an EPC rating of A–C, where the HRP is either unemployed or inactive. This accounts for 9.4% of London's EPC A–C rated properties and 4.4% of the city's entire stock.

This is a stark finding, but one that should be interpreted with caution; it is possible that some of these households are able to rely on savings or external income sources to afford energy. Nevertheless, living in a privately or socially rented property and/or having low income has consistently been linked to higher risk of fuel poverty (Belaïd, 2018; Boardman, 2009) and energy insecurity (ONS, 2023). Further, the London survey data in the following section show that energy insecurity does not differ significantly between EPC A–C and D–G rated homes. The omission of EPC A–C rated households, particularly among socially and privately rented tenures where the HRP is unemployed or economically inactive, is therefore highly likely to result in LILEE underestimating the true rate of households that are unable to afford energy.

4. Stage 2 analysis: results & discussion

4.1. Exploratory data analysis of London Survey data

As part of Stage 2, an exploratory analysis of the London survey data (collected in Q4 2022) was conducted. Respondents' energy security classification was determined by a range of questions, including trade-offs with other essential expenses (e.g., food and medicine); the inability to maintain adequate household temperature because of affordability or lack of access to heating equipment; and how often the respondent has fallen behind on energy bill payments (for full RECS energy security scale questions, see Harker Steele and Bergstrom (2021) and Appendix Table A1). The distribution of the dependent variable is shown in Fig. 4. *Very low*, *low*, *marginal* and *high* energy security correspond to levels 1–4 of the dependent variable, respectively.

Among the survey respondents, energy security was very low for 3.6%, low for 24.6%, marginal for 18.9% marginal and high for 52.9%. Fig. 4 is disaggregated by IMD rank of the LSOA where a respondent resides, "affluent" being the top three IMD deciles, "middling" the middle four IMD deciles (4–7) and "deprived" the bottom three. Interestingly, several respondents who reside in middling or affluent LSOAs are still deemed to have very low or low energy security. This may be the result of income heterogeneity within LSOAs, with some low-income households typical in middling and affluent areas; alternatively, it may indicate that rising energy costs are affecting many households

[4] Calculated as follows: $\left(\text{No. socially rented EPC A–C homes}/100\right) * \text{Proportion of tenure unemployed}$

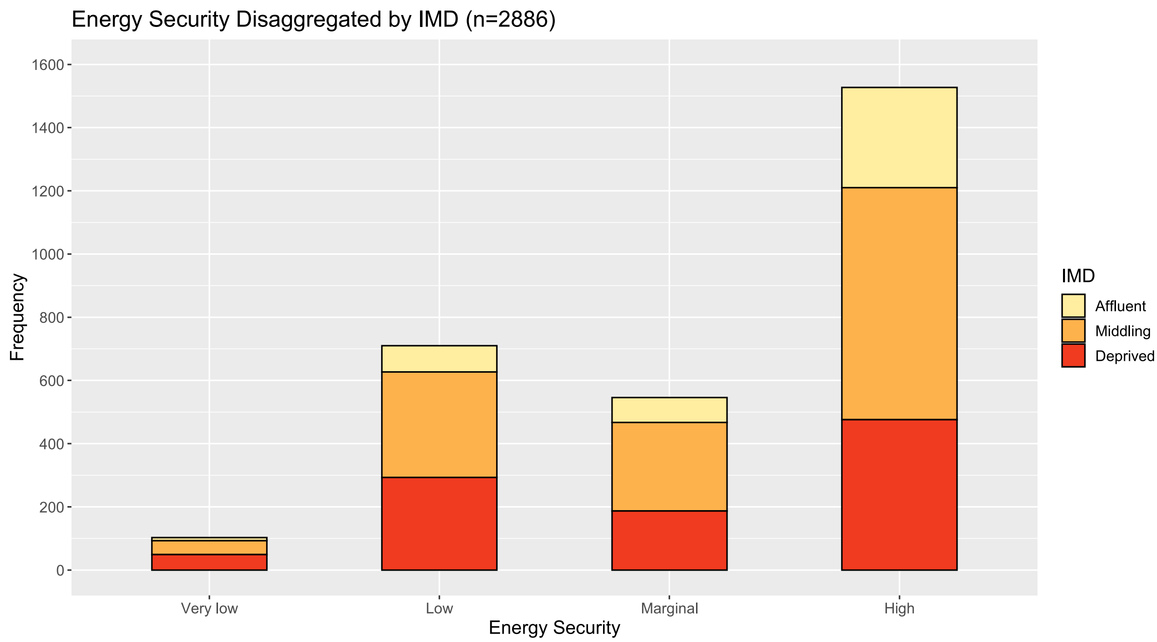

Fig. 4. Distribution of survey respondents' energy security disaggregated by LSOA IMD.

regardless of socioeconomic status. Fig. 5 shows the distribution of respondents' household EPC ratings disaggregated by energy security. 915 respondents (approximately a third) knew their home's EPC rating. As previously discussed, the LILEE fuel poverty metric omits EPC A–C rated households on the basis that they are implicitly too energy efficient to be considered fuel poor. However, Fig. 5 highlights that, despite living in an A, B or C rated property, there is still a considerable likelihood of the occupant(s) experiencing low or very low energy security.

Table 4 displays the proportion of respondents deemed to have either very low or low energy security (insecure) and those with either marginal or high (secure) energy security per EPC rating. The binary aggregation of the energy security outcomes in Table 4 allows comparisons to be made with LILEE fuel poverty statistics. Across all the respondents

Table 4
Binary energy security per EPC rating.

EPC rating (N = 915)	Very low or low energy security		Marginal or high energy security	
	Frequency	% of group	Frequency	% of group
A (n = 44)	13	29.55%	31	70.45%
B (n = 107)	34	31.78%	73	68.22%
C (n = 267)	65	24.34%	202	75.66%
D (n = 319)	84	26.33%	235	73.67%
E (n = 130)	41	31.54%	89	68.46%
F (n = 35)	15	42.86%	20	57.14%
G (n = 13)	6	46.15%	7	53.85%
Total	258	28.20%	657	71.80%

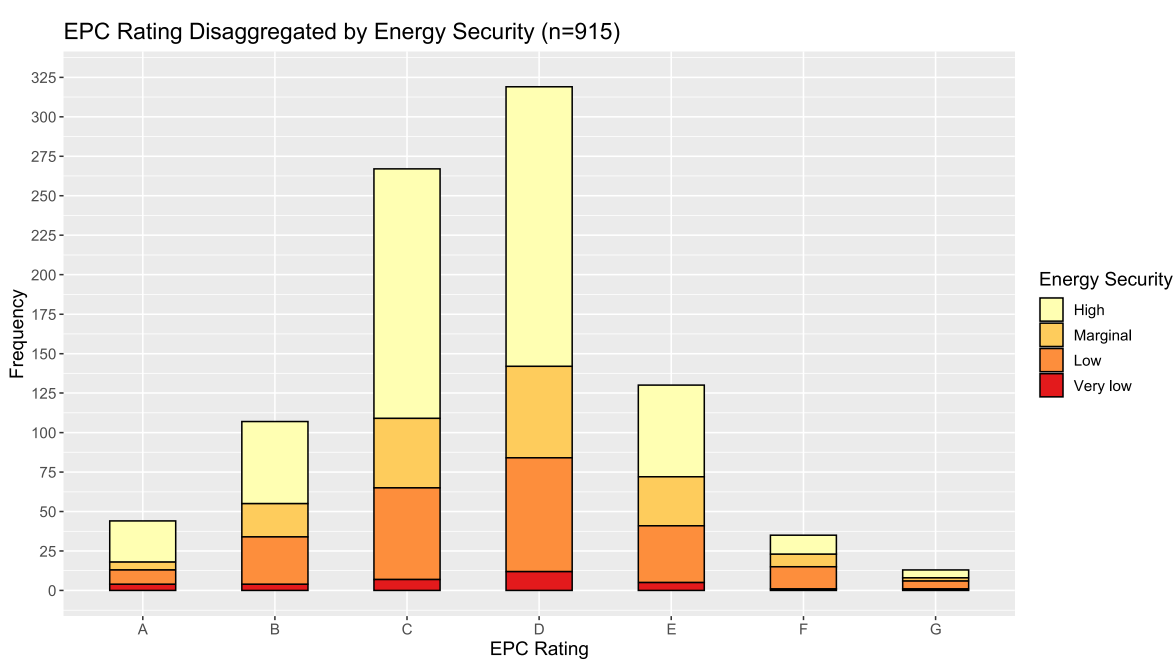

Fig. 5. Distribution of survey respondents' household EPC rating disaggregated by energy security.

who live in an EPC A–C rated property, 26.8% had very low or low energy security, which is slightly lower than the equivalent figure for EPC D–G rated properties (29.4%). This suggests that energy efficiency does play a modest role in decreasing the likelihood of energy insecurity.

Critically, a two-sample *t*-test was performed to test whether the rate of binary energy insecurity differed significantly between EPC A–C and D–G properties. The null hypothesis (H_0) is that the population means (i.e., rate of energy insecurity) are equal (H_0: $\mu_1 = \mu_2$), whereas the alternative hypothesis (H_A) is that the population means are not equal (H_A: $\mu_1 \neq \mu_2$). The test produced a statistically insignificant p-value of 0.39 (critical value = 0.05), therefore there is not sufficient evidence to reject the null hypothesis, that the mean rate of energy security in EPC A–C and D–G households is equal, despite a relatively large sample size.

The rate of very low or low energy security across the sample (28.2%) is considerably higher than the LILEE fuel poverty rate estimated for London (11.5%). This initially might seem surprising, given that research (Kearns, et al., 2019) previously found that fuel poverty rates are typically higher than the rate of those struggling to afford energy payments. While a conflict with previous results is possible, a plausible explanation lies in the likelihood that the LILEE metric is underestimating the true rate of fuel poverty due to its omission of EPC A–C rated properties; thus, an artificial gap between the fuel poverty rate in London and the rate of energy insecurity among the respondents is produced. The following section presents the main results for Stage 1, which is an estimation of the number of vulnerable households omitted from LILEE fuel poverty statistics in London. Results for Stage 2 of our analysis are then presented, with models of London exploring the sociodemographic, behavioural and perceptual factors impacting the energy security of survey respondents.

4.2. Statistical analysis of energy security in London

This section presents the RPOP model estimation results for the exploration of factors affecting energy security among the London survey respondents. Table 5 displays independent variables found to be statistically significant in the final model estimation.[5] Each independent variable is structured as a binary indicator, and an example of their interpretation is as follows: for the variable 'physical or mental health condition (1-yes, 0-no)', 18.39% (the indicator group) of the survey respondents have a physical or mental health condition, while the remaining 81.61% (the control group) do not. Table 6 displays the RPOP model estimation results, accompanied by average marginal effects, indicating that five sociodemographic and eight behavioural or perceptual characteristics of respondents were significantly associated with energy security. Independent variables were selected using forwards stepwise regression (an iterative selection algorithm based on AIC) using the R package 'MASS' (Venables and Ripley, 2002), while the final model was estimated using the R package 'Rchoice' (Sarrias, 2020).

Table 5
Descriptive statistics for statistically significant independent variables.

Variable Description	Indicator (%)
Sociodemographic characteristics	
Physical or mental health condition (1 if yes, 0 if no)	18.39%
Household income (1 if less than £14,900 per year, 0 otherwise)	20.05%
Age (1 if under 25, 0 otherwise)	9.08%
Age (1 if 25 to 34, 0 otherwise)	31.00%
Energy payment method (1 if prepayment meter, 0 if otherwise)	25.81%
Behavioural & perceptual characteristics	
Social connection (1 if relied on neighbours for food in the last year, 0 otherwise)	11.15%
Social connection (1 if relied on a community/faith group for food in the last year, 0 otherwise)	11.43%
Social connection (1 if relied on family and friends for food in the last year, 0 otherwise)	23.59%
Social reliance (1 if relies on family and friends to a large extent for help, 0 otherwise)	41.24%
Foodbank use (1 if used in the last 12 months, 0 otherwise)	11.57%
Food purchasing habits (1 if never avoids raw food, 0 otherwise)	57.05%
Financial anxiety (1 if worries about housing payments almost every month, 0 otherwise)	15.12%
Life satisfaction (1 if high/very high satisfaction, 0 otherwise)	45.20%

Model coefficients in Table 6 can be interpreted as follows: an independent variable with a significantly positive coefficient indicates that a given group (the indicator group) are significantly more likely to have high energy security (i.e., the highest level of the dependent variable, Y = 4) than the control group. Conversely, a significantly negative coefficient indicates increased likelihood of very low energy security (Y = 1). The '*t*-stat' column indicates the level of statistical significance associated with each independent variable (where a *t*-stat>1.96 corresponds to p-value<0.05 and >95% level of confidence (l.o.c.)). The RPOP framework also allows for the potential effects of unobserved heterogeneity to be accounted for through specification of certain independent variables as random parameters.

Three independent variables produced statistically significant random parameters (indicated by grey fill in Table 6): 'physical or mental health condition (yes)', 'age (under 25)' and 'social connection (relied on community/faith group)'. An example interpretation of the 'physical or mental health (yes)' variable is as follows: overall, those who have a physical or mental health condition are significantly more likely to have very low energy security when compared to those who do not have a health condition. However, this variable is also significant as a random parameter, which suggests that among those who do have a health problem levels of energy security are heterogeneous, despite the overall direction of the variable's effect being negative. A possible explanation may be that the variable erroneously combines respondents with different types of health conditions, when in reality there may be subgroups of health conditions within the variable that have opposing effects on energy security. It could also be that subgroups of disabled respondents are determined by characteristics related to household composition and employment status, as demonstrated by Snell et al. (2015).

Table 6 also presents the average marginal effects associated with each independent variable. In the case of binary independent variables, the marginal effects show the change in the dependent variable outcomes given a one-unit change in the independent variable, from 0 to 1. Each respondent has their own associated marginal effects, hence, 'average marginal effects' refers to this value averaged across the survey sample (Washington, et al., 2020). Considering the 'physical and mental health condition' variable for example, the interpretation of this variable's average marginal effects is as follows: the presence of a health condition means the probability of very low energy security is 0.070 higher (on average), the probability of low security is 0.035 lower, the probability of marginal security is 0.023 lower, and the probability of high security is 0.012 lower. The magnitude of the average marginal effects also provides insight into the relative importance of each

[5] Although the final model contains the most influential combination of independent variables, some relevant variables were omitted from the final model (as discussed further in Section 5) due to concerns over collinearity (a strong linear relationship between two or more independent variables). To account for collinearity, no independent variables with pairwise correlation coefficients >0.3 were included in the same model.

Table 6
Factors affecting energy security: RPOP model estimation results.

Variable Description	RPOP model		Average marginal effects			
	Coefficient	*t*-stat	Y = 1	Y = 2	Y = 3	Y = 4
Constant	2.570	21.251	–	–	–	–
Sociodemographic characteristics						
Physical or mental health condition (1 if yes, 0 if no)	−0.266	−3.511	0.070	−0.035	−0.023	−0.012
Standard deviation of parameter density function	*0.364*	*1.807*	–	–	–	–
Household income (1 if less than £14,900 per year, 0 otherwise)	−0.433	−5.948	0.118	−0.064	−0.036	−0.018
Age (1 if under 25, 0 otherwise)	−0.251	−2.152	0.066	−0.033	−0.022	−0.012
Standard deviation of parameter density function	*0.523*	*2.210*	–	–	–	–
Age (1 if 25 to 34, 0 otherwise)	−0.122	−1.977	0.031	−0.014	−0.011	−0.007
Energy payment method (1 if prepayment meter, 0 if otherwise)	−0.334	−5.192	0.089	−0.045	−0.029	−0.015
Behavioural & perceptual characteristics						
Social connection (1 if relied on neighbours for food in the last year, 0 otherwise)	−0.220	−2.455	0.058	−0.028	−0.019	−0.011
Social connection (1 if relied on a community/faith group for food in the last year, 0 otherwise)	−0.200	−2.156	0.053	−0.025	−0.018	−0.010
Standard deviation of parameter density function	*0.451*	*2.168*	–	–	–	–
Social connection (1 if relied on family and friends for food in the last year, 0 otherwise)	−0.272	−4.047	0.072	−0.035	−0.024	−0.013
Social reliance (1 if relies on family and friends to a large extent for help, 0 otherwise)	0.468	7.545	−0.124	0.055	0.045	0.024
Foodbank use (1 if used in the last 12 months, 0 otherwise)	−0.520	−5.489	0.142	−0.082	−0.041	−0.019
Food purchasing habits (1 if never avoids raw food, 0 otherwise)	0.895	14.665	−0.268	0.163	0.074	0.032
Financial anxiety (1 if worries about housing payments almost every month, 0 otherwise)	−0.923	−11.025	0.265	−0.178	−0.061	−0.026
Life satisfaction (1 if high/very high satisfaction, 0 otherwise)	0.267	4.499	−0.070	0.031	0.025	0.014
Threshold 1	2.010	20.218	–	–	–	–
Threshold 2	2.802	25.232	–	–	–	–
Observations	2170		–	–	–	–
Log-likelihood with constant only (LLc)	−2430		–	–	–	–
Log-likelihood at convergence (LLθ)	−1805		–	–	–	–
$AIC_{CONSTANT}$	4866		–	–	–	–
AIC at convergence (AIC_{RPOP})	3648		–	–	–	–

variable.

4.3. Sociodemographic factors affecting energy security

Model estimation results show that five sociodemographic variables significantly influenced energy security. The presence of a prepayment meter within the home was treated as a sociodemographic variable, given that use is often not the choice of the occupant and rather a consequence of household characteristics or low income (Burlinson, et al., 2022). Respondents with prepayment meters were significantly more likely to have very low energy security than those who pay in other ways. Prepayment customers are often charged a higher rate per unit of fuel in comparison to households that pay monthly (Boardman, 2009; Burlinson et al., 2022), further increasing the likelihood these households are unable to afford energy. It is also well documented that prepayment customers are more likely to be fuel poor than non-prepayment households regardless of the fuel poverty metric used (Boardman, 2009).

Two age related variables were also influential, with both those aged <25 and 25–34 being significantly more likely to have very low energy security than control groups (all other ages). A likely explanation is that younger adults tend to have lower household income and are more likely to live in privately rented accommodation than older adults (UK Government, 2023b). The ONS (2021a) recently found that rented properties are several times more likely to suffer energy insecurity than those who own their home outright. Significant heterogeneity was discovered among "under 25" respondents, suggesting that although the overall effect of this variable is negative (increased likelihood of insecurity), in some cases the variable has the opposite effect (increasing energy security). This is likely due to the misclassification of under 25s as a homogeneous group, as there may be exogeneous factors (e.g., demographic or behavioural characteristics not recorded in the survey) creating subgroups of under 25 respondents. One such sub-group might be delineable via employment status. Among under 25 respondents, 40.8% were students; the rate of energy insecurity (very low or low) among this group was 29.9%, whereas 40.0% of non-student under 25s were energy insecure. The rate of energy insecurity among students aged under 25 is not considerably higher than the rate across the whole sample (28.2%), which suggests that heterogeneity within the under 25 variable could be a result of the student contingent. Past research has shown that young adults who grow up in affluent areas are more likely to participate in higher education (Richardson, et al., 2020), with some under 25 students potentially more able to rely on familial wealth and subsequently less likely to suffer energy insecurity than non-students.

Those with a physical or mental health condition were significantly more likely to experience very low energy security than those with no health conditions, further evidencing prior observation of this relationship (Boardman, 2009; Kearns et al., 2019; ONS, 2023). The heterogeneous effects of this variable may be due to conflation of physical and mental health conditions, with Kearns et al. (2019) previously finding that those with mental health problems are particularly prone to fuel poverty. Care must be taken to consider the potential for reverse causality between physical or mental health conditions and energy insecurity; for example, qualitative studies have evidenced that experiencing energy insecurity can exacerbate mental health problems (Hernandez, 2016). Respondents with a household income less than £14,900 per year were also significantly more likely to have very low energy security compared to other income groups. Given that the RECS energy scale contains several questions related to the ability to afford sufficient energy and spending trade-offs with other necessities, it is unsurprising that respondents from lower income households are significantly more likely to have very low energy security. The link between income and energy security is a consistent theme in the literature (Belaïd, 2018; Memmott et al., 2021; ONS, 2023).

4.4. Behavioural and perceptual factors associated with energy security

Four variables gauging aspects of respondents' social connection or social reliance were found to significantly affect energy security. All three social connection variables – those who relied on either neighbours; a community/faith group; or family and friends for food – significantly increased the probability of very low energy security in comparison to their respective control groups (i.e., those who did not rely on these groups for food). This finding illustrates the complex and intertwined reality of poverty, as those who struggle to afford food at certain times throughout the year are also more likely to experience energy insecurity. Although general deprivation is a potential confounding factor, this is controlled for with the inclusion of the household income variable, with which none of the social connection variables were highly correlated.

The impact of the social connection variables provides tentative evidence that some of the survey respondents may have made involuntary food and energy trade-offs during winter 2022. Previous studies (Beatty, et al., 2014; Bhattacharya et al., 2003) have indicated that a substantial proportion of those relying on others for food have done so to afford energy during cold-weather shocks. However, due to the formulation of our variable (gauging behaviour over 12 months) it remains uncertain whether seasonal trade-offs were being made by the respondents here. The final social variable ('social reliance') had the opposite effect, with respondents who "rely on family to a large extent for help" significantly more likely to have higher energy security than those who did not. A possible explanation is that those with ability to rely on family to a large extent may also be more likely to receive financial assistance from family members to pay for necessities. The subjective nature of this variable should be noted, as respondents were asked to state the level of general "help" they receive from family members, which was likely interpreted in different ways.

Two variables describing food acquisition also proved influential. Intuitively, those who had used a foodbank in the last 12 months were significantly more likely to have very low energy security. In contrast, respondents who never avoid raw food when shopping were significantly more likely to have high energy security. The foodbank variable follows a similar interpretation to social connection variables, with those who rely on others for food being more likely to have limited disposable income, leading to trade-offs between necessities (Beatty, et al., 2014). The "never avoids raw food" variable provides insight into the link between the energy costs associated with cooking food and energy insecurity. The contingent that "never avoids raw food" are also presumably not concerned about the energy cost associated with cooking it and are more likely to have high energy security in comparison to those who avoid raw food sometimes or often.

The final variables significantly associated with energy security are related to the wellbeing of respondents. The first measured financial anxiety, with those who worry about housing payments every month (i.e., most frequently compared to other outcomes) significantly more likely to have very low energy security than those who worry less frequently. This finding reiterates the commonly observed relationship between poor mental health and energy insecurity (Boardman, 2009; Kearns et al., 2019; ONS, 2023), with the variable likely serving as a proxy for financial vulnerability and precarity (Petrova, 2018). Similarly, those with high or very high perceived life satisfaction were significantly more likely to have high energy security than those with middling (neutral) or low life satisfaction. Both of these findings concur with recent research (ONS, 2023) showing that those suffering depressive symptoms are significantly more likely to experience energy insecurity.

5. Conclusion and policy implications

In this study, we presented a critique of the LILEE fuel poverty indicator via a two-stage analysis of London to examine whether the metric accurately measures energy insecurity. Given LILEE's omission of EPC A–C rated households, we hypothesised that current fuel poverty statistics significantly underestimated the true rate of fuel poverty and/or both energy insecurity across England. To test this, we analysed LILEE in London, the UK's largest city, with well-known pockets of extreme wealth and destitution. Stage 1 included a spatial analysis of fuel poverty (see Section 3: Stage 1), illustrating that a number of highly deprived London neighbourhoods may have erroneously low fuel poverty rates under the LILEE metric. This discrepancy is likely due to the LILEE metric's exclusion of EPC A–C rated households, leading to an underestimation of energy insecurity or fuel poverty among "efficient households". To assess this, the number of EPC A–C rated vulnerable households omitted from LILEE fuel poverty statistics in London was estimated. We found that 4.4% (around 171,091 households) of the city's homes fitted this description; that is, those with an EPC rating of A–C, socially or privately rented tenure status, and an HRP who is either unemployed or economically inactive.

This finding highlights the obvious oversight of the LILEE metric's indiscriminate and universal omission of EPC A–C rated households from fuel poverty statistics. In addition, only unemployed and economically inactive HRP households could be considered in this study due to a lack of income data for other employment statuses, hence, the total number of omitted households is likely to be greater. To address some of the unanswered questions in the first analysis, Stage 2 considered directly surveyed respondents in London, UK. Exploratory analysis of the survey data showed that ~27% of respondents in EPC A–C rated households were energy insecure – a figure only marginally less than among EPC D–G rated properties (~29%). The considerable proportion of EPC A–C rated properties experiencing energy insecurity indicates that improving building efficiency is not synonymous with eradicating energy insecurity or fuel poverty, as is tacitly implied by the LILEE metric's EPC-centric criteria.

This finding demonstrates that the LILEE approach of omitting properties on the basis of building efficiency is unjustifiable from an energy security perspective. Although we focus specifically on the approach to measuring fuel poverty in England, the finding that EPCs have little effect on energy security is likely transferable to other countries with similar housing profiles and environmental conditions, i.e., in general, our findings suggest that measures of building energy efficiency should not be used to make absolute categorisations of fuel poverty.

The total rate of energy insecurity across the London-based survey sample (~28%) was 145% higher than the London LILEE fuel poverty rate, highlighting the likelihood that LILEE is considerably underestimating the proportion of households struggling to afford energy. It is worth noting the recency of the survey data (collected winter 2022) and the particular context of the data collection window. UK residents suffered rapid rises in inflation and energy prices, dwarfing price increases of recent times, therefore it is likely that the rate of energy insecurity observed among the sample is likely to be higher than previous years. In the formal analysis of Stage 2, an RPOP model highlighted the sociodemographic variables that significantly increase the probability of very low energy security. These included: being under the age of 34; the presence of a physical or mental health problem; low household income; and a prepayment meter in the home. The remaining influential variables were mostly related to food insecurity, social connection and mental wellbeing, and provided further understanding of the food versus energy trade-offs that financially vulnerable households are likely to make, as well as the mental toll associated with energy insecurity.

The findings of both analyses in London highlight serious concerns with metrics such as LILEE and their approach to measuring fuel poverty: i) the spatial distribution of LILEE fuel poverty raises concerns regarding the level of deviation between LSOA rates of fuel poverty and deprivation; ii) levels of energy insecurity in the survey sample are considerably higher than LILEE fuel poverty rate in London, begging the question as to why the LILEE metric does not accurately capture all households that are unable to afford energy; and iii) energy security was not found to differ significantly between EPC A–C and EPC D–G rated properties, casting substantial doubt on the rationale underpinning the omission of EPC A–C rated households from fuel poverty statistics.

The way in which fuel poverty is measured has often been a politically contentious issue in England, as illustrated by the evolution of the fuel poverty metric – from the 10% indicator, to LIHC and most recently to LILEE. In *Sustainable Warmth*, the government acknowledge that the LILEE metric omits some "homes who are unable to afford sufficient energy to keep warm" (UK Government, 2021). This contradicts most definitions of fuel poverty and energy security across the world

(European Commission, 2021) and prompts questions over whether the primary function of LILEE is to accurately measure fuel poverty or to incentivise energy efficiency upgrades. Although upgrading the energy efficiency of the English housing stock constitutes a vital step towards decarbonising the housing sector and reducing the burden of energy bills to some extent, it is evidently not equivalent to eradicating fuel poverty. We show that energy insecurity is still experienced by a considerable proportion of EPC A–C households, indicating that the successor to the LILEE approach should focus on the vulnerabilities that perpetuate energy insecurity in efficient homes. In line with previous research (Middlemiss, 2017), we also recommend that future metrics have a mechanism to account for fluctuations in energy costs.

In terms of policy implications, we demonstrate that metrics like LILEE do not consistently identify households that are unable to afford energy. Model estimation results unveil the sociodemographic characteristics associated with energy insecurity during winter 2022 in London, which might profitably be used to guide criteria for future fuel poverty or energy security metrics. One possible remedial amendment to the LILEE metric would be to apply the energy security criteria (e.g., the RECS scale) to those in EPC A–C rated properties (who are currently considered not fuel poor by default), which would provide extra protection to the demographics identified as being more at risk of energy insecurity, whilst retaining the potentially beneficial effects of LILEE as an incentive to upgrade the housing stock. We found no statistical evidence to suggest that the energy insecurity rates experienced by EPC A–C and D–G rated households varied significantly. This finding suggests that the inclusion of EPC ratings as an essential fuel poverty criterion is unwarranted. Future fuel poverty metrics might also benefit from non-binary categorisations; the complex nature of fuel poverty is not wholly recognised by simple designations of “fuel poor” and “not fuel poor”. The four-level scale used within our survey, for example, usefully delineates between those who are energy secure and insecure, whilst also expressing further intermediate degrees of energy security. There is no reason why this scale could not be further disaggregated to express a higher resolution understanding of fuel poverty or energy security, in a manner similar to the EPC banding system. This would undoubtedly benefit local and national fuel poverty strategies.

Several limitations of this study can be noted. Firstly, a lack of granular household income for the Stage 1 analysis hindered the accuracy of the estimation of vulnerable households omitted from the LILEE metric, such that some low-income households were unable to be accounted for. Secondly, London-related bias must be considered, with sociodemographic strata able to vary considerably between UK cities. Nonetheless, the application of the LILEE indicator and energy prices are practically consistent across English regions, therefore results are expected to be transferrable. The representativeness of survey respondents, i.e., those who chose to use a community sharing app (OLIO), was a further potential limitation considered. The IMD deciles of respondents’ home area, however, proved highly representative of the wider London population (as per Fig. 1). A final notable limitation concerns the modelling framework. To mitigate against multicollinear effects in the modelling framework, independent variables with pairwise correlation coefficients greater than 0.3 were omitted from the final model. For example, a variable gauging whether respondents were currently students was positively correlated with the ‘age (under 25)’ variable, with only the under 25 variable being retained based on improved model AIC with this variable in comparison to the student variable. Analyses able to consider variable interactions might prove a valuable extension.

Further research opportunities highlighted in this study include: i) further investigation of the LSOA outliers discovered in the exploratory spatial analysis, which could provide greater understanding of the geographical features leading to LILEE fuel poverty as well as the geographical clustering of fuel poor households, as observed in previous studies (Pérez-Fargallo, et al., 2020; Robinson et al., 2018). In a similar vein, it would be informative to conduct further geographical exploration of the distribution of LILEE fuel poverty and IMD in other English cities to allow intercity comparisons. ii) The allowance for random parameters in the modelling framework led to the discovery of significantly heterogeneous levels of energy security among under 25s and those with a physical or mental health condition. Further investigation as to the cause of this heterogeneity would be productive; for example, we hypothesize that there may be different types of health problems generating different experiences of energy insecurity. iii) The central contribution of this paper is a conceptual framework for an amended or new fuel poverty metric. Future studies may explore the design of an alternative metric in greater detail and conduct validation experiments; for example, by utilising the sociodemographic risk factors identified in this study, alternative metrics may be trialled to more accurately estimate the rate of households that experience energy insecurity.

The central contribution of this paper is not only a critique of metrics such as LILEE, but also a conceptual framework of significant co-varying sociodemographic, behavioural and contextual variables, able to underpin the criteria for an amended or new fuel poverty metric that more accurately reflects lived experience of energy insecurity. The LILLE metric prioritises building characteristics over the energy security of occupants and is arguably a decarbonisation incentive rather than a fuel poverty metric. The metric’s misrepresentation of fuel poverty in England risks counterproductive results, with fuel poverty policies based on LILEE statistics seemingly at risk of placing unjust focus on EPC upgrades, rather than directly assisting households that are most in need. Until the LILEE metric is amended to reflect on-the-ground fuel poverty experiences, mitigating policies will be based on misleading information and vulnerable households will continue to be overlooked.

CRediT authorship contribution statement

Torran Semple: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft. **Lucelia Rodrigues:** Conceptualization, Supervision, Writing – review & editing. **John Harvey:** Conceptualization, Data curation, Writing – review & editing. **Grazziela Figueredo:** Conceptualization, Supervision, Writing – review & editing. **Georgiana Nica-Avram:** Conceptualization, Data curation, Writing – review & editing. **Mark Gillott:** Conceptualization, Supervision. **Gregor Milligan:** Data curation, Writing – review & editing. **James Goulding:** Conceptualization, Data curation, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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Appendix

"… The following questions are about challenges your household may have had paying energy bills or maintaining heating in your home in the past 12 months …"

Table A1
RECS questions contributing to household energy security score (Harker Steele and Bergstrom, 2021)

Question No.	Question text	Response scale
1	How frequently did your household reduce or forego expenses for basic household necessities, such as medicine or food, in order to pay an energy bill?	i. Never ii. 1 or 2 months iii. Some months but not every month iv. Almost every month
2	In the past year, how frequently did your household keep your home at a cold temperature that you felt was unsafe or unhealthy?	i. Never ii. 1 or 2 months iii. Some months but not every month iv. Almost every month
3	In the past year, how frequently did your household run behind on payments for energy bills, or receive a notice to disconnect?	i. Never ii. 1 or 2 months iii. Some months but not every month iv. Almost every month
4	In the last year, was there ever a time your household was unable to use your main source of heat because you could not afford to pay for gas or electricity?	i. Yes ii. No
5	About how many days over the past year has your household gone without heat because you could not afford to pay for gas or electricity?	i. No. Of days
6	In the last year, was there ever a time your household was unable to use your main source of heat because the equipment was broken, and you couldn't afford to pay to repair or replace the equipment?	i. Yes ii. No
7	In the past year, did anyone in your household need medical attention because your home was too cold?	i. Yes ii. No

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