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# Extreme Events, Energy Security and Equality through Micro and Macro Levels: Concepts, Challenges and Methods

By

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## 1. Introduction

Globally, low-income households (LIHs) and communities have faced long-standing energy inequality and insecurity (EII) [1–3], defined as the lack of equal access to energy resources [3,4], and the inability to reliably pay utility bills [1,5], respectively. EII is a crucial dimension of the broader energy justice paradigm because it is often related to energy poverty, a particular form of energy injustice that happens to the "end-users" of the energy system [4,6]. LIHs are at greater risk of experiencing the negative effects of EII during extreme events, defined as severe weather events, fire, or a pandemic, than higher-income households. It is important to note that inequality and insecurity describe two different phenomena that have a strong relationship. First, inequality in energy resources results in increased energy burdens for LIHs; for example, inadequate insulation in poorly designed housing results in increased energy consumption. This situation, in turn, impacts energy insecurity by increasing household energy bills for those who can least afford to pay them. Increased time at home as a result of pandemic- or disaster-related isolation (i.e., having to shelter-in-place due to infrastructure damage or external safety concerns) has intensified energy and internet-related insecurity among LIHs as a result of financial insecurity, increased residential energy consumption [5,7], and increased need for internet access [8,9].

Extreme weather events during the pandemic, such as Winter Storm Uri in mid-February and Hurricane Ida in September 2021, have further burdened LIHs. Uri and Ida are good examples of the types of extreme events that are forecast to become more common in the future. They show how energy policy choices and a largely deregulated energy system can amplify negative impacts. Winter Storm Uri resulted in widespread power blackouts, especially in Texas. Over 9.9 million homes in the U.S. and Mexico went without power [10–12], the largest U.S. blackout since the Northeast blackout of 2003. Additionally, Hurricane Ida, one of the most powerful hurricanes ever to hit the U.S. mainland, leftover one million residents without power [13]. Residents in low-income and majority-Black neighborhoods were the first to experience power outages in Texas. The outages lasted for days and resulted in at least 111 deaths [14,15]. Furthermore, due to Texas' deregulated electricity market, increased demand from the storm caused electricity prices to increase dramatically [14,16], worsening LIHs' already high energy burdens [17]. The impacts of EII during extreme events are especially severe for vulnerable populations that are reliant on household energy for health, education, and well-being [18–20].

The overlapping impacts of the pandemic and other extreme events on EII, community resilience, and renewable energy implementation need to be anticipated to develop effective responses that reduce LIHs' vulnerability. Nearly all extreme events, such as pandemics, wildfires, floods, and heatwaves, have physical and social components. For simplicity, we refer to all events with concomitant losses of human life as "extreme events" while acknowledging the social factors that exacerbate or alleviate the impacts of and likelihood of experiencing physical events.

There is substantial literature examining EII, disasters, and, to some extent, their intersection, but research tends to adopt disciplinary foci so that, for example, analyses grounded in engineering have not always engaged with social science insights and *vice versa*. Our goal is to examine links across the literature and highlight overarching concepts that encourage more cross-disciplinary engagement and, ultimately, more realistic and valuable research. Further, we analyze the approaches to studying EII during extreme events. Drawing on macro-and micro-perspectives from several disciplines, we first address the impacts of extreme events on EII among LIHs. Second, we evaluate the driving factors of EII, including how they have changed due to extreme events. Third, we situate these inequalities into the broader energy system and pinpoint the importance of equitable infrastructure systems by examining the reliability, resilience, and role of renewable technologies. Then, we consider household-level factors that could influence energy consumption. Finally, this paper proposes research methods to study these issues. While we strive to develop a framework that can be applied to a wide range of extreme events, this paper often uses the effects of and responses to the COVID-19 pandemic as an example. It is also important to note that our definition of energy burdens does not include transportation energy. Transportation energy can be a crucial issue for many households but introduces complexities, and a range of literature, that we cannot address in this short review.

## 2. Impacts of disasters on energy inequality and insecurity

Potential drivers of EII, and means of addressing them, occur at both the micro and macro levels. Here, we define the macro-level as large-scale social processes and changes. In contrast, the micro-level refers to an individual's characteristics and behaviors, as well as their interactions with others. Micro-level constraints include sociodemographic and household factors that influence energy behavior and inefficient built environments; macro-level constraints include the quality of energy and internet infrastructures.

### *2.1. Addressing energy inequality and insecurity at the micro-level*

Energy insecurity in the U.S. is expected to rise due to increased electricity prices, inefficient appliances and homes, and extreme weather events. On average, the median household energy burden, defined as the percentage of a household’s income spent on energy bills, is approximately 3.1% across U.S. cities; however, for LIHs, this figure is more than 2.5 times as high, at 8.1% [17]. Similar statistics can be found in other countries; for example, LIHs in Germany spend 5.5% of their income on electricity and 7% on heating, compared to 3% and 4%, respectively, for other households [21].

Disasters have intensified these problems for LIHs in many ways [5]. During the COVID-19 pandemic, for example, LIHs were more likely to experience temporary or permanent layoffs that challenged their ability to pay for energy bills [22]. This financial stress was further compounded by increased home energy demand due to stay-at-home orders [7,23]. Additionally, public facilities that sometimes provide emergency heating, cooling, and internet services for LIHs were often closed or operated at reduced capacity [24,25]. Race, age, and gender inequalities exacerbate these effects [26,27]. Energy security is also crucial for those with complex health conditions, which potentially increases their need for energy and the risk of contracting COVID-19 [28].

When struggling with energy costs, LIHs may resort to unsafe behaviors, such as using ovens for heat and making tradeoffs between utility services, food, medicine, education, and other necessities. For example, many of the deaths resulting from Winter Storm Uri in Texas were caused by residents using unsafe heating alternatives [14,29]. LIHs are also more likely to live in older, less efficient, and poorer quality housing, and use older, less energy-efficient appliances and HVAC (heating, ventilation, and air conditioning) systems than higher-income populations [3]. This pattern is exacerbated by a greater reliance on the private rental sector, where poor housing quality is compounded by limited housing rights [30], leaving renters less able to invest in efficiency improvements. In contrast, owners of rental properties have little incentive to make such investments. In addition, a lack of quality energy infrastructure and utility services is typical in low-income areas [2].

Consequently, EII increases the likelihood of LIHs experiencing physical and mental health challenges, particularly during disasters [5]. In response to these problems, many governments have introduced emergency policies that protect energy consumers during such crises, including disconnection bans, payment extensions, and energy bill reductions [31]. However, most of these measures offset energy debts onto future bills, burdening low-income consumers in the long term [20]. In sum, households that suffer from EII face many potential short- and long-term negative impacts on their well-being and health (Table 1). These impacts highlight the importance of developing reliable, equitable, and resilient energy systems to protect LIHs.

**Table 1.**

Impacts of energy inaccess and insecurity on behavioral, physical, and social-psychological aspects of health at the micro-level

| Behavioral | Physical health | Social-psychological |
|---|---|---|
| ● Tradeoffs between household essentials: heat-or-eat; prioritizing rent or food over utilities; etc.<br>● Using inadequate heating sources: using the oven; using space heaters; etc.<br>● Using unsafe fuel alternatives: burning trash, wood, peat, etc.; using solid carbon-based fuels; etc.<br>● Unsafe financial behaviors: taking out payday loans; playing "catch up"; prioritizing other bills; etc. | ● Thermal discomfort: keeping the home warmer/cooler than needed; heightened risk of fire due to unsafe alternatives.<br>● Poor ventilation: poor indoor air quality; mold; excess moisture; dampness.<br>● Inability to access medical services/supplies: telemedical services; electricity needed for medical equipment.<br>● Inability to store and prepare food: lack of access to refrigeration; unsafe food storage and preparation. | ● Psychological stress: anxiety; maladaptive coping; depression; sleeping disorders; etc.<br>● Education and work: lower educational attainment; missing school or work due to illness; unable to work from home.<br>● Bundled hardships: food, housing, water, and energy insecurity; limited resilience reserve. |

Source: Authors

*2.2. Equitable and resilient infrastructure systems at the macro-level*

Disasters, the COVID-19 pandemic, and their intersections have exacerbated the effects of existing gaps in energy infrastructure [32–34]. For example, in the middle- and low-income countries, the COVID-19 crisis is hindering investments in renewable energy and other aspects of the energy transition [35]. The overall reliability, security, and resilience of energy infrastructure across macro-levels of communities, infrastructure service areas, and geographic regions can impact LIHs' daily lives. Stay-at-home orders during the pandemic have reduced overall weather-normalized energy demands [36], which, in turn, have reduced potential risks and impacts to energy infrastructure. Energy demand, however, has shifted to increased residential demand, yet commercial and industrial demands have decreased [23,37]. This change has brought new challenges for local electricity distribution systems. Four equity issues arise from these stresses on infrastructures: (1) resilience, (2) reliability, (3) renewable energy sources, and (4) internet access.

**Resilience** is defined as "[a community's] ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents" [38]. Resilient infrastructure can swiftly recover from and be repaired after such events [39]. Often, low-income communities are unable to recover quickly from damages due to limited resources, especially during disasters [40,41]. For example, the February 2021 Texas power outage affected 90% of the state's power system. Service areas with a high share of minority populations were four times more likely to lose power compared to predominantly white neighborhoods. Overall, there were eleven deaths and 1,400 emergency care situations due to people using unconventional heating sources. Black, Hispanic, and Asian populations were disproportionately impacted, making up 72% of carbon monoxide poisoning cases (compared to 52% of the overall population) [42]. It is estimated that it could take up to four years for vulnerable communities to recuperate from the storms' financial damages [29].

The Electric Reliability Council of Texas (ERCOT), which operates the power grid and manages the deregulated market for 75% of the state, does not mandate power plants to perform routine equipment updates or maintenance to help the grid withstand extreme temperature events [29]. Poorly maintained infrastructure can jeopardize public health during disastrous events; due to the lack of maintenance on power infrastructure, large industrial complexes in Houston released millions of pounds of pollutants after Hurricane Harvey when the plants and refineries were shut down and restarted [14]. Given that LIHs disproportionately live near industrial facilities, they are at heightened risk from such infrastructure failures. The impact of extreme weather events on energy systems is compounded when the impacts of climate change are considered [43]. As climate change exacerbates the stress on energy infrastructure systems (e.g., power distribution poles) through more frequent, intense, and stressful events, disruptions of critical health services in low-income communities can increase [41,44].

**Reliability of energy.** The impacts of disasters can exacerbate power outage impacts in areas with poor energy infrastructure. Power outages and service interruptions are caused, in part, by the aging and growing unreliability of electric grid infrastructure [32]. In areas with limited energy infrastructure or supply, electricity is generally supplied by a capacity-constrained grid, where the power service quality can vary both spatially and temporally. For example, voltage fluctuations that can damage appliances are more frequent for LIHs since they often live further down the distribution line [44,45]. LIHs are less likely than the relatively affluent to have in-home systems to mitigate such voltage drops (e.g., installing voltage stabilizers, buying a new device), and utilities often do not provide such devices. Additionally, energy system outages can increase energy prices due to the need to use more expensive fuels as substitutes for the supply lost, which, as noted above, tends to impact LIHs disproportionately.

**Renewable energy.** Renewable energy sources are a rapidly growing part of the energy supply, but many such systems do not have adequate capacity to provide 100% power and require demand response (DR) management to reduce peak demands. Research has found that, after extreme events, DR management has improved utility service restoration [46] and helped prevent blackouts [47]. However, LIHs likely lack the equipment or knowledge that supports participation in DR programs, such as direct load control programs requiring more automatic appliances [48]. Community-based strategies might effectively promote efficiency and renewable technologies with LIHs; for example, innovative financial solutions and community-based incentive programs could reshape the power infrastructure in LIH neighborhoods [49,50].

In many cases, renewable energy solutions could be implemented not at the household-level, but the community level (e.g., apartment building). In moving towards such community-level strategies, symbolic resources, including collective community identity, local autonomy, and community sustainability, have also been found to be practical mobilization tools [51]. Most current community solar adopters, however, are businesses and universities or higher-income households. Less than half of the community solar projects in the U.S. serve low-income neighborhoods [52]. Nonetheless, many states that have adopted low-income community solar projects have shown promising results; in Colorado in 2018, nearly 400 LIHs enrolled in eight state-wide solar projects that saved them 15-50% on their utility bills [52]. Many cities have also proposed new community solar projects, such as the New Orleans City Council in Louisiana, which authorized the building of low-income community solar projects to address systemic barriers to land and property ownership [53]. Community solar can mitigate many challenges to renewable energy resource access of LIHs if these programs are designed to meet their needs.

**Internet access.** Internet access is increasingly critical, especially during extreme events when work and school must be accessed remotely. However, LIHs are less likely to have internet-related equipment and have substantially lower internet access levels than more affluent households [4,6]. The Federal Communications Commission (FCC) stated that 92% of the U.S. population has a broadband service [54]. However, an analysis of user data shows that the use of the internet at broadband speeds, defined federally as 25 Mbps download and 3 Mbps upload, could be as low as 50% [55], indicating that many have access to unreliable and insufficient internet. Unsurprisingly, internet access disparities correspond closely with inequalities in income, education, race and ethnicity, age, immigration status, and geographic location [56]. However, the issues of internet access disparities that might be linked to the accessibility of energy-efficient programs, digital utility payment portals, materials to improve energy literacy, and in-home technologies that save energy and money, have not been adequately studied. Additionally, more research is needed on how limited internet access among LIHs influences energy costs and the resilience of households during disasters.

### *2.3. Social and behavioral factors influencing energy consumption*

Many social and behavioral factors influence energy consumption during extreme events. Increased insight into these factors can help researchers and policymakers understand how social and cultural contexts shape vulnerabilities. Such understanding can improve risk communication, inform the design of appropriate financial and social support programs for LIHs during such crises, and better address EII. This section discusses energy patterns and practices, as well as the social-psychological factors influencing LIHs' energy consumption and well-being.

#### *2.3.1. Increased residential energy demand and different energy practices*

During the onset of the COVID pandemic in 2020, increases in residential energy demand overall and during peak hours posed a severe burden for LIHs[31]. However, overall energy consumption in all sectors was lower. For example, in Ontario [37], Australia [31], and New York City [23], daytime energy use increased by 15%-23%, and the average morning peak load shifted to later in the day than before the pandemic as fewer people woke up early to commute or travel to school [57]. However, LIH peak hours tend to differ from those of higher-income groups [3], as they are more likely to stay at home during the day in non-pandemic periods [58] but are less likely to be able to work from home; therefore, the shifts in their consumption may be less substantial. Further research is required about how energy use profiles might shift among LIHs during extreme events.

Additionally, compared to higher-income households, LIHs have different energy behaviors; for instance, LIHs are more likely to set and maintain a constant thermostat setpoint due to a lack of knowledge of the benefits of adjusting setpoints, a lack of awareness of energy efficiency, or more significant time constraints than more affluent households [3]. LIHs also tend to set their thermostats at higher temperatures during the winter and lower temperatures in the summer compared to higher income groups, perhaps because of less efficient HVAC systems and leakier dwellings [59]. Such setpoints generally increase heating and air conditioning energy use, which accounts for nearly half of residential energy use in the U.S. The shifts that occur during disasters may or may not persist once the disaster has ended.

*2.3.2. Social-psychological factors influencing energy use and technology adoption*

Many social-psychological factors can influence individuals' energy use and technology adoption during disasters. For example, perceived behavioral control (one's perceived ability to take actions) can influence energy-saving behaviors among LIHs. They are time-constrained and, thus, less able to pursue energy efficiency than more affluent households. In addition, LIHs' thermal comfort needs may be greater than other households since LIHs are more likely to have seniors and household members with energy-reliant medical conditions [57,60]. Further, social norms can also influence pro-environmental behavior; therefore, shifting relatively inefficient energy-use patterns may require targeted efforts that are attentive to the needs, constraints, and perceptions of LIHs [61]. For example, LIHs tend to be more optimistic about saving energy [62] and perceive more significant risks associated with climate change than those with higher incomes [57,63]. Accordingly, LIHs have multiple motivations for increased energy efficiency, so overcoming the obstacles identified by catering to these motivations could tap a substantial pool of efficiency efforts that would benefit LIHs directly [3].

Additionally, perceived risks relate to technology adoption; there is evidence that LIHs, despite higher energy costs and burdens, were more likely than higher-income households to perceive themselves as low energy users and, thus, less willing to adopt home energy management systems [57,60]. Inefficiencies in the built environment may explain higher energy costs for LIHs, as well as differences in risk perceptions of exposure to extreme events like pandemics. or example, LIHs have been found to have a lower perceived risk of contracting COVID-19 [57] but are actually at a higher risk of contracting it [64]. Actual COVID-19 exposure risks within a household are significantly altered by heating and cooling system use; such systems can adjust the temperature, ventilation rates, and indoor humidity, thereby impacting occupants' exposure to aerosols and droplets expelled by an infected person [65]. Exposure risks can be further compounded by different HVAC system types, such as central systems serving multiple households versus localized systems serving individual households or the presence and types of filters used [66,67]. However, LIHs are less likely to afford HVAC systems than higher-income households, which may worsen LIH exposure to the virus [68,69].

## 3. Research methods and data challenges

Given the complexities identified in the previous sections, analysis of EII in the context of extreme events requires an interdisciplinary approach, using data and methods that span social science, engineering, and data science. In this section, we identify key opportunities and challenges to integrating data and methods in studying EII. Table 2 summarizes the dimensions, concepts, associated measures, and potential data sources for studying energy burdens. The COVID-19 pandemic is considered an example, while measures, dimensions, and concepts apply to other extreme events mentioned above. Future researchers can use this table to refine their measurement and research questions.

**Table 2.**

Dimensions of energy inequality and insecurity and considered measures in the context of disasters

| Dimensions | Concepts | Measures |
|---|---|---|
| *Contextual* | ● Changes in health, social, and economic context | ● Presence of lockdown<br>● Spread of COVID-19 cases and/or other diseases<br>● Shelter-in-place due to other disasters<br>● Impacts on the economic market |
| *Demographic* | ● Restrictions to certain populations<br>● Household characteristics<br>● Socioeconomic status<br>● Gender and race/ethnicity | ● Essential workers<br>● Older residents<br>● Household size<br>● Renter status<br>● Availability and affordability of insurance<br>● Income and employment change<br>● Gender and race/ethnicity<br>● Political party affiliation<br>● Education level |
| *Technical and home environment* | ● Built environment<br>● Availability of energy management technology, appliances, and digital services | ● Building and HVAC system characteristics<br>● Indoor environment quality<br>● Internet service<br>● Computer and IT technology availability |

| | | |
|---|---|---|
| | ● Energy service reliability and quality | ● Frequency of power outages |
| *Behavioral and economic* | ● Energy consumption behaviors<br>● Occupancy patterns<br>● Purchase behavior<br>● Electricity price<br>● Changes in other activities (e.g., not flying, driving, more people at home) | ● Frequency of appliance use and travel behavior<br>● Hourly energy/electricity demand<br>● Energy habits<br>● Hourly energy/electricity wholesale and retail prices<br>● Time of energy use<br>● Energy-related purchase |
| *Social-psychological* | ● Positive and negative emotions toward the pandemic<br>● Perceived mental and physical impacts<br>● Community environmental impacts | ● Perceived personal constraints, uncertainty<br>● Perceived fairness of social distancing policy<br>● Trust and social support<br>● Mental and physical health conditions<br>● Climate change perceptions |
| *Energy policy* | ● National and local policies for helping low-income households' energy issues | ● Energy assistance programs<br>● Utility disconnection policy<br>● Environmental Justice and Cumulative Impacts bill<br>● Families First Coronavirus Response Act<br>● Low-Income Home Energy Assistance Program (LIHEAP) |
| *Energy infrastructure* | ● Vulnerability of infrastructure systems<br>● Direct and indirect loss<br>● Infrastructure resilience and recovery | ● Vulnerability functions<br>● Fragility<br>● Fatality, injuries, and economic loss<br>● Downtime and loss of revenue<br>● Power outage, utility disruptions<br>● Poor housing conditions |

Source: Authors

*3.1. Direct versus non-direct measures*

In general, researchers can use three approaches to measure EII: direct measures, indirect measures, and model-based parameter fitting. A direct approach measures the exact information one is looking to measure. In contrast, an indirect approach, also known as proximate or latent measures, measures a variable using other relevant proxy variables when a direct measurement cannot be made. For example, direct measures of energy consumption, such as smart meter data, are ideal to answer research questions. Smart meters have been used in disaster recovery to automatically report service outages, which can help with repair mobilization [70]; however, smart meter data may be difficult to obtain, especially from LIHs who are less likely to have access to such technologies. When smart meter or utility bill data are not available in general, researchers can estimate the energy consumption of LIHs from the amount of time a household spends doing specific activities that consume energy (e.g., cooking or watching TV) or from aggregated data of utilities' energy sales from electricity, gas, and water divided by energy price and the number of LIHs in the area, obtained by matching census data with county-level energy sales data. In the context of disaster recovery, utility companies can also turn to social media for information on power outages to help strategize recovery [71,72]. This method acts as a proximate measure for energy consumption data but can be limited by the available information on individual households.

The last method, parameter fitting, determines the functional relationship between the system's noticeable feature(s) to understand the intricate and difficult-to-measure relationship between COVID-19 cases and EII, even when the measurable metrics and the desired data are not linearly correlated. Researchers can then use the relationship between EII and proximate measures, such as socioeconomic and health-related factors (e.g., population density, demographic structures, health vulnerability, COVID-19 cases, prevalence, or policy interventions), electricity price, or utility expenditure at the state- or county-level, and compare it to parallel data on energy consumption factors (e.g., electricity and natural gas usage, utility costs, or land use characteristics). In other extreme events, researchers can use similar socioeconomic factors, such as population densities, health vulnerability, public policy, deaths, and so on. This method enables researchers to estimate aggregated, quantitative, non-linear statistical relationships between COVID-19 cases or other extreme events and energy burdens. Of course, this type of statistical method cannot address social-psychological issues at the individual- or local level. Therefore, researchers must avoid the ecological fallacy when inferences about an individual are made based on aggregate data, by being cautious about conclusions drawn from aggregate data and striving to develop datasets at the household level [60].

Further, researchers can estimate unobservable data by fitting the outcomes of process-based models based on a theoretical understanding of how relevant factors interact to drive processes to observable outcomes [73,74]. With the context of the COVID-19 pandemic, researchers can then infer infection rates and measures that must be true to enable model projections to concur with real-world observations. For example, in epidemiology, without careful lab studies that purposefully attempt to infect volunteers, it is impossible to measure the transmissibility of an infectious disease. However, one can observe the number of new cases and use this observable estimate of the growth rate of the outbreak to backward infer the rate of transmission of the infection from infectious to susceptible individuals. This rate can then be applied to predict the impact of health interventions explicitly targeted at interrupting transmission. Agreement between model predictions and real-world outcomes proves that our understanding of the inferred parameter is appropriate. Energy research can analyze the relationships among COVID-19 infection and death rates, household conditions and socioeconomic status, and energy burdens; for instance, one study found that limited access to health and energy infrastructure and other socioeconomic constraints (e.g., income) can worse a county's COVID-19 infection and death rates [75].

While this path is vastly more complicated, it plays a critical role in gaining indirect access to data estimates without direct measures. Process-based models provide a valuable framework to incorporate specific responses to altered environmental conditions and can be applied to predict the effects of global change, while also offering more explicit assumptions and more straightforward interpretations than statistical or rule-based models using previously collected data [76].

### *3.2.1 Mathematical and statistical models*

Mathematical models are systems of equations or algorithms that capture a quantitative description of hypothesized causal relations between the states of objects or outcomes. Mathematical tools for projection rely heavily on techniques such as ordinary differential equations, hidden Markov models, matrix and tensor algebraic projections, and agent-based computational simulations. Mathematical models can take many forms, including dynamic systems, statistical models, differential equations, or game theory models [77]. While statistical models allow for predictions based on inter- or extrapolated analyses of prior observations, mathematical models are further capable of contrasting hypothetical scenarios that have not yet been observed or deconstructing observed scenarios to determine which factors were most critical in driving their outcomes [76]. In most applications, mathematical models are motivated primarily to simulate a system and often project its future state. For example, our developing understanding of future COVID-19 threats has relied heavily on mathematical models (mainly the systems of ordinary differential equations) and has been the primary means of understanding the role of pre-symptomatic transmission of infection. In addition, mathematical models have been used to predict the efficacy of "shelter-in-place" strategies and "flattening the curve," ensuring adequate healthcare capacity in hospitals over time and estimating the infection risks to vulnerable populations (e.g., LIHs) [78]. The majority of these models have used the systems of ordinary differential equations, but some critical insights have also relied on other methods, such as agent-based simulations. Furthermore, mathematical modeling has been used to predict the results of natural disaster events [79], estimate earthquake casualties [80], and develop flood management strategies [81].

In the context of energy use, we can use mathematical models to examine household temperature regulation appliances (e.g., HVACs) and occupant behaviors as a proxy for residential energy access. Since temperature affects both evaporation rates for disinfectants and the duration of viruses outside their hosts, limited access to HVAC regulation in a household may decrease residents' ability to limit infection transmission [82,83]. Furthermore, individual immunity can be compromised by prolonged exposure to cold temperatures [84]. Predicting how the combined factors of compromised cleaning efficacy, increased avenues of COVID infection transmission, and decreased physiological capability to withstand exposure is an important challenge for mathematical models. Such models can make visible the challenges of EII and disease transmission for LIHs, as well as illustrate how these challenges might spill over into the broader community, driving local epidemic dynamics. During heatwaves with coincident power outraged, mathematical models (e.g., thermal models of buildings) can help determine the increase of indoor temperature over time due to the loss of air-conditioning for each residential building, and estimate the impact of overheating on occupant's health, to inform emergency responses.

Similarly, statistical models are quantitative formulations meant to reveal patterns in observed data. Most statistical models begin with a mathematical model in the form of an equation or set of equations, that can then be used for simulation or projection. In most applications, statistical models estimate critical parameters from data on households, organizations, or geographic units, such as countries or regions. For example, regression models can be used to understand the factors that drive energy consumption (e.g., income, age of dwelling units, etc.) and, thus, can help understand patterns of energy consumption and energy burdens [60,85,86]. For example, Memmott et al. [28] utilized logistic regression models comparing the correlations of household energy insecurity from April 2019-April 2020 to patterns during typical circumstances, as well as the potential hardships (e.g., income loss) that these households experienced since the start of the pandemic. The authors found demographic, health, and housing characteristics to be negatively associated with at least two indicators of energy insecurity (e.g., inability to pay utility bills, receiving disconnection notices, or being disconnected) [28]. Similarly, Chen et al. [57] used statistical models (e.g., analysis of variance) to test different income groups' home energy management system (HEMS) adoption intention during the pandemic. The statistical models evaluated the differences in various income group responses to survey questions. They revealed that HEMS adoption intention is influenced by many social-psychological factors, including trust in utility providers, perceptions of climate change severity, and COVID-19 infection risk perceptions [57].

In addition to conventional statistical models, artificial intelligence (AI) and machine learning (ML) methods can provide powerful tools to analyze data, predict future events, and estimate their impacts on energy infrastructure, energy demand, and human health using large-scale data sets [87]. However, unless these methods are used to disentangle causal relations, one must be careful not to build on spurious relationships that can reproduce social biases (see the discussion below). ML methods, either supervised or unsupervised, can analyze existing data to decode patterns and predict future events or impacts [88]. Data fusion and assimilation techniques can analyze diverse data sets from various sources and domains. Utilizing ML algorithms with big and diverse data sets typically requires high-performance or Cloud computing [89]. Human-interpretable results from ML are a key challenge and require physics and/or social-informed ML. The use of visualization and GIS mapping on different socioeconomic neighborhoods, leveraging augmented reality and virtual reality technologies, is also a powerful tool to provide actionable information from data analysis to decision-makers in analyzing energy burdens and other EII issues.

Disaster researchers have recently utilized ML methods to analyze social media messages related to utility disruptions and disaster information, impacts, and relief [90–93]. Given the enormity of social media data, ML methods and deep learning can categorize and analyze large amounts of real-time messages to make insight extrapolating easier and faster. Additionally, the different data obtained through the various methods aforementioned can be used for disaster researchers to understand better the needs of residents, especially LIHs, in a community during extreme events. Given the additional challenges that LIHs face before a disaster, a more tailored pre-disaster planning in the community can better prepare residents to keep essential services available for real emergencies during a disaster. More importantly, a more specific plan targeting LIHs should be put in place relatively quickly for post-disaster recovery and rebuild based on the empirical data analysis. We address several challenges for energy and disaster researchers below.

### *3.3. Challenges of data collection and integration*

Collecting human data paired with physical data at a granular level can be particularly challenging for studying EII. This section addresses three primary data collection and integration challenges: 1) understanding sample characteristics, 2) understanding social bias in new forms of big data, and 3) data quality and privacy issues.

#### *3.3.1. Understanding sample characteristics*

First, there are several challenges to collecting household-level data among LIHs, including (a) language barriers – especially if LIHs' primary language is not English [94,95]; (b) lack of trust - many LIHs are wary of both scams and governmental intervention and may be concerned about participation in research efforts without a trusted source encouraging participation [57,96]; (c) time availability - LIHs may face time constraints and less predictability in their schedules than the more affluent, making data collection more challenging (especially during or after extreme events), and potentially making one-time survey data less meaningful than longitudinal data [97]; (d) renter status - many LIHs live in rental units where utilities may be provided and/or metered at the building-level, making it challenging to link individual household energy data and human subject data [98,99]; similarly, in rental units, collecting human subject data may require support from both the tenants and the property owner [95,98]; (e) older units - LIHs typically live in older housing units that may not have the modern electrical infrastructure to support sub-metered energy use data collection [97,100]; and (f) unreliable communication technologies – LIHs may not have the same access to internet, cellphones, or reliable sources of contact for diachronic human subject data collection compared to other households, making survey-based data collection challenging and costly to complete [8,101]. However, studies show that LIHs are more likely to use smartphones than other devices to access online content, so ensuring that online data collection methods are mobile-friendly is imperative [102,103].

There are measures that can be taken to improve the quality of LIH population data collection. In developing instruments and distribution methods several design variables should be considered. These include the total number of questions, reading and comprehension level of the target population, the language in which the survey is presented including accessibility to non-English speakers, the appeal of the survey design, amount and method of compensation, and physical or digital delivery [104]. Obtaining input from the target population during the instrument design phase is necessary to adapt materials and techniques to the specific participant characteristics. Focus groups, extended interviews, and pilot samples are beneficial in determining how to make a study's intent transparent to participants and understand participants' reasoning and thinking. Addressing the target population's desire and respect for dignity through methodology has been shown to be critical in producing high quality [105]. Since many research projects are intended to benefit the communities being studied, it can also be essential to engage members of that community as active collaborators in the research design and analysis [106].

### *3.3.2. Understanding the link between big data and social biases*

Second, the use of big data is growing in popularity and being applied in energy, computer science, and disaster fields; however, several precautions are warranted when applying this approach to issues that burden LIHs. For example, some forms of "big data" come from scraping information on social media or the Web. As we have emphasized, LIHs are less likely than others to be present on the Web or certain type of social media (e.g., Twitter), so analyses based on these sources have the potential to substantially underrepresented LIHs. Additionally, big data methods tend to make predictions or classifications based on correlations rather than causality. Some applications of ML methods have already been critiqued for reproducing social or ethical biases [107,108]. More importantly, big data is seldom generated based on theoretical understandings from the sciences [109]. Thus, at best, researchers must be cautious when linking the available information to underlying scientific concepts. At worst, it means that previous research, including decades of work on household energy consumption, tends to be ignored in favor of ad-hoc explanations based on what data happened to be available.

Nevertheless, research on energy consumption and pro-environmental behavior has led to a robust understanding of what influences such behavior, how inequities unfold, and what types of interventions are effective in which contexts. The challenge is to understand better how new forms of data can be used, both alone and in combination with existing sources, to advance current knowledge. We suspect that this means deploying new forms of data in tandem with traditional methods, such as in-person qualitative observation, surveys, and field and laboratory experiments.

Therefore, while purely exploratory methods are helpful at times, information that can be used to guide action, including public and private policy, require an understanding of causal processes [98]. Methods based on big data may under- or misrepresent LIHs and, thus, miss key issues impacting them, and, in turn, bias policies and programs informed by big data. The best way to connect with these hard-to-reach populations is to reduce the barriers to participation; for instance, bridging the digital literacy and ownership divide would increase the use of sources that big data is harvested from, as would addressing the social media and online privacy concerns of vulnerable populations [110].

*3.3.3. Understanding data quality and generation issues*

Third, several challenges arise from issues of data quality and privacy. One of the main challenges in integrating social science survey data with physical data lies in the fact that heterogeneous data could be obtained from different spatial-temporal granular levels (e.g., individuals, census tract, regional, and one-time surveys compared to hourly smart meter data) and, thus, accurately matching the data is difficult. For example, data quality assurance may become a serious challenge as the number of data sources increases [111]. Data validation and generalization in integrating various data sources are also significant challenges. In the U.S. context, there are several extant, nationally representative data sets, such as the Census [112], the American Time Use Survey (ATUS) [113], and the American Community Survey [114], that provide comprehensive data relating to household energy consumption, demographics, and behavioral patterns. Some critical and potentially flawed assumptions, however, must be made to translate these data so they can provide insights on household behavior and/or energy use [58]. These assumptions need to be verified through further detailed studies; for example, the ATUS includes household activities that can be translated to household schedules that can be linked to other data and/or used for modeling energy demand and consumption patterns over the day, which can be linked to other demographic data (e.g., income). Due to the limitations of the ATUS or similar data sets, household-level occupancy and consistency from day to day must be assumed because such data are not collected across multiple days. However, other countries collect daily data, which could be a starting point to assess the consistency of individual and household schedules.

Additionally, using data from multiple days across a diverse set of households can improve overall data availability. Data sources from individual studies are disparate, often from different climates, geographic regions, or demographic groups. This fragmentation poses a challenge in comparing results from multiple studies and reduces chances of identifying the factors that contribute to their differential influence on the findings of a particular study, and the implications for the broader population [115]. Finally, significant data collection efforts intended to answer social, economic, and demographic questions seldom ask about energy or the environment. Efforts to assemble energy databases (e.g., [116]) might engage social science researchers and, especially, those working on LIH issues, to examine ways to make databases more useful for those purposes.

## 4. Discussion and Conclusion

In this perspective, we address EII during disasters at both micro-and macro-levels. Our goal has been to link the extent of literature in social science and engineering so that future work in EII may be more integrative and, thus, more valuable scientifically and practically. We do this by providing answers to addressing the significance of equitable infrastructure systems through examination of the connections among infrastructure reliability and resilience, the role of renewable energy technologies, household and socioeconomic factors that influence EII, and energy consumption, such as energy practices, socio-psychological factors, and internet and renewable energy technology access. More importantly, we proposed research methods to investigate these issues and provided recommendations for researchers and policymakers.

Given the importance of EII for health and well-being, efforts to help households reduce physical and mental health risks should be increased. In the US context, this could be accomplished and by extending existing assistance programs (e.g., bill assistance, weatherization, or Low-income Home Energy Assistance Program, LIHEAP) [5]. Currently, LIH-specific policies are not only underfunded but are often ineffectively promoted to eligible households. For example, the U.S. federal COVID-19 relief funding process has been criticized for its flawed application and delivery system [117], in addition to its focus on industries more than individuals, lack of safeguards for workers, and the fact that relief was delivered in one-time payments rather than throughout the entire pandemic [118]. Furthermore, the LIHEAP was notoriously underfunded before the pandemic and only served 20% of eligible households [59]. Other policies, such as shutoff and eviction moratoria, appeared inconsistently across the country at the early stages of the pandemic. Still, states and service providers resumed disconnections and evictions as early as May 2020 [119,120]. For instance, Oklahoma resumed disconnections in June 2020, while other states like Washington and some towns in Virginia did not continue disconnections until the end of September 2021 [121,122]. Therefore, federal- and state-level policy needs to consider how they can support LIHs during disasters to alleviate EII.

Additionally, internet and online service accessibility among LIHs must be a priority for future programs. While there are considerable state and federal funds intended for infrastructure development [123], these policies focus purely on the technical availability of services. At the same time, the costs of such services are also a significant barrier for many. For example, in February 2021, the federal government launched an "emergency broadband benefit" subsidy to aid qualifying households. Still, like many federal assistance programs, this subsidy was open to a limited category of applicants and only available for a short period [124]. Therefore, more attention should be paid to the cost of broadband services, as well as the reliability of these services, especially in areas where there is only one internet provider. Further, state governments should investigate their legal and ethical obligations to support internet and utility accessibility and affordability during disasters, especially in vulnerable communities [125].

To ensure the success of any promotional efforts, energy efficiency programs should employ well-documented best- practices in communication [126]. For example, simple messages should clearly describe the positive and negative outcomes of energy-related behaviors (e.g., not effectively using a thermostat) or available benefits of alternative behaviors and then can define practical, concrete steps to decrease those risks or achieve those benefits. Messages should also be delivered frequently, via sources considered trustworthy by the target audience, and through media channels that LIHs typically rely on or use. However, racial or ethnic minorities and/or individuals with lower incomes and education levels, can be less trusting of others than those with higher incomes [96]. Then, it may be necessary for messages to come from sources who are demographically similar to the message recipients (e.g., of similar ethnicity, gender, or social status) [127]. The engagement of local communities, especially low-income and BIPOC communities who are less likely to be included in online or big data, in the design of these programs by linking scientific analysis with local voices is paramount [128,129].

There is a long history of energy consumption analysis that links computer science, engineering, and social sciences; however, previous research in infrastructure development and, in particular, on infrastructure vulnerability to disasters has often focused on techno-economic aspects, without sufficiently considering the social, psychological, and behavioral dimensions of

LIHs' EII. As more is done to realize the potential of inter-and transdisciplinary analyses to understand EII, social scientists and engineers can begin to incorporate social vulnerability measures into the broader measurement and modeling of community resilience [130], including health, education, economic, policy, communication, and demographic factors. Researchers must develop trans-disciplinary methods that conceptualize multiple fields of research in a combined, holistic, and analytical framework. Analysis should also engage the communities adversely impacted by EII, as their lived experiences can bring essential insights to the research process. Such community engagement also serves to build trust in the research and improve its potential impacts.

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