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Measurement matters: Non-random missing data and indicator divergence in energy poverty

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Abstract

Energy poverty is measured using a range of expenditure-based and experience-based indicators that differ in their data requirements and the dimensions of hardship they capture. We examined (i) the extent and social patterning of financial data missingness, (ii) how closely different indicators of energy poverty identified the same households, and (iii) the validity of a composite experience-based severity score. In a nationally representative online survey of 1,011 adults in Ireland, participants reported household income, energy expenditure, and six experience-based indicators. Expenditure-based energy poverty was defined as energy expenditure exceeding 10% of disposable household income. Experience-based energy poverty was defined primarily by inability to afford adequate warmth (IAAW), with five other experience-based indicators combined into a composite severity measure. More than four in ten participants lacked a point estimate for income, energy expenditure, or both, precluding calculation of the 10% indicator for these households. This missingness was not random. Lower educational attainment, lower occupational social grade, and unemployment were significantly associated with being unsure or unwilling to report income or expenditure. Among those with full data, agreement between the 10% and IAAW indicators was weak. The 10% measure identified twice as many households as the IAAW indicator and the households it identified were less socioeconomically disadvantaged. The composite severity score was sensitive to socioeconomic disadvantage and explained more variation in financial difficulty than IAAW alone. Financial non-response may systematically bias expenditure-based measures of energy poverty by underrepresenting disadvantaged households. Complementary indicators may be preferable for monitoring or policy targeting, rather than reliance on any single measure.

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JEL codes (optional):

Keywords: energy poverty; measurement; missing data; financial non-response; socioeconomic inequality

1 Introduction

As energy prices continue to rise, more households are at risk of energy poverty, typically defined as the inability to maintain adequate indoor heating or to afford necessary energy services (Bouzarovski & Petrova, 2015). Accurately measuring energy poverty is considered a matter of justice (Walker & Day, 2012). Indicators determine whose vulnerability is recognised, how energy resources and income are distributed, and how policy decisions are made. Yet there is no single agreed approach to measuring energy poverty across the European Union (EU) (European Commission, 2026).

Measures of energy poverty broadly fall into two categories: expenditure-based measures, which use household income and energy spending, and experience-based measures, which use reported experiences of energy deprivation (Wojewódzka-Wiewiórska et al., 2024). EU countries use both, although the specific indicators vary. The 10% expenditure threshold, a widely used expenditure-based indicator, classifies households as energy poor if they spend more than 10% of their income on energy. The EU Statistics on Income and Living Conditions (EU-SILC) indicator of inability to afford adequate warmth (IAAW) is an experience-based measure (European Commission, 2026).

Relatively few studies have directly compared expenditure- and experience-based measures within the same population. Existing evidence suggests that they differ in both how many and in which households they identify (Burlinson et al., 2021; Kinnear & Julienne, 2025; Maier & Dreoni, 2026; Menyhért, 2024; Ntaintasis et al., 2019; Waddams Price et al., 2012). Experience-based indicators tend to correlate with each other, but only weakly with expenditure-based indicators (Tovar Reaños et al., 2024).

Each approach has strengths and limitations (Thomson et al., 2017). Experience-based measures capture lived experience, but they are difficult to translate into clear thresholds for policy targeting and may be influenced by differences in expectations, perceptions, and reporting. Expenditure-based measures offer a relatively simple financial proxy that is often described as objective, and are therefore widely used in policy and research. This paper questions that description. Expenditure-based measures rest on two quantities, household income and energy expenditure, that are difficult to measure accurately, and the resulting errors and gaps may be socially patterned rather than random. If so, the “objective” indicator may systematically misrecognise particular groups.

1.1 Missing and Mismeasured Financial Data

Ideally, income and energy expenditure would be taken from administrative and energy supplier data. In practice, socially disadvantaged households may have variable or disparate income sources, and many households use several suppliers and fuels. For example, a household may combine an oil-fuelled boiler with wood-burning stove alongside electric heaters in certain rooms. Self-report is therefore needed to assess the household's total energy expenditure, but self-reporting such expenditure is demanding. Energy costs vary seasonally, span multiple fuels, and follow different billing arrangements Expenditure surveys show measurement error linked to recall, survey design, and the type of expenditure (Bee et al., 2012; Crossley & Winter, 2014) and misreporting is not random (Fricker et al., 2015; Li & Wang, 2024).

Income is similarly difficult to report. Respondents may struggle to recall it or be reluctant to disclose it. Income reporting errors are also unlikely to be random: reporting difficulties are greater at the lower and upper ends of the income distribution (Ayala et al., 2022). Respondents who withhold or are unable to report their income information may differ from those who do in important socioeconomic characteristics (Jabkowski & Piekut, 2024; Kim et al., 2007).

Survey design can reduce some of this burden. Disaggregated questions tailored to respondents' circumstances can improve reporting accuracy (Comerford et al., 2009; Hurd & Rohwedder, 2012; Shier, Timmons & Lunn, 2026). Such design is not a guaranteed fix, however, so whether a carefully designed instrument eliminates socially patterned missingness is an empirical question. Missing financial data poses obvious challenges for expenditure-based indicators like the 10% threshold, but households may still be classified as energy poor by experience-based indicators; relying on expenditure-based analyses may therefore change who is recognised as energy poor.

1.2 Construct Validity

Missing data are not the only limitation of the 10% indicator. Because it is a ratio, it can classify higher-income households with high consumption as energy poor (Kez et al., 2024) . It can also miss households that under-consume because they cannot afford to heat their homes. A household may report being able to afford heating, but only because it cuts spending on other essentials. Such coping strategies can produce hidden energy poverty, whereby hardship is not apparent from measures focused on thermal comfort or ability to afford energy alone (Cong et al., 2022). Qualitative research reveals aspects of energy deprivation that conventional indices miss, including compensatory behaviours, such as restricting energy use or foregoing other

essential expenditures, as well as affective experiences, like worry (Longhurst & Hargreaves, 2019; Middlemiss, 2022).

Because no single indicator appears to fully capture energy poverty, it is increasingly treated as dimensional (Estévez & Reaños, 2026; Kinnear & Julienne, 2025; Maier & Dreoni, 2026). Researchers have responded by combining multiple indicators into composite measures (Nussbaumer et al., 2012; Siksnelyte-Butkiene et al., 2021) and more recently by using factor-analytic approaches to examine the underlying structure of energy poverty and build data-driven composites (Taltavull de La Paz et al., 2022; Tovar Reaños et al., 2025). However, these approaches have primarily incorporated indicators that depend on the accurate reporting of financial information, including household income and expenditure, and so inherit the reporting error and missing data outlined above. Composites built only from experience-based indicators avoid this dependence but bring their own concerns. These include preferences and cultural differences in reporting, and the possibility that experiences such as worry and thermal discomfort reflect distinct constructs rather than a single dimension. Whether such a composite is coherent and adds value is therefore a further empirical question.

1.3 Country Context

We use data from a nationally representative survey of over 1,000 adults in Ireland. Ireland has one of the highest household electricity prices in Europe and experienced substantial energy inflation after Russia's invasion of Ukraine in 2022 (Euronews, 2026). Compared to the rest of Europe, Ireland's housing profile in Ireland is characterised by more recently built homes (McGowan & Sicari, 2025) but with greater reliance on oil and solid, carbon-based fuels for central heating (SEAI, 2018). Ireland's official expenditure-based indicator identifies households that spend more than 10% of their net income on energy as energy poor, though the government's Energy Poverty Action Plan calls for more research on how to measure energy poverty (Department of Climate, Energy and the Environment, 2021; Department of the Environment Climate and Communications, 2022).

1.4 Present Study

Expenditure-based indicators depend on financial data that are error-prone and may be missing in socially patterned ways, so the households they recognise as energy poor may not be the households experiencing energy deprivation. This study examines how serious that problem is, how it affects who is identified, and whether a composite that avoids financial reporting is a valid alternative. Accordingly, we address three research questions:

1. Is missingness in self-reported income and energy expenditure socially patterned across socioeconomic groups, even when the survey uses disaggregated questions informed by behavioural economics?

2. To what extent do the 10% indicator and the experience-based IAAW indicator identify the same households? How do households identified by each measure differ in their financial and socioeconomic circumstances?

3. Do experience-based indicators form a coherent energy poverty severity score, and does a factor-derived score add information beyond a simple additive score?

This study forms part of a broader research project examining the behavioural, environmental, and health dimensions of energy poverty in Ireland.

2. METHODS

2.1 Participants

Our sample was recruited through a market research and polling agency[a] using quota by age, gender and region. Of 1,342 people who started the survey, 206 (15.4%) exited before the final page and a further 125 (9.3%) were rejected after failing a comprehension tutorial for a household diary interface that forms part of a separate study. The final sample was 1,011 participants (75.3% of those who started). Participants were paid €3 for taking part and entered into a raffle for a €100 digital Mastercard voucher.

Data collection took place in winter, when heating demand is highest. A pilot wave of 100 participants was recruited during the first week of December 2025 and the remaining participants completed the survey between February and March 2026. The average temperature in County Dublin over the study period was 6.9 °C. The escalation of the Iran-United States conflict began on 28 February 2026 in the final days of data collection. Most responses (791, 78.2%) were collected before this date and before the effects on energy prices became apparent. Consequently, the post-conflict subsample was too small for comparison. The data therefore reflect household experiences before any downstream effects of the conflict on energy markets.

Table 1 shows participants' sociodemographic characteristics. The sample was broadly nationally representative (CSO, 2022), though with slightly more aged 18-39 years (40.1% vs. 36.9% nationally) and slightly more living in urban areas (68.4% vs. 63.6% nationally). Results are not sensitive to these discrepancies, as all models include controls for these socio-demographic characteristics.

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Table 1. Socio-demographics (numbers and proportions) of the total sample (N=1011) and nationally representative proportions, as estimated by the Central Statistics Office (2022).

		Total sample (N=1011)	Ireland census data
Gender	Male	472 (46.7)	(49.0)
	Female	539 (53.3)	(51.0)
Age	18 to 39 years	398 (39.4)	(36.8)
	40 to 59 years	353 (34.9)	(36.5)
	60+ years	260 (25.7)	(26.7)
Education*	Below undergraduate degree	610 (60.3)	(63.9)
	Undergraduate degree or above	401 (39.7)	(36.1)
Urbanicity	Urban	692 (68.4)	(63.6)
	Rural	319 (31.6)	(36.4)
Region	Leinster (incl. Dublin)	569 (56.3)	(55.7)
	Munster	275 (27.2)	(26.6)
	Connacht/Ulster	167 (16.5)	(17.6)

*The population education estimate is calculated using the Census data that most closely matches the education question used in our survey. “Degree or above” includes degree, masters or doctorate. The CSO estimate for educational attainment excludes those who did not report their attainment (i.e., who reported their status as ‘other’, who did not state a level or who reported being in education without stating the level of education attained).

2.2 Procedure

Ethical approval was obtained [*redacted for anonymity*]. All procedures were conducted in accordance with relevant ethical guidelines and regulations, and all participants provided informed consent prior to participation. Methods and analyses were preregistered on the Open Science Framework but are now available on ResearchBox (researchbox.org/10074?PEER_REVIEW_passcode=RLEVLF).

Participants completed an online survey hosted on Gorilla Experiment Builder, which was compatible with laptop, tablet, and mobile devices (Anwyl-Irvine et al., 2020). The survey link was distributed to members of the national market research panel through a recruitment agency.

At the start of the survey, participants provided demographic information required for quota screening and then reviewed the study information sheet, provided consent, and completed measures assessing household finances, energy expenditure, experience-based energy poverty, and sociodemographic characteristics.

2.3 Measures

Household financial circumstances

We measured income in detail to maximise the accuracy of self-reported financial information. The survey provided definitions of household (individuals sharing income to meet household expenses) and disposable household income (total take-home income after tax from all sources, including employment, pensions, social welfare, and other income), alongside examples of who should and should not be included in the household. Respondents selected the reporting period that was easiest for them (weekly, monthly, or annual income), identified an income band (i.e., the range within which their income fell), and then provided a more precise estimate using a slider constrained to the selected range. This two-stage approach reduced respondent burden while encouraging more accurate reporting. Participants were encouraged not to guess and could select “Unsure” or “Prefer not to say” or skip questions. We refer to the slider response as the point estimate.

To complement the income measure, two additional items measured financial circumstances: 1) Financial difficulty was assessed by asking how easy or difficult it was for their household to make ends meet, and 2) Subjective socioeconomic status

was measured by asking participants to compare themselves with others in society in terms of job, education, income, and housing.

Household energy expenditure

We measured energy expenditure separately for each energy source used in the home (e.g., electricity, mains gas, heating oil, biomass, or solid fuels), rather than as a single total, to improve recall (Comerford et al., 2009). Questions matched respondents' payment arrangements. For billed fuels (e.g., electricity and mains gas), respondents first gave their billing frequency (monthly, bi-monthly, or prepayment meter) before reporting expenditure. They also indicated whether the most recent bill had been paid in full; if not, we recorded both the amount paid and the total bill. For delivered fuels (e.g., heating oil, biomass, and other solid fuels), respondents reported the frequency of fuel top-ups and the cost of their most recent purchase. As with income, each expenditure measure used the two-stage response format in which participants first selected an expenditure band (i.e., the range within which their energy expenditure fell) before providing a more precise estimate using a bounded slider within that range. Participants were again encouraged not to guess and could select "Unsure" or skip.

Experience-based energy poverty

We assessed experience-based energy poverty with six pre-registered indicators:

1. the inability to afford adequate warmth (IAAW) measure from the EU-SILC survey
2. Going without heating due to lack of money (also from the EU-SILC survey)
3. Perceived thermal comfort (how warm or cold the home feels)
4. Difficulty paying household energy bills
5. Reducing spending on essentials to meet energy costs
6. Worry about the cost of household energy

Together, these indicators capture perceptual, behavioural, and affective dimensions of energy poverty. We pre-registered an eight-indicator experience-based measure but used a harmonised six-indicator version that excluded two behavioural checklist

items.[b] These items differed in format and length from the other indicators, which were binary or numeric-scale items, and were therefore excluded to improve consistency in the measurement format and scope of the composite. Excluding them had negligible impact on the composite score (r (1009) = 0.99, $p < 0.001$).

Sociodemographic and dwelling characteristics

Sociodemographic measures included gender (male, female), age group (18-39, 40-59, ≥60 years), educational attainment (below undergraduate degree, undergraduate degree or higher), region (Leinster, Munster, Connacht/Ulster), employment status (employed, unemployed/economically inactive), marital status (partnered, single/widowed/divorced/separated), housing tenure (renting, homeowner/living rent free), urbanicity (urban, rural) and occupational social grade based on the occupation of the household's chief income earner (higher, lower). Dwelling characteristics included home age (built before 2008, built in 2008 and later), and home type (Detached house, apartment/flat, terraced house, semi-detached/end of terrace house, other).

2.4 Data preparation

Expenditure-based energy poverty index

The preregistration specified multiple expenditure-based indices (Estévez & Reaños, 2026). For the present analyses, we use the 10% energy expenditure indicator for two reasons. It is the official national definition of energy poverty in Ireland (Department of Climate, Energy and the Environment, 2021). It also does not require equivalised household income, improving comparability with official statistics and avoiding additional assumptions about equivalisation (Barrett et al., 2022).

[b] The questions were: (1) In the past month, have you done any of the following only because you were worried about the cost of electricity or heating? - Kept heating off, even though you wanted it on - Kept the heating low, even though you wanted it warmer - Kept off lights, even though you wanted them on - Kept the heating down or off in some rooms, even though didn't want to - Only heated and used one room at a time - Kept windows closed - Kept vents closed - Used less hot water than you wanted - Had fewer hot meals or hot drinks than you'd like - Left the home - None of the above
And (2) In the past month, have you done any of the following to stay warm while you were in your home? - Worn extra clothes including outdoor clothes - Worn thermal underwear - Used blankets or quilts - Stayed in one room with others - Used hot water bottles - Went to bed early to stay warm - Kept windows closed - Kept vents closed - Had hot drinks just to warm up - Closed curtains during the day - Blocked drafts with towels or door stoppers - None of the above

We converted reported point estimates for disposable income to a monthly estimate, with weekly income multiplied by 52 and divided by 12, and annual income divided by 12. We calculated monthly household energy expenditure by summing point estimates for expenditure across all reported energy sources, after converting each estimate to a monthly equivalent using the reported payment frequency.

Households were classified as experiencing expenditure-based energy poverty when monthly household energy expenditure exceeded 10% of monthly disposable household income. This binary indicator was coded as 1 (in energy poverty) and 0 (not in energy poverty).

Experience-based energy poverty severity index

Our primary single-item indicator of energy poverty was the inability to afford adequate warmth (IAAW), which was coded as a binary measure (1 = in energy poverty, 0 = not in energy poverty). We chose it because it is collected across EU countries through the SILC and has been used to report trends in energy poverty in Ireland over time (Barrett et al., 2022).

We also calculated an experience-based energy poverty severity score by combining the six indicators outlined above. We recoded these indicators so that higher values represented greater energy hardship, rescaled each to a 0 to 1 range, and summed them to create a continuous score from 0 to 6. 46 participants selected “Not applicable” for bill difficulty, which was treated as 0 for the sum score calculation. Higher scores indicate greater severity of energy poverty experiences. We weighted indicators equally because there was no strong theoretical or empirical basis for assigning greater importance to any individual domain.

2.5 Statistical analysis

All analyses were conducted in R (version 2026.01.1, Build 403). The analysis plan was preregistered on the Open Science Framework but are now available on Research Box (researchbox.org/10074?PEER_REVIEW_passcode=RLEVLF). Analyses were conducted in accordance with the preregistered plan, with deviations and additional exploratory analyses reported below.

Missing financial data and reporting behaviour

We examined patterns of missingness and non-response for household income and energy expenditure data descriptively. Logistic regression models examined whether

employment status, educational attainment, and occupational social grade were associated with non-response to household income and/or energy expenditure point estimates. Models adjusted for age group, gender, urbanicity, region, home age and home type.

Comparison of expenditure-based and experience-based energy poverty indicators

Among participants with complete data, we assessed agreement between the expenditure-based 10% index and the experience-based IAAW indicator using cross-tabulations, Cohen's kappa (κ), and McNemar's test. We classified households into four categories:

1. Not energy poor by either measure;
2. Experience-based energy poverty only;
3. Expenditure-based energy poverty only;
4. Energy poor according to both measures.

The preregistration proposed multinomial regression models of sociodemographic correlates, but we instead used the four-category classification descriptively, and fit separate logistic regression models examining the association between each indicator and two markers of socioeconomic disadvantage: self-reported financial difficulty and low subjective economic status. This approach enabled direct comparison of the extent to which each indicator identified households experiencing socioeconomic disadvantage. Financial difficulty and subjective socioeconomic status were dichotomised as low (score ≤ 3) versus high (score ≥ 4). Models were adjusted for age, gender, urbanicity, and region, home age and home type.

Construct validity of the experience-based severity index

Linear regression models tested associations between energy poverty severity and theoretically relevant sociodemographic characteristics, including employment status, educational attainment, occupational social grade, financial difficulty, and socioeconomic status. Models adjusted for age, gender, urbanicity, region, home age and home type. Additional exploratory analyses examined associations with marital status and housing tenure, which were not specified in the preregistration.

A further exploratory analysis compared the explanatory value of the severity index with the single IAAW indicator. Separate logistic regression models with financial difficulty

as the dependent variable were estimated for each measure, adjusting for age, gender, urbanicity, region, home age and home type. Model fit was compared using McFadden and Nagelkerke pseudo-R^2 values and Akaike Information Criterion (AIC).

Factor analysis of experience-based energy poverty indicators

We used exploratory factor analysis to examine whether the six experience-based indicators reflected a common underlying energy poverty construct. Given the mixture of binary, ordinal, and continuous indicators, a heterogeneous correlation matrix was estimated prior to factor analysis.

We assessed the number of factors to retain using eigenvalues, Kaiser's criterion, and parallel analysis. We fitted maximum likelihood factor models using the fa function from the *psych* package in R, using oblique rotation because we expected underlying dimensions to correlate. We calculated factor scores as the weighted sum of each participants' response to that indicator (factor score = sum(indicator response*weight)) and compared them with the additive composite severity score using Pearson correlation.

3. RESULTS

3.1 Missing financial data (RQ1)

Figure 1A shows participants' preferred reporting period for household income. Most chose a period, with 286 participants (28.3%) selecting annual, 293 (29.0%) selecting monthly, and 320 (31.7%) selecting weekly. A further 71 participants (7.0%) were unsure, while 41 (4.1%) preferred not to report household income.

We compared participants who selected a reporting period (weekly, monthly, or yearly; n = 899) with those who responded "Unsure" or "Prefer not to say" (n = 112) (Figure 1B). Controlling for age, gender, urbanicity, region, home age and home type, three socioeconomic characteristics predicted non-response. Participants who were unemployed or economically inactive were more likely to be unsure or unwilling to report their household income (B = 0.47, SE = 0.22, z = 2.12, p = .034). Adjusted predicted probabilities of missing income data were 14.2% for unemployed/other respondents and 9.3% for employment respondents, a difference of 4.9 percentage points.

Participants without an undergraduate degree were also more likely to be non-responders than those with an undergraduate degree or higher (B = 0.68, SE = 0.24, z = 2.80, p = .005). In adjusted predicted probabilities, missing income data was predicted for 13.9% of participants below undergraduate level compared with 6.7% of those with an undergraduate degree or higher, representing a 7.2 percentage-point difference.

Participants from households with lower occupational social grades were also more likely to be non-responders than those from higher social grades (B = 0.55, SE = 0.22, z = 2.47, p = .013). The adjusted predicted probability of missing income data was 13.6% among lower social grade households compared with 8.4% among higher social grade households, a difference of 5.2 percentage points.

Figure 1C shows the availability of point estimates. Of 1,011 participants, 629 (62.2%) reported a point estimate for household income, meaning that nearly four in ten (382, 37.8%) did not provide. A higher proportion (806, 79.7%) provided at least one point estimate for household energy expenditure, although one in five (205, 20.3%) participants did not. In total, 447 participants (44.2%) did not provide a point estimate data for household income, energy expenditure, or both.

To further examine potential non-response bias, we compared participants who provided both income and energy expenditure point estimates (n=564) with those

missing one or both measures (n=447) (Figure 1D). Consistent with the analysis of income reporting preferences, lower educational attainment was associated with missing point estimates (B = 0.59, SE = 0.14, z = 4.14, p < .001), a difference of 14.1%-points in predicted probability (49.8% vs 35.7%). Participants who were unemployed or economically inactive (B = 0.28, SE = 0.15, z = 1.86, p = .063) and those from lower occupational social grade households (B = 0.25, SE = 0.14, z = 1.85, p = .065) showed the same direction of association, though the differences were not significant at conventional thresholds.

Although missing financial data were systematically associated with the above socioeconomic characteristics, missing data were not significantly associated with either the experience-based IAAW energy poverty indicator (B = 0.03, SE = 0.19, z = 0.15, p = .884) or the composite experience-based energy poverty score (B = -0.10, SE = 0.07, z = -1.45, p = .148), after controlling for age, gender, urbanicity, region, home age and home type. This suggests that, although financial non-response was socially patterned, participants with missing financial data were no more or less likely to report experiences of energy poverty.

The above results relate to missing point estimates for financial data (i.e., exact values for monthly income and energy expenditure). We additionally conducted exploratory analyses on whether the 10% experience-based indicator could be estimated using income and energy expenditure bands (i.e., ranges within which income and energy expenditure fell). In total, 112 (11.1%) households were missing banded income data and 82 (8.1%) were missing banded energy expenditure data. Using the banded data, the 10% experience-based indicator could be estimated for 848 (83.9%) households. Of these, 232 (27.4%) were classified as being in energy poverty according to the 10% indicator. Among the 564 households with data available to calculate the 10% indicator using both point estimates and banded estimates, the two approaches showed high level of agree, κ = 0.80, z = 19.1, p < .001.

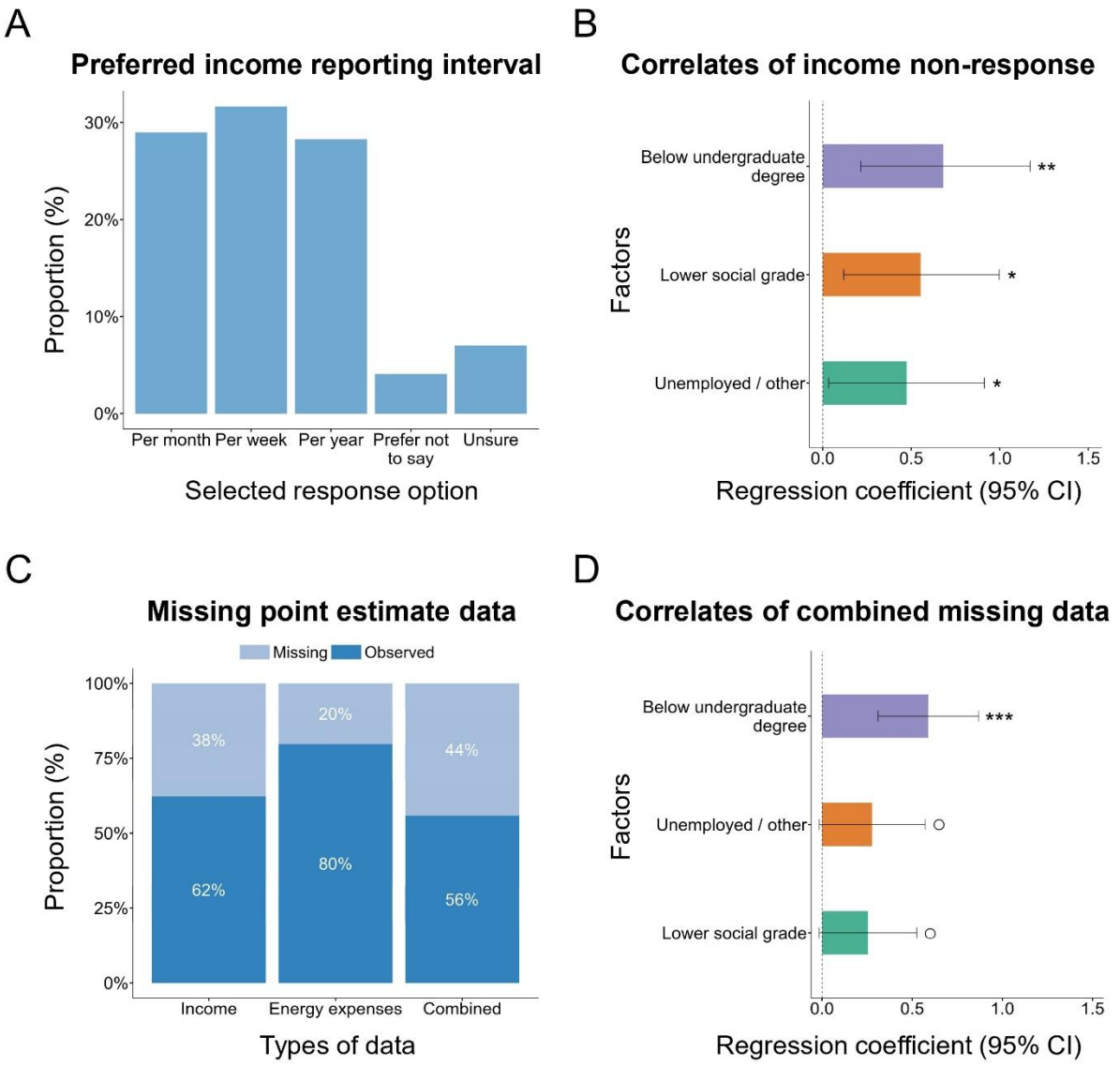


Figure 1. Missing income and energy expenditure data. (A) Preferred household income reporting period. **(B)** Correlates of non-response to household income reporting period. **(C)** Availability of household income and energy expenditure point estimates. **(D)** Correlates of missing household income and/or energy expenditure point estimates.

3.2 Agreement between 10% and IAAW indicators (RQ2)

We compared the 10% energy expenditure index with the experience-based IAAW indicator among participants with complete income and energy expenditure data (*n* = 564). The 10% indicator identified twice as many households as being in energy poverty

(143, 25.4%) compared with the experience-based IAAW indicator (72, 12.8%). The proportion of households identified as being in energy poverty using the IAAW indicator was similar among households with missing data for the 10% indicator (60, 13.4%; n = 447).

Overall, among households with complete income and expenditure data (*n* = 564), 380 participants (67.4%) were classified as not experiencing energy poverty by either measure, while 31 participants (5.5%) were classified as experiencing energy poverty by both measures (Table 2). However, disagreement between the two indicators was common. A further 112 participants (19.9%) were classified as experiencing expenditure-based energy poverty according to the 10% index but not according to the experience-based IAAW measure, whereas 41 participants (7.3%) were classified as experiencing energy poverty according to the IAAW measure but not the 10% index.

Table 2. Energy poverty classification for expenditure- and experience-based indicators

Energy poverty classification	**n**	**%**
Not energy poor by either measure	380	67.4
Energy poor by both measures	31	6.05.5
Energy poor by 10% expenditure-based indicator only	112	19.9
Energy poor by IAAW experience-based indicator only	41	7.3

Agreement between the two indicators was statistically significant but weak ($\kappa = 0.14$, $z = 3.70$, $p < .001$), indicating limited overlap beyond chance. McNemar's test indicated asymmetric disagreement ($\chi^2(1) = 32.03$, $p < .001$), with significantly more households classified as being in energy poverty by the 10% expenditure index than by the IAAW indicator.

The distribution of financial difficulty differed significantly across the four energy poverty classifications ($\chi^2(3) = 42.2$, $p < .001$). As shown in Table 3, nearly all households classified as experience-based energy poor only (95.1%) or by both measures (93.5%) reported high financial difficulty, compared with 77.7% of households identified by the 10% expenditure index alone and 58.7% of households classified as not energy poor by either measure.

Table 3. Financial difficulty across energy poverty classifications

Energy poverty classification	n	High financial difficulty, n (%)
Neither measure	380	223 (58.7%)
10% expenditure-based only	112	87 (77.7%)
IAAW experience-based only	41	39 (95.1%)
Both measures	31	29 (93.5%)

We fitted separate logistic regression models to examine the relationship between each indicator and financial difficulty, controlling for age, gender, urbanicity, and region. Both indicators were associated with higher levels of financial difficulty (10%: B = 0.87, SE = 0.25, z = 3.50, p < .001; IAAW: B = 1.97, SE = 0.36, z = 5.55, p < .001). The predicted probability of reporting high financial difficulty was 81% for households classified as energy poor for the 10% indicator and 62% among households not classified. For the IAAW indicator, the predicted probability of reporting high financial difficulty was 93% among households classified as energy poor, compared with 64% among those not. Therefore, the IAAW indicator shows a larger difference in predicted probability between energy-poor and non-energy-poor households (29 percentage points) than the 10% index (19 percentage points). Importantly, these estimates are based on different analytic samples: the model using the 10% index is restricted to households with available data for this measure ($n = 564$), whereas the IAAW model uses the full sample ($N = 1011$). The difference in magnitude of the associations may thus be driven by missingness in financial data. However, when the IAAW model is re-estimated using the same sample as the 10% index ($n = 564$), the IAAW indicator continues to show a larger difference in predicted probabilities: 92% versus 65% among households classified as

energy poor and not energy poor, respectively (difference = 27 percentage points; B = 1.71, SE = 0.49, z = 3.52, p < .001), compared with a 19-percentage-point difference for the 10% index. This suggests that the stronger association observed for the IAAW indicator is not driven solely by differences in the analytic samples.

Subjective socioeconomic status showed a similar pattern. Its differed significantly across energy poverty classifications ($\chi^2(3) = 61.82$, $p < .001$; Table 4). Among households classified as IAAW experience-based energy poor only, 32 of 41 participants (78.0%) reported lower socioeconomic status, compared with 56 of 112 (50.0%) classified as 10% expenditure-based energy poor only. The IAAW-only group (78.0%) and group classified by both measures (80.6%) were similar in magnitude, whereas households classified as not energy poor by either measure were least likely to report lower socioeconomic status (31.3%).

Table 4. Socioeconomic status across energy poverty classifications

Energy poverty classification	n	Lower socioeconomic status, n (%)
Neither measure	380	119 (31.3%)
10% expenditure-based only	112	56 (50.0%)
IAAW experience-based only	41	32 (78.0%)
Both measures	31	25 (80.6%)

Using separate logistic regression models, both indicators were associated with socioeconomic status, controlling for age, gender, urbanicity, region, home age and home type (10% index: B = -0.78, SE = 0.21, z = -3.76, p < .001; IAAW: B = -1.63, SE = 0.21, z = -7.64, p < .001). Adjusted predicted probabilities showed that the probability of being in the high socioeconomic-status category was 64% among those not classified as energy poor and 43% among those classified as energy poor on the 10% indicator, a difference of 21 percentage points, while the predicted probability of being in the high socioeconomic-status category decreased from 67% among those not classified as energy poor to 28% among those classified as energy poor on the IAAW indicator, a

difference of 39 percentage points. Although the IAAW estimates were based on the full sample (N = 1,011), the stronger association remained when the IAAW model was re-estimated using the reduced sample with available 10% indicator data (n = 564): B = -1.41, SE = 0.30, z = -4.69, p < .001. In this reduced sample, the predicted probability of high socioeconomic status was 69% among households not classified as energy poor and 35% among those classified as energy poor, a difference of 34 percentage points. Thus, the stronger association between the IAAW indicator and socioeconomic status was not driven solely by differences in the analytic samples.

3.3 Validity of the composite severity score (RQ3)

Figure 2A presents the correlation matrix for the six experience-based indicators (from r = 0.24 to r = 0.62) which suggests that they share underlying variance. The composite severity score (Figure 2B) ranges from 0 to 6 (median = 1.17).

Energy poverty severity was socially patterned across multiple indicators of socioeconomic disadvantage. Figure 2C presents the regression coefficients and 95% confidence intervals for each socioeconomic characteristic, controlling for age, gender, urbanicity, home age, home type, and region. Participants who were unemployed or economically inactive reported significantly higher energy poverty severity scores than those who were employed (B = 0.36, SE = 0.10, t = 3.49, p < .001). Those without an undergraduate degree reported higher energy poverty severity than those with higher educational attainment (B = 0.27, SE = 0.10, t = 2.81, p = .005), while those from lower occupational social grade households also reported greater energy poverty severity (B = 0.44, SE = 0.09, t = 4.68, p < .001).

Household circumstances were also associated with energy poverty severity. Participants who were single reported higher energy poverty severity than those who were married or cohabiting (B = 0.29, SE = 0.09, t = 3.14, p < .001), while those living in rented accommodation reported higher severity scores than homeowners and those living rent free (B = 0.89, SE = 0.12, t = 7.67, p < .001).

The strongest associations were observed for broader indicators of socioeconomic disadvantage. Participants reporting greater difficulty making ends meet had higher energy poverty severity scores than those reporting lower financial difficulty (B = 1.23, SE = 0.09, t = 13.63, p < .001). Likewise, participants reporting lower socioeconomic status had greater energy poverty severity than those reporting higher socioeconomic status (B = 1.07, SE = 0.09, t = 12.27, p < .001).

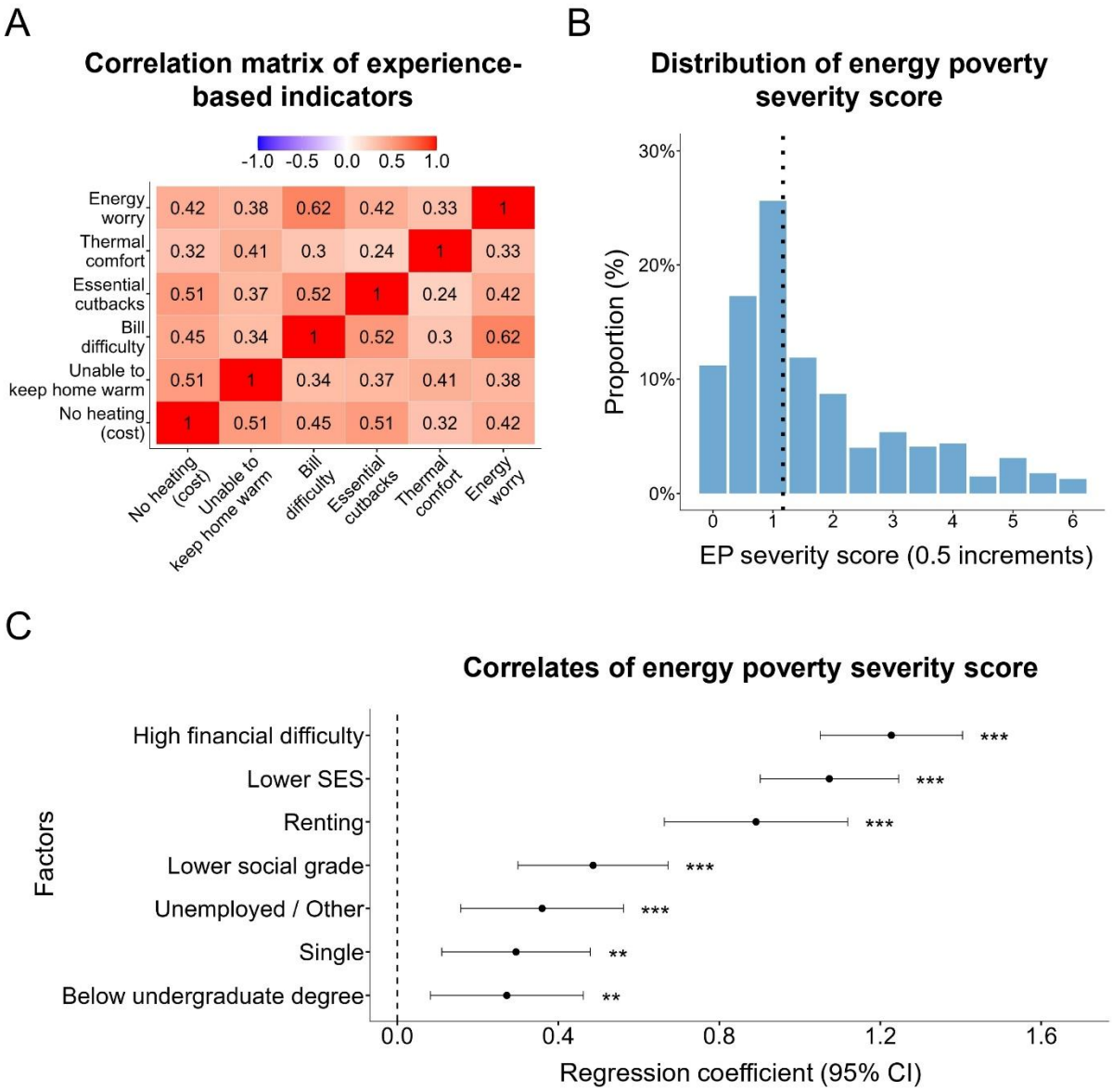


Figure 2. Construction and validation of the composite experience-based energy poverty severity score. (A) Correlations between experience-based energy poverty indicators. **(B)** Distribution of the composite energy poverty severity score. **(C)** Socioeconomic correlates of energy poverty severity.

To assess whether the severity index explained financial hardship better than the single IAAW indicator, we fitted two logistic regression models adjusting for age, gender, urbanicity, home age, home type and region. Both measures were significantly associated with financial difficulty (IAAW indicator: B = 1.97, SE = 0.36, z = 5.55, p <

.001; composite score: *B* = 1.66, *SE* = 0.15, *z* = 10.99, *p* < .001). However, model fit statistics indicated that the composite severity index provided greater explanatory value. The IAAW indicator model had a McFadden pseudo-R^2 of 0.08 and a Nagelkerke pseudo-R^2 of 0.14, whereas the composite severity model had a McFadden pseudo-R^2 of 0.22 and a Nagelkerke pseudo-R^2 of 0.33. The composite severity model also demonstrated improved fit (AIC = 1029.6) compared with the single indicator model (AIC = 1201.1), despite both models having equivalent complexity.

3.4 Factor structure (RQ3)

Examination of factor structure provided mixed evidence regarding dimensionality: although Kaiser's criterion suggested retention of a single factor (Figure 3A), parallel analysis indicated the possibility of three dimensions. Given the conceptual basis for treating energy poverty as a latent construct and the positive correlations between indicators (Figure 2A), a single-factor solution was estimated. Indicator loadings for the energy poverty factor are presented in Figure 3B, and regression-based factor scores for each participant were derived from this model, with 46 participants excluded from the factor score estimation as they selected “Not applicable” for bill difficulty.

The factor-derived score showed a very strong correlation with the simple additive severity score (Pearson's *r* = .99, 95% CI [0.99, 0.99], *p* < .001), demonstrating strong convergence between the two approaches (Figure 3C). The two scoring methods shared approximately 98% of their variance, indicating that the additive index closely approximates the factor-derived measure.

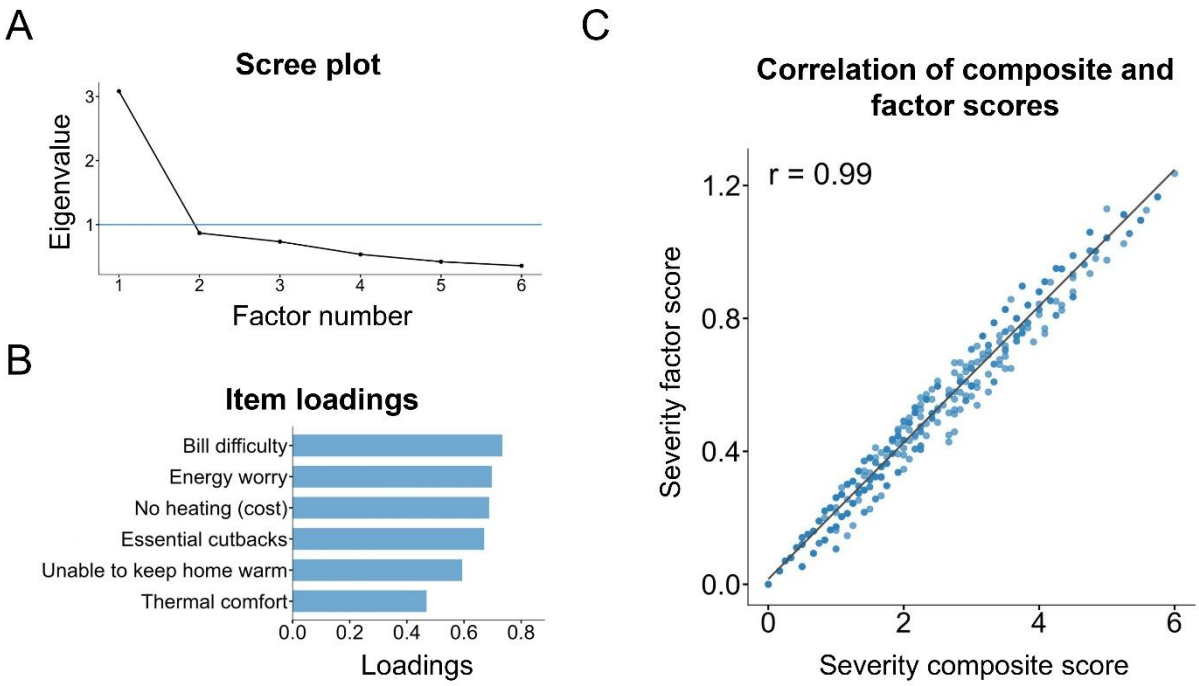


Figure 3. Factor structure and comparison of energy poverty scoring approaches. **(A)** Assessment of energy poverty factor dimensionality. **(B)** Indicator loadings for the energy poverty factor. **(C)** Convergence between additive and factor-derived energy poverty scores.

4. General Discussion

Energy poverty is a persistent challenge across Europe and the validity of the measures used to identify and quantify it is increasingly important. Expenditure-based energy poverty indicators are often favoured by policy, but depend on financial information that respondents often cannot or will not provide. This study investigated the implications of relying on expenditure indicators. Missing financial data were substantial and socially patterned (RQ1). The 10% and IAAW indicators identified largely different households, and the 10% indicator could be calculated for only just over half the sample (RQ2). A composite of six experience-based indicators, which does not need financial disclosure, was coherent and tracked socioeconomic disadvantage, but a factor-derived version added nothing to a simple sum (RQ3). Taken together, the findings support the argument that who is recognised as energy poor depends heavily on how energy poverty is measured.

4.1 Missing Financial Data

More than four in ten participants did not report income, energy expenditure, or both. This is striking because the survey was anonymous and designed to facilitate accurate reporting, including simplified questions, disaggregation of complex numerical information (e.g., Comerford et al., 2009). The degree of missingness for point estimates may be somewhat higher than in other income and expenditure surveys, because participants were instructed not to guess when they were uncertain, but remained at 1 in 6 households when only income and expenditure bands were analysed. The point estimate missingness further gives an indication of respondents' ability to give reliable figures in other surveys.

Importantly, missingness was not random. Participants with lower educational attainment were less likely to provide complete financial information, with similar patterns observed for occupational social grade and employment status. This pattern is consistent with previous research showing that self-reported income is socially patterned (Jabkowski & Piekut, 2024; Kim et al., 2007). While previous research has documented misreporting in general expenditure data (Fricker et al., 2015), our findings extend this literature by showing that missingness in household energy expenditure data is also systematically associated with socioeconomic characteristics. Our findings therefore suggest that missing financial data may reflect underlying social and socioeconomic differences, rather than simply limitations in survey design or respondent recall.

We found no significant association between missing financial data and either IAAW or the composite score. This is reassuring in one respect, since experience-based estimates were not obviously distorted by who answered the financial questions. Analyses that rely on complete data for self-reported income or energy expenditure may therefore disproportionately exclude disadvantaged households. Furthermore, while imputation methods can correct patterning that depends on observed characteristics, it will struggle to do so for unobserved characteristics and complex expenditure patterns. Experience-based indicators do not need financial disclosure and so present a helpful alternative with greater universality.

4.2 Agreement between indicators

The 10% indicator and IAAW identified overlapping but distinct groups, with the 10% indicator classifying twice as many households as energy poor. This divergence is consistent with previous research showing that expenditure-based indicators identify more households (Burlinson et al., 2021; Kinnear & Julienne, 2025; Waddams Price et al., 2012) and weak agreement in our study matches the low correlations between indicators observed elsewhere (Tovar Reaños et al., 2024).

The 10% expenditure index identified a larger group of households experiencing high energy expenditure relative to household income, including many households who reported lower financial hardship. In contrast, the experience-based IAAW indicator identified a smaller group of households who were more consistently characterised by higher financial difficulty and lower socioeconomic status. This may reflect a limitation of using an arbitrary 10% threshold as an indicator of energy poverty, as energy expenditure relative to income may not adequately capture households' underlying financial constraints or ability to heat their homes. For example, exceeding the 10% threshold may partially reflect high energy needs, such as those associated with larger homes, rather than financial hardship alone. Therefore, some households may spend more than 10% of their income on energy without experiencing major financial hardship, whereas households spending less may nonetheless face energy poverty because their limited income must be allocated to other essential expenses or because their homes are difficult to heat, leading them to adopt alternative coping strategies (Cong et al., 2022).

Expenditure-based measures alone may risk systematically overlooking some of the most financially vulnerable households, with direct implications for how national indicators are used, further perpetuating energy poverty as an issue of injustice (Walker & Day, 2012). Almost all of the 7% of households identified only by the IAAW indicator were overwhelmingly financially stretched. In addition, 447 households could not be

classified by the 10% indicator at all, and these had disproportionately lower levels of educational attainment. Moreover, over 1 in 10 households with missing income and expenditure data were identified as being in energy poverty using the IAAW indicator. An indicator that is described as objective, yet leaves disadvantaged groups unclassified or misclassified, can systematically misrecognise them. Targeting based on the 10% indicator alone would therefore have missed the IAAW-only households and could not have assessed the 447 unclassifiable ones.

Across measures of socioeconomic disadvantage (socioeconomic status and financial difficulty), the IAAW measure showed stronger associations than the 10% index, suggesting that experience-based energy poverty is more closely aligned with broader experiences of financial difficulty, in line with prior research (Burlinson et al., 2021).

4.3 Validity of the Composite Severity Score

The IAAW indicator captures only one aspect of energy poverty and energy poverty is increasingly seen as a multifaceted construct (Longhurst & Hargreaves, 2019; Middlemiss, 2022; Nussbaumer et al., 2012; Siksnelyte-Butkiene et al., 2021). The composite score was higher among people who were unemployed or economically inactive, renting, single, with lower educational attainment and in lower social grades. These findings support the score's construct validity. The composite also explained about three times as much variation in financial difficulty than the IAAW indicator alone.

Two points qualify this result. First, a continuous 0 to 6 score carries more information than a binary item, which would favour the composite's explanatory power. Second, financial difficulty overlaps conceptually with two composite items (difficulty paying bills and cutting back on essentials) and is also self-reported, which may inflate the association. The analysis shows that the score is sensitive to socioeconomic disadvantage, but does not show that the score separates energy poverty from general financial hardship. The extent to which energy poverty represents a distinct construct rather than simply a manifestation of broader financial hardship remains an important conceptual question (Watson & Maître, 2015).

While recent research has used data-driven methods to derive and weight dimensions of energy poverty (Taltavull de La Paz et al., 2022; Tovar Reaños et al., 2025), our findings provide evidence that a simpler additive scoring approach can also capture variation in the severity of energy poverty. This suggests that a transparent sum score may provide a robust and readily interpretable alternative to more complex factor-

based approaches, without requiring additional assumptions about how individual indicators should be weighted.

4.4 Policy implications

The choice of indicator is not simply a methodological issue: where measures are used to identify households for support or to allocate limited resources, differences in measurement can influence which households are recognised as experiencing energy poverty. Our findings support using complementary indicators and caution against relying on a single indicator, particularly one that depends on self-reported financial information.

In the established literature, the 10% threshold is frequently described as an "objective" measure of energy poverty (e.g., Waddams Price et al., 2012; Wojewódzka-Wiewiórska et al., 2024), in contrast to measures based on households' reported experiences, which are typically characterised as 'subjective'. This label may be misleading. Although some expenditure may be observable through energy providers, other forms of energy use and payment, such as the purchase of logs, turf, or other solid fuels, are unlikely to be captured in administrative records. Consequently, even where administrative data are used to measure household income, the energy expenditure component of a 10% energy poverty measure will require self-report. The distinction between "objective" and "subjective" indicators therefore risks implying a greater degree of objectivity than the underlying data support. We therefore deliberately avoid referring to the 10% measure as an 'objective' indicator in this study, as doing so could obscure the limitations inherent in its reliance on self-reported energy expenditure.

Our findings also highlight a distinction between measuring energy poverty and targeting policy support. An indicator that is useful for estimating the prevalence of energy expenditure relative to household income is not necessarily an appropriate stand-alone criterion for determining who should receive assistance, despite its administrative convenience. For example, the 10% measure captures the relationship between reported energy expenditure and household income, but does not necessarily capture whether households can afford adequate energy services, the extent to which they are reducing energy use to manage costs, or the consequences of doing so. Similarly, welfare receipt may provide a practical mechanism for identifying households experiencing financial disadvantage, but receipt of welfare support is not synonymous with experiencing energy poverty. Some households experiencing energy hardship may not receive welfare support, while some households receiving income support may not experience energy hardship to the same extent.

This raises questions about the extent to which existing approaches to targeting energy support capture the full population in need. Future research that examines whether households experiencing energy poverty but not receiving welfare support are systematically overlooked by current eligibility and targeting mechanisms would be helpful. Understanding the characteristics of these households, and the reasons why they fall outside existing support systems, could help determine whether additional or alternative approaches to identification are required.

4.5 Limitations

This study has several limitations. First, participation required respondents to be English-speaking and to have reliable access to the internet and a digital device capable of completing an online survey. These requirements may have excluded some groups who are potentially at greater risk of energy poverty, including individuals experiencing economic disadvantage that limits access to the technology required to participate online. We did, however, make efforts to recruit a sample that is nationally representative of the population of Ireland. In the broader research programme, we over-sampled participants from areas of socioeconomic disadvantage in Ireland via face-to-face methods. Notably, the research team was advised not to ask participants in disadvantaged areas any questions related to income and expenditure in-person, due to the socially sensitive nature of these questions. They were consequently not included in the current study, and this instruction by the market research company presents another mechanism through which socio-economic disadvantage may be missed in standard energy poverty metrics.

Second, our findings cannot be interpreted as establishing that the additive score is the optimal representation of energy poverty. The use of an additive score involves a pragmatic assumption that each component contributes equally to the overall measure. It also assumes that the individual indicators can appropriately be combined into a single continuum. The present findings demonstrate that the resulting score is systematically related to socioeconomic disadvantage, but they do not establish that equal weighting is psychometrically superior to alternative approaches. The additive approach is therefore best understood as a transparent and interpretable way of summarising multiple experience-based dimensions, while recognising that alternative methods may provide different ways of capturing the underlying structure of these indicators.

4.6 Conclusion

The study has three main contributions to the literature on measuring energy poverty. First, missing income and energy expenditure data were substantial and socially patterned, indicating that financial non-response may systematically bias expenditure-based measures. Second, expenditure- and experience-based indicators identified distinct households with limited overlap, with the experience-based measure showing stronger associations with socioeconomic disadvantage and financial difficulty. This suggests that experience-based measures may be particularly sensitive to the broader social and financial circumstances in which energy poverty is experienced. Third, a simple additive score combining multiple experience-based indicators captured variation in energy poverty severity and its socioeconomic gradient, supporting a transparent composite approach. Together, these findings highlight the value of using complementary indicators and caution against relying on any single measure, especially one that depends on self-reported financial data, as a complete assessment of energy poverty or as a stand-alone basis for policy targeting.

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