Ensuring that all energy poor households benefit from public energy assistance programs

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Key Messages for Policymakers

- Public energy assistance programs that use simple rules and traditional metrics based on income to determine eligibility unfairly exclude a large fraction of the energy poor population.
- Data-driven machine learning models can reduce unfair exclusion by identifying hidden patterns of energy poverty in households.
- Models using data from 28 high-income European countries reveal that housing conditions, household type, and other policy and market conditions predict energy poverty better than income alone.
- These models can be applied to federal and state programs in the United States, where energy poverty is widespread, and many energy poor residents are currently excluded from assistance.

Policy Context

In the U.S. and globally, many households are unable to meet their energy needs for heating, cooling, and other essential services [1,2]. Such energy poverty has significant implications for human health, as it is associated with respiratory, mental health, and cardiovascular conditions [3]. Energy poverty is widespread, as one-third of U.S. households experience some form of it [4], but it may be alleviated by well-targeted assistance programs. Eligibility for such programs is frequently set using strict income thresholds or narrow proxies, such as the share of household income spent on energy services [5]. These criteria fail to capture 'hidden' dimensions of energy poverty, such as poor housing quality, limited energy efficiency, volatile energy market trends, and inadequate behavioral coping strategies. Although evidence suggests that assistance programs are working to lower energy bills for qualified households, existing eligibility screens and limited program reach leave many in-need households without assistance [5].

Research Findings

Spandagos et al. (2023) developed a machine learning framework to identify hidden patterns of energy poverty across the member-states of the European Union and the United Kingdom. The framework employed both objective, publicly available data and subjective measurements to identify predictors of energy poverty. In addition to income, the strongest predictors across all countries include dwelling condition, household composition, social protection payments, gas prices, energy efficiency, and fuel supplier switching rates. These additional variables enable the authors to quantify *the expanded eligibility for energy assistance* metric, based on the share of non-recipient households that experience energy poverty and are therefore incorrectly excluded from energy assistance due to overly narrow eligibility criteria. As Figure 1 illustrates, that share is approximately 16–33% under commonly-used income threshold eligibility rules. The share of non-recipients who experience energy poverty rose to approximately 44% and 54% under two other commonly-used eligibility criteria: the 10% rule and the Low Income High Cost (LIHC) metric (the former classifies households as energy poor if their energy expenditures exceed 10% of their income, and the latter if a household has both below-average income and above-average energy expenditures). Similarly, using receipt of old-age or unemployment benefits as the only criteria for eligibility would exclude approximately 51% and 56% of non-recipients, whom the model classifies as energy poor. These results imply that to fully alleviate energy poverty, programs must move beyond simple eligibility rules. Data-driven tools like our model reveal hidden patterns of energy poverty and improve program targeting.

Research Design

Spandagos et al. (2023) developed a unique database comprising more than 2 million observations by merging household-level and country-level data from reputable European sources of statistics (e.g., the European Union Statistics on Income and Living Conditions and Eurostat). Using this database, they trained multiple machine learning models to classify each household as either energy poor or non-energy poor based on the self-reported ability of the subject to keep their home adequately warm. This subjective assessment best approximates the energy poverty literature's emphasis on lived experiences, such as unsafe temperatures, bill

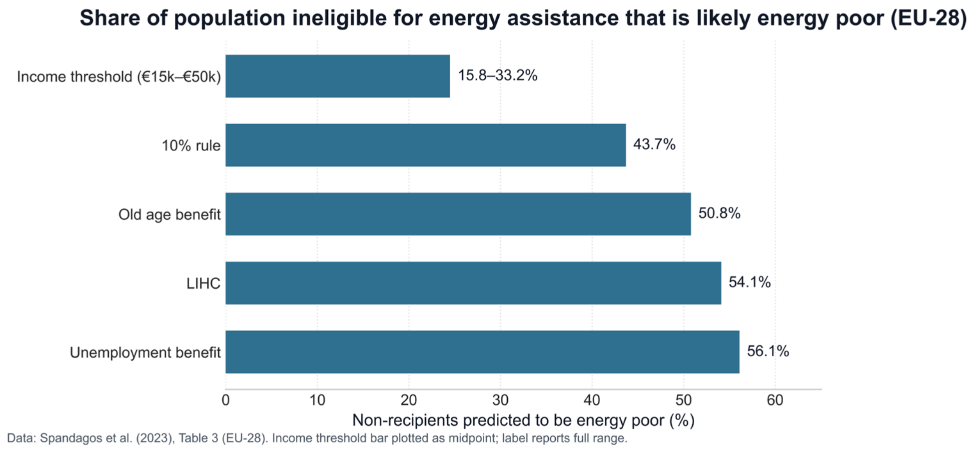

Figure 1: The share of the non-recipient population (under common targeting rules) that is likely energy poor, indicating the potential to expand energy assistance eligibility with improved targeting. Source: Spandagos et al. (2023).

trade-offs, and disconnections [5] (space heating accounts for the largest share of energy consumption in European households). To ensure the credibility of the models' findings and in line with typical machine learning practices, the original dataset was downsampled by randomly removing observations from the dominant class (non-energy poor). This resulted in a balanced set of approximately 50% energy poor and 50% non-energy poor households, further strengthening the models' ability to distinguish between the two classes. Subsequently, a wide variety of configurations were tested for their ability to make accurate predictions based on new batches of data previously unseen by the system. Eventually, a Random Forest configuration that optimizes both predictive power (providing prediction accuracies in the order of 80%) and interpretability was selected for subsequent steps. Specifically, that configuration was used to identify hidden predictors of energy poverty and to simulate common eligibility rules, thereby quantifying the potential expansion of energy assistance eligibility under multidimensional targeting. Overall, that design provides an innovative framework to identify and predict energy poverty across multiple jurisdictions using publicly available data, while evaluating the fairness of common targeting strategies.

Policy Implications

This research project demonstrates that energy assistance programs that use income thresholds, expenditure-based proxies, or typical social welfare measures as standalone eligibility criteria exclude many households that are energy poor. Many federal programs do so. Future policy efforts should consider multidimensional targeting, drawn from high-accuracy machine learning models, that incorporates additional indicators of energy poverty, such as housing quality and lived experiences. Where appropriate, administrators may use program data and market context to refine such models, thereby further improving targeting.

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Original Paper

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