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Power outage-risk integrated social vulnerability analysis highlights disparities in small residential communities

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Individuals experience varying levels of social vulnerability to power grid outages caused by disasters. Neglecting social vulnerability in energy resilience strategies can lead to uneven recovery, which has become a major concern in the U.S. However, few studies consider environmental and infrastructural factors in their social vulnerability analysis. Here we introduce a conceptual Power Outage-Risk integrated Social Vulnerability Index (PO-RSVI) to assess vulnerability of small residential communities to prolonged outages. The proposed index comprises dimensions of prolonged outage susceptibility, community coping capacity, and community accessibility, each with indicators evaluating social hardship during power outages. Additionally, an extensive analysis investigates the relationship between PO-RSVI and willingness to pay for emergency power supplies during such event. Through an extensive analysis of three Texas communities using survey and online datasets, PO-RSVI effectively highlights disparities missed by conventional assessments and provides valuable insights for policymakers and energy resilience planners.

The increasing impact of climate change has changed behaviour of power outages, including frequency and duration. Climate change and severe weather have been recognized as the primary cause of extended outages throughout the U.S[1,2]. Power disruptions can lead to breakdown of essential services, including water treatment centres and health services, which can affect various public sections even migration policies over time[3]. One example is Winter Storm Uri (2021) that affected 25 states in the U.S. and over 150 million Americans[4]. Uri caused widespread power and water disruptions across the nation, with Texas experiencing the most impact[5]. The power outages lasted for up to five days and left tragic loss of hundreds of lives due to carbon-monoxide poisoning, extreme cold, exacerbation of health conditions, and many more[6]. Another example is Hurricane Beryl (2024) that swept through southeast Texas, causing widespread damage to the power system. The hurricane left nearly 2.3 million customers without electricity for several days during the intense heat[7]. Near one third of fatalities associated with Beryl were due to heat exposure for a long time[8].

Following power disruptions, risk mitigation strategies are undertaken to fortify critical electricity infrastructures. The effectiveness of such strategies has been thoroughly investigated in multiple studies[9,10] and has shown promising results in preventing and mitigating impacts of widespread outages. However, social vulnerability (SV) is often overlooked. Vulnerability is a system's susceptibility to possible future harm[11,12]. From a social perspective, vulnerability determines the extent to which individual's life and possessions are prone to harm of hazards due to a lack of adapting capacity[13]. Individuals usually exhibit varying degrees of vulnerability to power disruptions, which initiate from diverse demographic and socioeconomic characteristics. It is widely acknowledged to take SV into account when formulating and implementing such fortifying strategies.

Over the past few years, there has been a growing emphasize on measuring SV in the scope of power outages. Flanagan et al.[14] proposed a census tract-level Social Vulnerability Index (SVI) for disaster management that has been inspired by other researchers in the context of power outages. The authors proposed an SVI using fifteen census variables that can be categorized into socioeconomic status, minority status/language, household structure/disability, and housing/transportation. Nejat et al.[15] utilized the aforementioned SVI structure and applied it to Texas counties. The authors then analysed county-level outage/recovery data from Winter Storm Uri 2021 to explore potential links between county attributes and their share of

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outages. Montoya-Rincon et al.[16] developed another SV structure for power outages, incorporating indicators from the SVI alongside three additional indicators: road density, proximity to supermarkets and hospitals, and the presence of private vehicles. They employed this vulnerability index to assess the efficacy of two power grid strengthening strategies implemented in Puerto Rico. Using a different structure, Dugan et al.[17] proposed a three-dimensional metric for long-duration power outages, which explores SV through dimensions of health, preparedness, and evacuation, purely focusing on socio-economic and demographics. Through an inductive structural design, principal component analysis and pareto ranking were employed to identify the most influential factors that included socio-economic and demographic features.

The existing literature mostly considers population characteristics for SV. Nevertheless, it has recently been suggested that conventional analysis need to be updated and incorporate environmental and infrastructural characteristics of areas[17]. Power outages typically result in injuries, food/water shortage, limited medical aid access, and more. During these times, individuals' accessibility to food/water supplies and health services is necessary to meet their needs and ensure survival. Having said that, the level of individuals' access to such facilities is often uneven during outages. Accessibility of services depends on both individuals' socio-economic status and the proximity of such facilities. Despite being a crucial aspect of social vulnerability, accessibility is underrepresented in literature. Moreover, utilities often provide data illustrating how power restorations are influenced by various factors such as restoration priorities, maintenance plans, redundancy, etc.[18–20]. Disparities in the duration of outages and restorations can intensify social suffering by exposing communities to prolonged outages and heightening overall social vulnerability. While vulnerability reflects the coping capacity of individuals, here exposure refers to the degree to which individuals may experience longer-duration outages. Although exposure and social vulnerability are distinct concepts, Adger (2006) highlights their interconnectedness and suggests that integrating exposure into assessments of social vulnerability can provide a better understanding of the risks faced by communities[13]. Thus, the literature suggests that integrating accessibility and exposure factors into social vulnerability assessments appears to enable a more comprehensive evaluation.

Willingness to pay (WTP) is an economical term that is utilized in regulatory decisions for enhancing quality of power supplies and price to the customers[21]. WTP is defined as the maximum amount an individual is willing to pay to secure the change in a product or service supply[22]. Study of WTP provides essential evidence for service providers to support their expenditure plans before regulators, addressing both normal grid operations and emergency power supplies. For grid normal operations, WTP analysis reveals which aspects of service quality customers value the most and how much they are willing to pay for these attributes, helping to set appropriate prices. In emergencies, WTP helps determine how much customers are willing to pay for enhanced reliability, resilience, or quicker restoration times. Utilizing WTP, service providers can make informed decisions about investments for both scenarios[21].

The literature review on WTP highlights extensive research, particularly in the residential sector, and showcases the development of multiple methods for estimating WTP[23–25]. In this regard, Morrissey et al.[26] employs a mixed logit model combined with socio-demographic and household variables to analyse WTP heterogeneity for consistent electricity supply during power outages across different households. The authors found that gender, age, employment status, and heating system type significantly affect WTP heterogeneity. Irfan et al.[27] analysed the influencing factors in consumers' intention and WTP for renewable energy (RE) through household surveys. Their findings show attitude, perceived behavioural control, and subjective norms positively moderate the relationship between consumers' intention and WTP for renewable energy, while environmental concern has no significant effect. However, belief about RE costs moderates this relationship negatively. Using contingent valuation (CV), Deutschmann et al.[28] presented new evidence on WTP for service quality improvements in Senegal. Their findings reveal that while households and firms are willing to pay more for uninterrupted electricity, WTP for marginal improvements is notably lower, indicating the necessity for significant quality enhancements to justify tariff increases. Wen et al.[29] investigated residential preferences and WTP for improving electricity supply quality across different attributes including daily supply hours, unplanned power-cuts, appliance diversity (peak capacity), and monthly fees. Their findings show that reduction of power cuts is less prominent than other attributes, with main-grid households showing higher WTP for improved electricity, while preferences vary significantly by gender, age, education, and income. Baik et al.[24] implemented a survey-based method to estimate residential WTP for back-up electricity during long duration power outages in winters. Their study provided three major implications including impact of previous outage experiences on WTP, households' mutual support, and impact of outage cause on WTP.

While the existing literature on WTP provides invaluable insights on consumers preferences and behaviour shaping WTP, we did not find studies analysing the relationship between SV to power outages and WTP for emergency power supplies. Understanding this relationship could be beneficial for developing equitable energy policies and improving service quality. It allows utilities and decision makers to target resources effectively, justify infrastructure investments, design policies that address the specific needs of vulnerable communities, and decide the value of backup services to socially vulnerable customers[24,30]. By aligning investments with the financial capabilities and risks of these communities, utilities can enhance resilience, promote social equity, and ensure that all areas receive the support they need and can afford during power outages.

This study contributes to the literature by proposing a three-dimensional Power Outage-Risk integrated Social Vulnerability Index (PO-RSVI) for small residential communities in which area susceptibility to prolonged outages (SI_1), community coping capacity (SI_2), and community accessibility (SI_3) comprise the index. We build on the widely utilized concept of community coping capacity (SI_2) and propose two new dimensions based on community operational, infrastructural, and environmental characteristics where SI_1 addresses the likelihood of facing extended outages and SI_3 evaluates the level of community accessibility to essential and emergency centers during power outages. In this structure, SI_1 plays as a risk of facing extended outages, which is believed to further exacerbate social suffering. The proposed PO-RSVI differs from existing studies using a multi-faceted approach that provides a more holistic view of a community's vulnerability and needs, offering deeper insights into their capacity to cope with power disruptions.

In addition to developing the PO-RSVI, we employ the CV method to assess residential WTP for emergency power supplies during outages. In our study, we employ CV and present individuals with a hypothetical scenario involving an extended power outage and inquiring their willingness to pay for renewable emergency power supply. Unlike existing approaches that emphasize precise monetary amounts, we evaluate WTP relative to households' current electricity rates, expressed as a percentage increase. By evaluating WTP, our research explores its relationship with PO-RSVI, identifying key household features correlated with WTP. We also apply advanced machine learning techniques to analyse how PO-RSVI household-related indicators impact WTP estimation, providing valuable insights for decision-makers in modelling and determining WTP for targeted consumers.

Our PO-RSVI and WTP analysis focus on small communities to allow for detailed data collection, particularly for environmental and infrastructural factors, and precise assessment of localized vulnerabilities, which might be overlooked in larger-scale. Additionally, small communities enable direct resident engagement and manageable pilot testing, facilitating effective validation and refinement before scaling up. To extend the study to larger communities, data collection methods should be scaled up to include broader populations, while incorporating variations in risk factors and needs. Insights from pilot testing should also be used to refine and adapt the index for different community sizes.

Our analysis of PO-RSVI, compared to the traditional SVI, reveals significant differences in identifying socially vulnerable communities by incorporating prolonged outage susceptibility and accessibility factors. The observed negative relationship between PO-RSVI and willingness to pay (WTP) underscores the importance of addressing disparities in resilience strategies. Key factors such as medical aid access, food/water access, household leadership, and children influence WTP estimations. Overall, our PO-RSVI framework provides critical insights for policymakers and energy resilience planners, advocating for tailored strategies to enhance energy resilience across diverse communities.

Modelling PO-RSVI

The concept of vulnerability, a central theme in the literature on natural hazards, is used to examine the potential impacts of various types of hazards. Vulnerability encompasses three primary elements: exposure, sensitivity, and adaptive capacity[12]. Exposure refers to the potential for impact from a specific hazard, sensitivity denotes the magnitude of potential harm should the hazard occur, and adaptive capacity describes the ability to mitigate either exposure, sensitivity, or both[12,31]. Building on these foundational elements, we propose a model to quantify SV of small residential communities to power outages using three sub-indices: prolonged outage susceptibility (SI_1), community coping capacity (SI_2), and community accessibility (SI_3).

The inclusion of prolonged outage susceptibility dimension (SI_1), which represents the risk of exposure to prolonged outages, aligns with multiple studies that provide empirical evidence of social and spatial disparities in exposure to prolonged power outages during climate hazards[32,33]. These extended outages are one of major contributor to heightened social and health damages during such events[34,35]. For example, during Hurricane Ida's outages, non-coastal, lower-income zip codes had a 1.00-day longer median recovery time, while areas with a higher percentage of Black population had a 2.00-day longer recovery[32]. These disparities, that can be attributed to policy-operational, infrastructural, and logistical factors, can lead to heightened health risks and increased economic burdens in vulnerable communities[17,36,37]. In this regard, studies suggest that incorporating an exposure factor into SV assessment, can provide a more comprehensive approach to developing effective resilience strategies.

The community coping capacity dimension (SI_2) is regarded as a fundamental and conventional component of the proposed PO-RSVI. Studies on multiple major blackouts in the U.S. have shown that socioeconomic and demographic factors, such as age, gender, race, health condition, income, education, and language, are among the most influencing determinants of individuals' hardships during outages[15,38,39]. This dimension is widely recognized in the social vulnerability literature as a key factor for assessing vulnerability to various hazards, including power outages, and is considered the most basic yet crucial component for identifying at-risk populations[14,16,17].

Lastly, the community accessibility (SI_3) dimension is well-justified in the literature as a critical component of vulnerability to power outages. Prolonged outages can substantially disrupt access to essential services and facilities, disproportionately affecting vulnerable populations[1,35,37]. Studies show that a lack of access to healthcare and critical facilities and services during outages can exacerbate health and safety risks, particularly for those with chronic conditions and disabilities[34]. Hence, the inclusion of accessibility in SV assessments is widely recognized as enhancing the accuracy of identifying at-risk populations[14,40].

The key difference between proposed PO-RSVI and traditional hazard risk indices is that our model integrates the risk of prolonged power outages directly into the social vulnerability calculation. Traditional hazard risk indices typically focus on assessing the likelihood and intensity of hazardous events (e.g., flooding or power outages)[41,42], whereas our PO-RSVI combines the risk of prolonged outages with social vulnerability factors. This integration allows our index to provide a more comprehensive measure of community vulnerability, considering both the physical threat posed by outages and the social conditions that may exacerbate or mitigate their impact. This approach enables the identification of communities that are not only exposed to risks but also less equipped to handle the consequences, offering a more holistic framework for resilience planning[40].

The complementary nature of these dimensions in the proposed PO-RSVI is further supported by Hinkel and concept of layered vulnerability, which suggests that vulnerability within a specific context is determined by the compounded impact of multiple characteristics[12]. The PO-RSVI model captures this layered approach, addressing both the physical risk and social factors that contribute to overall vulnerability. Furthermore, non-overlap property of dimension is reinforced by the distinct focus of each sub-index. This separation ensures that each dimension contributes unique information to the vulnerability assessment, avoiding overlap in the model.

Prolonged outage susceptibility

Power outages arise from diverse causes, encompassing planned events like load shedding and unplanned incidents such as equipment failures, supply shortages, natural disasters, cyberattacks, physical attacks, and wildlife interference[43]. Planned outages occur during scheduled maintenance or to manage demand and are often guided by energy management policies, grid reliability standards, and regulatory frameworks aimed at preventing widespread power failures. For unplanned outages, utility maintenance crews are dispatched after detection to identify the root cause(s) and begin restoration efforts. Besides the severity of damages, studies show that restoration duration varies across regions due to restoration policies, availability of maintenance crews, and transportation conditions[44]. Regardless of the category, prolonged outages can exacerbate social hardship of affected individuals by subjecting them to extended disruption of essential services.

Here, we explore the various factors influencing the duration of power outages, which collectively contribute to the dimension of prolonged outage susceptibility. Through a comprehensive review of the literature and widely referenced online sources, we examine the policy-operational, infrastructural, and environmental factors affecting outage durations. Key contributors to SI_1 are identified, including load-shedding policies, power restoration policies, power supply redundancy, proactive measures, and transportation.

Load shedding policies

A balance between power supply and demand is required for stability and reliability of electrical power systems. When electricity demand exceeds supply, load shedding is employed to maintain the power system stability[45]. Load shedding is the procedure of selectively and rotationally powering down regions that may be grouped together based on some predefined criteria. To maintain the power system stability, certain areas are strategically designated for regular and extended load-shedding[19,46]. Several factors may influence load shedding policies, including population density, crime rate, and critical facilities[47]. Regions marked by high population density and heavy traffic flow, such as business districts, typically have a reduced probability of load shedding[47,48]. This is primarily due to the substantial electricity demand within these areas. Furthermore, neighborhoods situated near high population density regions may also benefit from reduced risk of load shedding, as they often share critical infrastructure components such as transmission lines, substations, and distribution networks. In some countries, such as South Africa, load shedding policies may exempt neighbourhoods with a high crime rate from rolling blackouts since the absence of electricity makes it easier to break into private properties. Finally, public well-being and safety facilities, including hospitals and police stations, are typically exempted from rotational load shedding due to their critical nature[19,49].

Building upon the factors above, we propose three indicators: community population density, neighbours' population density, and critical facilities within the community. As discussed earlier, higher population density tends to prioritize power consumption in an area, thereby reducing the likelihood of experiencing load-shedding schemes. The number of neighbouring communities with higher population density is proposed as

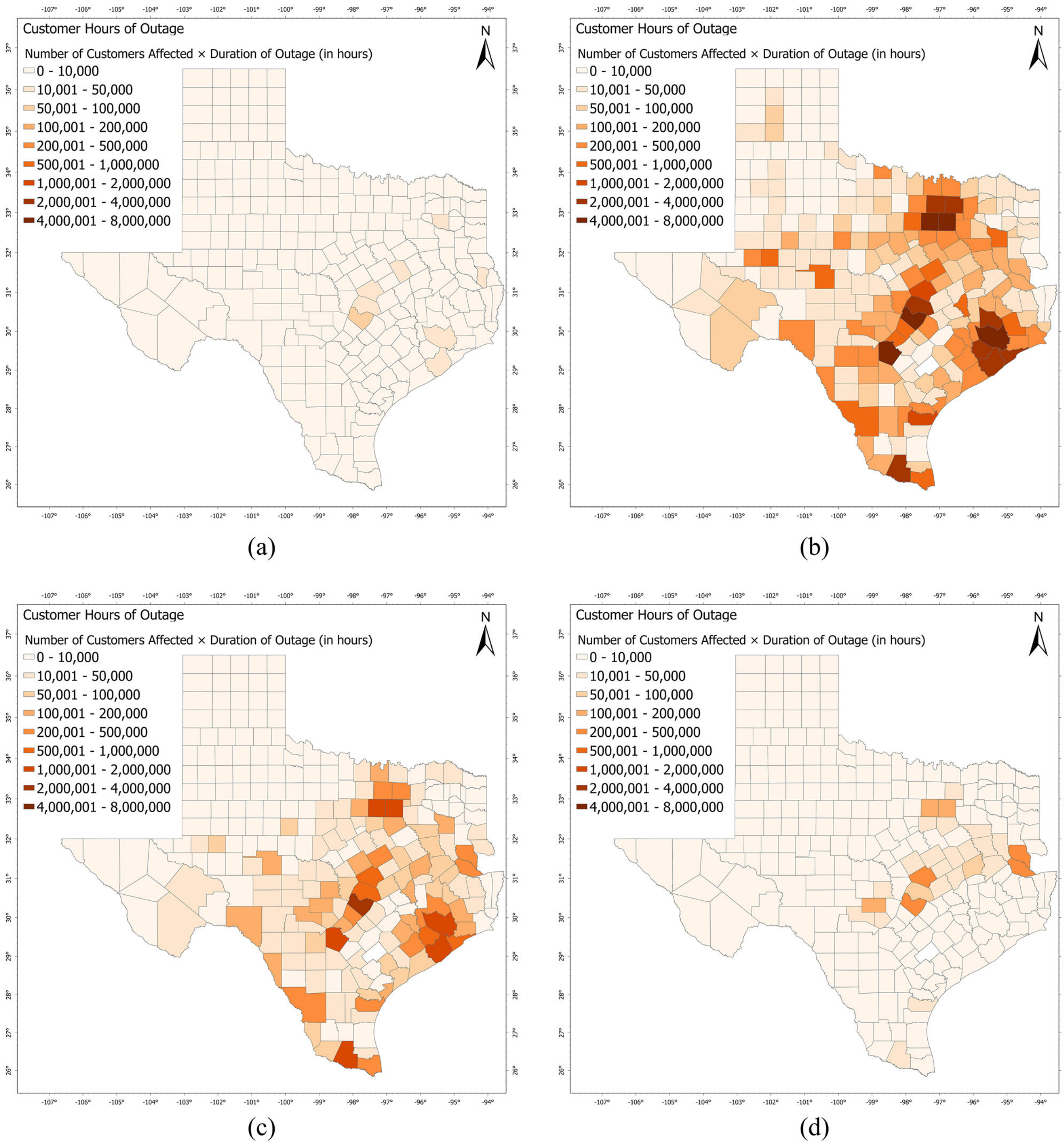

Fig. 1 | The customer hours of outage caused by Winter Storm Uri (2021). Customer hours of power outage in Texas counties in (**a**) February 11-the day the storm struck, (**b**) February 16-when the blackouts were at the peak, (**c**) February 18 and (**d**) February 20 during power restorations (publicly available dataset: HARC & PowerOutage.US).

an indicator, as shared critical infrastructure may help reduce the frequency and duration of load shedding in the target community. We also propose the number of critical facilities within a community as the third indicator, as it further decreases the probability of load shedding.

Power restoration policies

During unplanned widespread outages, utilities implement specific policies to prioritize areas for power restoration efforts. In case of extended outages, utilities are the sector who are blamed by residents for their inefficient policies[3]. These policies can lead to a swift restoration of power within a few hours for some areas, while others experience outages for days. In this regard, Fig. 1 illustrates the uneven power restoration across counties in Texas during Winter Storm Uri (2021). Restoration policies first mandate that critical facilities, including hospitals and health centres, police and fire stations, as well as water treatment centres, be assigned the highest priority for restoration[49]. Consequently, areas hosting these facilities are the first to undergo the power restoration. In addition, recent studies on extensive outages and restoration times reveal that regions with low population density, neighborhoods predominantly inhabited by Hispanic and African American/African households, and residents served by municipally-owned or rural cooperative utilities encounter considerably delayed and uneven restorations[36,41,50].

Based on the factors discussed, we propose two indicators for power restoration policies sub-index: race/ethnicity composition and the dominance of municipal and cooperative utilities within the community. The race/ethnicity composition indicator quantifies the percentage of households that are Hispanic or African/African-American, with higher percentages indicating a greater risk of experiencing slower power restoration. The dominance of municipal and cooperative utilities serves as the second indicator, as communities primarily served by these types of utilities are at a higher risk of slower restoration processes. Although the presence of critical facilities does influence restoration efforts, it is not included in this sub-index to avoid redundancy, as it is already considered in the load shedding factor.

Redundancy

Redundancy in power supply is a proactive technical action to enhance a power system functionality, reliability, and operation safety[51]. Redundancy can potentially reduce the duration of power outages by providing alternative pathways for electricity to flow if a primary line fails[43]. In the event of a fault in a primary power line, a redundant system allows electricity to be rerouted through alternative routes, minimizing the disruption. This can help maintain power supply even when one part of the grid is compromised. Redundancy can also enable faster restoration by allowing the grid operators to isolate the faulty section and continue supplying power through alternate lines while repairs are made. Redundant systems can share the electrical load more effectively, preventing overloading of any single line, which can otherwise lead to failures. Redundancy plays a crucial role in reducing the impact of power outages, particularly for socially vulnerable populations. Research shows that communities with higher social vulnerability are more susceptible to prolonged power disruptions[1]. Redundant power supplies, including backup generation and network interconnections, help ensure continued access to electricity during outages, reducing the burden on vulnerable groups who may lack alternative means to access critical services like healthcare, food, and communication[32]. While implementing redundancy may involve complexity and substantial costs, regions equipped with multiple power sources experience reduced risk of extended outages, benefiting the affected communities.

We propose using the number of distinct transmission lines passing through a community or its boundaries as an indicator of redundancy. This measure reflects the capacity of the power grid to offer alternative pathways for electricity in case of a failure, ensuring a more reliable and resilient power supply. Communities with more transmission lines are better positioned to maintain service during disruptions, reducing the duration of power outages and lessening their negative impacts.

Proactive measures

Failure to take proactive measures, such as regular maintenance and vegetation trimming plans can lead to prolonged power outages[41,52,53]. Studies show that these proactive measures are unevenly applied across regions, leading to disparities in outage durations and recovery times[54]. Optimal functionality of a distribution system requires regular maintenance of infrastructure alongside modernization efforts[43]. This involves power distribution system inspection for equipment defects, replacing worn-out components, and incorporating automation using the latest technology. Neglecting such measures makes power restoration time-consuming and challenging. Additionally, the proactive measure of vegetation trimming near power lines is crucial to minimize potential damages. Vegetation growth into power lines presents a substantial risk, as contact with the lines can ignite fires and result in supply disruptions[55]. The uneven application of such proactive measures increases social vulnerability by disproportionately affecting lower-income communities, which rely more on public infrastructure and have less capacity to mitigate prolonged outages. This disparity deepens systemic inequities in service provision and recovery times[56].

For proactive measures, we include two indicators: equipment maintenance and vegetation trimming. These indicators assess whether a community regularly receives any proactive maintenance for power distribution equipment and vegetation trimming around power lines. If a community is receiving regular proactive practices, then it may not face prolonged outages. Obtaining accurate data for these indicators can be challenging due to the potential lack of records on the frequency of such actions. However, through community engagement and input from local leaders, it is possible to estimate the current level of proactive practices.

Transportation

Power outages typically disrupt transportation, particularly in high traffic density areas, leading to extended restoration times[36]. During an outage, elements of transportation such as traffic lights, fare collection equipment, and road lighting systems fail to function properly[18]. Additionally, in the event of area isolation due to flooding or landslides, transportation difficulties are further exacerbated. Transportation blockage disrupts not only the community daily life, but also the prompt efforts of maintenance crews to reach affected areas and resolve damages[41]. Transportation issues also pose difficulties for community residents to meet their essential needs and seek assistance. Studies on post-disaster transportation and public health demonstrate that transportation difficulties are closely linked to social vulnerability, as disruptions create additional challenges for residents in accessing critical medical services, employment, healthcare, food resources, and social activities[57,58].

Here, we consider the history of transportation blockages in the corresponding community as the indicating variable. The indicator is suitable as it reflects past challenges in accessing the community, which can predict future risk of blockages. Areas with frequent blockages are likely to face prolonged outages due to difficulties in both maintaining and restoring services. This historical data provides a practical measure of how transportation disruptions might impact the community's social hardships from power outages.

Community coping capacity

In the community coping capacity (SI_2), our focus is on individuals' capacity to cope appropriately with harm of power outages. Power outages leave a range of physical and psychological impacts on affected individuals in an un-uniform manner. Outages commonly give rise to various medical complications and exacerbation of existing health conditions, disruption of livelihoods, and psychological health damages[38]. After a comprehensive review of relevant studies, we identify the key social factors that greatly affect individuals' coping capacity during power outages. Based on these factors, we establish the relevant indicators and corresponding measures of SV.

Extensive research demonstrates that age stands out as one of the foremost factors influencing individuals' capacity to cope with the harm of power outages[31,39,59,60]. The findings indicate older adults aged over 65 and children under 5 are particularly susceptible to experiencing adverse effects from extreme indoor temperatures caused by the absence of power. Children are also more susceptible to combined risks of food, water, and carbon monoxide (CO) poisoning, which occurs when generators or burning firewood are used inappropriately as sources of warmth during winter[37]. CO poisoning is also more prevalent among immigrants and people of color[37]. From a medical standpoint, individuals who rely on electricity-dependent medical equipment, those with mobility limitations, and individuals with specific health conditions such as heart disease and diabetes are at risk of experiencing adverse health conditions during power outages[34,38,59–61]. Understanding the mental preparedness of individuals during power outages has been investigated in various studies. Research on power outage preparedness and concern among New York City residents show that older individuals expressed greater health and preparedness concern, but concern appeared to be greater for older respondents who lived alone[61]. Research on power blackouts caused by Winter Storm Uri (2021) and Hurricane Irma (2017) reveals that larger households with children and those with non-English speaking members reported more stress and pressure[39,61–63]. Additionally, research indicates that Hispanic and African/African-American households often face challenges in preparedness for disasters due to limited availability of resources, and cultural differences that affect both the perception of risk and the communication strategies used by emergency response and preparedness planners[64–66]. Other studies detail how a higher level of education (specifically over high-school) is linked to increased preparedness in recovering from power outages[67,68] and higher income facilitates the purchase of non-perishable food, generators, and fuel, and is linked to reduced stress during blackouts[39,61]. The study on households' response to Hurricane Irma (2017) also show that female adults and female-headed households are less prepared in disasters and consequent blackouts[67,68]. The community crime rate and fear of looting is another factor that impacts levels of stress experienced by individuals during power outages, as the absence of power provides a favourable environment for people to break into private properties[48,69]. Finally, studies indicate that having generators contributes to feeling of preparedness for power outages and reduces corresponding levels of concern[39,70].

Building upon the information above, we categorize factors affecting community coping capacity into socio-economic status, health sensitivity, and emergency management. In each factor, there will be multiple indicating variables quantifying the level of community's ability to cope with harm of power outages.

Socio-economic status

Socio-economic status factor examines socio-economic indicators that influence households' coping capacity, and they include education level and income. A higher level of education correlates with greater preparedness, while higher income enables households to access and store non-perishable food, create safe and comfortable accommodations, and evacuate effectively in emergencies. We use the percentage of households with high school as the highest educational attainment to quantify education level and the median annual income of the head of the households to assess income.

Health sensitivity

Health sensitivity factor evaluates how health issues affect individuals in the community during power outages. This factor includes two age-related indicators and health impairments. For age, the percentage of households with children under 5 and seniors over 65 quantifies vulnerability, with higher percentages indicating increased risk of health-related issues such as CO poisoning, food poisoning, and extreme temperature issues. For health impairments, we consider the percentage of households with members experiencing physical, mental, or sensory disabilities or diseases. A higher percentage reflects greater community vulnerability to serious health conditions and, in the worst cases, fatalities.

Emergency management

Emergency management assesses how individuals manage emergency situations in terms of stress, anxiety, and appropriate adaptation. Based on the reviewed studies, we use the following indicators: gender of the head of household, language, race/ethnicity, crime rate, and presence of generators. For the gender of the head of household, we consider the percentage of households led by females, as they are less prepared for emergencies, with a higher percentage indicating greater vulnerability. Language is assessed by the percentage of households where English is not their primary language, reflecting increased vulnerability. The percentage of households with members of Hispanic or African/African-American is used to represent racial/ethnic diversity, as minority races often experience higher stress levels. The crime rate indicator is the history of property crime per 1000 individuals, reflecting the increased fear of looting and property damage. Lastly, the presence of emergency generators is considered, as households with generators are better equipped to meet their power needs during outages, reducing their stress and increasing preparedness. Income, age, and education also impact emergency management but are covered in socio-economic status and health sensitivity to avoid redundancy.

Community accessibility

In community accessibility (SI_3), we focus on the level of community access to essential and emergency facilities to meet their needs during power outages. The availability of essential resources such as clean water, food, and medical assistance becomes increasingly strained during outages, especially for low-income households and families with children[61]. These groups often possess inadequate storage of essential supplies in their household, leaving them less equipped to cope with long power outages[59]. Individuals who do not own a vehicle, face greater difficulties in accessing the resources and may struggle with timely evacuation during emergencies as well[71,72]. Public transportation is crucial in providing with access to those services and resources, thereby supporting individuals' ability to meet essential needs and effectively respond to emergencies[1,73]. Availability and accessibility of shelters equipped with backup generators, as well as suitable locations such as schools that can serve as shelters, play a crucial role in either reducing or exacerbating the vulnerability of individuals, especially during blackouts caused by disasters[39,74].

Table 1 | Proposed PO-RSVI dimensions and the corresponding contributing factors

PO-RSVI Dimension	Contributing Factors
Prolonged Outage Susceptibility (SI_1) The degree at which a community is at risk of experiencing prolonged power outages.	Load shedding Power restoration policies Redundancy Proactive measures Transportation
Community Coping Capacity (SI_2) The capacity of the community to effectively cope with the potential harm of power outages and achieve a prompt recovery.	Socio-economic status Health sensitivity Emergency management
Community Accessibility (SI_3) The degree at which the community households have access to essential and emergency facilities in case of power outages.	Essential supplies Emergency facilities Transportation

For this dimension, we consider three key factors: essential supplies, emergency facilities, and transportation. For essential supplies, we evaluate community access to food, water, and health resources using two indicators: the number of supermarkets and the number of hospitals within a 5-mile radius. Additionally, we quantify households' self-reported difficulty in accessing these resources using two other indicators of access level. The reason for including self-reported difficulties is to assess how households perceive their access to resources and estimate their efforts to meet their needs. Lower number of resources and lower self-reported access is associated with higher SV. For emergency facilities, we quantify the community's access to shelters and schools, which can be used as shelters. Similar to essential supplies, we use two indicators: the number of such facilities within a 5-mile radius and self-reported difficulties in reaching them. The same relationship with SV holds for these indicators. Lastly, for transportation, we quantify household access to transportation means using three indicators: the percentage of households with private vehicles, the number of bus stations within a 5-mile radius, and the history of transportation blockages. A lower percentage of households with vehicles, fewer bus stations, and record of transportation blockages indicate higher SV.

The PO-RSVI dimensions and the contributing factors are presented in Table 1, with Table 2 providing a detailed description of the corresponding indicators. The relationship between the indicators and the PO-RSVI is illustrated by assigning positive (+) and negative (−) signs. A positive (+) sign is used for indicators where a higher value indicates greater vulnerability, such as crime rate, household size, and past transportation blockages. Conversely, a negative (−) sign is assigned to indicators where a higher value signifies lower vulnerability, such as median income, community population density, and redundancy in power supply.

Once the vulnerability indicators are determined, normalization, weighting, and aggregation are applied to construct the sub-indices. Normalization ensures that all indicators are placed on a dimensionless measurement scale[43]. This process allows for meaningful comparisons and aggregation of indicators that may have different units. Here we utilize popular method min-max scaling to transfer the data into the range [0, 1] and preserve the distance between data points. Regarding weighting, although it ensures that indicating variables are reflecting their relative importance, assigning precise weights to indicators requires a

Table 2 | Proposed PO-RSVI contributing factors and corresponding indicating variables with their description

Factor	Indicating Variable	Description
Load shedding	(−) Community population density[36,47,48,50]	Number of people per square mile in the community census tract
	(−) Neighbours' population density[47,48]	Number of neighbouring communities (census tracts) with a higher population density, measured in people per square mile, than the target community
	(−) Critical facilities within community[19,49]	Number of critical facilities (police and fire stations and hospitals) within 5-mile radius from the community
Power restoration policies	(+) Race/ethnicity[36,50]	Percentage of Hispanic and African/African-American households in the community
	(+) Municipality and cooperative utilities[36,50]	Dominance of municipal-owned or cooperative utilities serving the community
Redundancy	(−) Redundancy in transmission lines[43]	Number of transmission lines passing the community or community boundaries
Proactive measures	(−) Equipment maintenance[52,53]	Receiving regular maintenance measures of power equipment in the community
	(−) Vegetation trimming[52,55]	Receiving regular vegetation trimming around power lines in the community
Transportation	(+) History of transportation blockage[18]	Past community blockage of transportation system due to severe weather
Socio-economic status	(−) Income[37,61,67,68]	The median income of households within the community
	(+) Education[49,50]	Percentage of households with high school degree or lower as their highest educational attainment
Health sensitivity	(+) Age (under 5)[37,39,59,60]	Percentage of households with children under 5
	(+) Age (over 65)[34,39,59–61]	Percentage of households with seniors over 65
	(+) Health impairment[34,38,59–61]	Percentage of households with members having any health impairments
Emergency management	(+) Head of household[67,68]	Percentage of households headed by females
	(+) Language[39,61–63]	Percentage of households speaking a language other than English
	(+) Race/ethnicity[37,62,70]	Percentage of Hispanic and African/African-American households in the community
	(+) Crime rate[48,69]	The community's average property crime per 1,000 individuals
	(−) Power generators[39,70]	Percentage of households with power generators in their household
Essential supplies	(−) Food/water resources[39,71,72]	Number of supermarkets within 5-mile radius from the center of community
	(−) Medical aid resources[39,71,72]	Number of health centres within 5-mile radius from the center of community
	(−) Food/water access[39,71,72]	Household's self-perception of the level of access to sources of food and water
	(−) Medical aid access[39,71,72]	Household's self-perception of the level of access to health centres
Emergency facilities	(−) Emergency facility resources[39,74]	Number of shelters and schools within 5-mile radius from the center of community
	(−) Emergency facility access[39,74]	Household self-perception for the level of access to emergency facilities within 5-mile radius from the center of community
Transportation	(−) Private vehicles[71,72]	Percentage of households with private vehicles
	(−) Public transport[1,73]	Number of bus stations within 5-mile radius from the center of community
	(+) History of transportation blockage[18]	The community isolation experiences in the past due to severe weather

comprehensive understanding of their relationships and impact on overall index. Since capturing these relationships are challenging, we use the alternative but reasonable approach of assigning equal weights to all indicating variables. For constructing the sub-indices, we utilize L2-norm method due to its distance-based properties and providing more reasonable basis for comparison. Lastly, the overall PO-RSVI is constructed using the proposed model provided in Methods. The construction steps are depicted in Fig. 2.

The way the three sub-indices construct the over PO-RSVI index is the multiplication of prolonged outage susceptibility (SI_1) by the aggregation of community coping capacity (SI_2) and community accessibility (SI_2). The rationale behind the structure is that the susceptibility to prolonged outages plays as a multiplier that exacerbates or mitigates the effects of the community's coping capacity and accessibility. For example, if two sub-indices SI_2 and SI_3 have a small value, but SI_1 is relatively large, then the vulnerability further increases comparing with simple aggregation. This formulation highlights the multifaceted nature of our SV index in the context of power outages.

Lastly, to validate the credibility of the proposed PO-RSVI and provide a comparative perspective, we calculate the SVI proposed by Flanagan using the available data and compare it with the PO-RSVI. The data collection and construction process for the SVI is detailed in the Methods section. This comparison highlights the added value of incorporating power outage-specific factors, demonstrating how the PO-RSVI offers a more nuanced assessment of social vulnerability in the context of prolonged outages.

WTP Estimation

In this study, willingness to pay (WTP)—representing the monetary amount households are willing to pay to avoid power outages—is determined through structured surveys designed for community households. The survey evaluates households' WTP for electricity during a simulated power outage scenario, presenting price increases ranging from 10% to 100% above their current utility rates. This approach minimizes the impact of absolute income differences since the WTP is evaluated relative to an individual's baseline cost. In addition, it inherently normalizes the WTP values relative to each household's existing electricity costs in the same range across communities, mitigating the need for additional normalization methods.

To ensure that WTP accounts for disparities among respondents, we employ multiple stratification analysis based on PO-RSVI, income level, and size of households. The first step involves stratifying the data by PO-RSVI to examine how varying levels of social vulnerability influence WTP. Following this, income and household size stratifications are applied either to the entire dataset or within each community, depending on the outcomes of

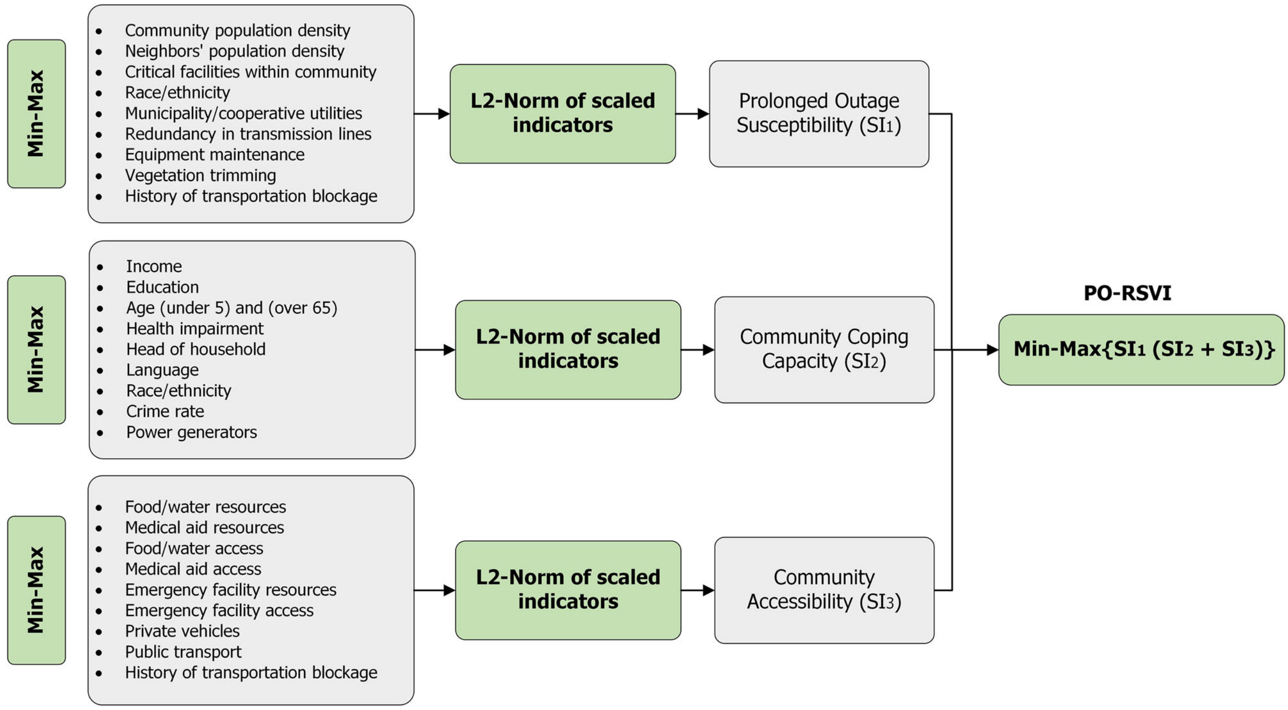

Fig. 2 | PO-RSVI construction process. Construction starts with min-max scaling to standardize all indicators within each factor across all communities. Subsequently, within each dimension, the scaled indicators undergo L2-norm, resulting in sub-indices. Vulnerability score is calculated by min-max scaling the scores obtained by the adopted model.

the PO-RSVI stratification. This stratification process serves as a tool to assess whether WTP accurately reflects respondents' true willingness, independent of financial constraints.

To further explore the relationship between WTP and household features, we examine correlations between the obtained WTP and various household characteristics, such as education level and household size, using appropriate correlation methods to account for the specific types of available data. This approach helps identify features that are significantly correlated with WTP and their incorporation into WTP estimation provide more accurate results.

Lastly, to estimate WTP, we employ various machine learning classification methods, using household data as features and WTP as the response variable. The reason for adopting classification is that the WTP values span an ordinal discrete range. The adopted classifiers include Logistic Regression (Logit), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Random Forest (RF), and Support Vector Classifier (SVC).

Logit is a linear classifier used for binary classification, which can be extended to multi-class problems. In this study, Logit is used with key hyperparameters: regularization strength (C = 1.0), solver type (solver = 'lbfgs'), penalty (penalty = 'l2'), and multi-class classification mode (multi_class = 'ovr'). LDA is a linear classifier used for dimensionality reduction while maximizing the separation between multiple classes. In this study, LDA is employed to model the relationship between input features and class labels. The model key hyperparameters include solver = 'lsqr' and regularization strength (shrinkage= 'auto'). QDA is a probabilistic classifier that models the covariance structure of each class separately. It is suitable when classes have different covariance matrices. In this study, QDA is used with hyperparameter regularization strength (reg_param = 0.1). RF is an ensemble classifier that builds multiple decision trees and aggregates their results for classification. It is robust to overfitting and well-suited for multi-label classification tasks. Here, RF is used with hyperparameters: number of trees in the forest (n_estimators=100), maximum depth of the trees (max_depth = 10), minimum samples required to split a node (min_samples_split = 2). Lastly, SVC is a powerful classifier that works well in high-dimensional spaces, such as in multi-label classification. In this study, SVC is employed with hyperparameters: radial basis function (kernel = 'rbf'), regularization strength (C = 1.0), kernel coefficient (gamma = 'scale'), and multi-label classification strategy (decision_function_shape = 'ovr').

To validate the performance of these classifiers, a 10-fold cross-validation process was employed, ensuring robustness, and minimizing potential biases. The dataset was split into 80% for training and 20% for testing, with shuffling applied prior to the split. The performance is then evaluated using accuracy and F1-score to assess predictive performance comprehensively (see Methods). These metrics provide insights into overall prediction accuracy and the balance between precision and recall (F1-score). The fittest model is then trained by the best combination of hyperparameters, and the final model performance is evaluated using five metrics: accuracy, recall, precision, F1 score, and log-loss (see Methods). Lastly, the most influential features are extracted from the predictor list and an analysis is applied on the outcomes.

Results

PO-RSVI numerical analysis

The proposed PO-RSVI is applied to three small residential communities in Texas, with data collection details (e.g., power transmission lines as shown in Figure 3) described in the Data Availability section. Figure 4 provides the distribution of indicators contributing to the PO-RSVI for each community and Table 3 reports the normalized scores in each dimension. By examining this figure, conclusions can be drawn regarding the in-detail aspects of PO-RSVI. In the domain of prolonged outage susceptibility, it is evident that Rogers Washington stands out as the most vulnerable community to extended power outages ($SI_1 = 1.0$). Most influential indicators to this elevated sub-index are low population density, absence of proactive maintenance, a dominance of municipality-owned/cooperative utilities, and past transportation blockage experiences. For Dove Springs ($SI_1 = 0.56$), besides the two latter influencing variables for Rogers Washington, low population density of neighbouring communities, low number of critical facilities in 5-mile radius, and high proportion of non-white households affect the sub-index. Sunnyside exhibits the lowest vulnerability score in this

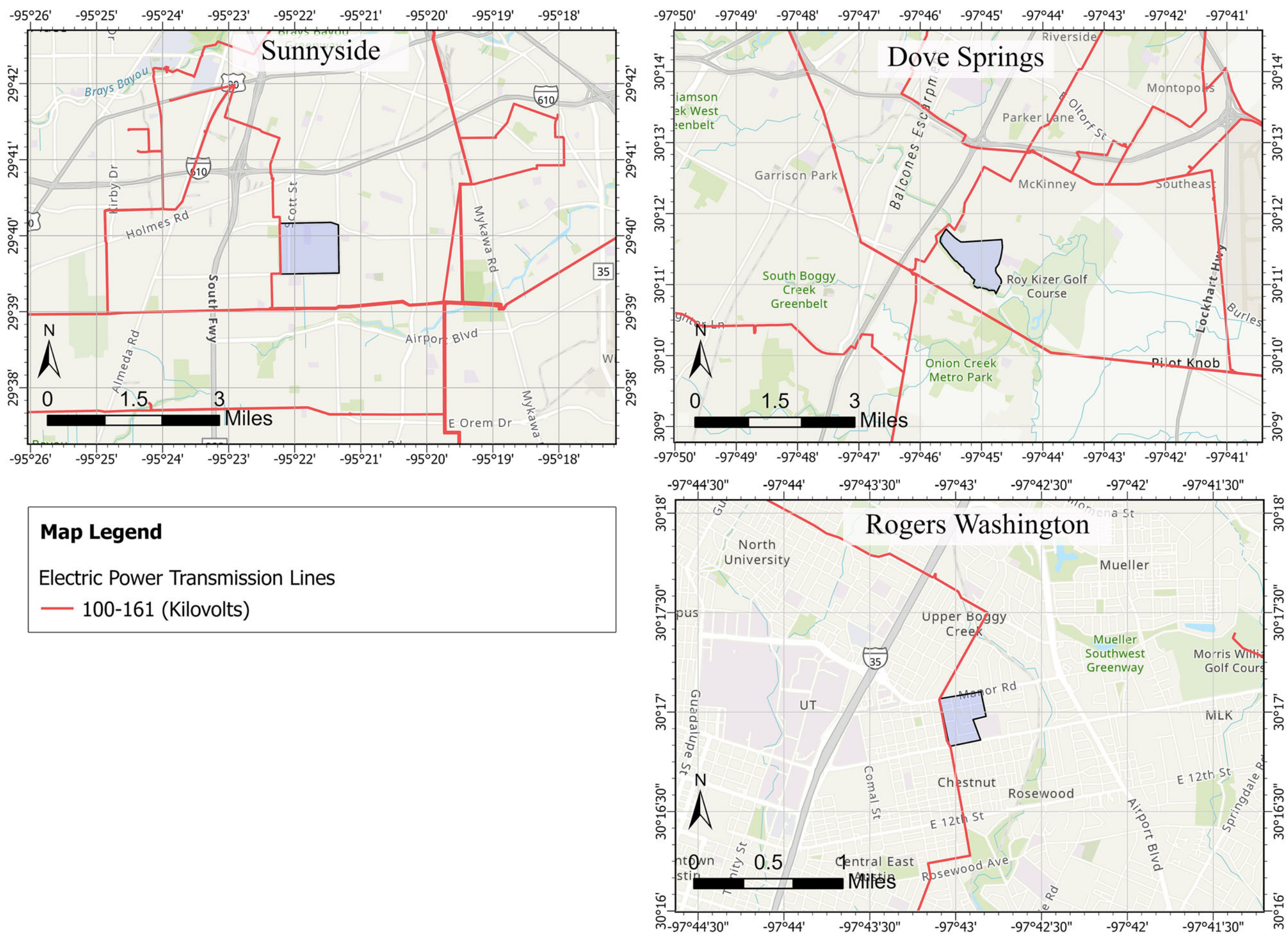

Fig. 3 | Electricity transmission lines passing the communities. The community boundary is presented using a purple-filled bordered polygon in the map. The lines laying on the topographic map depict types of power transmission lines. Maps are used to determine the redundancy in power supply (publicly available dataset: Homeland Infrastructure Foundation-Level Data (HIFLD)).

domain ($SI_1 = 0.00$). Nevertheless, the contributing factors influencing its L2-norm include the lowest population density, a population composed entirely of non-white residents, and a notable absence of proactive measures.

Concerning community coping capacities, Dove Springs demonstrates the highest ($SI_2 = 1.0$). This heighted sub-index primarily stems from low median income, low education level, presence of children under 5, and prevalence of non-English speaking households. Furthermore, female-headed households, non-white population, and less households with generators make moderate contributions to this sub-index. In the case of Sunnyside ($SI_2 = 0.97$), the most influential indicators include a high prevalence of health impairments, a greater number of female-headed households, a high composition of African race, and a notably high property crime rate. Median income, educational attainment below high school, and the presence of more seniors in households play as moderate variables. Lastly, Rogers Washington exhibits the lowest population coping capacity vulnerability score ($SI_2 = 0.00$). The most influential indicators affecting this score are more households with seniors over 65 and without generators. It is worth noting that households in Rogers Washington display the highest median income and a higher level of education in comparison to the other communities. This observation reduces its vulnerability in this respect.

Within the accessibility dimension, Dove Springs ($SI_3 = 1.0$) is ranked as the most vulnerable, with Sunnyside following closely in second place. In nearly all indicators, Dove Springs confronts with insufficient accessibility. The most influential factors for this community encompass access to essential resources, number of schools within a 5-mile radius, availability of private vehicles, and history of transportation blockage. Moderately influential factors include number of supermarkets and shelters within a 5-mile radius, as well as access to public transport. Regarding Sunnyside ($SI_2 = 0.68$), lower number of supermarkets, shelters, and bus stations within a 5-mile radius, and lower self-reported access to shelters are the primary contributors. Conversely, for Rogers Washington ($SI_2 = 0.00$), it is evident that the community exhibits the highest level of accessibility across nearly all indicators, making it the least vulnerable.

After combining the three sub-indices, the overall PO-RSVI is derived (Table 3). The results reveal that Dove Springs exhibits a high vulnerability in both coping capacity and accessibility, coupled with a moderate risk of experiencing prolonged outages. This results in the highest PO-RSVI= 1.00 among the cases. Conversely, Rogers Washington faces the greatest risk of prolonged outages but has the lowest vulnerability in terms of coping capacity and accessibility, making it the least vulnerable community with PO-RSVI= 0.00. Lastly, Sunnyside households show significant SV while being at low risk for extended outages, positioning it as a medium-vulnerability case study with PO-RSVI= 0.59.

A comparison between the proposed PO-RSVI and popular SVI developed by Flanagan (2011) for disaster management reveals a significant divergence in the assessment of community vulnerability. Based on Flanagan's SVI, Sunnyside community is ranked as the most vulnerable, followed by Dove Springs in second place. However, the PO-RSVI ranks Dove Springs as the most vulnerable community, with Sunnyside coming second. This difference arises because the PO-RSVI indicators are specifically tailored to assess vulnerability in the context of power outages. In contrast, the SVI incorporates a broader range of indicators that may not be directly related to power outages, such as housing factors. Furthermore, the PO-RSVI incorporates the risk of prolonged outages, a factor that is quite

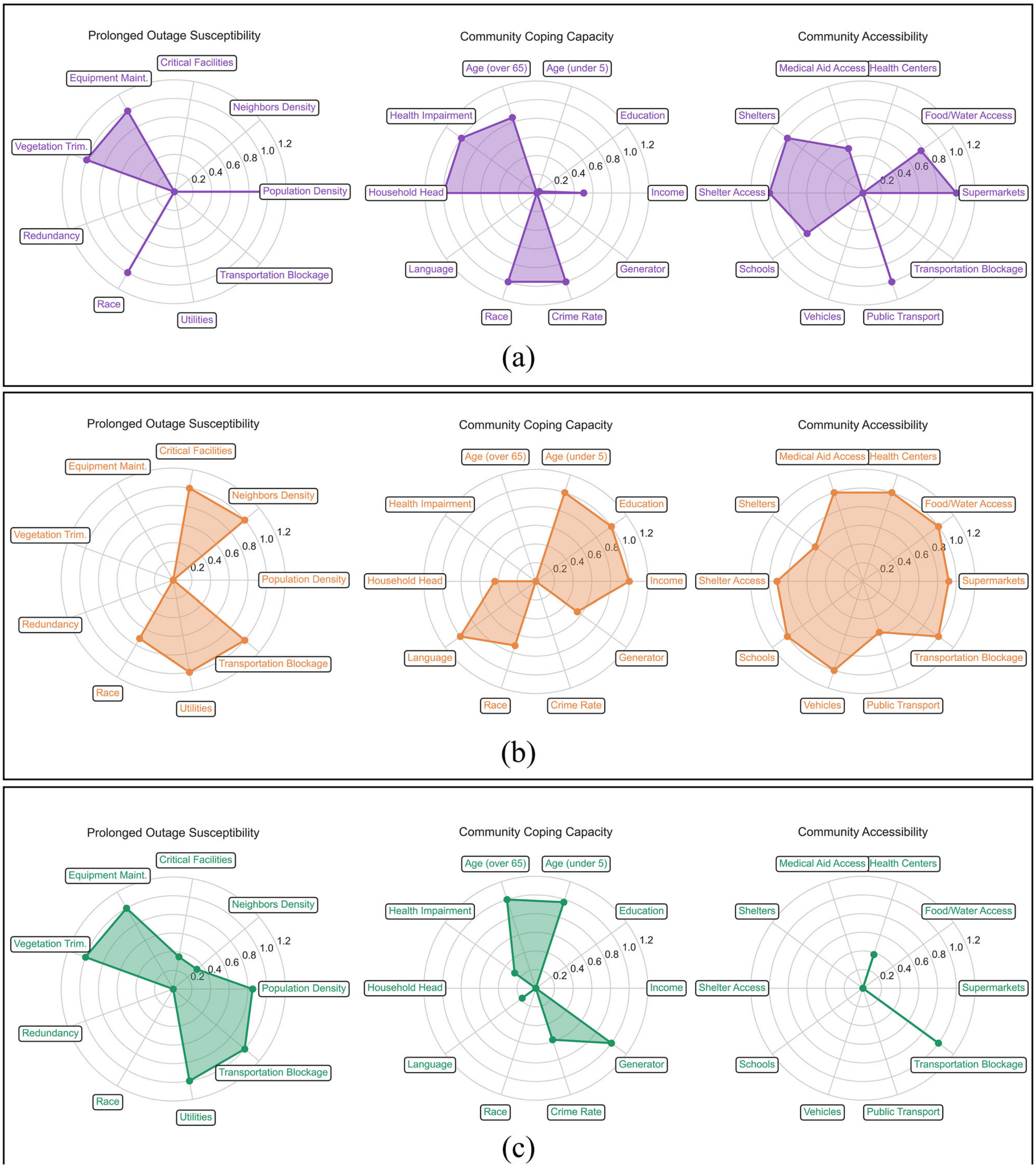

Fig. 4 | The spider plot of indicators in PO-RSVI. **a** Sunnyside, (**b**) Dove Springs, (**c**) Rogers Washington communities. Each spider plot illustrates the distribution of vulnerability over all indicators in each dimension. A higher value signifies greater vulnerability.

Table 3 | Numerical results for overall PO-RSVI and sub-indices

Communities	SVI	PO-RSVI	Degree	SI$_1$	Degree	SI$_2$	Degree	SI$_3$	Degree
Sunnyside	1.00	0.59	Medium*	0.00	Low	0.97	Very high	0.68	High
Dove Springs	0.58	1.00	Very high	0.56	Medium	1.00	Very high	1.00	Very high
Rogers Washington	0.00	0.00	Very low	1.00	Very High	0.00	Very low	0.00	Very low

*The degree is classified as follows: [0.0, 0.2) very low, [0.2, 0.4) low, [0.4, 0.6) medium, [0.6, 0.8) high, [0.8, 1.0] very high.

pronounced for the Dove Springs community. When combined with other high-scoring dimensions, this results in a higher PO-RSVI score, reflecting a more precise and context-specific measure of vulnerability compared to the broader, less focused SVI.

This observation is supported by Cutter (2003)[40] explaining that social vulnerability can vary substantially depending on the specific hazards and the scope of the vulnerability factors included. This distinction underscores the utility of the PO-RSVI in more precisely addressing the specific risk factors associated with power outages, which is crucial for communities like Dove Springs, where prolonged outages are more likely due occur and the population lacks sufficient capacity.

WTP numerical analysis

Here, we explore the stratified analysis of the relationship between WTP and the calculated PO-RSVI. Due to the small number of PO-RSVI values, statistical correlation analysis is not feasible. Therefore, we use boxplots of WTP to visualize the relationship. As shown in Fig. 5, Rogers Washington, with the lowest PO-RSVI, exhibits the highest average WTP ($\overline{WTP} = 51.57$). In contrast, despite a WTP similar to Sunnyside ($\overline{WTP} = 27.64$), Dove Springs, the most vulnerable community, shows the lowest average WTP ($\overline{WTP} = 27.64$). This suggests that more vulnerable communities are less willing to pay for emergency power supply during power outages, in other words, social vulnerability plays an important role in influencing WTP.

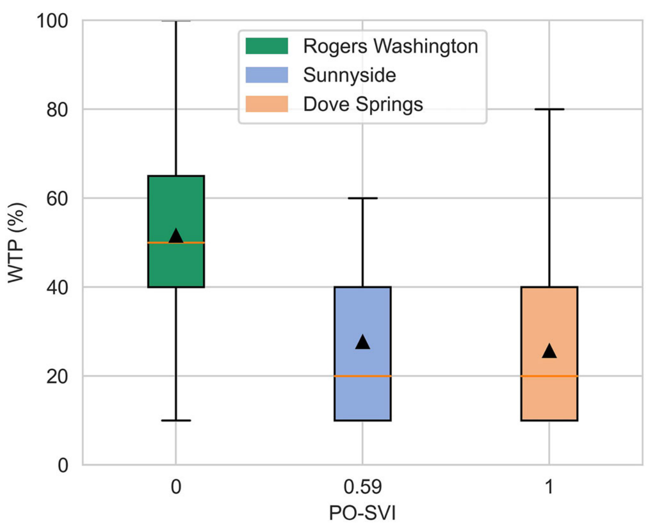

Fig. 5 | Boxplots of the variations in WTP with the corresponding PO-RSVI. The box represents the interquartile range (IQR), with the orange line indicating the median and the black triangle representing the mean.

The stratification analysis of income within each community shows that while higher WTP is associated with higher income in Rogers Washington, the variations do not follow a clear pattern in both Dove Springs and Rogers Washington (Fig. 6). This suggests that financial constraints may not be the main factor influencing WTP, and there are other factors influencing its value. Similarly, stratification based on household size reveals no prominent trend between WTP and household size, as shown in Fig. 7. This indicates that WTP values are not influenced by income or household size, but rather reflect respondents' true willingness to pay for power.

These observations suggest that the WTP data, with PO-RSVI included, across all communities can be aggregated for further analysis, such as machine learning models, which is the focus of this study. Therefore, the subsequent analysis will be conducted on the aggregated dataset across communities with PO-RSVI added as an influencing feature. Although all household features and their relationship with vulnerability are already captured in this index, PO-RSVI inclusion allows the ML models to capture policy/operational, infrastructural, and environmental factors incorporated in the PO-RSVI assessment.

WTP machine learning estimation

Prior to applying ML, the data obtained from household surveys is preprocessed, and a correlation analysis with WTP is conducted to retain only the features that greatly contribute to the model. The available features are either categorical, such as health impairment, or ordinal, such as education level. Categorical features are transformed into dummy variables, while ordinal features are transformed into the appropriate format using staircase coding. The correlation between features is determined using Cramer's V statistic and is reported in Table 4 in a descending order. Features with a Cramér's V value less than 0.2 are removed, as they show no major correlation with WTP. The dataset is split into training and testing sets, with 80% allocated for training and 20% for testing, following a random shuffling of the data to eradicate order patterns.

In Table 4, we observe that WTP is highly correlated with indicators medical aid access levels 4 (Corr = 0.73) and 3 (Corr = 0.69), white race (Corr = 0.71), food and water access (Corr = 0.67), female headed households (Corr = 0.64) and no children under 5 in household (Corr = 0.62), and female household head (Corr = 0.61). The association of PO-RSVI comes next with Corr = 0.58 supporting the observation in the stratification analysis. The results show a strong relationship between the features above and WTP, highlighting their potential influence on WTP estimation. The correlation between income and WTP is 0.53, indicating a moderately strong relationship. However, this supports the unbiased nature of the WTP data collection, suggesting that WTP is not solely determined by

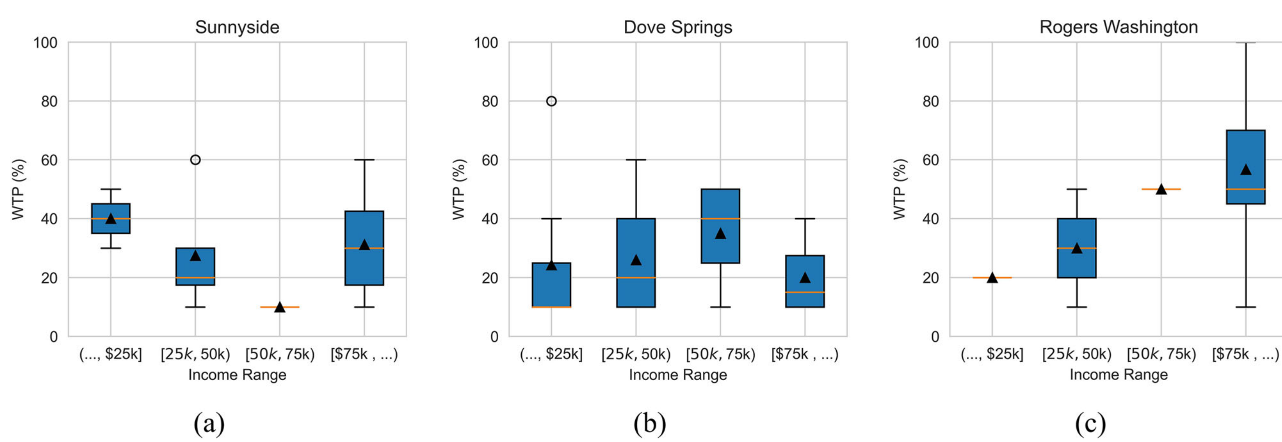

Fig. 6 | Boxplots illustration of the variation in WTP across different income levels within each community. **a** WTP variations in Sunnyside community. **b** WTP variations in Dove Springs community. **c** WTP variations in Rogers Washington community. The box represents the IQR, with the orange line indicating the median and the black triangle representing the mean. Whiskers extend to 1.5 times the IQR, and circles denote outliers.

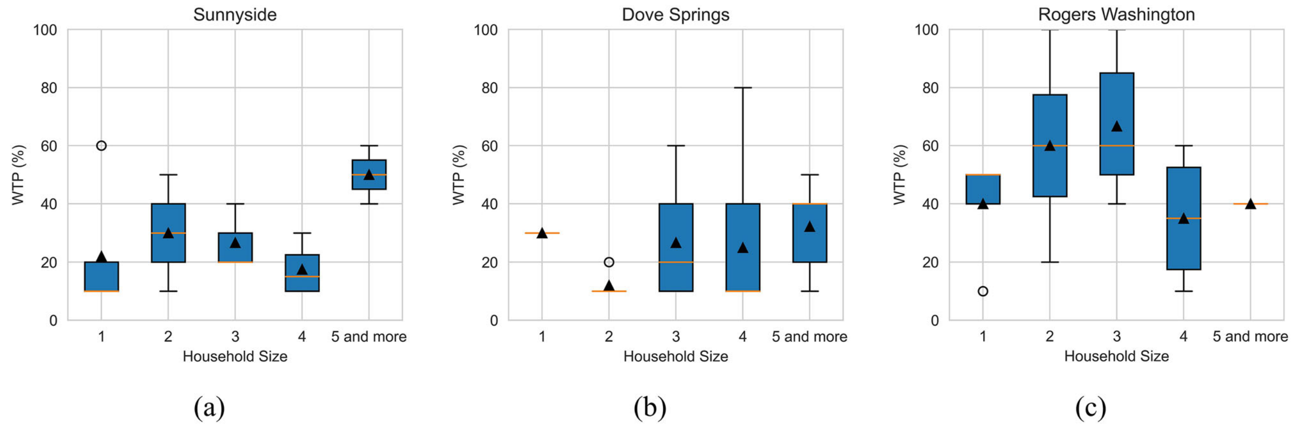

Fig. 7 | Boxplot illustration of the variation in WTP across different household sizes within each community. a WTP variations in Sunnyside community. **b** WTP variations in Dove Springs community. **c** WTP variations in Rogers Washington community. The box represents the IQR, with the orange line indicating the median and the black triangle representing the mean. Whiskers extend to 1.5 times the IQR, and circles denote outliers.

Table 4 | The Cramer's V correlation (only above 0.2) between WTP and household survey data

Feature	Corr.	Feature	Corr.	Feature	Corr.	Feature	Corr.
Medical Aid (4)	0.73	Household Head (Male)	0.52	Race (Hispanic)	0.46	Generator (Yes)	0.38
Race (White)	0.71	Household Size (3)	0.52	Household Size (4)	0.45	Education (Undergraduate Degrees)	0.38
Medical Aid (3)	0.69	Education (High School)	0.51	Language (Spanish	0.43	Generator (No)	0.38
Food/Water (4)	0.67	Language (English)	0.51	Education (Below High School)	0.41	Food/Water (1)	0.38
Household Head (Female)	0.64	Income ($25k-$50k)	0.5	Food/Water (2)	0.4	Impairments (Yes)	0.35
Children (No)	0.62	Seniors (No)	0.5	Food/Water (3)	0.4	Medical Aid (2)	0.3
PO-RSVI	0.58	Seniors (Yes)	0.48	Household Size (1)	0.39	Income (<$25k)	0.26
Income ($50k-$75k)	0.53	Impairments (No)	0.46	Shelter (Yes)	0.39	Medical Aid (1)	0.26
Race (Afr./Afr.-Amr.)	0.53	Shelter (Not aware)	0.46	Household Size (2)	0.38	Shelter (No)	0.25

Table 5 | The average accuracy of classifiers obtained through separate 10-fold cross validation techniques

Classifier	Logit	LDA	QDA	RF	SVC
Accuracy Score	0.714	0.686	0.579	0.729	0.721
f1 Score	0.692	0.666	0.519	0.691	0.690

income levels and is also influenced by various non-income-related factors. We retain only those features with a Cramér's V value greater than 0.2 for the ML classification model. Features with lower values are excluded as they show little to no impact on WTP estimation. Including them could potentially degrade model performance by introducing noise and misleading the classifier.

To identify the most suitable classifier, we perform 10-fold cross-validation on the previously introduced models, using data with features selected through correlation analysis. The models are evaluated in terms of performance using two scoring metrics: 1) accuracy, which measures the proportion of correctly classified instances among the total instances, and 2) F1-score, the harmonic mean of precision and recall, which balances the trade-off between false positives and false negatives and is particularly helpful when there is an imbalance in the data. The higher value for both scores indicates better performance. The performance of the classifiers is presented in Table 5. Random Forest achieves the highest scores in both accuracy and F1 metrics, establishing it as the most effective model for WTP estimation. While SVC and Logistic Regression (Logit) are also viable options, the slightly higher accuracy and F1-score of Random Forest make it the more promising choice.

To determine the optimal architecture for the RF classifier, hyperparameter tuning was conducted manually. This process involved iteratively adjusting key parameters and evaluating the model's performance on both training and testing sets. The parameters considered during tuning included the number of estimators, impurity criterion, maximum tree depth, and the minimum number of samples per leaf. The most accurate configuration was selected based on its performance, as reported in Table 6. The high values for performance metrics including accuracy, recall, and precision indicate that the model is making accurate predictions. Additionally, the small gap between training and testing performance suggests that the model generalizes well to unseen data. The elevated F1-score reflects a well-balanced trade-off between precision and recall. Although the cross-entropy loss (Log-Loss = 0.870) indicates an acceptable goodness-of-fit for the available data, it also suggests that the model lacks sufficient confidence in its predictions, which might initiate from the small size of dataset. Addressing this issue could be explored as a potential avenue for future research.

Figure 8 showcases the top 15 features ranked by their importance, as determined by the Random Forest model. The results reveal that medical aid access level 4 with feature importance (FI) 0.120 has the greatest importance in the purity of branching in the model. This feature's high correlation with WTP (Corr = 0.73) supports the conclusion that households with better access to healthcare services place high value on resolving health issues promptly and this influences the estimation of WTP. The second most important feature, PO-RSVI (FI = 0.095), further emphasizes the critical role of social vulnerability in shaping WTP. also emerges as a key factor, indicating that access to essential resources strongly influences households' WTP. Food/water access level 4 (FI = 0.080) also emerges as a key factor, indicating that access to essential resources strongly influences households'

Table 6 | The evaluation metrics of implementing Random Forest classifier on test data to estimate the WTP

n-estimators = 80, criterion = 'entropy min-samples-leaf = 4, max-depth = 7	Accuracy	Recall	Precision	F1	Log-Loss
Train	0.864	0.860	0.885	0.860	0.792
Test	0.800	0.838	0.788	0.792	0.870
Absolute Train-Test Gap	7.44%	2.47%	10.95%	7.89%	9.95%

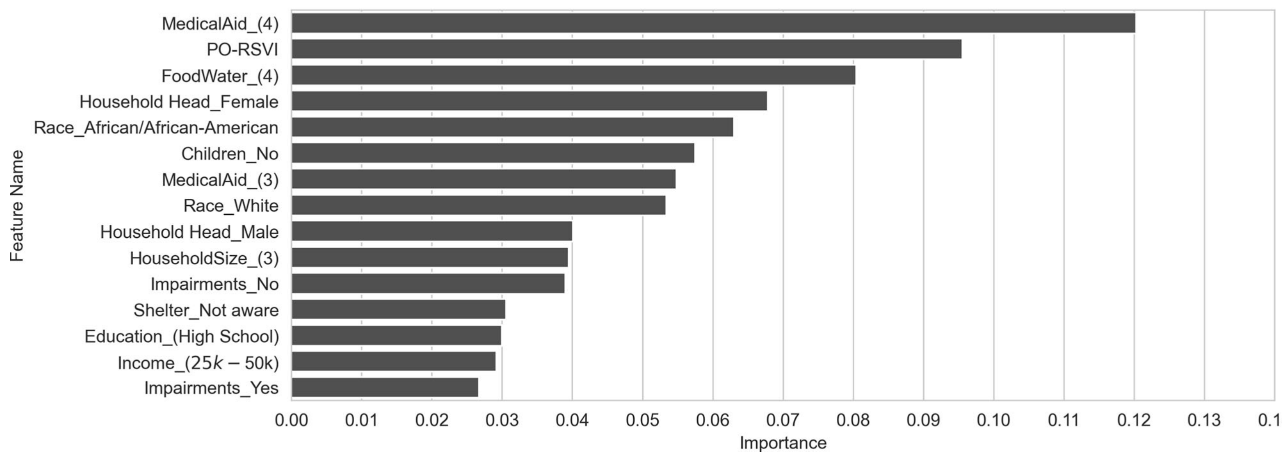

Fig. 8 | The importance of features used by Random Forest classifier. This figure illustrates the relative contribution of each feature in making predictions, with higher values indicating greater influence on the model's decision-making process.

WTP. Overall, these findings suggest that access to healthcare and food/water resources, besides social vulnerability to power outages significantly impact WTP, underlining the necessity of considering these factors by decision makers for more accurate WTP predictions. The next group of features with moderate importance includes household head (female), race (African/African-American), no children under 5 in the household, medical aid access level 3, and race (white). These features exhibit considerable correlations with WTP, reinforcing the conclusion that they play a meaningful role in the estimation of WTP.

Discussion

While numerous studies have assessed SV to power outages[14–17], few have considered policy-operational, environmental, and infrastructural factors into estimations. Additionally, community accessibility to essential resources has been observed to influence SV but has been neglected in the literature. Our Power Outage-Risk integrated Social Vulnerability Index (PO-RSVI) analysis incorporates these two aspects and highlights several key implications in this regard. First, our analysis highlights disparities in the risk of extended power outages among communities, driven by various policy-operational, environmental, and infrastructural factors. By concentrating on these disparities, at-risk communities can be identified more efficiently. This focus allows for the development of targeted strategies and solutions to mitigate risk by addressing the most influential factors and indicators. Secondly, in addition to assessing households' coping capacity that is the foundation, we evaluate SV through accessibility—a dimension that has been narrowly studied in the literature and is gaining attention[16]. Our findings indicate that analysing disparities in accessibility can enhance the identification of communities with limited access to essential resources, offering a more comprehensive assessment of vulnerability.

The study comparison between PO-RSVI and the traditional Social Vulnerability Index (SVI) highlights a key limitation of the SVI—it fails to account for power outage-specific factors, leading to mis-assessment of social vulnerability levels. While the SVI provides a broader perspective on vulnerability, it does not capture the nuanced risks associated with extended power outages. As a result, communities like Dove Springs, which are particularly susceptible to prolonged outages, may be overlooked in broader assessments. PO-RSVI, with its tailored focus on power outage risks and accessibility to essential resources, offers a more accurate and context-specific vulnerability measure. This refinement enables decision-makers to better identify at-risk communities and design more targeted, effective strategies for enhancing resilience to power disruptions.

Despite existing research on WTP for electricity and emergency power, the relationship between WTP and SV has not been extensively explored. Additionally, there is limited research on how household characteristics impact WTP estimates. Our study addresses these gaps and provides valuable contributions to the literature. Firstly, a negative relationship between the proposed PO-RSVI and WTP reported by households was observed. We note that the estimated average WTP for the studied communities is 25.67%, 27.64%, and 51.57% higher than the current electricity price for the Dove Springs, Sunnyside, and Rogers Washington communities with PO-RSVI 1.00, 0.59, 0.00, respectively. The stratification analysis between WTP and two household features income and household size indicated that financial constraints are not a leading factor in this negative relationship. This implication suggests a need for equitable policies and pricing strategies that consider social vulnerability of vulnerable households during power outages. This is crucial because studies have shown that an unfair distribution of renewable energy policies and pricing noticeably influence people's WTP and engagement in these initiatives[75]. This suggests that unfair policy and pricing mechanisms for socially vulnerable communities may further decrease their WTP for emergency power and negatively impact related investments. Note that our study is pioneering in investigating the relationship between PO-RSVI and WTP specifically in the context of power outages. Therefore, future research can further explore this topic and examine how these dynamics vary across different service areas.

Secondly, this study elucidates the influence of various environmental and socio-demographic features on WTP estimation. Building on the results from the machine learning Random Forest classifier, the most influential features for WTP include medical aid access, PO-RSVI, food/water access, head of households, race, and children under 5. Some of these findings align with literature[24,29,76], while others, including all access level-related features, health impairments, and presence of generators represent pioneering contributions in exploring the targeted relationship. These disparities, alongside the findings for relationship between WTP and PO-RSVI, further highlight the need for tailored approaches that address the varying capacities and needs of different communities, ensuring that policies are equitable and effectively support those most affected by power outages.

A key difference between our estimates and those from prior work on in the residential sector is that we used percentage values rather than exact monetary amounts for WTP. Using percentages provides a clearer understanding of the relative value households place on electricity compared to their current expenditure, making it easier to compare across different contexts and adjust for varying price levels. Finally, direct comparison of the results from this study with estimates reported in other studies is challenging due to variations in the scales of study, study designs, utilized techniques, as well as underlying assumptions.

The proposed PO-RSVI and the research findings for WTP offer invaluable insights that can be inspired not only for Texas communities, but globally and in larger scale, if modified accordingly. By investigating multiple dimensions of vulnerability, the PO-RSVI provides a more general framework that can be applied in different socio-cultural and geographical settings. Among the proposed dimensions, susceptibility to prolonged outages serves as the newly proposed domain which can be efficiently generalized to and evaluated for various communities around the world. We also note that additional factors related to geographical and infrastructural differences in the studied area may influence this dimension. For instance, in South Africa, crime rates influence load shedding policies, whereas such policies are not implemented in the U.S. Hence, it is suggested that these factors be explored and reflected in the PO-RSVI. The insights from this research emphasize the importance of community-tailored strategies to enhance energy resilience in the face of power disruptions.

Despite the existing literature on the impact of various indicators on the susceptibility to prolonged power outages, there are currently no studies that incorporate these factors into vulnerability assessments. As such, this study primarily relies on evidence from online resources and reports provided by utilities and related organizations to derive these factors. This approach is innovative in that it pioneers the integration of such indicators into vulnerability models, offering a framework that can be further explored and refined in future research.

Additionally, we acknowledge several limitations that could influence the interpretation and generalizability of our findings. First, biases in data collection may arise from our reliance on publicly available online resources and reports for some indicators. While surveys help mitigate bias, these sources may not fully capture community diversity or the most recent data, potentially impacting the accuracy of the vulnerability assessment. Second, the method used to collect data on proactive measures and transportation factors may lack accuracy. Although surveys of community leaders provided valuable insights, future research could explore more precise data collection methods. Third, the findings are based on specific communities, and caution is needed when generalizing to larger, more diverse populations, as exposure to prolonged outages may vary across geographic regions and socioeconomic groups. Lastly, validating the proposed PO-RSVI is challenging due to its data-driven approach, which lacks labelled ground truth for direct validation. Observing community behaviour during power outages could be a potential solution, but such an approach would be costly and demanding, requiring careful planning.

Methods

Data collection

The community selection is applied through initial engagement meetings involving several community leaders in Houston and Austin metropolitan areas. Three residential communities are then chosen for the empirical investigation. The selected communities include Sunnyside situated in Harris County on the southern periphery of Houston city, covering Block Group 3312001-2, Dove Springs located in Travis County on the south-eastern fringes of Austin, Census Tract 002412-3, and Rogers Washington-Holy Cross located in Travis County on the east of Austin as a part of Cherry Wood neighbourhood, Block Group 000402-3. The chosen communities are actively pursuing the integration of solar energy and energy storage solutions for residential use during power outages. Furthermore, they express concern for the safety of residents during severe weather conditions and the occurrence of power outages. These distinguishing characteristics significantly facilitated the research team's efforts in gaining interest and securing active participation. The methodology utilized in this study for data collection is divided into categories: 1) surveys designed for households, 2) surveys designed for community leaders, and 3) online datasets.

Household surveys

Fully structured household surveys collect the majority of indicators for SI_2 and SI_3 dimensions. The reason for selecting a fully structured survey is ensuring the consistency and comparability of the responses. These surveys were conducted in-person, each taking a duration of 10-15 min, during special events organized by community leaders and authorities. In total, the team surveyed 17 individuals from Sunnyside, 37 individuals from Dove Springs, and 19 individuals from Rogers Washington communities. The key questions were formed by an extensive review of the literature on vulnerability of populations to prolonged power outages[34,37–39,59–62,67,68,71,72,77]. To uphold the anonymity and confidentiality preferences of the subjects, households were not identified by name. Most of the respondents filled out the surveys in-site during the events with few completing it in their convenience. Supplementary Table S1 provides the profile of participants in household surveys.

Community leader surveys

Establishing contact with community representatives proved to be an important asset for this study, facilitating outreach to households within the community. Given that community leaders serve as widely recognized and trusted representatives, they were able to furnish valuable insights into the community's status and prevailing concerns. Using a comparable methodology, structured surveys were conducted with community leaders or representatives. The community leaders are well-informed about the community's previous experiences of transportation blockage resulting from severe weather conditions and subsequent power outages. Therefore, the survey questions included addressing and gathering this information. In addition, gathering data about the primary utilities supplying electricity to the community is a challenging task. Nonetheless, community leaders possess a thorough understanding of the predominant utilities serving the community, and as such, these details are also addressed during the surveys. Lastly, the community leader surveys included inquiring about the equipment and vegetation trimming maintenance plans implemented by utility services in the community. Supplementary Table S2 provides the data collected through this type of surveys.

PO-RSVI model

We utilized min-max scaling to normalize indicators in each dimension across all communities (Eq. (1)), assigned equal weights for weighting process, and use L2-norm for calculating each domain score due to its distance-based nature (Eq. (2)). The overall PO-RSVI is calculated as described in Eq. (3).

$$\mathrm{VI}_{j,k} = \frac{I_{j,k} - \min_{j\in\mathcal{J}_k}\{I_{j,k}\}}{\max_{j\in\mathcal{J}_k}\{I_{j,k}\} - \min_{j\in\mathcal{J}_k}\{I_{j,k}\}}, \forall k \in \mathcal{K} := \{1,2,3\}, j \in \mathcal{J}_k \quad (1)$$

$$\mathrm{SI}_k = \sqrt{\sum_{j\in\mathcal{J}_k} \mathrm{VI}_{j,k}^2}, \forall k \in \mathcal{K} \quad (2)$$

$$\mathrm{PO-RSVI} = \mathrm{SI}_1(\mathrm{SI}_2 + \mathrm{SI}_3) \quad (3)$$

Where I_{jk} and $\mathrm{VI}_{j,k}$ are the unscaled and scaled indicator j in domain k, SI_k is the sub-index of domain k, and PO − RSVI is the overall vulnerability index. In Eq. (3), population coping capacity (SI_2) and accessibility (SI_3) sub-indices are aggregated and multiplied by prolonged outage susceptibility (SI_1) because they both contribute to vulnerability when the community confronts a prolonged outage. Using this formulation, if two communities have equal population coping capacities and service accessibilities, but one faces a higher degree of facing prolonged outages, it will be assigned a higher vulnerability score.

SVI calculation

Flanagan's SVI consists of 12 distinct indicators across four categories: socioeconomic factors, household composition, minority status and language, and housing and transportation. For indicators such as poverty rate, income, education level, age (65 +), health impairment, and vehicle ownership, we used survey data specific to our study. For other indicators not included in the surveys, we approximated values using Block Group data from the United States Census Bureau's American Community Survey for each community. The indicators were then standardized and aggregated following the steps outlined by Flanagan et al. (2011) to construct the final SVI scores for each community, which were used for comparison with the proposed PO-RSVI.

Machine learning evaluation metrics

Using the confusion matrix, representing the type of predictions which include True-Positive (TP), True-Negative (TN), False-Positive (FP), and False-Negative (FN) the evaluation metrics are calculated for classifiers as follows:

$$\text{Accuracy} = \frac{\sum_{c\in\mathcal{C}} \mathrm{TP}_c}{|\mathcal{C}|} \tag{4}$$

$$\text{Recall} = \frac{\sum_{c\in\mathcal{C}} \frac{\mathrm{TP}_c}{P_c}}{|\mathcal{C}|} \tag{5}$$

$$\text{Precision} = \frac{\sum_{c\in\mathcal{C}} \frac{\mathrm{TP}_c}{R_c}}{|\mathcal{C}|} \tag{6}$$

$$F1 = \frac{2(\text{Recall} \times \text{Precision})}{\text{Recall} + \text{Precision}} \tag{7}$$

$$\text{Log} - \text{Loss} = \sum_{c\in\mathcal{C}} -\frac{1}{|\mathcal{N}|}\sum_{i\in\mathcal{N}} y_{i,c}\cdot ln\left(p_{i,c}\right) \tag{8}$$

Where $\mathcal{N}$ is the set of test samples, $\mathcal{C}$ set of classes, P_c total number of samples in class $c \in \mathcal{C}$, R_c total number of samples predicted for class c, $y_{i,c}$ the unit vector indicating the true class of sample i, and $p_{i,c}$ the probability of assigning sample i to class c by the classifier. The log-loss metric can take values in $[0, +\infty]$, with 0 representing the ideal performance.

Ethical considerations

This study complies with all relevant ethical regulations for research involving human participants. The study protocol was reviewed and approved by the University of Houston, Division of Research, Institutional Review Board (IRB) under IRB ID: STUDY0000459. Household surveys were conducted with prior oral informed consent obtained from all participants, ensuring their agreement to the use of their data for research purposes.

Data availability

Most datasets used in the study are publicly available. For neighbourhood population characteristics, including factors like population density and neighbouring communities, public datasets sourced from the US Census Bureau, American Community Survey 5-Year Data (2009-2023)[78] were utilized. The study drew upon public dataset provided by Texas Water Development Board[79], which includes critical infrastructure locations, such as hospitals, fire stations, national shelters, and schools. Data of supermarkets were collected through Google Maps API. The paths of transmission lines passing through the communities were determined using Esri U.S. Federal Datasets, U.S. Electric Power Transmission Lines[80]. For the location of bus stations, public data provided by City of Houston[81] and City of Austin[82] were utilized. The 2023 public datasets provided by the Houston Police Department[83] and the Austin Police Department[84] were leveraged to gather relevant data regarding property crime incidents within the communities. According to FBI definition for property crime, incidents falling into categories such as burglary, larceny-theft, motor vehicle theft, and arson were taken into account to determine the crime level in communities[85]. Lastly, survey data used in this study is publicly available in the Figshare database under the https://doi.org/10.6084/m9.figshare.28582940.

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Author contributions

F.E., Q.X., and Z.S.D. designed the study and analysed the main results. F.E. led the manuscript writing, with Z.S.D. supervising the writing process. J.J. and A.V. assisted in survey design and data collection, while V.Y. contributed to survey implementation. T.P. provided guidance on the development of the PO-RSVI model and contributed to the discussion of findings along with P.K.; All authors participated in manuscript editing and discussions.

Competing interests

The authors declare no competing interests.

Additional information

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