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Using Q-methodology to discover disaster resilience perspectives from local residents

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ABSTRACT

Finding ways to increase local community resilience is important, therefore, this study explores how to use individual disaster resilience indicators and provides new ways to quantify them. Specifically, Q-methodology is used as a combined approach of qualitative and quantitative techniques to examine the shared perspectives among the residents in the Dove Springs community of Austin, Texas. To maintain adaptability and eliminate repetition and ambiguity, the initially retrieved set of 95 indicators was reduced down to 45 through two cycles of revision with subject matter experts. A total of 41 respondents were engaged in our study, and they prioritized the indicators based on their understanding of community well-being. Participants also identified their perspective of the two most important and unimportant statements. As a result, four types of perspectives were identified as informing the status of resilience: housing and food security, education and employment, equity, and disaster preparedness. Subsequently, we proposed a weighted quantification strategy to derive a single resilience value within a hierarchy from indicator level through category level. The findings and suggestions from our mixed-method study lay the groundwork for a better quantitative assessment of disaster resilience in a local context that can be beneficial for decision-making.

1. Introduction

Ongoing climate change, urbanization, and globalization have posed serious concerns about resilience of social, economic, institutional, infrastructural, environmental, and community capital. In an effort to mitigate these impacts, academic and governmental decision-makers have developed various disaster resilience assessment strategies [1–5]. Scholars have undertaken extensive research to develop various quantitative and/or qualitative assessment frameworks including scorecards, toolkits, and indicators for measuring community resilience [6–11]. Despite the absence of a unanimous consensus on a singular framework for assessing resilience [12,13],

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the prevailing practice within the disaster community is to leverage quantifiable metrics to facilitate decision-making processes by translating the complex dynamic aspects of community resilience into measurable values [14].

A review of the prior literature demonstrates that many of the existing measurement schemes have limitations when it comes to aggregating individual indicators to generate a high-level representative value [6,15–17]. These tools lack a rigorous focus on the standardization of individual metrics, resulting in poor consideration of the geographical importance of different aspects of resilience. For example, in the Baseline Resilience Indicators for Communities (BRIC) established by Cutter et al. [18]: Age (% of non-elderly population), Communication capacity (% population with a mobile phone), Transportation access (% of people with a vehicle), Language competency (% population with English as second language), and etc., are treated as equally important components of the social resilience category; however, it is difficult to tell whether each of these indicators has the same level of importance on understanding resilience across various regions. Also, on a higher level, it is unjustified to assume that the social resilience value aggregated by the equally weighted indicators should be treated as equally important to the other resilience categories. Not all communities experience the same resilience challenges. For instance, despite some suburban communities adjacent to large cities receiving comparable or equal state-level infrastructure support and having resilience scores that are numerically equivalent to large cities, these places may be less resilient to disasters due to other factors, such as topography, necessitating additional capacity and resources. Therefore, quantitative indicators should be assessed relative to each specific geographic area when trying to understand the decision-making process. However, inequities may arise if the resilience quantification is processed without taking the local context into consideration.

This study questions the conventional practices of resilience measurement that place equal importance on individual indicators to reflect local context to advance their adaptability in the decision-making process. To better understand the diverse needs of the residents on the different aspects of resilience and customize the aggregation process based on the importance of each indicator, this study demonstrates how to prioritize the resilience indicators reflecting the needs of a suburban community, the Dove Springs neighborhood of Austin, Texas. BRIC and the Austin Area Sustainability Indicators (A2SI) [19,20] were selected as a set of baseline indicators for measuring the resilience of the community. A statistical method called Q-methodology was conducted to collect individual perspectives within a localized context. The Q-methodology results generated shared local perspectives, thus enabling this study to propose an importance-based weighting strategy for aggregating individual indicators. This effort of integrating local context into current disaster resilience measurement schemes may, in turn, help policy decision-makers better understand and increase community resilience.

2. Literature review

2.1. Disaster resilience measurement

From the review studies on the previous literature regarding resilience measurement [14,21–23], it could be observed that researchers have developed numerous types of frameworks, including scorecards, toolkits/models, and indicators, which have different characteristics in terms of disaster types (e.g., general, climate, earthquake, drought), spatial units (e.g., global, country, city, community), methods (e.g., objective or subjective), data sources (e.g., primary or secondary), target audiences (e.g., government organization, local authorities, community), data types (e.g., qualitative or quantitative). However, given the unique pros and cons of each framework and their varying adaptability to the dynamic nature of resilience, it is important to note that there is no single dominant framework that is universally satisfying every condition and requirement. In this regard, this study specifically focused on the index-based framework, which offers quantifiable data with spatiotemporally publicly accessible values on a regular basis.

Given the requirement to support decision-making and the federal government's interest in disaster resilience, Cutter et al. (2010) provided a baseline set of criteria to quantify community resilience. Indicator selection yielded five resilience categories of social, economic, institutional, infrastructural, and community capital resilience, with seven to eight variables in each category. They calculated disaster resilience scores for 736 counties in southeastern U.S. states and averaged those sub-index scores with equal weights to calculate a single composite resilience score per county. The indicators set was later extended to include environmental resilience which yielded a larger number of 49 indicators for six subcomponents [18]. The study scope was also expanded to cover the contiguous U.S., and the same aggregation technique was applied to calculate a composite score. In a subsequent study [23], various existing resilience assessment tools, indices, and scorecards were reviewed with specific focus given to the spatial unit and methodology. Cutter et al. (2016) found that validating the practicality of the literature-driven indicators in a local context was an important step; in other words, the co-production of knowledge by researchers and the local community is a crucial process to satisfy the demands of both decision-makers and community leaders in measuring resilience. This observation was further supported by a study that sought to discover the differences between urban and rural regions in terms of measuring community resilience [24]. According to their analysis, the authors cautiously revealed a limitation of using their mesoscale indicators for microscale disaster resilience (e.g., local community-level), and they suggested an ideal approach that should tailor disaster resilience by fusing those indicators with regional specificity and unique local characteristics.

As mentioned earlier, several other researchers have proposed quantitative measurement schemes and reviews of disaster resilience with similar but slightly distinct conceptual framing and units of analysis [4,22,25–30]. Examination of these methodological tools showed that there has been little empirically based research at the community level, which clearly demonstrates the necessity for community involvement in the resilience measurement process to better understand the local landscape for customization as well as to establish rationales for the chosen indicators [31]. In alignment with the identified research gap, this study seeks to understand which indicators play a key role in explaining resilience of the local community and how those indicators should be weighted for more accurately reflecting a resilience score.

2.2. Q-methodology and its applications

Q-methodology, originally developed by Stephenson [32], was designed to describe human subjectivity through a rigorous statistical approach, combining the strengths of both qualitative and quantitative research traditions [33]. The main objective of Q-methodology is to identify shared viewpoints among the participants, not to measure the distribution of views in a population [34–39]. Compared to a standard factor analysis, also known as R-methodology, Q-methodology is an inverted factor analysis which analyses the correlations between the participants, not between the variables. Since Q-methodology incorporates more of the qualitative perspective (e.g., why and how the shared viewpoints are constructed) rather than the quantitative perspective (e.g., a size of the distribution), it requires a fairly small sample size (between 40 and 60) when compared to other pure interpretative methods [33,40,41]. Thus, the major benefits of Q-methodology include not only its lower cost but also the fact that the achieved result is quantitatively reliable due to structured inputs in a pre-defined distribution and that its semi-structured format enables the collection of qualitative inputs from various subjective perspectives to enrich the context and depth of understanding.

Q-methodology has been applied in a variety of fields with the purpose of quantifying subjective information, including but not limited to: politics [42,43], engineering [44,45], healthcare [46,47], statistical production [48] and education [49,50]. Q-methodology applications have also been used within a broad range of resilience-related studies.

Nhem and Lee [51] investigated local opinions in Cambodia regarding the implementation of community-based forestry to achieve sustainable forest management using the Q-methodology. Literature review related to forest policy and management produced an initial Q-set of 160 statements, and these were trimmed down to 43 statements at the final stage after expert examination. A set of 52 participants were selected from the 13 local community forestry sites. The Q-sort resulted in four factors with a total of 35% explained variance, and the degree of agreement was analyzed for four predefined criteria.

Mabon and Shih [52] assessed social vulnerability to a climate-related hazard where drivers of heat vulnerability in Taiwanese cities were identified through Q-methodology. In total 36 statements were identified through the literature review of the factors relevant to certain keywords, and an expert group of 18 people was established as participants to sort the statements with relevance to a driver of heat vulnerability. A key finding was that *elderly people living alone, elderly people over 75,* and *outdoor workers* were experienced particular forms of vulnerability. The priority results of the statements were compared with peer-reviewed empirical literature.

To analyze resilience perspectives of practitioners implementing resilient urban infrastructure systems, Kim et al. [53] used Q-methodology to prioritize the resilience strategies. Nineteen resilience strategies were retrieved from the literature for developing a Q-set, and a total of 16 practitioners working in governmental institutions in the Phoenix area were invited as final participants. By performing three different Q-sort exercises with distinct questions, this study determined the viability of the given strategies for various practical aspects including geographical, meteorological, institutional, and technological conditions.

Wainger et al. [54] used Q-methodology to prioritize socioecological services derived from coastal marshes and communities with the goal of identifying people's preferences for services to aid in coastal adaptation decision-making processes. The participants were drawn from a diverse group of representatives from the local community, state and federal government agencies, and academic researchers, and the analysis showed that residents demonstrated more interest in local economic well-being, while the academic group put more focus on intangible benefits such as the marsh condition.

An analog to our study is found from Tariq et al. [14] where Q-methodology was used to define measurable indicators for community disaster resilience in the built environment. A total of 317 initial indicators were reduced to establish a Q-set of 128 statements, and they were grouped into three categories that included anticipatory capacity, absorptive capacity, and restorative capacity. Participants were placed into three groups (one for each capacity) to achieve a consensus on prioritizing the indicators in each of three categories. Despite having a comparable objective of identifying the relevant importance of the resilience indicators, the application of Q-methodology was limited because only the prioritized results were provided and there was no qualitative information, furthermore, the correlation between all of the indicators was not examined, making it challenging to quantify the resilience from the selected indicators.

Summarizing previous studies that used Q-methodology, we find the collected statements were prioritized by the deliberately chosen participants to assess the shared and divergent aspects of various views on a specific topic for assisting science-based decision-making processes. However, the application of Q-methodology regarding the disaster resilience measurement was limited. In relation to the quantitative measurement of disaster resilience, while the top-down approach targeting a wider scale (e.g., state-level) might be leaning towards an objective measure of the resilience for a consistent comparison with other regions, it is very important to consider that local values, contexts, and expertise need to be incorporated into aggregation processes of individual indicators. In this context, Q-methodology holds promise since it can demonstrate diverse views on the importance of each indicator from the local community, and ultimately, provide a basis for an importance-based weighting strategy to form a composite indicator.

2.3. Other multi-criteria decision-making approaches

Regarding the resilience measurement, multi-criteria decision-making (MCDM) approaches have been widely applied for the performance evaluation of the resilience indicators [11]. Table 1 provides a summary of the relevant case studies that employed MCDM for measuring resilience.

The objective of MCDM is to find the most suitable alternatives from a set of options from conflict criteria. A commonly used method for assessing disaster resilience is Analytic Hierarchy Process (AHP), which is a structured approach to quantify the preferences and priorities of the participants through pairwise comparisons and mathematical analysis [55]. While the computation process for assessing criteria importance is convenient, it faces limitations when dealing with interdependence among alternatives, necessitating an additional step to generate a composite index using the calculated weights. On the other hand, approaches including the Tech-

Table 1
MCDM approaches for resilience assessment.

Author	Method	Objective	Participants	Qualitative contextual feedback	Weighted composite index
Orencio and Fujii [18] (2013)	AHP	Assessment of indicators for disaster-resilient coastal community	20 experts/decision makers	X	X
Alshehri et al. [11] (2015)	AHP	Measurement of community resilience to disasters	16 local and international experts with in average 5 years experience	X	X
Zarei et al. [19] (2021)	AHP	Resilience engineering assessment in process systems	10 experts with in average 20 years experience	X	X
Liu et al. [20] (2022)	AHP	Assessment of local resilience to the public health disaster	15 experts	X	X
Mojtahedi et al. [21] (2021)	TOPSIS	Prioritization of hospitals for emergency disaster management	X	X	O
Zhang et al. [22] (2021)	TOPSIS	Resilience measurement to flood disasters	X	X	O
Moghadas et al. [23] (2019)	AHP/TOPSIS	Comparative assessment of flood resilience	5 experts for AHP	X	O
Mabrouk and Haoying [24] (2023)	AHP/TOPSIS/ VIKOR/WSM	Resilience assessment for flood-exposed risky districts	113 experts for AHP	X	O
Our study	**Q-methodology**	**Resilience assessment of a local community**	**41 local residents**	**O**	**X**

nique for Order of Preference by Similarity to the Ideal Solution (TOPSIS), VIKOR, and Weighted Sum Model (WSM) provide an aggregation solution for generating a composite index. However, these approaches evaluate alternative rankings solely on the numerical values attributed to each criterion, overlooking their respective importance. In essence, the weights are derived from quantitative data, and such decision-maker inputs are not reflected [56,57]. To overcome these limitations, there were recent attempts to blend these two types of approaches by calculating the weights through AHP and applying TOPSIS and/or others to calculate the composite indicator [58,59].

Yet, as indicated in Table 1, the MCDM approaches mostly require expert participation and lack the inclusion of qualitative feedback. A major limitation derived is that the absence of qualitative contextual feedback leads to a potential oversight or elimination of subjectivity by relying purely on expert knowledge and experience. In addition, this can subsequently pose challenges in validating the rationale behind the final outcome. On the other hand, the semi-structured process in Q-methodology can resolve these limitations through reflecting both qualitative and quantitative viewpoints of the any targeted participants for analyzing the importance of the given criteria (i.e., indicators). However, Q-methodology does not inherently offer weights or an aggregation function as part of its internal process. Consequently, this study aims to address this gap by introducing a weighted-average approach that utilizes the outcomes of Q-methodology.

3. Study area

3.1. Austin, Texas

The Austin-Round Rock-San Marcos metropolitan area (2.3 million residents) is the fastest growing large metropolitan area in the U.S [60]. Austin is also one of the nation's most economically segregated cities, with increasing gentrification and displacement intensifying infrastructure inequity [61,62]. The city is also located in an area of globally-significant and extreme seasonal flooding, resulting in the region's nickname of “Flash Flood Alley” [63]. Climate change and growing impervious cover interact to intensify frequency and size of flood events [64]. In addition, scientists project that the climate crisis is also amplifying Austin's “feast or famine” weather patterns, also resulting in more severe and frequent droughts, higher temperatures, and growing risk of wildfire [65].

3.2. Dove Springs neighborhood, Austin, Texas

Fig. 1 depicts the geographical location of the Dove Springs neighborhood. The Dove Springs neighborhood of Austin (48,000 population) is characterized by a diverse and socially vibrant population that suffers from economic challenges, severe flooding, and increasing urban heat. The neighborhood includes many families (71% of households vs. 36% City of Austin), Hispanic/Latinx residents (75% vs. 34% City of Austin), and residents who are not citizens of the U.S. (25% vs. 13% City of Austin). The median income of the area is $45,000 (vs. $87,000 City of Austin), with 25% of households below the poverty line (vs. 13% City of Austin) [60]. Climate and social vulnerability analyses find the neighborhood to be one of the most at-risk areas of Austin [66].

After a severe flood that caused loss of life and property, residents and a community-serving organization – Go Austin! Vamos Austin! (GAVA) – identified the need for a safe and secure online portal where residents can: 1) share knowledge about their community, climate events, and other chronic stressors, and 2) find information needed to prepare for and respond to climate events. In the fall of 2020, GAVA and researchers at the University of Texas at Austin partnered to begin developing a community-designed online portal where residents can access and share information related to urgent concerns such as climate disasters, as well as chronic challenges like food insecurity. This work was supported by the National Science Foundation. The project seeks to: 1) produce a commu-

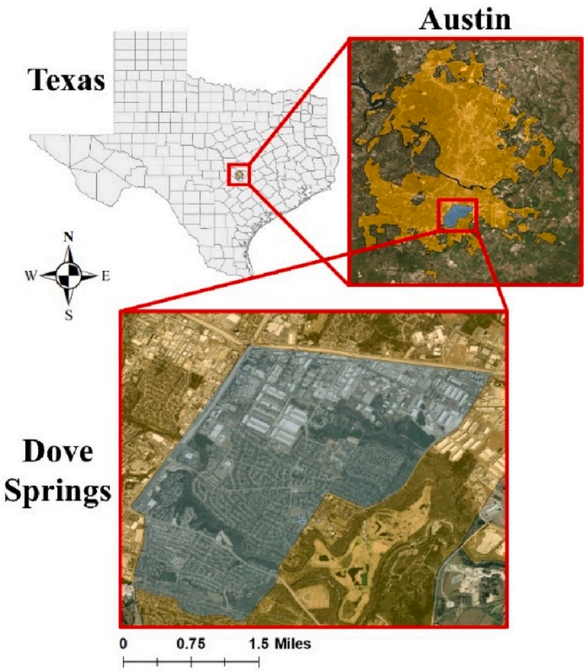

Fig. 1. Location of the study area in terms of state, city, and neighborhood.

nity-led data interface to help residents prepare for acute shocks while reducing chronic stressors, 2) collect information that can be used to integrate local knowledge into climate adaptation planning, and 3) increase community-organizing and climate preparedness knowledge and skills held by residents. Municipal, NGO, and household decision makers can then use these new data and strengthened relationships to address climate and health stressors.

4. Methodology

Following the protocols presented by Brown [67] and Stephens et al. [68], this study conducted Q-methodology in four steps: 1) developing a concourse and a Q-set, 2) collecting a P-set—the participants, 3) completing the Q-sort, and 4) and analyzing and interpretating the results.

A concourse is a collection of a wide range of perspectives for a given topic, which may be about any aspect of human life [67,69]. A Q-set, a selection of the collected statements, is then drawn from the concourse to be administered to participants in the form of a Q-sort. It is crucial that the Q-set contains the local context and ensures comprehensiveness and representativeness of a range of opinions regarding the topic of interest. A Q-set typically consists of 40–80 statements (Watts and Stenner [70]).

The second step is to collect the participants to implement the Q-sort, who are referred to collectively as the P-set. In contrast to R-methodology, the participants function as variables rather than samples in the analysis, requiring a relatively small number for the Q-sort. A general guideline from previous studies is to select the number of participants between 40 and 60 for gathering the viewpoints [33,71].

Q-sorting requires the participants to rank order the Q-set with regard to their level of agreement based on the given topic of interest. Participants are asked to place the statements in the Q-set in a score board that follows a certain distribution format chosen by the researcher. Though the distribution shape is proven to show statistically no significant effect [67], a quasi-normal distribution is mostly utilized for the convenience of the participants where a small number of statements are on the extreme ends of the distribution [33,39,72–74].

When the distribution is completed with all the statements, each individual response is regarded as a Q-sort. The first step of the analysis begins with creating a correlation matrix between the Q-sorts, and a multivariate data reduction technique such as principal component analysis is applied to reduce the matrix into components [75]. The Q-sorts that represent the most of each component (hereinafter referred to as factor) are then flagged to identify more distinguishable points of view, and the z-score is calculated per statement by weighted averaging the flagged Q-sorts on the given statement to determine how much each factor agrees with the statement. The final result of the analysis is a set of selected factors where each factor represents a shared perspective from the participants. The factor arrays appear as completed Q-sorts, each statement holding a value as the participant ranked.

The last stage of the analysis is to describe each factor with the aid of qualitative information provided by the participants during an exit interview on the most extreme-rated statements and compare the absolute difference in z-scores for each pair of chosen factors to identify 1) the statements that are distinctive among other factors, i.e., distinguishing statements, and 2) the statements that are similar among the factors, i.e., consensus statements.

4.1. Concourse & Q-set

This study established a concourse with the integration of the Baseline Resilience Indicators for Communities (BRIC) [6] and the Austin Area Sustainability Indicators (A2SI). BRIC was established to quantify resilience across a broad spatial coverage of the United States, whereas A2SI places specific focus on local context in Austin and Central Texas. A total of 95 indicators were initially retrieved into a pool of six categories: Social (12), Economic (15), Infrastructure (25), Institutional (27), Community capital (11), and Environmental (5) resilience. [b] A Q-set was then extracted from the concourse through two cycles of revision with 16 subject matter experts for the purpose of maintaining adaptability and eliminating repetition and ambiguity. The subject matter experts included graduate researchers and faculty members in the University of Texas at Austin with four distinct areas of research expertise and the research group from which A2SI was developed. For the review process, the subject matter experts were invited to an online collaboration visual platform called Mural. Their role was to identify relevant indicators within the local context of the Dove Springs region in Austin. Appendix A illustrates our inclusion criteria developed for the selection of the most relevant indicators. At the end of the process, a total number of the indicators was reduced down to 45, which also satisfies the approximate number for Q-methodology [40,41].

Based on feedback from the subject matter experts, we reduced the number of indicators for four key reasons: to ensure appropriateness for the local community, if a publicly available source was lacking, if a criterium was repetitive, and to increase language accessibility. For example, we excluded indicators that do not relate closely to the context of the study, such as “Nuclear plant accident planning,” as there is no nuclear power plant in the area. To ensure transparency and reproducibility of our methodology, we excluded indicators that lack a publicly available source or that are hard to quantify (such as “Strong city-wide identity and culture”). In interest of ensuring that the list of indicators was manageable for the participants, we deleted repetitive terms (e.g., “Gender income equality” and “Income and equality”). And to ensure that participants from the local community could understand the indicator descriptions, we removed or rephrased indicators with ambiguous meanings while maintaining their original contexts, such as replacing “Housing capital” with “Ability to purchase and own a home if would like to do so.” Appendix A shows a full list of modified or excluded indicators. Table 2 below provides the list of the final 45 indicators extracted from the concourse.

4.2. Q-sort participants

The intent of implementing Q-sort was to investigate the shared perspectives of residents about the priority of the indicators (i.e., Q-set) related to improving the resilience of the community. Thus, the participants were drawn from the community, and they were interviewed in a recreational park and in an elementary school within the Dove Springs community, in Southeast Austin, Texas, resulting in a total of 41 participants. Researchers collected self-reported demographic data as part of the Q-sort. Most of the participants were culturally or ethnically Hispanic/Latino (85%), and their race was mostly White (Hispanic [75%] and non-Hispanic [7%]) where 12% and 5% belonged to African-American and Other, respectively. The age group range varied greatly, and the distribution was as follows: 10–20 years old (15%), 20–30 years old (15%), 30–40 years old (42%), 40–50 years old (18%), and 50–60 years old (10%). The highest level of education obtained by the participants was as follows: 39% completed less than high school, 29% completed high school, 10% earned a bachelor's degree from 4-year college, 20% earned a degree from other colleges, and 2% completed graduate program beyond a bachelor's degree.

4.3. Q-sort instruction and implementation

To conduct a semi-structured interview using the Q-methodology, we prepared indicator cards with a score board for quantitative prioritization. Also, a paper-based survey was administered to collect participants' contextual justifications for their decisions and their demographic information. The data collection and analysis protocols were reviewed and approved by the University of Texas at Austin's Institutional Review Board. Researchers provided all written materials in both Spanish and English and 63% preferred Spanish for the interpretation. The researchers worked directly with each individual participant to have them complete the Q-sort. Fig. 2 depicts the detailed steps that was followed in our experiment.

Firstly, we introduced background information and the topic of interest to each participant and provided them a score board (Fig. 3) to let the participant rank the 45 statements in the Q-set. Assuming each statement in our Q-set represents an aspect of community well-being, we instructed the participants to rank order the statements on a scale from “least important” (leftmost) to “most important” (rightmost). To ease understanding of the Q-sort instruction, we asked participants to split all the statements into three piles [70]: 1) statements that are important, 2) statements that are not important, and 3) statements that they feel relatively neutral. After the statements were organized, with the statements that are important, we asked the participants to rank order the statements starting from the most important (from right to left), and this same protocol was used for the statements that are not important. When all statements were placed on the score board, we provided participants another chance to shift the statements per their preference. Before exiting the interview, we collected reasoning support on the two most important and unimportant statements participant's chose to be used in our qualitative analysis.

5. Results

5.1. Q-methodology results

The Q-sort generated four factors that contained the combined different opinions of 41 individual respondents. The extracted solution accounted for 50.3% of the total variance in the importance of individual indicators. Unlike factor analysis, which interprets factors based on factor loadings, Q-methodology examines the results using factor scores [67,76]. The factor score is the average value of each factor's Q-sorts, and it represents how each statement is viewed by the factor. Table 3 displays the consensus and distinguishing

Table 2
The final 45 statements extracted from the concourse under six resilience categories.

Social resilience
• Equal access to education (e.g., % college education vs % less than high school for population over 25)
• Access regardless of age (e.g., % of non-elderly population – under 65)
• Transportation access (e.g., % of population with personal vehicle)
• Access to communication (e.g., mobile phone, internet) capacity (e.g., % of population with a mobile phone)
• Ability to speak English (e.g., % of population where English is second language)
• Special needs (e.g., % of population with physical, mental disability)
• Health coverage (e.g., % of population with health insurance coverage)
• Healthcare availability (e.g., mental and physical care)
• Food access
• Safe and affordable housing (e.g., housing support policies)
Economic resilience
• Ability to purchase and own a home if would like to do so e.g., % of home owner population)
• Business size (e.g., % small business compared to % large business)
• Employment (e.g., % of employed population, female labor, part-time vs full-time)
• Big box stores/location of department stores (e.g., Large retail stores such as Walmart per 10,000 persons)
• Federal employment
• Income and equality (e.g., Males vs Female/distribution of income across a population)
Infrastructure resilience
• Housing type (e.g., % housing units that are not mobile homes – trailer or caravan, etc)
• House construction quality (e.g., # housing units built prior to 1970or after 2000)
• Temporary housing availability (e.g., # vacant rental units per 10,000 persons)
• Sheltering needs (e.g., # of hotels and motels per square mile)
• Medical capacity (e.g., # of hospital beds per 10,000 people)
• Physical access to schools (Public schools per 10,000 persons)
• Emergency medical care (e.g., # Hospital beds per 10,000 persons)
• Availability of high-speed internet
• Evacuation routes (e.g., major road egress points per 10,000 persons)
• Diverse and affordable transport networks (e.g., roads to bus stops, train stations, and/or airports)
Institutional resilience
• Neighborhood or city-scaled disaster planning (e.g., % population covered by a recent hazard mitigation plan)
• Flood insurance coverage (e.g., % housing units covered by National Flood Insurance Program)
• Local disaster training (e.g., % population covered by citizen corps programs)
• Ease of understanding relationships of different government agencies and departments (e.g., # of government and special districts)
• Distance from county center to state capital
• Effective coordination between public services and your community (e.g., effective coordination with governments of neighbor regions - # governments and special districts per 10,000 persons)
• Distance from city services
• Population change over previous 5-year period
• Diverse protection of livelihoods following a disaster event
Community capital resilience
• People feel attached to this community (e.g., % of a population who say they belong in their neighborhood)
• Social capital-- religion (e.g., Number of religious people per 10,000 people)
• Social capital-- disaster volunteerism (e.g., # of Red Cross volunteers per 10,000 persons)
• Resident disaster preparedness and response skills (e.g., # Red Cross training workshop participants per 10,000 persons)
• Political engagement (e.g., % voter participation in the election)
Environmental resilience
• Local food suppliers
• Natural areas that protect your community from flooding (e.g., % land in wetlands)
• Energy use (e.g., megawatt hours per energy consumer)
• Covered surfaces where water can't soak into the ground, leading to flooding (e.g., rooftops, roads, pavement, etc.)
• Adequate access to water services (e.g., ratio of water demand to water supply)

statements with their factor scores. All factors shared a view that political engagement (e.g., voting participation in the election) is not important towards defining the community resilience, and understanding the organizational relationship within the government remained as a neutral statement among the factors. It is noteworthy to observe that despite there being agreement that education accessibility is important, there was a considerable degree of variation in factor scores. The factors expressed opposite views on the statements of English ability and sheltering needs. Statements that were not in consensus or disagreement were considered for interpreting each factor which will show differences in perspectives. The statements with the high and low scores for each factor are shown in Table 4 to ease the interpretation. For the analysis, this study focused on the statements with four extreme factor scores of ± 3 and $\pm$ 4.

Factor 1 Housing and food security

The first factor accounted for 16.96% of explained variance, and 12 Q-sorts loaded on this factor. This factor perceived social aspects as the most important element in terms of resilience of their community. The most basic elements of life, food security and safe housing, were given the highest score, and other social elements regarding health coverage and care received a high score. Table 5

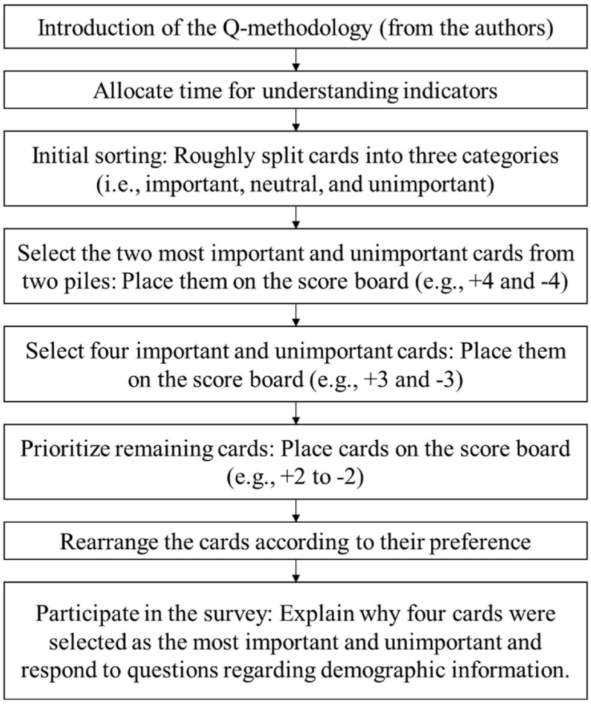

Fig. 2. Q-methodology guidelines for participants.

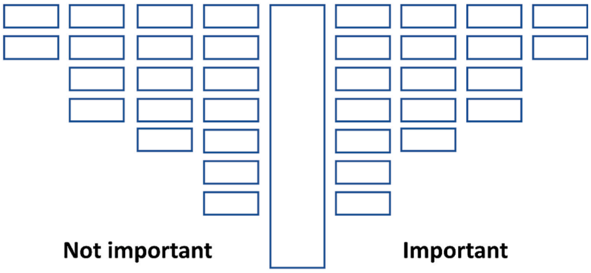

Fig. 3. Score board with 36 boxes for important and not important statements and a large box for neutral statements.

Table 3
Consensus and disagreement statements with their factor scores.

	Statements	Factor 1	Factor 2	Factor 3	Factor 4
Consensus	(CC) Political engagement	−2	−3	−3	−2
	(INS) Ease of understanding relationships of different government agencies and departments	−2	−2	−1	0
Disagreement	(S) Equal access to education	3	4	1	0
	(S) Ability to speak English	−3	1	3	−2
	(INF) Sheltering needs	2	1	−2	3

shows the opinions of the Q-sort participants who belong to this factor. By examining this group of people, we can see that economic aspects had an essential influence in determining the importance of the social aspects. While food and safe housing are not affordable, business sizes and the presence of big box stores received the lowest rankings. Instead of big box stores, there was a demand for increased access to and affordability of food, and residents need reasonable housing options or policies that support housing affordability.

Factor 2 Education and employment

The second factor explained 15.18% of the variance, and 11 Q-sorts loaded here. This factor showed a strong concern about the fundamental solutions to the needs addressed in the first factor. This group was particularly concerned with education and employment. In accordance with the statements with high scores in Table 4 and it can be seen in Table 6 that the participants highlighted the need for equal education and recognized the ripple effect of education, believing that employment can support housing and their fam-

Table 4
Statements with high and low factor scores for describing four identified factors.

Factor score	Factor 1: Housing and food security	Factor 2: Education and employment	Factor 3: Equity	Factor 4: Disaster preparedness
+4	• Food access • Safe and affordable housing	• Equal access to education • Employment	• Physical access to schools • Safe and affordable housing	• Flood insurance coverage • Medical capacity
+3	• Equal access to education • Health coverage • Healthcare availability • Ability to purchase and own a home if would like to do so	• Healthcare availability • Safe and affordable housing • Income and equality • Energy use	• Ability to speak English • Ability to purchase and own a home if would like to do so • Employment • Natural areas that protect your community from flooding	• Local disaster training • Diverse protection of livelihoods following a disaster event • Sheltering needs • Covered surfaces where water can't soak into ground, leading to flooding
−3	• Ability to speak English • Federal employment • Social capital – religion • Distance from county center to state capital	• Political engagement • Distance from county center to state capital • Population change over previous 5-year period • Housing type	• Federal employment • Political engagement • Distance from city services • Evacuation routes	• Access to communication capacity • Business size • Social capital – disaster volunteerism • Diverse and affordable transport networks
−4	• Business size • Big box stores/location of department stores	• Social capital - Religion • Big box stores/location of department stores	• People feel attached to this community • Business size	• Housing type • Local food suppliers

Table 5
Participants' comments on the most/least important statements from Factor 1 - *Housing and food security*.

	Statements	Participants' comments
Most important	**Food access**	• "Important for everyone to have a meal a day; Not everyone has money for food" • "Food needs to be walking/biking distance because many people cannot afford a car to drive for food. The food should be inexpensive grocery stores/not just over price/unhealthy (Dollar General)" • "This is a basic necessity for everyone, regardless of age or other diverse characteristics
	Safe and affordable housing	• "Not everyone can afford housing" • "I am on housing and it's impossible to find decent houses in safe neighborhoods. Our communities need safe and clean neighborhoods a more parks more trees and nature" • "As someone who is currently homeless and has experienced abuse in the past, safe housing is most important to me & providing a home makes me feel safe" • "Many people do not have great jobs/enough income to afford nice housing. Housing needs to be affordable/safe because people can't afford more from the area/need family nearby to help with kids, etc." • "Another basic necessity as everyone needs some where to live"
Least important	**Business size**	• "I chose this because I think a business should care about its size because they could expand any good moment" • "I think business size is not as important. Bigger stores like Walmart normally have better prices, but could be harder to get to."
	Big box stores/location of department stores	• "Although we need more big box stores, our community has always different stores." • "We don't need any more stores."

Table 6
Participants' comments on the most/least important statements from Factor 2 - *Education and employment*.

	Statements	Participants' comments
Most important	**Equal access to education**	• "Everyone needs education" • "Does not matter nationality and/or race gender, we all need education" • "We all have the right to learn" • "Education gives benefits in the future and helps obtain employment and learn how to respect others" • "We all need same education"
	Employment	• "Need employment" • "The employment helps to survive and this is the basic to have dignity" • "Without employment we don't have money to pay the bills" • "To support family (I'm assuming most likely financially, but didn't specify)"
Least important	**Social capital – Religion**	• "Religion is not important in our society, just being nice to each other is enough." • "Religion has little to no place in anywhere" • "Religion is a more personal thing which does not give the value"
	Big box stores/location of departments stores	• "This is only important for department stores." • "Even though there are small food store here still food" • "There are a lot of food stores around"

ilies. Similar to the previous factor, they believed that the existence of a big box store was of low importance along with religion. This group took a view that religion has little bearing on preserving a community's resilience.

Factor 3 Equity

This factor accounted for 12.19% of the explained variance, and 8 Q-sorts loaded here. This group of people emphasized combined perspectives of the first two factors. This factor underlined the importance of education, but they placed a slightly different emphasis on the need for infrastructure support for equitable future education. In addition, there was a strong desire for affordable housing with regards to increasing real estate costs. The supporting statements are found in Table 7, which emphasizes the importance of housing, employment, and English proficiency, given that a large percentage majority of the members of this region are native Spanish speakers. Also, there was a concern about the protection from flooding in natural areas. The statements with the lowest importance from this factor were business size and community attachment, and while they stated the importance of employment, there was low attention to employment in the federal government. Additionally, civic engagement (such as voting), availability of city services, and number of evacuation routes were given low importance.

Factor 4 Disaster preparedness

The last factor showed 5.92% explained variance from five Q-sorts. The shared perspective of this group was mostly driven by disaster preparedness which includes giving statements of flood insurance coverage and medical capacity the highest scores. Being resilient from disaster was a major concern, and as a result, local training, post-event protection, sheltering needs, and flood-prone surface regions were given high importance. Reflecting this opinion, this group was skeptical about housing type (e.g., one or two story) and local food suppliers (Table 8), and they expressed that communication, business size, and transportation networks were also of low importance.

5.2. Proposed weighting strategy

Using the four factors derived from this Q-methodology, this study presents a weighted-average approach to generating a single representative factor.

Table 9 and Table 10 illustrates the overall procedure, and Appendix B shows the factor scores calculated for 45 statements. Below are equations used for calculating each variable in the procedure.

Weight per statement (WS),

$$\mathrm{WS}_i = \left(EV_1 \times FS_{1,i} + EV_2 \times FS_{2,i} + EV_3 \times FS_{3,i} + EV_4 \times FS_{4,i}\right) / \sum EV \tag{1}$$

where i represents the statement id and EV and FS represents explained variance of each factor and factor score per statement, respectively.

Normalized weight per statement (NWS),

$$NWS_i = WS_i / \sum WS \tag{2}$$

Weight per category (WC),

$$WC_j = Average\ \left(NWS_{i \in C_j}\right) \tag{3}$$

Table 7
Participants' comments on the most/least important statements from Factor 3 - *Equity*.

	Statements	Participants' comments
Most important	**Physical access to schools**	• “University after school” • “All kids can access to school no matter the social status of them” • “For our community, we have more future and more educate people.”
	Safe and affordable housing	• “The price needs to be more accessible to everyone” • “Austin's housing is not affordable and price are increasing” • “Because each day the housing cost is rising and also is more insecure”
Least important	**Business size**	• “The importance is that there exist stores”

Table 8
Participants' comments on the most/least important statements from Factor 4 – *Disaster preparedness.*

	Statements	Participants' comments
Most important	**Flood insurance coverage**	• “This was my most important because we live around many rivers that are known for flooding and it's scary to think that if a flood were to happen we would not have anything left”
Least important	**Housing type**	• “This was not very important to me because I feel as no matter what house you have. Being a two story or one. If your house floods there is still so much damage that will need to be fixed” • “It doesn't matter what house you live.”

Table 9
Strategy for calculating normalized weight per statement and category.

Normalized weight per category	Eq. (4) (Ranging from 0 to 1)	0.217	0.158	0.199	0.182	0.101	0.144
Weight per category	Eq. (3)	0.028	0.020	0.026	0.024	0.013	0.019
Category		Social	Economic	Environmental	Infrastructural	Community Capital	Institutional
Normalized weight per statement	Eq. (2) (Ranging from 0 to 1)	0.038	0.036	0.035			0.004
Weight per statement	Eq. (1) + 4 (Ranging from 0 to 8)	6.990	6.490	6.460			0.720
	Eq. (1) (Ranging from −4 to +4)	2.990	2.490	2.460			−3.280
Factor score per statement	Factor 4, $EV_4 = 5.92\%$	−2	−1	0			−3
	Factor 3, $EV_3 = 12.19\%$	+4	+3	+1			−4
	Factor 2, $EV_2 = 15.18\%$	+3	+4	+4			−2
	Factor 1, $EV_1 = 16.96\%$	+4	+2	+3			−4
		Statement 1	Statement 2	Statement 3			Statement 45

Table 10
Weighting strategy to calculate a single resilience score.

Total resilience score	Eq. (6)	0.505					
Normalized weight per category	Eq. (4) (Ranging from 0 to 1)	0.217	0.158	0.199	0.182	0.101	0.144
Resilience score per category	Eq. (5)	0.485	0.496	0.492	0.453	0.533	0.610
Category		Social	Economic	Environmental	Infrastructural	Community Capital	Institutional
Normalized weight per statement	Eq. (2) (Ranging from 0 to 1)	0.038	0.036	0.035			0.004
(Random) Resilience score per statement		0.532	0.781	0.236			0.065
		Statement 1	Statement 2	Statement 3			Statement 45

where j represents the category id.

Normalized weight per category (NWC),

$$NWC_j = WC_J / \sum WC \tag{4}$$

Resilience score per category (RS),

$$RS_{j\in C} = \frac{\sum_{i\in C_j} RSS_i \times NWS_i}{\sum_{i\in C_j} NWS_i} \tag{5}$$

where RSS represents resilience score per statement.

Total resilience score (TRS),

$$RS = \sum RS_j \times \mathrm{NWC}_j \tag{6}$$

The first step involves calculating the normalized weight per statement to determine its relative importance in the context of resilience compared to other statements. The explained variances were used to weigh the factor scores of each statement, and a certain value (in our case, +4) was added to remove negative values. These weights were then normalized into 0 to 1. Statements having the 6 highest and lowest weights are shown in Table 11.

Aggregating the opinions from four factors identified in Dove Springs, the residents indicated that social aspects, including housing, education, food, and health along with economic aspects, were most important. Business size and existence of big box stores were the least important, and federal employment, distance from state capital, political participation, and religion were also less important resilience indicators.

Considering that each category has a varied number of indicators, the next step is to determine the weight of each category (e.g., importance of social resilience category). This can be calculated by averaging the normalized weights of the statements that belong to each category. These weights of the categories were then normalized to make an identical scale ranging from 0 to 1. The results indi-

Table 11
Weighted average of the factor scores.

Rank	Representative factor
1–2	Safe and affordable housing
	Employment
3–6	Equal access to education
	Healthcare availability
	Food access
	Health coverage
40–43	Federal employment
	Distance from county center to state capital
	Political engagement
	Social capital – religion
44–45	Big box stores/location of department stores
	Business size

cate that the perceived importance of each category of the residents in Dove Springs is ranked in ascending order as follows: social, environmental, infrastructural, economic, institutional, and community capital.

After the normalized weight per statement (*NWS*) and per category (*NWC*) were calculated, it is straightforward to derive a final total resilience value. Assuming resilience scores are obtained for all statements, resilience scores of the categories can be calculated by dividing the sum of multiplication of the resilience score and normalized weight per statement with the sum of normalized weight per statement within each category. A total resilience score can then be calculated by summing the multiplications of the resilience score and normalized weight per category. A crucial aspect of the proposed process is the calculation of the relative importance of each statement and category when measuring the resilience of specific areas like Dove Springs. This approach ensures the inclusion of community perspectives and results in a single score that represents the community's resilience.

6. Discussion

Although a variety of disaster indicators have been developed for representing global and/or regional resilience, there is a gap in reflecting local characteristics due to dynamic geographical environment as well as complex interactions within the communities [5,23]. To be specific, while each region has unique strengths and weaknesses in terms of social, economic, community capital, institutional, infrastructural, and environmental aspects—which form the basis of the Q-set employed in this study—there has been little advancement in research that takes these factors into account for measuring resilience. This study aims to advance existing measurement schemes by considering local context. By applying Q-methodology, our study was able to reduce the identified gap by extracting shared beliefs of local community residents of Dove Springs in Austin, Texas and qualitatively describe which indicators are of particular importance to improving community resilience. Our analysis revealed how residents perceive the varying importance of the individual indicators for defining their community resilience, and we identified four shared perspectives: housing and food security, education and employment, equity, and disaster preparedness.

Although the outcomes from Q-methodology reflect the current, localized demand, understanding those factors itself has certain limitations in terms of making crucial assessments of the situation. Quantitative assessment allows for better understanding of community resilience [77,78] and aids decision-makers in developing practical strategies for enhancing resilience [79]. Thus, numerous measurement tools have been developed to identify the indicators as well as to quantify them for producing a resilience score [4,26,29]. Despite these attempts at quantification, the aggregation processes have a key flaw in that the relative importance of the individual indicators is not carefully considered. To resolve this issue and provide a basis for an intuitive decision-making process, this study presented a weighting strategy to represent resilience by prioritizing the importance of the indicators based on the findings from the Q-methodology. Factor scores and explained variances were used for calculating the weights of the statements, and the weight of each category was subsequently calculated to derive resilience scores per category-level as well as per community level. Our weighting method not only integrates the different importance levels of the indicators in the aggregation, but also we produce resilience scores in the same range (0–1) as the existing scheme, making it comparable across regions and broadening its applicability to the global scale.

6.1. Limitations & future directions

This study's primary goal was to evaluate the applicability of Q-methodology in investigating the relative importance of the measurable indicators within a local context. Two macro and regional scale indicator sets, BRIC and A2SI, were benchmarked for establishing a concourse during Q-methodology implementation. There exists no such standardized resilience measurement scheme due to diverse understanding of the resilience context and differing needs as well as the selected data and scope of the study. However, in order to effectively apply the suggested methodology in the decision-making process, a more stringent procedure must be employed to select an indicator set by taking into account regional factors.

A main advantage of using qualitative analysis is the ability to gain rich insights into the context by focusing on participants' perspectives through explanatory information. However, a drawback of relying solely on qualitative assessment is its inability to provide objective indicators, making it difficult to compare with other regions or cases within decision-making processes. To address this issue, the study adopted Q-methodology to enable both qualitative and quantitative analysis for enhancing the context understanding as well as the clarity of relative comparison. Yet, this study was conducted exclusively within a particular region, Dove Springs in Austin. To enhance the practicality of the proposed methodology, it is essential to expand the application's scope to encompass a more diverse and larger set of areas. In addition, local perceptions of resilience can evolve not only across spatial variances but also over time due to factors like policy changes or the aftermath of disasters. In our study, we applied the Q-methodology to the Dove Springs region once, and while that provided considerable insight, we must also acknowledge that perceptions of resilience change over time. In the scope expansion process, strategies for raising resilience awareness of the community and their active engagement must be considered. Also, instead of confining the local context to residents' knowledge and experience, local authorities' perspectives should also be taken into consideration as they have knowledge of realistic conditions and the power to implement change.

Our work can enable multi-modal analysis by extracting local knowledge in terms of disaster resilience which can be incorporated with other data streams such as static and dynamic resources of geographical and economical information and heterogeneous sensor data. A database with spatially granular and community-informed data can be created with the help of integrative modeling from two-way dialogue between municipal officials and local residents, which can ultimately enable making a context-rich decision to increase the local community resilience.

7. Conclusions

This study adopted Q-methodology to gather common local perspectives on disaster resilience indicators and prioritized them based on their varying importance. To improve the conventional quantification method of calculating resilience values by assuming equal importance of individual indicators, we proposed a weighting technique that starts at the indicator level and works its way up to the category level with the goal of establishing a single resilience score. This strategy can facilitate decision-making by assisting in prioritizing items that a local community views as important for their own resilience. Although the results are limited to the Dove Springs community, this study shows practical implications for decision-makers by demonstrating how the Q-methodology-based approach can be used for measuring localized resilience in a qualitatively informed quantitative approach.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Inclusion and exclusion criteria of the disaster resilience indicators

1) **Adaptable for the local community.** Indicators with the context of resilience that have low relation to the chosen study area were excluded.

Examples (removed).
(EC) Non-dependence on primary/tourism sectors.
(EC) Single sector employment dependence (e.g., farming, fishing, forestry, and extractive industries).
(INF) Effective sanitation (i.e., clean water in house) at community scale. This indicator was removed since it is provided at a city scale (i.e., City of Austin).
(INS) Nuclear plant accident planning.
(INS). Crop insurance coverage.

2) **Publicly available source.** To ensure transparency and reproducibility of our methodology, the indicators that are not quantitatively measurable and available from publicly available sources were excluded.

Examples (removed).
(CC) Strong city-wide identity and culture.
(CC) Innovation.
(CC) Proactive corruption prevention.

3) **Avoiding repetitiveness.** Indicators that have redundant or highly correlated meanings were merged into one that has the same context.

Examples (merged).

(S) Mental health support & (S) Healthcare availability.
(S) Enough education for all community & (S) Equal access to education.
(EC) Gender income equality & (EC) Income and equality.
(INF) Established, safe and reliable evacuation routes & (INF) Evacuation routes.
(INS) Effective coordination with other governmental bodies & (INS) Jurisdictional coordination.

4) **Understandable by the target audience.** The Q-sort conducted in this study is aimed for people residing in the local community. To enable the participants to intuitively understand and form opinions during Q-sort, the indicators with ambiguous meanings were removed or rephrased while maintaining their original contexts. We determined these indicators needed clarity by pilot testing the item with our participants.

Examples (rephrased).
(S) Educational equity - > Equal access to education.
(S) Language competency (where English is second language) - > Ability to speak English.
(EC) Housing capital - > Ability to purchase and own a home if would like to do so.
(CC) Place attachment - > People feel attached to this community.
(INS) Performance regimes-state capital - > Distance from county center to state capital.
(INS) Jurisdictional coordination - > Effective coordination between public services and your community.
(INS) Population stability - > Population change over previous 5-year period.
(INF) Shelter capacity - > Temporary housing availability.
(INF) High speed internet infrastructure - > Availability of high-speed internet.
(EN) Natural flood buffers - > Natural areas that protect your community from flooding.
(EN) Pervious surfaces - > Natural areas that protect your community from flooding.
(EC) Large retail-regional geographic distribution - > Location of box stores/department stores.

Appendix B
Factor scores computed for 45 statements through Q-methodology.

	Statements	Factor 1[a]	Factor 2[b]	Factor 3[c]	Factor 4[d]
Social resilience	Equal access to education	3	4	1	0
	Access regardless of age	−1	−2	−1	0
	Transportation access	1	−1	0	1
	Access to communication capacity	−2	−1	−2	−3
	Ability to speak English	−3	1	3	−2
	Special needs	2	2	0	0
	Health coverage	3	2	1	2
	Healthcare availability	3	3	2	0
	Food access	4	2	1	1
	Safe and affordable housing	4	3	4	−2
Economic resilience	Ability to purchase and own a home if would like to do so	3	0	3	1
	Business size	−4	−2	−4	−3
	Employment	2	4	3	−1
	Big box stores/location of department stores	−4	−4	−1	−1
	Federal employment	−3	0	−3	−2
	Income and equality	1	3	2	1
Infrastructure resilience	People feel attached to this community	−1	−1	−4	0
	Social capital - religion	−3	−4	−2	0
	Social capital - disaster volunteerism	−2	−1	0	−3
	Resident disaster preparedness and response skills	0	0	−1	2
	Political engagement	−2	−3	−3	−2
Institutional resilience	Neighborhood or city-scaled disaster planning	−1	0	−1	2
	Flood insurance coverage	0	−1	2	4
	Local disaster training	0	0	0	3
	Ease of understanding relationships of different government agencies and departments	−2	−2	−1	0
	Distance from county center to state capital	−3	−3	−1	−1
	Effective coordination between public services and your community	1	−1	−2	−1
	Distance from city services	−1	−2	−3	2
	Population change over previous 5-year period	0	−3	−1	−1
	Diverse protection of livelihoods following a disaster event	0	1	0	3
Community capital resilience	Housing type	1	−3	1	−4
	House construction quality	0	1	1	−1
	Temporary housing availability	2	0	1	0

(*continued on next page*)

Appendix B (*continued*)

	Statements	Factor 1[a]	Factor 2[b]	Factor 3[c]	Factor 4[d]
	Sheltering needs	2	1	−2	3
	Medical capacity	0	1	0	4
	Physical access to schools	0	1	4	1
	Emergency medical care	2	2	0	−2
	Availability of high-speed internet	−2	−1	2	−1
	Evacuation routes	0	0	−3	2
	Diverse and affordable transport networks	−1	0	−2	−3
Environmental resilience	Local food suppliers	1	1	0	−4
	Natural areas that protect your community from flooding	1	−2	3	1
	Energy use	−1	3	1	0
	Covered surfaces where water can't soak into the ground, leading to flooding	−1	0	0	3
	Adequate access to water services	1	2	2	1

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