Measuring What Matters: Rethinking Energy Insecurity Metrics

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Introduction

One in four American households experiences energy insecurity, forcing trade-offs between paying utility bills and buying essentials like food and medicine. Despite billions of dollars invested in federal aid, a critical measurement gap hampers an effective response. The national reliance on traditional metrics, such as energy burden, provides only a fragmented view of hardship, leaving policy interventions misaligned with the needs of vulnerable communities.

This digest addresses this gap by synthesizing the landscape of existing metrics and proposing a new conceptual framework. This framework organizes metrics into three layers to provide a holistic view of hardship, from its visible symptoms to its underlying causes and systemic consequences: 1) diagnostic; 2) sensitivity and exposure; and 3) energy system reliability performance.

A more comprehensive package of metrics can help policymakers and regulators better and more holistically recognize household energy hardships, redesign assistance programs, and evaluate interventions to help households maintain essential energy services.

Measuring What Matters

Energy insecurity is a widespread, yet underrecognized issue in the United States. In the 2020 Residential Energy Consumption Survey (RECS), approximately 27% of responding households (33.6 million) report at least one form of energy insecurity, such as difficulty paying energy bills, forgoing basic needs, or keeping their home at unsafe temperatures. Energy insecurity can generate significant financial, physical, and emotional challenges for these households (Bouzarovski and Petrova 2015; González-Eguino 2015; Middlemiss and Gillard 2015; Sovacool 2015).

The burdens of energy insecurity are not evenly distributed across the U.S. In many cases, energy insecurity perpetuates inequalities, disproportionately affecting low-income households (Memmott et al. 2021), communities of color (Bednar et al. 2017; Dogan et al. 2022; Graff et al. 2021; Lyubich 2020), renters (Chen et al. 2022), and those who live in older, less energy-efficient housing (Konisky et al. 2022; Memmott et al. 2021; Reames 2016; Xu and Chen 2019).

Without access to affordable and reliable energy, energy insecure households face disadvantages that make them more likely to fall behind on utility bills and less resilient to the resulting consequences. When missed utility bill payments accumulate, disconnection by utility companies becomes the harshest and most immediate consequence of energy insecurity (Cicala 2021).

In the U.S., the primary federal responses to household energy insecurity have been the Low Income Home Energy Assistance Program (LIHEAP) and the Weatherization Assistance Program (WAP). For nearly fifty years, these programs have provided billions of dollars in bill assistance and energy efficiency upgrades to millions of households (Bednar and Reames 2020).

They are known, however, to reach only a small share of the eligible population—just 18% of income-eligible households received LIHEAP assistance in 2023 (U.S. Department of Health and Human Services 2024). More critically, their impact is typically evaluated on metrics, such as the number of households assisted, that fail to fully capture the most severe aspects of hardship.

To meaningfully address energy insecurity, it is essential to develop and apply robust metrics that capture the key dimensions of energy hardship and guide policy interventions aimed at improving quality of life (Baker et al. 2023; Cong et al. 2022). An evolving field of research aims to measure energy insecurity (see, e.g., Mohr 2018; Wang et al. 2021), with early studies focusing primarily on economic affordability (e.g., income-based indicators like energy burden) (Brown et al. 2012; Teller-Elsberg et al. 2016; Kontokosta et al. 2019; Moore and Webb 2022), and later expanding to incorporate indicators (e.g., behavioral or environmental) that capture deeper patterns of hardship and vulnerability (Boateng et al. 2020; Cong et al. 2022; Graff et al. 2021; Kruyt et al. 2009; Nussbaumer et al. 2012; Steele and Bergstrom 2021).

Economic affordability metrics provide observable signals of exposure and distress due to energy insecurity. However, while these surface-level metrics are a critical starting point, they are often insufficient, as they do not reflect lived experiences or nuanced situations, such as differences in housing quality, energy efficiency, or climatic and infrastructural conditions that shape real energy needs (Kryk and Guzowska 2023; Castaño-Rosa et al. 2019), which therefore limits the efficacy of resultant policy interventions (Cong et al. 2022).

In response to these limitations, scholars seek to develop alternative or complementary measures that explore how and why certain households or communities are more vulnerable to energy insecurity than others. These include measures of behavioral coping strategies (Carley et al. 2022), climate exposure and subsequent ability to adapt (Kwon et al. 2023), and access to sufficient energy services (Bouzarovski and Petrova 2015).

In this digest, we organize the typical energy insecurity metrics into three categories:

1. Diagnostic Metrics
2. Sensitivity and Exposure Metrics
3. Energy System Reliability Performance Metrics

These categories of metrics reflect different layers of visibility and play distinct roles in diagnosing hardship, explaining vulnerability, and demonstrating broader systematic risk. We summarize and display these metrics in Figure 1 and develop the concepts in the following sections.

Figure 1: The Depths of Energy Insecurity Metrics

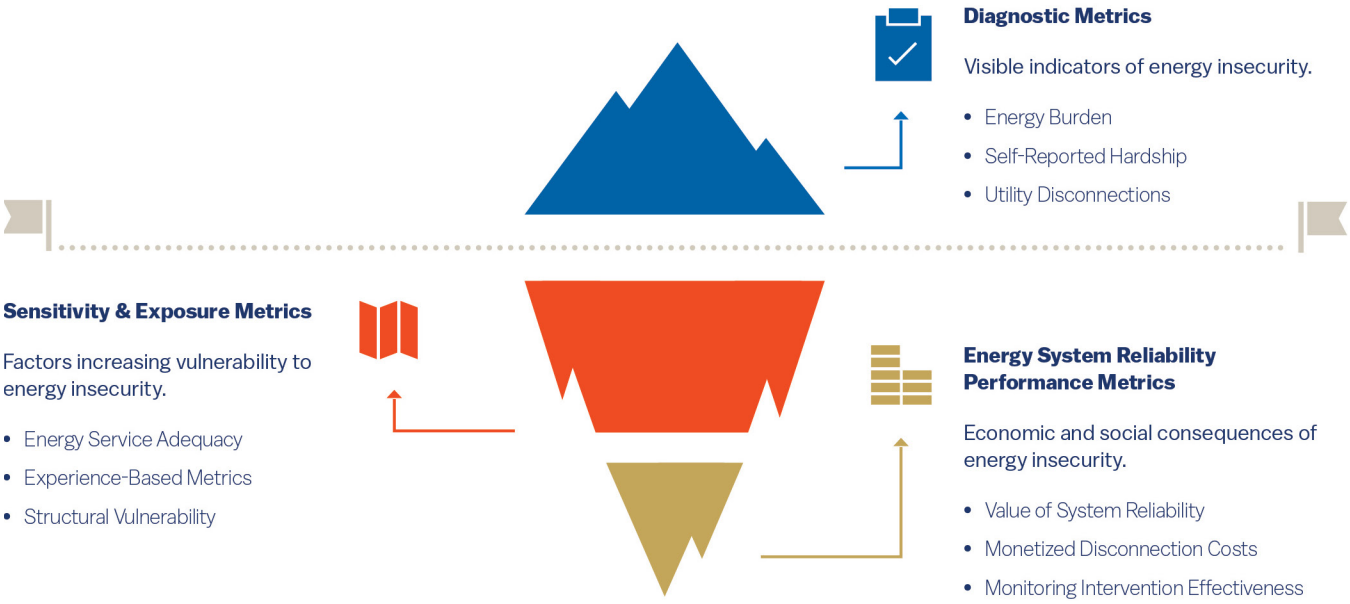

Figure 1 shows the categorization of the depths of energy insecurity metrics, including sensitivity and exposure metrics, diagnostic metrics, and energy system reliability performance metrics.

Diagnostic Metrics

Diagnostic metrics assess energy insecurity by capturing specific, observable indicators of hardship. They typically focus on one primary dimension of exposure, such as affordability, self-reported energy hardship, and utility disconnection. These metrics commonly rely on pre-existing datasets previously collected for general economic or social purposes.

Despite their limited scope, when designed carefully and paired with other metrics, diagnostic tools can play an important role in identifying and tracking emerging hardship. We identify three main types of diagnostic metrics: energy burden, self-reported indicators, and utility disconnections.

Energy Burden as an Affordability Indicator

Energy burden traditionally served as the most commonly used affordability metric for energy insecurity research (Baker et al. 2023). Within the context of fuel poverty, Boardman (1991) defines energy burden as the percentage of household income required to maintain adequate home energy services and proposes a ten percent threshold to indicate hardship.

The American Council for an Energy-Efficient Economy (ACEEE) decreased this threshold recently: a household is now considered energy burdened if it spends more than six percent of its income on utility bills, with that ten percent threshold noted to mark a severe burden (Drehobl et al. 2020).

The U.S. Department of Energy tracks energy burden across the country using the Low-Income Energy Affordability Data (LEAD) tool (Ma et al. 2019). While energy burden is a helpful gauge of energy insecurity and a metric that one can use to make policy decisions, it also has limitations.

A household may fall below the established threshold, yet still experience energy hardship, especially if it relies on restrictive coping strategies, such as limiting heating or cooling to unsafe levels (Mohr et al. 2018). Furthermore, annual energy burden calculations often obscure seasonal fluctuations, and thereby fail to capture the acute financial strain during extreme weather events, when energy costs commonly surge (Lang et al. 2021).

To address these shortcomings, recent work applies advanced data-driven methods to capture complex household energy challenges, from diagnosing hardship to optimizing interventions. For instance, one study creates machine learning models to identify predictors of energy burden through analysis of miscellaneous variables, which shows that while factors such as household income and size are important, other variables such as geographic location and the number of adults in the household are the primary indicators for predicting energy insecurity in low-income households (Vosoughkhosravi et al. 2024). In a different application, a machine learning model estimates U.S. energy burden between 2015 and 2020, and compares their findings to the state allocation of LIHEAP to find a method of optimizing the distribution of funds (Batlle et al. 2024).

Self-Reported Indicators of Energy Hardship

A second metric category relies on self-reported assessments of energy deprivation, typically conducted through survey work. These indicators provide direct, perception-based accounts of energy hardship, helping to diagnose visible symptoms of energy insecurity. Such surveys capture households' perceptions of their energy security levels and are widely used in European and U.S. studies (Thomson et al. 2017).

The European Survey on Income and Living Conditions (EU-SILC) includes key indicators such as the inability to keep homes at adequate warmth, arrears on utility bills, and housing deterioration due to energy poverty (e.g., damp walls, mold growth) (Bouzarovski 2014). In the U.S., data for these indicators comes from national household surveys such as the RECS (U.S. Energy Information Administration 2023b), the U.S. Census Bureau's more recent Household Pulse Survey (HPS) (U.S. Census Bureau 2025a), and the American Housing Survey (AHS) (U.S. Census Bureau 2025b).

These surveys capture households' energy expenditures and consumption, as well as their experiences and

perceptions of energy hardship. Common questions posed in these types of surveys include:

- "Can your household afford to keep its home adequately warm?" (EU-SILC)
- "What was the reason your household was uncomfortably cold for 24 hours or more?" (AHS)
- "In the past year, how many months did your household receive a disconnection notice, shut-off notice, or nondelivery notice for an energy bill?" (RECS)
- "In the last 12 months, how many months did your household reduce or forego expenses for basic household necessities, such as medicine or food, in order to pay an energy bill?" (HPS)

Utility Disconnection as a Consequential Metric

Utility disconnections for nonpayment are discrete, time-stamped events that offer a direct, observable indicator of the most severe form of energy insecurity. While few studies directly quantify the impact of utility disconnections, recent efforts began to address this gap through data-driven tracking tools.

For instance, the Utility Disconnections Dashboard developed by the Energy Justice Lab offers a state-level overview of disconnection protections and shutoff events, providing a foundation for tracking and analyzing trends across states and utilities (Carley and Konisky 2025).

The data available on the dashboard, however, are only available if the utility company reports these numbers, either voluntarily or due to state requirements. In any given year, less than half of all electric utility customers are covered in the data due to non-reporting.

Addressing this disconnection data availability gap requires better metrics and greater transparency from both utility companies and their regulators. State public utility commissions (PUCs) can mandate systematic, standardized public reporting of de-identified utility disconnection data. These data should include details on the frequency and duration of disconnections, arrearages, geographic location (e.g., zip code or census tract), and reconnections.

When linked with demographic and spatial data, these reports can serve as a foundation for identifying communities and geographic areas that are more prone to energy insecurity and utility disconnections, and can allow for more tailored targeting of energy assistance and other types of support.

Sensitivity and Exposure Metrics

While diagnostic indicators help to identify visible signs of energy hardship, they remain limited in their ability to reflect the dimensions that shape energy insecurity (Castaño-Rosa et al. 2019; Kryk and Guzowska 2023; Thomson et al. 2017). Sensitivity and exposure metrics address this gap by combining multiple indicators to explain how and why different households experience energy insecurity in varied and compounding ways. These frameworks often integrate service adequacy, behavioral adaptations, housing quality, and disadvantages that reflect underlying structural and contextual risks.

Energy Service Adequacy Metrics

Across the world, the Multidimensional Energy Poverty Index (MEPI) is a widely applied tool to assess energy poverty (Rizal et al. 2024). The MEPI calculates the incidence and intensity of energy poverty at the household level. It analyzes deprivation across key energy-related services, including access to lighting, refrigeration, clean cooking (i.e., avoiding burning of solid fuels), and telecommunications (i.e., access to radio, computer, phone) (Nussbaumer et al. 2012).

Scholars have introduced similar metrics as well. Thomson and Snell, for example, quantify fuel poverty based on three indicators:

1. Ability to pay to keep the home adequately warm
2. Arrears on utility bills
3. Presence of poor physical housing conditions (2013)

These indicators reflect whether a household can afford energy and attain an adequate standard of living.

Another approach involves the direct measurement of energy services, particularly thermal comfort. One example is the energy equity gap, which quantifies disparities in thermal comfort by identifying the outdoor temperatures at which high- and low-income households begin using either air conditioning or heating. Research shows that low-income households often delay using these systems until temperatures reach significantly uncomfortable or unsafe levels, increasing their exposure to health risks (Cong et al. 2022).

Researchers also use the cooling slope to measure the increase in electricity consumption for each degree increase in outdoor temperature once air conditioning is used. Low-income households generally exhibit steeper cooling slopes, indicating lower per-degree energy use and greater vulnerability to heat-related illnesses (Kwon et al. 2023). Similarly, energy audits and electrification studies offer insights into how heating and cooling patterns differ by income, and how interventions such as insulation retrofits or HVAC upgrades and adoption of heat pumps can mitigate energy hardship (Woo-Shem et al. 2023; Ye et al. 2025).

While direct measurement metrics provide valuable insights into physical energy deprivation, they often face practical limitations, such as the fact that no single entity collects systematically indoor temperature data (Herrero 2017). These data gaps led researchers to complement quantitative measurements with approaches that capture households' lived experiences and coping strategies.

Experience-Based Measures

Experience-based approaches prioritize the lived realities of households facing energy insecurity. These frameworks build on behavioral and self-reported indicators of energy insecurity, and in some cases combine them into multidimensional models. One such example is the Energy Poverty Barometer, developed in Belgium (Meyer et al. 2018), which distinguishes between three categories of energy poverty:

1. Measured (e.g., high energy burden)
2. Perceived (e.g., self-reported inability to maintain comfort)
3. Hidden (e.g., households who suppress usage to stay within budget)

This proposed barometer combines subjective and objective measures of energy insecurity, to reveal a more nuanced depiction of energy insecurity than one can glean from national surveys or census data.

One study quantifies hidden energy poverty in the U.S. by calculating the difference between a household's actual spending on energy services and its theoretically required energy expenditure, thus measuring a behavioral response to hardship (i.e., energy-limiting behavior) (Barrella et al. 2022).

Another recent study assesses a broader set of coping behaviors, including bill balancing, forgoing food or medicine to pay utility bills, and risky heating practices, as behavioral manifestations of energy hardship (Carley et al. 2022). These experience-based metrics can help improve current energy assistance programs by identifying households who might be overlooked by traditional energy burden metrics, and can suggest specific ways to target assistance such as through cooling technologies, food aid, or medical protections.

Structural Vulnerability Frameworks

Structural vulnerability frameworks aim to identify energy insecurity within broader socioeconomic systems, showing how factors such as income, housing quality, and location influence a household's risk beyond just energy costs.

The Structural Energy Poverty Vulnerability (SEPV) index is a comprehensive approach that measures structural vulnerability across three core domains: economic vulnerability, housing and energy infrastructure, and demographic sensitivity (Recalde et al. 2019).

Similarly, the multidimensional Energy Poverty Vulnerability Index (EPVI) combines ten structural indicators related to building efficiency, socioeconomic status, and climate exposure and household ability to adapt (e.g., temperature variation, heating/cooling season length) (Gouveia et al. 2019).

Another framework conceptualizes energy vulnerability as a function of three key dimensions: exposure to a stressor (i.e., a policy-induced price change), the sensitivity of a population to that stressor (based on demographic and socioeconomic characteristics), and the community's adaptive capacity to cope with the impacts (Carley et al. 2018).

The Texas Energy Poverty Research Institute (TEPRI) develops the Energy Vulnerability Index (EVI) Dashboard, which links household-level energy insecurity with demographic and geographic vulnerability by integrating survey data on disconnection risk, energy-limiting behaviors, and perceived affordability across Texas (TEPRI 2025).

Scholars cite the need for formal policy recognition of energy insecurity, such as through legislation that recognizes it as a material hardship (Bednar and Reames 2020). This recognition would advance standardized measurement practices, which is essential to incorporate sensitivity and exposure metrics across energy assistance programs (i.e., LIHEAP, WAP, and utility payment and arrearage management plans) and jurisdictions (i.e., PUCs, local organizations, and community action agencies).

Federal and state regulatory bodies could consider requiring the adoption and use of a broader suite of energy insecurity metrics. Embedding these indicators into assistance program design, regulatory filings, and reporting requirements would help identify hidden hardship and align assistance with the actual need of those living in the U.S. who experience energy insecurity.

Both states and utility companies could optimize existing energy assistance mechanisms and consumer protection rules by recognizing energy insecurity as a multidimensional hardship. The full spectrum of advanced metrics could inform targeted assistance programs (e.g., weatherization, bill assistance) and enhance the responsiveness of consumer protections to address the root causes of energy insecurity.

For instance, structural vulnerability indicators can help prioritize energy efficiency upgrades for the most inefficient housing occupied by vulnerable populations, while ongoing reporting of disconnections and reconnections can be used to design more responsive bill assistance, rather than relying on seasonal application cycles, as is the case for programs such as LIHEAP.

Energy System Reliability Performance Metrics

In a third class of metrics, analysts evaluate the energy system's performance in delivering equitable outcomes and quantify the cost of events such as power outages, disconnections, and assistance programs.

These metrics shift the focus from the household's individual hardship to the capacity of institutional and community systems to ensure energy access, and thereby capture both the societal benefits of continuous service and the consequences when that access falls short. From a performance perspective, utility disconnections represent a critical inability of the system to serve its most vulnerable customers.

Valuing Reliability and Service Continuity

One method of measuring energy system performance is to assign a dollar amount to the service it provides. Existing literature quantifies the economic impact of service interruptions through metrics designed for unplanned and planned outages.

The most widely used metrics include the Value of Lost Load (VoLL), which estimates the monetary cost per kilowatt-hour (kWh) of electricity not supplied to a household, and Customer Interruption Costs (CIC), which capture customer-specific trade-offs and preferences during outages. These metrics are central to utility planning, reliability standards, and market design, and they help to establish the idea that reliable energy service has a quantifiable economic value (Baik et al. 2018; Macmillan et al. 2023; Sullivan et al. 2015).

Researchers estimate these costs by using both direct and indirect methods. Direct approaches rely on the preferences of the household, collected using surveys, such as household willingness-to-pay (WTP) to avoid an outage, or through discrete choice experiments,

which infer value from choices made in hypothetical scenarios. For instance, one study demonstrates that households are willing to pay between $1.70 and $2.30 per kWh to maintain electricity during a ten-day unplanned blackout, highlighting the premium placed on extended resilience (Baik et al. 2020).

By contrast, indirect approaches use market data and observed economic behavior to estimate costs. For example, scholars analyze state-level electricity prices and consumption patterns to estimate residential planned outage costs across the U.S., which range from $0.12 to $0.34 per kWh unserved (Woo et al. 2021). Another study of U.S. generator sales estimates households' willingness to pay for reliability at about $1.57 per kWh of avoided outage (Harris 2023).

These metrics present some limitations in fully capturing the social dimension of reliability. Studies find that WTP values estimated through direct approaches are correlated with factors such as season, outage duration, and socio-economic characteristics, including age, income, and gender (Morrissey et al. 2018; Reichl et al. 2013).

A few studies found that low-income groups tend to report a lower WTP (Baik et al. 2020; Praktiknjo 2014). This correlation with income reveals an income effect: not because they place less importance on reliable electricity, but because their constrained budgets limit their stated willingness to pay (Baik et al. 2020; Macmillan et al. 2023). Therefore, relying on these metrics alone might lead to undervaluing reliability for certain groups, suggesting they should be paired with other measures to better ensure equity in system resilience investments.

Measuring the Costs of Utility Disconnection

The economic consequences of utility disconnections consist of both private costs to the household and social costs to others. Disconnected households could experience food spoilage, medication loss, missed work or school days, and worsened health outcomes.

Households may also face fees for reconnection, deposits, and could require alternative shelter, further compounding financial strain. More generally, utility disconnections impose administrative costs on utility companies and state agencies, and strain emergency services and public health and housing systems. Nonprofit organizations, mutual aid networks, and local governments often step in to provide emergency assistance, diffusing costs beyond the utility–customer relationship.

Similarly to how eviction is now a widely accepted indicator of housing insecurity (Desmond and Bell 2015), utility disconnections should be recognized as a central metric in energy insecurity research and regulation. Developing a cost-based disconnection metric that reflects both private and social burdens, and that identifies their structural drivers, would support more effective affordability policy, targeted outreach, and disconnection protections.

Metrics for Monitoring Intervention Effectiveness

Federal energy assistance programs, such as LIHEAP and WAP, are traditionally evaluated based on their reach and energy efficiency outcomes. However, this focus does not capture non-energy benefits (NEBs) that directly impact a household's wellbeing and stability.

A growing body of research highlights that NEBs (e.g., improved comfort, reduced utility disconnections, better health outcomes, and increased housing stability) are often the most meaningful outcomes for energy assistance program participants (Outcault et al. 2022; Schweitzer and Tonn 2003).

For instance, when considering low-income energy efficiency programs, utility NEBs (e.g., reduced arrearages and fewer shutoffs), participant NEBs (e.g., improved indoor air quality, reduced sick days), and societal NEBs (e.g., lower emissions and health burdens) can add between 35% to over 300% of value of the energy savings themselves (Skumatz and Gardner 2005).

To ensure that interventions remain effective and responsive to the evolving nature of energy insecurity, states could establish dynamic monitoring systems that have regional "living indices" that continuously integrate time-sensitive data. The federal LIHEAP

Performance Management Website and Data Dashboard track indicators such as household eligibility, benefit levels by heating or cooling need, and demographic reach across states, on both quarterly and annual bases.

While these platforms are a step toward greater accountability and data accessibility, program administrators could strengthen them with more granular data collection (i.e., monthly) and should integrate NEBs to reflect tangible improvements in household wellbeing.

Assistance program performance assessments could evaluate outcomes that reflect household wellbeing and lived experience, including comfort, health, and housing stability, rather than relying solely on traditional assessment methods such as counting LIHEAP recipients or calculating WAP's savings-to-investment ratio.

However, implementing and maintaining such evaluation systems would require additional administrative capacity, data infrastructure, and coordination across agencies. Future research should assess the feasibility and cost-effectiveness of these efforts to ensure that expanded metrics can be realistically integrated into program design.

Below, in Table 1, we provide a summary and analysis, detailing the measurement focus, and specific examples, addressed by each of the metric types we discussed above.

Table 1: Analysis of Energy Insecurity Metrics

Metric Type	Example / Subtype	Measurement Focus	Examples
Diagnostic Metrics	Energy burden	Economic affordability—% of income spent on utility bills	>6% or >10% income thresholds
	Self-reported indicators	Perceived energy hardship	EU-SILC questions (e.g., inability to keep homes warm, arrears on utility bills, housing deterioration)
	Utility disconnections	Direct incidence of service denial	Utility records, Utility Disconnections Dashboard
Sensitivity and Exposure Metrics	Energy service adequacy	Access to essential domestic energy services across multiple dimensions	Multidimensional Energy Poverty Index (MEPI), Energy Equity Gap, Cooling Slope
	Experience-based measures	Lived experience of energy insecurity and usage suppression	Energy Poverty Barometer (measured, perceived, hidden energy poverty), coping behaviors for energy hardships
	Structural vulnerability frameworks	Long-term exposure to systemic risk factors (e.g., housing, income, demographics)	Structural Energy Poverty Vulnerability (SEPV) index, Energy Poverty Vulnerability Index (EPVI)
Energy System Reliability Performance Metrics	Valuing reliability and service continuity	Economic valuation of uninterrupted access to energy	Customer Interruption Costs (CIC), Value of Lost Load (VoLL), VoLL-based outage metrics
	Costs of utility disconnection	Monetized consequences of service loss due to disconnection	Private and social costs resulting from utility shutoffs
	Monitoring intervention effectiveness	Assesses the multidimensional outcomes of energy assistance programs	Non-energy benefits (NEBs)

Conclusion

The U.S. response to household energy insecurity is constrained not only by a lack of investment, but also in how assistance program effectiveness is currently measured. Adopting a holistic set of metrics would better help to understand energy insecurity and lead to more effective solutions, such as curtailing utility disconnections and expanding household access to assistance programs. The long-standing reliance on traditional metrics provides a fragmented view of insecurity and evaluate programmatic outputs rather than the alleviation of household hardship.

In this digest, we address this gap by organizing the landscape of indicators into a comprehensive, three-tiered framework. This approach moves away from exclusive reliance on diagnostic metrics that directly identify hardship, to incorporate sensitivity and exposure metrics that reveal behavioral and structural vulnerability, and energy system reliability performance metrics that quantify utility service reliability, broader costs of utility disconnections, and assistance program effectiveness.

To fully operationalize this diagnostic framework, we recommend that policymakers and regulators prioritize a coordinated approach to improving energy insecurity metrics. This approach should include:

1. Advancing the formal recognition of energy insecurity as a distinct policy challenge
2. Strengthening data transparency through standardized reporting on disconnections
3. Embedding more comprehensive metrics into the design and evaluation of assistance programs, and explicitly using them as outcome variables to assess efficacy
4. Investing in dynamic monitoring systems to ensure these tools remain responsive to regularly reported data

Together, these actions would enable a more accurate diagnosis of hardship, ensure that interventions reach those most at risk, and align regulatory oversight with the lived realities of household vulnerability.

Bibliography

Baik, S., A.L. Davis, and M.G. Morgan. 2018. "Assessing the Cost of Large Scale Power Outages to Residential Customers." *Risk Analysis*, 38(2), 283–296. https://doi.org/10.1111/risa.12842

Baik, S., A.L. Davis, J.W. Park, S. Sirinterlikci, and M.G Morgan. 2020. "Estimating What U.S. Residential Customers Are Willing to Pay for Resilience to Large Electricity Outages of Long Duration." *Nature Energy*, 5(3), 250–258. https://doi.org/10.1038/s41560-020-0581-1

Baker, E., S. Carley, S. Castellanos, D. Nock, J.F. Bozeman, D. Konisky, C.G. Monyei, M. Shah, and B. Sovacool. 2023. "Metrics for Decision-Making In Energy Justice." *Annual Review of Environment and Resources*, 48, 737–760. https://doi.org/10.1146/annurev-environ-112621-063400

Barrella, R., J.C. Romero, J.I. Linares, E. Arenas, M. v, and E. Centeno. 2022. "The Dark Side of Energy Poverty: Who Is Underconsuming in Spain and Why?" *Energy Research and Social Science*, 86, 102428. https://doi.org/10.1016/j.erss.2021.102428

Batlle, C., P. Heller, C. Knittel, and T. Schittekatte. 2024. "U.S. Federal Resource Allocations Are Inconsistent with Concentrations of Energy Poverty." *Science Advances*, 10(41), eadp8183. https://doi.org/10.1126/sciadv.adp8183

Bednar, D.J. and T.G. Reames. 2020. "Recognition of and Response to Energy Poverty in the United States." *Nature Energy*, 5(6), 432–439. https://doi.org/10.1038/s41560-020-0582-0

Bednar, D.J., T.G. Reames, and G. Keoleian. 2017. "The Intersection of Energy and Justice: Modeling the Spatial, Racial/Ethnic and Socioeconomic Patterns of Urban Residential Heating Consumption and Efficiency in Detroit, Michigan." *Energy Buildings*, 143, 25–34. https://doi.org/10.1016/j.enbuild.2017.03.028

Boardman, B. 1991. *Fuel Poverty: From Cold Homes to Affordable Warmth*. London, England: Belhaven Press.

Boateng, G.O., M.R. Balogun, F.O. Dada, and F.A. Armah. 2020. "Household Energy Insecurity: Dimensions and Consequences For Women, Infants and Children in Low- and Middle-Income Countries." *Social Science and Medicine*, 258, 113068. https://doi.org/10.1016/j.socscimed.2020.113068

Bouzarovski, S. 2014. "Energy Poverty in the European Union: Landscapes of Vulnerability." *WIREs Energy and Environment*, 3(3), 276–289. https://doi.org/10.1002/wene.89

Bouzarovski, S. and S. Petrova. 2015. "A Global Perspective on Domestic Energy Deprivation: Overcoming the Energy Poverty–Fuel Poverty Binary." *Energy Research and Social Science*, 10, 31–40. https://doi.org/10.1016/j.erss.2015.06.007

Brown, L.H., P.G. Buettner, and D.V. Canyon. 2012. "The Energy Burden and Environmental Impact of Health Services." *American Journal of Public Health*, 102, e76–e82. https://doi.org/10.2105/AJPH.2012.300776

Carley, S., T.P. Evans, M. Graff, and D.M. Konisky. 2018. "A Framework for Evaluating Geographic Disparities in Energy Transition Vulnerability." *Nature Energy*, 3(8), 621–627. https://doi.org/10.1038/s41560-018-0142-z

Carley, S., M. Graff, D.M. Konisky, and T. Memmott. 2022. "Behavioral and Financial Coping Strategies Among Energy-Insecure Households." *Proceedings of the National Academy of Science*, 119(36), e2205356119. https://doi.org/10.1073/pnas.2205356119

Carley, S. and D.M. Konisky. 2025. "Utility Disconnections Dashboard." Energy Justice Lab. Retrieved June 13, 2025, from https://utilitydisconnections.org/dashboard/index.html

Castaño-Rosa, R., J. Solís-Guzmán, C. Rubio-Bellido, and M. Marrero. 2019. "Towards a Multiple-Indicator Approach to Energy Poverty in the European Union: A Review." *Energy and Buildings*, 193, 36–48. https://doi.org/10.1016/j.enbuild.2019.03.039

Chen, C., J. Greig, H. Nelson, and F. Li. 2022. "When Disadvantage Collides: The Concentrated Effects of Energy Insecurity and Internet Burdens in the United States." *Energy Research and Social Science*, 91, 102713. https://doi.org/10.1016/j.erss.2022.102713

Cicala, S. 2021. "The Incidence of Extreme Economic Stress: Evidence from Utility Disconnections." *Journal of Public Economics*, 200, 104461. https://doi.org/10.1016/j.jpubeco.2021.104461

Cong, S., D. Nock, Y.L. Qiu, B. Xing. 2022. "Unveiling Hidden Energy Poverty Using the Energy Equity Gap." *Nature Communications*, 13, 2456. https://doi.org/10.1038/s41467-022-30146-5

Desmond, M. and M. Bell. 2015. "Housing, Poverty, and the Law." *Annual Review of Law and Social Science*, 11, 15–35. https://doi.org/10.1146/annurev-lawsocsci-120814-121623

Dogan, E., M. Magaleno, R. Inglesi-Lotz, and D. Taskin. 2022. "Race and Energy Poverty: Evidence from African-American Households." *Energy Economics*, 108, 105908. https://doi.org/10.1016/j.eneco.2022.105908

Drehobl, A., L. Ross, and R. Ayala. 2020. "How High are Household Energy Burdens? An Assessment of National Metropolitan Energy Burden Across the United States." American Council for an Energy-Efficient Economy. https://www.aceee.org/sites/default/files/pdfs/u2006.pdf

Konisky, D.M., S. Carley, M. Graff, and T. Memmott. 2022. "The Persistence of Household Energy Insecurity During the COVID-19 Pandemic." *Environmental Research Letters*, 17(10), 104017. https://doi.org/10.1088/1748-9326/ac90d7

González-Eguino, M. 2015. "Energy Poverty: An Overview." *Renewable and Sustainable Energy Reviews*, 47, 377–385. https://doi.org/10.1016/j.rser.2015.03.013

Gouveia, J.P., P. Palma, and S.G. Simoes. 2019. "Energy Poverty Vulnerability Index: A Multidimensional Tool to Identify Hotspots for Local Action." *Energy Reports*, 5, 187–201. https://doi.org/10.1016/j.egyr.2018.12.004

Graff, M., S. Carley, D.M. Konisky, and T. Memmott. 2021. "Which Households are Energy Insecure? An Empirical Analysis of Race, Housing Conditions, and Energy Burdens in the United States." *Energy Research & Social Science*, 79, 102144. https://doi.org/10.1016/j.erss.2021.102144

Graff, M., S. Carley, D.M. Konisky, and T. Memmott. 2023. "Opportunities to Advance Research on Energy Insecurity." *Nature Energy*, 8, 550–553. https://doi.org/10.1038/s41560-023-01265-0

Harris, R.I. 2023. "Willingness to Pay for Electricity Reliability: Evidence from U.S. Generator Sales." Working Paper. https://www.dropbox.com/scl/fi/eo1kxsd13hgh4hm2j1aig/Harris_JMP_2022_Reliability.pdf?rlkey=5g8koaxqd18ya1l412i73wxl8&e=3&dl=0

Herrero, S.T. 2017. "Energy Poverty Indicators: A Critical Review of Methods." *Indoor and Built Environment*, 26(7), 1018–1031. https://doi.org/10.1177/1420326X17718054

Kontokosta, C.E., V.J. Reina, and B. Bonczak. 2019. "Energy Cost Burdens for Low-Income and Minority Households." *Journal of the American Planning Association*, 1–17. https://doi.org/10.1080/01944363.2019.1647446

Kruyt, B., D.P. van Vuuren, H.J.M. de Vries, and H. Groenenberg. 2009. "Indicators for Energy Security." *Energy Policy*, 37(6), 2166–2181. https://doi.org/10.1016/j.enpol.2009.02.006

Kryk, B. and M.K. Guzowska. 2023. "Assessing the Level of Energy Poverty Using a Synthetic Multidimensional Energy Poverty Index in EU Countries." *Energies*, 16(3), Article 3. https://doi.org/10.3390/en16031333

Kwon, M., S. Cong, D. Nock, L. Huang, Y. Qiu, and B. Xing. 2023. "Forgone Summertime Comfort as a Function of Avoided Electricity Use." *Energy Policy*, 183, 113813. https://doi.org/10.1016/j.enpol.2023.113813

Lang, M., R. Lane, K. Zhao, S. Tham, K. Woolfe, and R. Raven. 2021. "Systematic Review: Landlords' Willingness to Retrofit Energy Efficiency Improvements." *Journal of Cleaner Production*, 303, 127041. https://doi.org/10.1016/j.jclepro.2021.127041

Lyubich, E. 2020. "The Race Gap in Residential Energy Expenditures." *Energy Institute at Haas*. https://www.energy.gov/sites/default/files/2022-07/17.%20The%20race%20gap%20in%20residential%20energy%20expenditures.pdf

Ma, O., K. Laymon, M. Day, R. Oliveira, J. Weers, and A. Vimont. 2019. "Low-Income Energy Affordability Data (LEAD) Tool Methodology." *National Renewable Energy Laboratory*. https://www.nrel.gov/docs/fy19osti/74249.pdf

Macmillan, M., K. Wilson, S. Baik, J.P. Carvallo, A. Dubey, and C.A. Holland. 2023. "Shedding Light on the Economic Costs of Long-Duration Power Outages: A Review of Resilience Assessment Methods and Strategies." *Energy Research & Social Science*, 99, 103055. https://doi.org/10.1016/j.erss.2023.103055

Memmott, T., D.M. Konisky, and S. Carley. 2024. "Assessing Demographic Vulnerability and Weather Impacts on Utility Disconnections in California." *Nature Communications*, 15(1), 9548. https://doi.org/10.1038/s41467-024-53913-y

Memmott, T., S. Carley, M. Graff, and D.M. Konisky. 2021. "Sociodemographic Disparities in Energy Insecurity Among Low-Income Households Before and During the COVID-19 Pandemic." *Nature Energy*, 6(2), 186–193. https://doi.org/10.1038/s41560-020-00763-9

Meyer, S., H. Laurence, D. Bart, L. Middlemiss, and K. Maréchal. 2018. "Capturing the Multifaceted Nature of Energy Poverty: Lessons from Belgium." *Energy Research & Social Science*, 40, 273–283. https://doi.org/10.1016/j.erss.2018.01.017

Middlemiss, L. and R. Gillard. 2015. "Fuel Poverty From the Bottom-Up: Characterising Household Energy Vulnerability Through the Lived Experience of the Fuel Poor." *Energy Research & Social Science*, 6, 146–154. https://doi.org/10.1016/j.erss.2015.02.001

Mohr, T.M. 2018. "Fuel Poverty in the U.S.: Evidence Using the 2009 Residential Energy Consumption Survey." *Energy Economics*, 74, 360–369. https://doi.org/10.1016/j.eneco.2018.06.007

Moore, D. and A.L. Webb. 2022. "Evaluating Energy Burden at the Urban Scale: A Spatial Regression Approach in Cincinnati, Ohio." *Energy Policy*, 160, 112651. https://doi.org/10.1016/j.enpol.2021.112651

Morrissey, K., A. Plater, and M. Dean. 2018. "The Cost of Electric Power Outages in the Residential Sector: A Willingness to Pay Approach." *Applied Energy*, 212, 141–150. https://doi.org/10.1016/j.apenergy.2017.12.007

Nussbaumer, P., M. Bazilian, and V. Modi. 2012. "Measuring Energy Poverty: Focusing on What Matters." *Renewable and Sustainable Energy Reviews*, 16, 231–243. https://doi.org/10.1016/j.rser.2011.07.150

Outcault, S., A. Sanguinetti, N. Dessouky, and C. Magaña. 2022. "Occupant Non-Energy Impact Identification Framework: A Human-Centered Approach to Understanding Residential Energy Retrofits." *Energy and Buildings*, 263, 112054. https://doi.org/10.1016/j.enbuild.2022.112054

Praktiknjo, A.J. 2014. "Stated Preferences Based Estimation of Power Interruption Costs in Private Households: An Example from Germany." *Energy*, 76, 82–90. https://doi.org/10.1016/j.energy.2014.03.089

Reames, T.G. 2016. "Targeting Energy Justice: Exploring Spatial, Racial/Ethnic and Socioeconomic Disparities in Urban Residential Heating Energy Efficiency." *Energy Policy*, 97, 549–558. https://doi.org/10.1016/j.enpol.2016.07.048

Recalde, M., A. Peralta, L. Oliveras, S. Tirado-Herrero, C. Borrell, L. Palència, M. Gotsens, L. Artazcoz, and M. Marí-Dell'Olmo. 2019. "Structural Energy Poverty Vulnerability and Excess Winter Mortality in the European Union: Exploring the Association Between Structural Determinants and Health." *Energy Policy*, 133, 110869. https://doi.org/10.1016/j.enpol.2019.07.005

Reichl, J., M. Schmidthaler, and F. Schneider. 2013. "The Value of Supply Security: The Costs of Power Outages to Austrian Households, Firms and the Public Sector." *Energy Economics*, 36, 256–261. https://doi.org/10.1016/j.eneco.2012.08.044

Rizal, R.N., D. Hartono, T. Dartanto, and Y.M.L. Gultom. 2024. "Multidimensional Energy Poverty: A Study of Its Measurement, Decomposition, and Determinants in Indonesia." *Heliyon*, 10(3), e24135. https://doi.org/10.1016/j.heliyon.2024.e24135

Schweitzer, M. and B. Tonn. 2003. "Non-Energy Benefits of the U.S. Weatherization Assistance Program: A Summary of Their Scope and Magnitude." *Applied Energy*, 76(4), 321–335. https://doi.org/10.1016/S0306-2619(03)00003-5

Skumatz, L.A. and J. Gardner. 2005. "Methods and Results for Measuring Non-Energy Benefits in the Commercial and Industrial Sectors." *Proceedings of the 2005 ACEEE Summer Study on Energy Efficiency in Industry*. Skumatz Economic Research Associates, Inc. https://www.aceee.org/files/proceedings/2005/data/papers/SS05_Panel06_Paper15.pdf

Sovacool, B.K. 2015. "Fuel Poverty, Affordability, and Energy Justice in England: Policy Insights from the Warm Front Program." *Energy*, 93, 361–371. https://doi.org/10.1016/j.energy.2015.09.016

Steele, A.J.H. and J.C. Bergstrom. 2021. ""Brr! It's Cold in Here" Measures of Household Energy Insecurity for the United States." *Energy Research & Social Science*, 72, 101863. https://doi.org/10.1016/j.erss.2020.101863

Sullivan, M., J. Schellenberg, and M. Blundell. 2015. "Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States (No. LBNL--6941E, 1172643; p. LBNL--6941E, 1172643)." *Ernest Orlando Lawrence Berkeley National Laboratory*. https://doi.org/10.2172/1172643

Teller-Elsberg, J., B. Sovacool, T. Smith, and E. Laine. 2016. "Fuel Poverty, Excess Winter Deaths, and Energy Costs in Vermont: Burdensome for Whom?" *Energy Policy*, 90, 81–91. https://doi.org/10.1016/j.enpol.2015.12.009

Texas Energy Poverty Research Institute (TEPRI). 2025. "Community Voices in Energy: Energy Vulnerability Index Dashboard." https://tepri.org/cves2025/

Thomson, H., S. Bouzarovski, and C. Snell. 2017. "Rethinking the Measurement of Energy Poverty in Europe: A Critical Analysis of Indicators and Data." *Indoor and Built Environment*, 26(7), 879–901. https://doi.org/10.1177/1420326X17699260

Thomson, H. and C. Snell. 2013. "Quantifying the Prevalence of Fuel Poverty Across the European Union." *Energy Policy*, 52, 563–572. https://doi.org/10.1016/j.enpol.2012.10.009

U.S. Census Bureau. 2025a. "Household Pulse Survey." https://www.census.gov/programs-surveys/household-pulse-survey.html

U.S. Census Bureau. 2025b. "American Housing Survey (AHS)." https://www.census.gov/programs-surveys/ahs.html

U.S. Department of Health & Human Services, Administration for Children and Families. 2024. "LIHEAP Data Warehouse: Custom reports (FY2023). LIHEAP Performance Management." Retrieved June 20, 2025, from https://liheappm.acf.hhs.gov/datawarehouse/custom_reports

U.S. Energy Information Administration. 2023a. "Table HC11.1 Household Energy Insecurity (2020)." U.S. Energy Information Administration. https://www.eia.gov/consumption/residential/data/2020/hc/pdf/HC%2011.1.pdf

U.S. Energy Information Administration. 2023b. "Residential Energy Consumption Survey (RECS)." https://www.eia.gov/consumption/residential

Vosoughkhosravi, S., S. Sheikh, E. Kamel, and A. Jafari. 2024. "Analyzing Energy Performance in American Low Income Households: A Data Driven Approach with Machine Learning Insights." *Journal of Building Engineering*, 89, 109305. https://doi.org/10.1016/j.jobe.2024.109305

Wang, Q., M.-P. Kwan, J. Fan, and J. Lin. 2021. "Racial Disparities in Energy Poverty in the United States." *Renewable and Sustainable Energy Reviews*, 137, 110620. https://doi.org/10.1016/j.rser.2020.110620

Woo, C. K., A. Tishler, J. Zarnikau, and Y. Chen. 2021. "Average Residential Outage Cost Estimates for the Lower 48 States in the U.S." *Energy Economics*, 98, 105270. https://doi.org/10.1016/j.eneco.2021.105270

Woo-Shem, B., K. Pattawi, H. Covington, P. McCurdy, C. Wang, T. Roth, C. Nguyen, Y. Liu, and H. Lee. 2023. "Comparing Economic Benefits of HVAC Control Strategies in Grid-Interactive Residential Buildings." *Energy and Buildings*, 286, 112937. https://doi.org/10.1016/j.enbuild.2023.112937

Xu, X. and C.-F. Chen. 2019. "Energy Efficiency and Energy Justice for U.S. Low-Income Households: An Analysis of Multifaceted Challenges and Potential." *Energy Policy*, 128, 763–774. https://doi.org/10.1016/j.enpol.2019.01.020

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