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Inclusive Decision Making: Applying Human Factors Methods to Capture the Needs and Voices of Marginalized Populations

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Keywords

climate change, community engagement, decision support systems, marginalized populations

Disciplines

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Comments

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Inclusive Decision-Making:

Applying Human Factors Methods to Capture the Needs and Voices of Marginalized Populations

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Abstract

As urban areas face uncertain climate futures, leaders are challenged with making decisions to mitigate the effects of climate events on vulnerable populations. However, these populations have historically been excluded from many parts of the decision-making process. To promote more equitable decision-making, an inclusive, data-driven decision support methodology was developed to include the needs and voices of populations in economically and culturally marginalized areas. The approach was applied by the Sustainable Cities Decision-Making research team at Iowa State University in collaboration with local civic, non-profit, and residential partners in Des Moines, Iowa. The team identified evidence-based approaches for the integration of human behavior data, building energy use characteristics, future climate scenarios, and near-building microclimate data to inform decisions about how to adapt their city and its neighborhoods to changing climate conditions. Using this methodology, best practices were developed to gather data from community members and stakeholders. The data were then used in models, visualizations, and action projects that closed the loop between data gathering and results dissemination to benefit the local community. This work can be used to inform decisions being made by individuals and policymakers. Importantly, the process is iterative: after decisions are made, the cycle may begin again with data collection to evaluate the outcomes of these actions.

Keywords: climate change; community engagement; decision support systems; marginalized populations

Introduction

In the face of large-scale climate change and growing populations, urban leaders must make strategic decisions about how to adapt their city and its neighborhoods to changing climate conditions. These decisions are particularly critical in low-resource neighborhoods where many residents face marginalization, and are often the most vulnerable to climate events (e.g., extreme heat) (Bolin & Kurtz, 2018). Despite higher vulnerability, individuals in these neighborhoods have historically been the *least* involved in community-level decision-making (Lasker & Guidry, 2009). Additionally, the unique needs of these residents are often overlooked when preparing information and resources for public dissemination.

To address this need, methodologies that integrate human factors and community development practices have been designed to engage marginalized populations in data collection efforts and information dissemination. These methodologies not only provide human behavior data for a suite of integrated simulation models, but also specifically collect this data within an action-based approach that provides direct community benefit. These data-driven models can provide decision-support for policymakers and other city stakeholders to create more equitable, forward-thinking, and sustainable cities. However, to ensure that the models *accurately* represent the needs and voices of the whole community, it is necessary to understand and include the specific needs of the marginalized populations within that community. Data data collection methods operate within a framework such that the process itself strengthens community assets and connections.

Human factors, psychology, and the social sciences share many concepts and methods; these disciplines are concerned with understanding how users think, make decisions, and are influenced by internal and external factors (Ingram, Shove, & Watson, 2007). Human factors applies cognitive psychology principles to understand the role of attitudes, beliefs, and emotions in decision-making (Isen, Daubman, & Nowicki, 1987; Klein, Moon, & Picard, 2002; Graesser, Chipman, Haynes, & Olney, 2005). Similarly, user-centered design (UCD) processes borrow concepts and methods from fields as diverse as ethnography, computer science, social science, and psychology (Rogers, Sharp, & Preece, 2007). For instance, Sociological theories of consumption and practice can inform the design of consumer products (Ingram, Shove, & Watson, 2007).

To design an effective and useable system, it is imperative to understand users, tasks, and the context of use. UCD processes focus on the needs, capabilities, and limitations of users of a system. Practitioners have developed many sets of design guidelines, cognitive principles (e.g., attentional limits), and interface design heuristics (Norman and Draper, 1986; Shneiderman, Plaisant, Cohen, Jacobs, Elmqvist, & Diakopoulos, 2016). UCD involves users at every stage of development, which increases the utility and usability of final designs (Lee, 1999). This multi-stage, iterative process requires designers to continuously validate assumptions about how the system will support the needs of users.

UCD typically occurs in four phases iterated across multiple cycles: *requirements gathering*, *design*, *implementation*, and *evaluation*. Requirements are determined by users' needs and should be justified by analyses of user data. This process is further informed by contextual inquiry methods, which include interviews, questionnaires, observation, and the study of artifacts (Beyer, Holtzblatt, and Baker, 2004). Task and user analyses develop a set of representative tasks that cover the functionality of the system. Similarly, work models consolidate the data into forms that can be organized, stored, and shared, and use cases capture the sequence of events involved in interacting with the system (Rasmussen, Pejtersen, & Goodstein, 1994). By involving users at every stage of development, systems developed through UCD should be more usable, better meet user needs, and be more acceptable to end users (Nielsen, 1994; Mayhew, 1999).

Human factors practitioners are well placed to develop a rich understanding of users to inform the development of technology and programs in communities. Human factors practitioners are advocates for users, and can serve as an interface between users and designers to ensure that users' needs are met by the design (Dabbs, Myers, Mc Curry, Dunbar-Jacob, Hawkins, Begey, et al., 2009). SomeOther methods envision users as participants in UCD rather than mere sources of information. Instead of focusing solely on product design, a focus on "user experience" considers designing users' collective and holistic interactions with the product, related events, and location of use (Sanders, 2003). In short, human factors engineering has a wide variety of methods available for understanding users, including observation (i.e., what people do); focus groups, interviews, and surveys (what people say or think); and participatory design (what people make and why) (Sanders, 2003).

The Sustainable Cities Decision-Making research team at Iowa State University (ISU Sustainable Cities 2018; Passe, Anderson, De Brabanter, Dorneich, Krejci, Poplin, et al., 2016) is collaborating with local civic, non-profit, and residential partners in Des Moines, Iowa, to identify evidence-based approaches for the integration of human behavior data, building energy use characteristics, future climate scenarios, and near-building microclimate data. The research process incorporates approaches and principles that are generalizable to other geographical and social contexts even as the team's specific work acknowledges the precise vulnerabilities and assets of our target population.

Tackling the environmental, spatial, and human complexities of sustainable cities requires a transdisciplinary, systems-based approach that emphasizes strong stakeholder involvement (Foth, Choi, & Satchell 2011). This project seeks to develop a neighborhood-wide urban energy model that combines data on (a) interactions between humans and their built environment and (b) ecosystem services related to urban forestry and microclimate. The goal is a data-rich, replicable decision support systems that engages researchers, community stakeholders, residents and city officials in data collection and decision-making to create sustainable futures. These models will provide stakeholders with feedback suggesting how different choices can create different outcomes, allowing them to make more informed decisions. By integrating principles of data-driven science with community engagement practices, this research advances knowledge on environmental and social challenges in ways that make communities full partners in the scientific and development processes.

For the past three years (2016-2018), the researchers' focus has been on modeling the interactions among buildings, climate, and energy conservation techniques to develop design and policy recommendations that affect vulnerable populations. The team partnered with the City of Des Moines, Iowa. In 2012, Des Moines became a Pilot Community in the recently launched Sustainability Tools for Assessing & Rating (STAR) Communities rating system. The STAR rating system uses a total of 526 indicators to assess "social, economic, and environmental progress" with respect to how "communities address sustainability and prioritize future investment" (STAR Communities, 2019). City officials recognize an urgent need for better documentation of existing systems, improved data analytics, and enhanced use of data in co-designed decision-making.

The research has focused on three resource-vulnerable neighborhoods. To build models that can inform stakeholders and support their local decision-making, human data collection efforts have been tailored to address residents' needs and strengths, as well as empowering them as part of the research process. Building sustainable communities must happen at multiple levels and scales, from local spaces (e.g., buildings, lots, yards, and blocks) to the whole community (e.g., neighborhood and social networks).

This chapter will outline an inclusive, data-driven approach for supporting decision-making while meeting the needs of stakeholders in resource-vulnerable neighborhoods. The components of the approach (i.e., gathering data, using and interpreting data, decision-making-, and results and actions) are derived from the four components of the decision-making process itself: acquiring and integrating information, interpreting the meaning of the information, choosing a course of action, and monitoring and correcting the results of the action (Lee, Wickens, Liu, & Boyle, 2017). This approach has been applied to multiple projects, such as (a) gathering data on weatherization and energy use, (b) creating models to aid in decision-making, and (c) community action projects. The next sections will detail each component of the approach, followed by case studies that illustrate the team's findings.

A Data-Driven Approach for Decision-Making

Overview

Figure 1 outlines the overall approach to data collection, use, and dissemination. Data is first gathered from communities of interest, then used in models, visualizations, and action projects that integrate data collection with relevant local benefit. This integrated work helps to inform decisions made by individuals and policymakers. The process is iterative: after decisions and actions are taken, the cycle begins again with additional data collection to evaluate outcomes of these actions. The work at each stage leverages theory and knowledge from multiple disciplines (e.g., human factors, social science, and human-computer interaction) to ensure that the data gathered and tools built will faithfully represent the needs of local residents and produce equitable, representative, and actionable results.

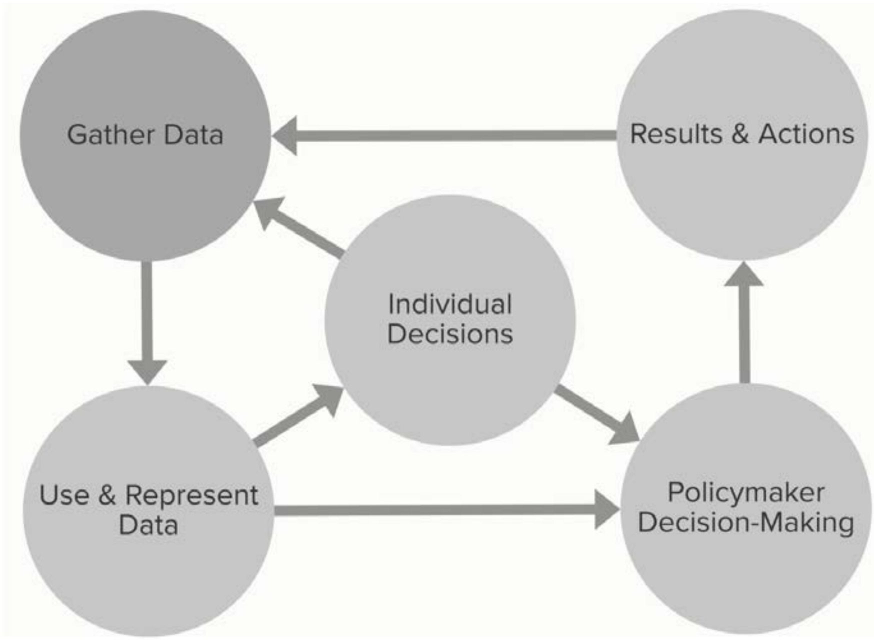

Figure 1. Process for data-influenced decision-making.

Step 1: Gather Data

Data collection is challenging and multifaceted due to issues such as access, time, language, economic resources, and trust (Haight, Quan-Haase, & Corbett, 2014; Sun, Hu, Wong, He & Le, 2013). For instance, it is important to build relationships with the community before eliciting data. To do this in a productive and respectful manner, best practices and implementation strategies were developed (see Table 1) through literature review and narratives of other researchers (Stonewall, Fjelstad, Dorneich, Shenk, Krejci & Passe, 2017).

Table 1. Best Practices and Implementation Strategies for Gathering Data from Marginalized Populations

Best Practices	Implementation Strategies
Earn Trust through Partnership	• form a partnership with trusted community members or a population important to the community • ask a trusted public figure to endorse the research • co-brand literature or recruitment material with trusted groups
Be Multilingual and Inclusive	• prepare multilingual surveys, consent forms, and recruitment materials • offer materials in appropriate languages • if children act as translators, record interviews so that they may be translated and cross-checked later

Communicate for Understanding	• use images to bridge language and culture barriers • check images for cultural relevancy • use language that is familiar and accessible to participants
Respect Schedules and Cultural Norms	• use public areas to initially meet with participants • be aware of "off-limit" times
Offer Something Useful	• offer a useful gift card or product as compensation for time spent with researcher • offer necessary accommodations (e.g., travel assistance, child care) to avoid burden on participants

Earn trust through partnership. Trust must be developed when collaborating with a population facing marginalization. For researchers, this bond may be formed by partnering with an existing trusted public figure (Cetin & Novoselac, 2015) or an organization that works positively within the community. These collaborations serve as gateways to community events and foster a trusting relationship between researchers and participants.

Be multilingual and inclusive. Potentially marginalized communities are often multilingual and may include many non-English speaking individuals (May, 2006). For primarily English-speaking researchers, this presents challenges for inclusivity related to communication, data capture, and information dissemination. Before embarking upon a study, researchers must understand the languages spoken, level of multilingualism, and resident preferences. When translating materials for multilingual communities, it is important to be wary of direct or literal translations—researchers must understand linguistic nuances that emerge from a community’s culture (e.g., colloquial word meanings, slang, and metaphors) (May, 2006). In some communities, informal translators such as children and adolescents accompany non-English speakers (Tse, 1995). Thus, before beginning data collection, it is also necessary to examine materials for situations that could cause difficulty or emotional distress for adult participants with young translators.

Communicate for understanding. Written communication should be visually engaging and easily interpretable. In practice, researchers should employ images and familiar language. Images can “bridge barriers of language and culture” (Horton, 1993, p. 68) and succinctly represent complex information (Otten, Cheng, & Drewnowski, 2015). Images also serve a practical purpose, as they require less translation than a text-based document (Horton, 1993).

Perceived dissimilarities between researchers and participants can introduce additional barriers to effective communication (Rogers & Bhowmik, 1970), especially related to the dimensions of race, ethnicity, and sex (McPherson, Smith-Lovin, Cook, 2001; Shrum, Cheek, & MacD Hunter, 1988). To overcome these barriers and increase perceived similarity, it is important to use language that is familiar and accessible, such as informal styles of speech and writing that mirror the language used by participants (Heylighen & Dewaele, 1999). Notably, this technique is already in practice for government communications to citizens. Several countries (including the U.S. in 2010) have begun to enact legislation mandating professional communications written in "plain language" accessible to a wider audience (Schriver, 2012).

Respect schedules and cultural norms. Populations may vary greatly in preferences for when and where to participate in research (Cetin & Novoselac, 2015). Some research teams have been successful with "door to door" data collection, whereas other teams have encountered communities that are less receptive to individuals approaching their homes. Recruiting participants in public areas (e.g., community centers and grocery stores) can be effective because the public space is familiar and widely trusted (Stokes, Villanueva, Bar, & Ball-Rokeach, 2015). Additionally, collaborating with community event planners can be helpful in understanding schedules while also earning trust.

Offer something useful. Members of marginalized populations often have less discretionary time. Thus, if possible, it is crucial to respect the time they spend on research by offering compensation. One strategy is to offer gift card incentives for local businesses, which are more accessible to participants and support the community economy. In addition to compensation, participating in the research should not be a burden to participants. For example, participants may rely on public transportation; therefore, offering a transit voucher or the ability to meet locally may not only increase participation but also demonstrate inclusivity. Furthermore, offering childcare services might afford caregivers more opportunities and time to participate (Cetin & Novoselac, 2015).

Step 2: Use and Interpret Data

The use and interpretation of gathered data may take the form of models, visualizations, and action projects. For example, agent-based models (ABMs) allow researchers to represent individual decision-makers as autonomous agents capable of social behaviors and interactions with other agents (Bonabeau, 2002). The team has also developed a prototypical workflow for a neighborhood energy model for weatherization strategies (Jagani & Passe, 2017) and integration of urban trees (Hashemi, Marmur, Passe, & Thompson, 2018). Data and model outputs may also be visualized. These visualizations focus on allowing users to draw their own conclusions and answer the questions most relevant to them. One such visualization is a website that allows individuals to understand and answer "what-if" questions about factors affecting their indoor climate. Finally, data and an attention to the specific needs and assets of the community have also informed action projects, including a technology-enhanced leadership program for youth in the community, that help residents understand and make decisions regarding their indoor and outdoor environments, as well as provide venues for additional human data collection (Shenk, Krejci, & Passe, 2019). Examples of some of these approaches are provided below.

Agent-based models. Agent-based modeling is a computational simulation method that represents real-life actors (e.g., individuals and households) using self-contained computer programs (i.e., "agents") that are capable of autonomous action based on perceptions of the environment and their design objectives (Wooldridge & Jennings, 1995). ABM enables researchers and stakeholders to explore how the micro-level decisions of these individual agents can lead to changes in overall macro-level system behavior. In such systems, macro-level behaviors and properties arise from micro-level interactions and adaptations over time, and thus often cannot be predicted by simply examining the behavior of the individual agents (Pathak, Day, Nair, Sawaya, & Kristal, 2007). Such *emergent* system behavior and resultant properties can be counterintuitive and surprising (Chi, Roscoe, Slotta, Roy, & Chase, 2012). In ABM, agents may be programmed to adapt to changes in their environment. These agent adaptations result in new agent interactions and decisions, thereby creating a feedback loop between the micro- and macro-level behaviors (Miller & Page, 2007). ABM can thus be used to predict emergent behavior in complex systems. In particular, ABM can be used to perform experiments that test the effects of changing environmental parameters and/or agent attributes on outcomes for social systems. An ABM can help decision-makers to better understand resident behavior and examine "what-if" scenarios as they consider policy alternatives, such as understanding how households make socially-influenced decisions to weatherize their homes (Krejci, Passe, Dorneich, & Peters, 2016; Huang, Krejci, Dorneich, & Passe, 2017; Huang, Krejci, Passe, Dorneich, Shenk, & Stonewall, 2019).

Traditionally, agent decision logic and behavioral rules have been derived from theory and/or modeler assumptions. To make accurate and reliable predictions, modeling logic should be derived from realistic assumptions that are supported by empirical data (Axelrod 1997; Vespignani 2009). In particular, empirical human behavior data can serve as the basis for the mathematical and logical statements that determine agents' decisions and behaviors. For example, surveys and interviews might be used to elicit urban residents' interest in weatherizing their homes, their willingness to seek financial assistance, and their perceptions of the barriers preventing them from taking action. These responses could then be statistically summarized and categorized, and the resulting mathematical functions could be embedded within "resident" agents of a simulated urban neighborhood to inform their decisions. Just as real-life residents' beliefs and preferences will likely vary from person to person, agents can be designed with heterogeneous logic. This approach represents all residents more authentically, rather than making assumptions about "average" users that might not capture the diversity of the neighborhood residents.

Occupancy models. In models currently used to simulate building energy use, interactions between buildings and their environments are oversimplified (Moonen, Defraeye, Dorer, Blocken, & Carmeliet, 2012), as are the relationships between human behavior and overall energy consumption. Recent energy modeling research highlights the importance of occupancy behavior on energy consumption (Yan, Hong, Dong, Mahdavi, D'Oca, Gaetani, & Feng, 2017). However, it is common to model building occupancy by simply giving every person a generic schedule that defines when they are in the building and how they use the building equipment and lighting. These generic schedules become inputs in the model, but do not reflect actual behaviors of people in buildings. To refine the input for residential neighborhoods, it is critical to understand the level of precision that must be implemented in the model and the sensitivity of certain approximations. More realistic and precise occupancy behavior models were develop based on a survey on energy use that was sent to all addresses in the neighborhoods included in the study, and on data from the national Time-Use Survey (TUS). This data resulted in occupancy schedules that differed in schedule and equipment use, more accurately mirroring how residents behaved in their neighborhood. The outcome of urban building energy modeling with these more realistic occupancy models showed a difference in energy use of 9% compared to generic schedules, demonstrating that modeling occupant behavior accurately can impact energy modeling results. Furthermore, using real data contributes to better understanding of the impact of the diversity of residential schedules on urban energy consumption.

Data visualization. Data visualization is commonly used to make information more intuitive and provide additional context for interpretation (Golemati, Vassilakis, Katifori, Lepouras, & Halatsis, 2009; Huang, Tory, Aseniero, Bartram, Bateman, Carpendale, & Woodbury, 2015). Large corporations, organizations, data analysts, and researchers often use data visualizations in which users are assumed to have in-depth knowledge of the content. However, the impact and utility of data visualizations are magnified if they are designed for use by broader audiences. Therefore, frameworks have been created for building visualizations for *non-expert* users (Gough, Bednarz, de Bérigny, & Roberts, 2016). General requirements for effective data visualization focus on intuitiveness and accurate representation of data. Ignoring these factors results in ineffective visualizations (Amar & Stasko, 2005; Borkin, Vo, Bylinskii, Isola, Sunkavalli, Oliva, & Pfister, 2013; Gough, Wall, & Bednarz, 2014). Understanding the background and knowledge level of the intended audience of a data visualization is essential, because these factors influence what makes the visualization effective (Borkin et al., 2013; Gough et al., 2016; Pousman, Stasko, & Mateas, 2007). The location of the visualization (e.g., bus stop, website, or bulletin board) and its format (e.g. interactive site or poster) also affect the design's features (Amar & Stasko, 2005; Pousman et al., 2007).

Data help inform decisions, and informed decisions are, logically, more representative of the desires of the decision-maker. Therefore, data make for better decisions (Huang et al., 2015).At the individual level, interpretations of data are impacted by one's environment, personal experiences, skill set, background knowledge, and social network (Huang et al., 2015). Individuals often follow a "guess-and-check" method when using data to make decisions

(Phillips, Prybutok, & Peak, 2014). Therefore, an effective and persuasive visualization might support this process by guiding the audience through strategic “what-if” questions and scenarios.

The team has employed such frameworks to develop a website prototype that assists individuals in making decisions about their indoor climates. The website allows users to customize features of their home (e.g., age and size) and visualize the effects of different actions on quantities (e.g., temperature and cost). For example, a resident may be simultaneously concerned about higher home temperatures during the summer along with the costs of cooling. The website allows the resident to investigate “what-if” scenarios for actions such as using air conditioning, fans, or opening windows. Exploring these hypothetical situations improves residents’ understanding of the effects of various actions, which in turn facilitates decision-making about how to cool their homes.

Step 3: Decision-making

In decision-making, individuals interpret and evaluate available information to select among alternatives, often with some degree of uncertainty about the outcome.(Lee, Wickens, Liu, & Boyle, 2017). Decision-making typically involves four stages: acquiring relevant information, interpreting the information, planning and choosing an action, and assessing the outcome of the decision, making changes if necessary (Lee et al., 2017). However, there are many situational factors that may impact decision-making. Specifically, economic status, cultural values, and educational differences can influence how people approach problems and their final decisions (Adamkovič & Martončik, 2017).

Research on poverty and decision-making has observed that individuals with insufficient means often make decisions that appear short-sighted from an outside perspective (Shah, Mullainathan & Shafir, 2012). For instance, individuals might choose short-term solutions that are more affordable, yet are less effective or more costly over time (e.g., obtaining loans with excessive interest rates). However, there are both logical and psychological explanations for these actions: a solution that saves money in the long-term does not matter if the individual cannot afford the initial investment (Shah et al., 2012). Additionally, an inability to meet basic needs can lead individuals to fixate on immediate problems, perhaps leaving fewer mental resources to evaluate other problems and make decisions (Shah et al., 2012). This unavailability of resources can lead to working memory deficits (Adamkovič &Martončik, 2017). The manifestation of this deficit can vary among populations. For example, children living rural poverty show differences in working memory deficits relative to children living in urban poverty (Tine, 2014). When developing decision support tools it is crucial to understand the stressors and barriers marginalized populations face when making decisions.

Consider a family of four living in an un-air conditioned home. Recently, they have begun to worry about the health effects of the extremely high temperatures inside their home in the summer. They have been opening windows and using fans during the day, but it never seems to feel any better. At this time, it is not feasible for them to purchase an air conditioner. Using the weatherization website, however, the family might realize that opening windows at night would cool their home more effectively than opening windows and using fans during the day.

For community decision-makers, barriers to decision making might be very different. Through interviews, the team learned about the decision-making process of city planners working to improve communities facing marginalization. For these individuals, difficulty can often arise in the first (i.e., acquiring relevant information) and second (i.e., interpreting the information) stages of the decision-making process. In many instances, data storage protocols limit access to necessary information. Additionally, even when data are available, they may be in forms or formats that hinder interpretation. By using models and visualizations to consolidate and represent data, the decision-making process could be improved.

For example, policymakers may need to design city-initiated programs for encouraging residents to weatherize their homes. Policymakers could use an ABM to evaluate the relative effectiveness of alternatives, such as encouraging neighborhood leaders to weatherize their own homes, or increasing funding to weatherization assistance programs. Experimentation with an ABM of residential weatherization adoption suggests that increasing assistance program funding could promote weatherization adoption but with diminishing returns (Huang et al. 2017), whereas encouraging trusted community leaders to weatherize (i.e., as role models) would encourage many more residents to weatherize their homes (Huang et al., 2018).

Step 4: Results and Actions

The team's community engagement process seeks to empower these residents and strengthen their relationships with researchers and civic leaders. Many stakeholders do not typically attend meetings, trust researchers, or connect on a regular basis with decision-makers. Inclusive engagement processes therefore require (a) addressing residents' direct needs and strengths, (b) empowering groups of residents as leaders, (c) connecting residents to local community leaders, and (d) fostering trust by anchoring data collection within action projects that provide tangible and relevant benefits. Integrating action and local support within data collection not only builds trust—a critical means of bringing stakeholders into partnership with researchers and city leaders—but also facilitates the data collection that informs integrated simulation models for long-range planning and city decision-making. This process is iterative rather than linear; once decisions are made and acted upon, the process can begin again to understand the outcome or effectiveness of the decision or policy.

Putting the Approach to Use

The research team collaborates with stakeholders who live in three of the most resource-vulnerable yet ethnically and culturally rich neighborhoods in Des Moines. An important goal is to tailor decision-making support and data collection to stakeholders' needs and strengths. In these neighborhoods (Table 2), the median income is about half that of Des Moines: nearly 30% of the population is living below the poverty line (i.e., $16,240 for a family of two or $24,600 for a family of four). All neighborhoods have high percentages of minority residents, and a significant percentage speak a first language other than English. About 30% of adults do not have a high school diploma or other higher education, and these neighborhoods have larger populations (about 8% larger) of young people ages 5-17 than the city overall (Iowa State University Planning Team, Capitol East Neighborhood Association & City of Des Moines, 2014; Martin Luther King Jr. Park Neighborhood Association, City of Des Moines & Polk County Board of Supervisors, 2014). These neighborhoods thus experience significant challenges as well as reasons for pride. Their cultural diversity is often celebrated at local events and is evident in the nature of the local shops and grocery stores. Of particular pride and importance to all three neighborhoods is their youth, and this component forms a central facet of the research team's approach to engaging and supporting these particular neighborhoods.

Table 2. Demographics of the Three Participating Neighborhoods

	Neighborhood 1	Neighborhood 2	Neighborhood 3
Population (2010)	3,187	2,605	2,584
%White/Black/Asian/Other	54/13/8/25	60/14/2/24	55/41/2/2
% Hispanic/Not Hispanic	41.5/58.5	32/68	26/74
Median Household Income	$24,300	$20,803	$32,706
% Own/Rent	54.3/45.7	56.1/43.9	59.5/40.5
% English/Spanish	66.2/31.7	76 22.5	73 /24.2

Integration of Data Collection with Action Projects

In response to the residents' interest in youth, the research team developed a leadership program in partnership with a local chapter of the Boys & Girls Club (Shenk, Krejci, & Passe, 2019; Poplin, Shenk, Krejci, & Passe, 2017). This program—called "Iowa State Community Growers"— is informed by participatory action research and community practice methods (Kemmis, McTaggart, & Nixon, 2013; Weil, Reisch, & Ohmer, 2013) wherein youth are co-designers of the research and action processes that are designed to foster inclusivity and equity. The young people develop priorities for action, often by working with simplified versions of the research team's simulation models (e.g., ABMs and urban energy models). Using these technologies as decision-making tools, the youth create leadership action projects in collaboration with local community leaders—an empowered position of leadership new to nearly all the program's participants. These action-projects connect youth to leaders (e.g., team's community partners). In turn, youth share these action projects at community events where they give back to their community while the research team distributes surveys to collect data.

The youth have worked with such community partners as Habitat for Humanity, Green Iowa (Americorps), Eat Greater Des Moines, Community Housing Initiatives, and the Citizens' Sustainability Task Force. The team's work with the youth establishes credibility with residents in these neighborhoods, gives back to the community, and gives researchers the opportunity to collect data directly from residents who might not otherwise respond to surveys. This approach involves the following components and corresponding strategies, guided by the Best Practices (refer to Table 1).

Selecting a data collection venue at local community events. The team collected data at existing local community events, such as a holiday party at a local middle school and a neighborhood's National Night Out picnic. The team occasionally organized and co-hosted events with community partners (e.g., Citizens' Sustainability Task Force and Eat Greater Des Moines) and worked closely with neighborhood organizations to respect their schedules and cultural norms. The team set up booths to offer something useful to the participants through youth action projects (Best Practices #1 and #5) as well as provided a children's activity to be inclusive to families (Best Practice #2).

Creating a survey instrument. The weatherization survey was provided to residents in English and Spanish (Best Practice #2).Several answers options in the survey were accompanied by images, designed to make the document more accessible and to overcome possible language and literacy barriers (Best Practice #2 and #3; see Figure 2). Finally, the survey was ere intentionally free of potentially sensitive information to respect trust and privacy concerns (Best Practice #1).

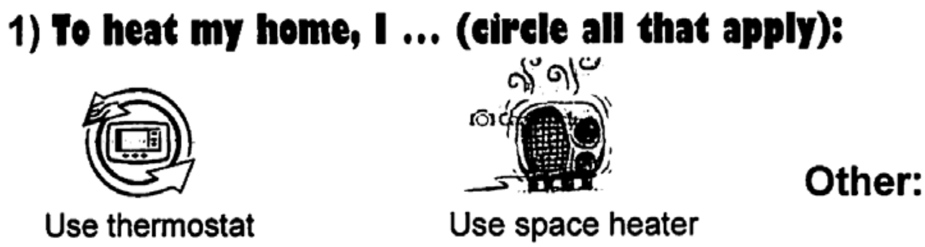

Figure 2. Sample question with accompanying images

Providing useful incentives. Participants who completed the weatherization survey could win a gift card to a local hardware store on the bus line (Best Practice #5). Adults were also offered weatherization rope caulk and shown how to use it, along with the chance to win other prizes. Children received play clay for participating in an energy conservation and weatherization game. These activities allowed parents to complete the survey without worrying about their children (Best Practice #5). The team advertised these opportunities to win prizes and the services offered at the booth (e.g., information on weatherization, tool lending services, and rope caulk tutorials).

Summary of Select Findings

Surveys

The weatherization survey revealed residents' attitudes toward home efficiency, energy use, and energy-saving home improvements. These insights have informed an ABM which models residents making socially-influenced decisions on whether to weatherize their homes..

Participants (*n* = 31) were asked if they would be more likely to make a change to their home if they heard about or saw a neighbor making a change. Twenty-two participants answered "yes" (71%) whereas nine participants responded "no" (23%). Participants were also asked to indicate their methods of obtaining information about home efficiency, and to list steps they might follow to lower their energy bills. The most commonly reported method for obtaining information was the use of a city or government website (Figure 3).

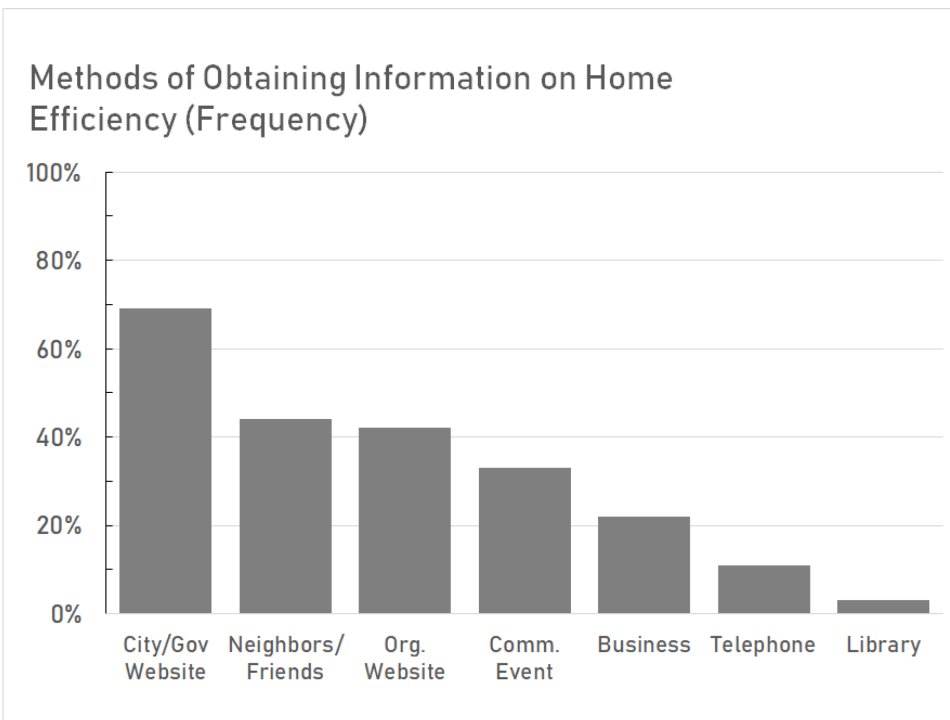

Figure 3. Percent of respondents (n = 36) who reported each information-seeking method. Participants could select more than one method for lowering energy costs.

The most popular first step was to use the rope caulk provided by the researchers (Figure 4).

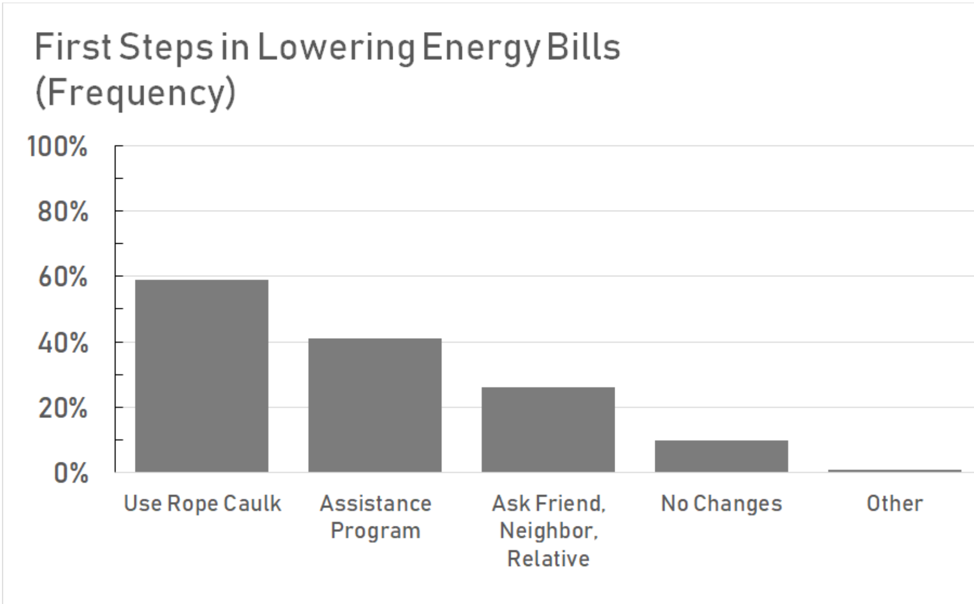

Figure 4. Percent of respondents (n = 36) who selected each first step for lowering energy bills. Participants could select more than one answer.

Action Projects and Earning Trust through Partnership

Action projects and data collection were combined to link the work with direct community benefit (Best Practice #5). For example, youth wanted to help community residents lower energy bills and have warmer homes. In this project, youth were able to learn about weatherization and residential energy consumption through simplified versions of the research team's ABM and urban energy model. Researchers also used the activity with the ABM to strengthen the youth's relationships with each other and other civic leaders (Shenk, Krejci, & Passe, 2019). As a result, the youth came to view themselves as leaders who also connected with civic leaders to share expertise.

The group partnered with the non-profit organization, Green Iowa, which provides residents with free energy audits and basic weatherization assistance. The youth independently initiated a community partner meeting with Green Iowa, and subsequently became the *first* group allowed to conduct recruitment for energy audits. In addition, the youth partnered with the Citizens' Sustainability Task Force to gather ideas from their neighborhood about making the city more "inclusive" and "green." At a single local community event, youth enrolled residents for the energy audits, taught residents how to use the weatherization rope caulk, and helped the Task Force solicit ideas about how to make the city more welcoming and environmentally friendly. By participating in these projects and "Iowa State Community Growers" program, the youth learned (a) principles of using technology for decision-making, (b) leadership and partnership skills, and (c) weatherization strategies. This integrated approach empowered youth and created action projects that strengthened the team's credibility in these neighborhoods (Best Practice #1).

Agent-Based Models (ABM)

Data from community weatherization surveys (e.g., data on adoption behaviors and applying for financial assistance) guided the development of a preliminary ABM, in which 29 "household" agents interacted via a social network and made decisions about weatherizing their homes over a period of 24 simulated months. Survey data constrained the agents' decision logic. For example, 71% of participants reported that their decisions about home improvements (i.e., weatherization) were influenced by their *neighbors'* decisions. Thus, when a non-weatherized agent interacted with a "weatherized" agent in the model, their probability of weatherization was set to .71. Similarly, 72% of respondents reported consulting city or government websites for information about lowering energy bills. Therefore, when agents had access to city or government websites in the model, their "probability of learning energy-related information" was set to $p = .72$.

Experimental results from a previous ABM effort suggest that increasing community connectedness and increasing the frequency of residents' social interactions can increase weatherization adoption rates, even in the face of barriers (e.g., inconvenient assistance application processes) (Krejci, et al., 2016). The experimental results of the preliminary ABM described here demonstrated that agents that weatherized chose to "self-weatherize" (81%) rather than using the assistance program. This pattern is consistent with the weatherization survey, which found that 68% of participants would self-weatherize their houses through tools and information received at the community event, whereas only 41% would seek assistance (Figure 4) (Stonewall, Huang, Dorneich, Krejci, Shenk, & Passe, 2018). Finally, the ABM indicates that when influential community leaders share information about weatherization benefits, other community members may also increase adoption (Huang, Krejci, Passe, Dorneich, Shenk, & Stonewall, 2019).

Conclusion

The Sustainable Cities Decision-Making project employed rigorous human factors methods in collaboration with local civic, non-profit, and residential partners. Specifically, we encouraged strong stakeholder involvement throughout the process of developing decision-making aids for residents, community organizations, and city officials. Despite the fact that low-resource neighborhoods are often most vulnerable to climate events, residents have historically been the least involved in planning; their unique needs are often overlooked in community-level decision-making. The methods described in this chapter were developed precisely because human factors methods are designed to capture the voice of the user. Given the unique challenges of residents of marginalized neighborhoods, best practices were developed to assist future researchers in designing data gathering instruments. Early work purposefully employed action projects to integrate action and leadership of residents in the data gathering process.

Empirically-driven agent-based models enable policymakers to test different policies in an environment that embraces the uniqueness of different agents, rather than designing systems for an "average" user. Human factors practitioners focus on understanding the actual needs of users, and thus are well-placed to capture the voice and needs of residents of marginalized communities to inform decision-making. Applying human factors methods for human behavior data elicitation allowed for a more authentic representation of community members' decision-making and behaviors in the ABM and improved the model's validity and ability to predict the impacts of different policy implementations on community health and well-being. Because these models may be used at both the community and city level to inform policy, it is important that the model be based on accurate representation of the residents' voice, behaviors, and attitudes.

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