Indoor Climate Control Data Visualization Tool for Marginalized Individuals

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The impact of data visualization is a well-established field, but these visualizations tend to be designed with an expert audience in mind. Current efforts to provide similar information to the average citizen focus on brochures, billboards, or other one-way communications which are proven to be less ineffective in portraying complex concepts. Because of the vast amount of data that exist, data visualizations have the potential to assist uninformed individuals with decision making. Potential applications include decisions related to energy use or health. This pilot study is focused on providing marginalized individuals with a tool to make informed decisions about indoor climate control during extreme heat events. The intended system will provide marginalized individuals with customizable, clear, and informative data visualizations to help build intuition in the presented topics.

INTRODUCTION AND BACKGROUND

This paper explores creating data visualizations focused on viewers who face marginalization. Data visualization is a broad field that focuses on presenting data in a more human-readable and intuitive manner. However, much of the current research in the field focuses on presenting data to other experts of their field. The interactive visualizations presented in this paper are an attempt to benefit a population that is not often presented with visualized data like graphs or charts.

The “marginalized population” in this context refers to low-income communities who are currently being underserved by the city and are struggling unnecessarily because of this. These citizens are more vulnerable to environmental factors relating to temperature, energy, and water because they lack resources.

Data visualization is a well-recognized method of making information more intuitive and providing context (Golemati et al., 2009; Huang et al., 2015). Data visualization is often used by large corporations, organizations, data analysts, and researchers. The people viewing these visualizations are assumed to have an in-depth knowledge of the content. Because of this, we sought an effective way of creating data visualizations for non-experts or people without a background in the data presented to them. Unlike professional analysts, non-expert users may be unfamiliar with charts and graphs in general. Using this information, frameworks have been created for building visualizations for non-expert users (Gough, Bednarz, de Bérigny, & Roberts, 2016). While companies or groups have used data visualizations, there are some data visualizations created for individuals. These personalized visualizations have the potential to provide insight; however, they require additional design considerations (Huang et al., 2015). Data visualization has many potential applications with different audiences and contexts that all greatly affect the design process.

Knowing the intended audience of a data visualization is essential because it significantly influences what makes the visualization effective (Borkin et al., 2013; Gough et al., 2016; Pousman et al., 2007). Similarly, the type of data changes the type of visualization that should be used (Robertson et al., 2008). Where the data visualization is located (e.g. bus stop, website, bulletin board) and the form it is in (e.g. interactive site, poster) also affect the design and evaluations (Amar & Stasko, 2005; Pousman et al., 2007). The visual appeal of a data visualization is also shown to influence its effectiveness (Cawthon & Moere, 2007). Similarly, color and familiarity affect the memorability of a visualization (Borkin et al., 2013). General requirements for an effective data visualization focus more on intuitiveness and the accurate representation of data. Ignoring these various factors results in ineffective data visualizations (Amar & Stasko, 2005; Borkin et al., 2013; Gough, Wall, & Bednarz, 2014).

At the individual level, “data interpretation and insight development are mediated by personal context, including environments, settings, personal experiences, skill sets, prior knowledge, and social influences” (Huang et al., 2015). Data help inform decisions, and informed decisions are, logically, more representative of the desires of the deciding agent. Data, therefore, make for better decisions at the individual level (Brandon, Victor, Daniel, 2014), (Huang et al., 2015). Individuals follow a guess-and-check method when using data to make decisions (Phillips, Prybutok, & Peak, 2014), so an effective and persuasive visualization should support this process by providing a method for the audience to process “what-if” questions.

When considering decision making, it is possible to frame the question as “how do humans make decisions?” However, there are many situational differences that may impact decision making. Specifically, economic status, cultural values, and educational differences can influence how people approach problems and what decisions they come to (Adamkovič & Martončik, 2017). Research in the area of poverty and decision making indicates that often, people with insufficient means will make decisions that appear irrational from an outside perspective (Shah, Mullainathan & Shafir, 2012). For example, people sometimes attempt affordable short-term solutions when the long-term result costs more money, such as taking out loans despite excessive interest rates. However, there are both logical and psychological explanations for this. For example, often it doesn’t matter if there is a long-term solution that saves money if the individual does not have the ability to pay the initial investment (Shah et al., 2012). Additionally, being unable to meet one’s needs can lead to a focus on fixing that problem to the point where mental resources are unavailable to deal with other problems, leading to worse decision-making abilities (Shah et al., 2012). This situation can lead to working memory deficits (Adamkovič, Martončik, 2017). While most research focuses on this effect generally, it varies for specific populations. For example, children in rural versus urban poverty show differences in this deficit (Tine, 2014).

There is a clear gap in the literature regarding the intersection of these disciplines. Marginalized individuals are rarely the subject of decision-making research, and rarely the subject of data visualization research. The influence of data visualization on decision making for marginalized individuals is largely unknown but has important applications in mitigating the effects of extreme heat events.

METHOD

Frameworks

Because of the target audience of our data visualizations, a website was chosen to prototype the graphics. A website provided increased accessibility over other proposed platforms. The website used the React and D3 (Data Driven Documents) frameworks for faster processing and easy implementation. React implements a virtual DOM (Document Object Model) which allows the website to update quickly and efficiently. D3 allowed for the creation of adaptive visualizations that the user interacted with to receive real-time feedback. These adaptive visualizations enhanced two-way or interactive learning, which has been proven to increase the effectiveness of learning new concepts (Huang et al., 2015). Users manipulated the data through a series of checkboxes, input fields, and number ranges, shown in Figure 1, that were defined in a configuration (config) file. These controls allowed the user to manage features of their home, such as opening their windows at a certain time of the day or purchasing an air conditioning unit for their home. When features were changed, the resulting state of the home representation was sent to the underlying physics model and the visualizations were updated according to the

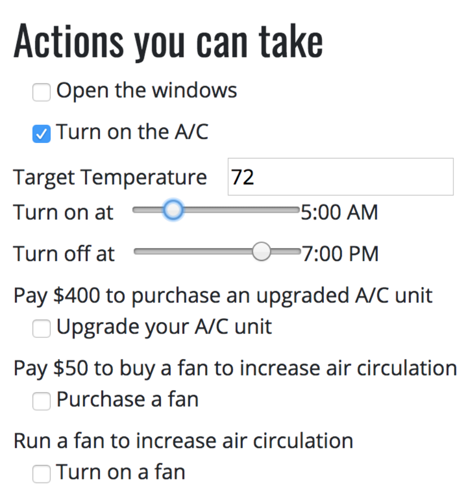

Figure 1. Screenshot of the list of checkboxes, input fields, and number ranges that manipulated the backend state of the home.

returned output. This gave the users instant responses to how the changes would affect the indoor temperature of their home. Instant responses also allowed for two-way communication. Because of the Component feature of the React framework, each of the house parameters and interactive actions were defined in a config file and implemented based on the config type. When a new feature was added to the config file, if the config type was already defined, no additional work was required in the frontend code. This drastically improved the adaptiveness of the website and increased the ease of making future changes. Since the majority of the target audience did not speak English as their first language, the website also implemented the ability to switch between languages easily. This was accomplished by establishing a lookup string for all of the text areas on the screen. The text displayed was chosen depending on the current language identifier. A new language was implemented by adding a new language file with the correct translations for each of the lookup strings.

Structure

We chose to separate functionality between visuals and calculations. This separation allows for simple expansion into a client-server architecture in the future. Our physics-based indoor heating model is a simple approximation based on conduction and radiation to/from the outside environment, but because of the separation between this model and the rest of the program, it would be trivial to move the calculation to a server dedicated to the simulation of a more complex and accurate system. This design decision also informed several others: data transfer to and from the backend is kept to a minimum and the backend has no persistent state.

Design

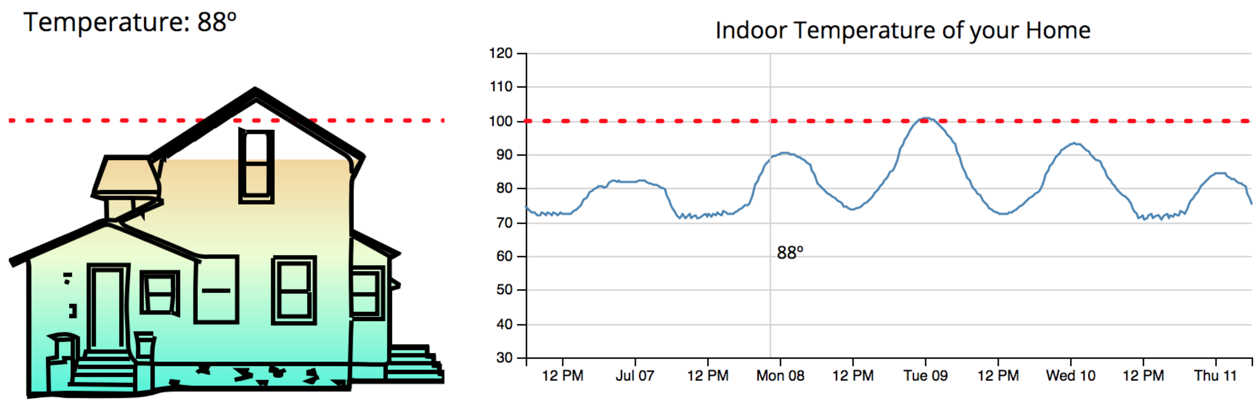

Figure 2. The home visualization (left) and the graph of the indoor home temperature (right).

Because of the user-oriented focus of the data visualization, an essential component of the design process was the creation of user stories. The requirements of the application were adjusted according to insights into the lives of potential users. An example of this is the use of graphs as intuitive data visualizations. Since reading graphs is a learned skill, some members of the marginalized population may be uncomfortable with the interactive site or even unable to use it. To account for this, an additional graphical representation of the data in the form of a house was added to show indoor temperatures at certain times of day as shown in Figure 2. The main concern was to represent the data in an easily recognizable and intuitive way. The user chooses custom settings to make the interactive model mimic their home environment. This information affects the data represented in the visualization and the home graphic. Since aesthetics and color play an important role in the influence of data visualization, these factors were considered when creating the layout, icons, and color scheme (Borkin et al., 2013). Color within this application corresponds to the temperature: blue for cool and orange for hot. Red is reserved for highlighting dangerous indoor temperatures on the graph and indicating when the house is overheating on the house graphic as shown in Figure 3.

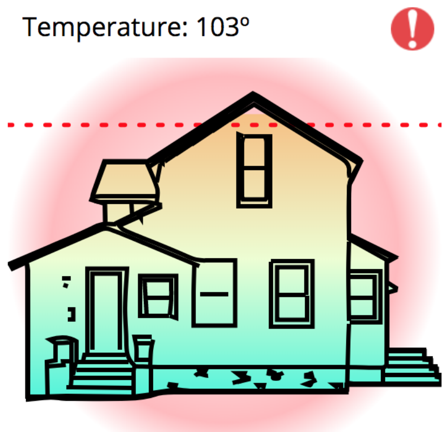

Figure 3. The home graphic when the indoor temperature is at a dangerous level.

Evaluation

Survey Development. The survey was developed to evaluate whether or not the application was able to help the user gain a better understanding of indoor climate control concepts. To determine helpfulness, pre- and post-surveys were conducted to record participants' thoughts before and after using the interactive website. The system usability scale was also included in the post-survey to record a numerical representation of the usability of the application. The post survey also included a series of qualitative questions, such as "name three potential areas of improvement."

Procedure and Process. Seven participants recruited from Iowa State University were walked through a series of three stages: a pre-survey, scenarios, and a post-survey. The pre-survey was conducted to determine each participant's initial confidence when answering three questions related to climate control. After this pre-survey, the participant began the scenario stage. During the scenario stage, the participant used our website to develop a more educated answer to each of the climate control questions asked during the pre-survey. A survey assistant watched the participant and recorded what the participant commented on or questioned (but did not provide answers until the end of the evaluation). Each participant was encouraged to describe their thoughts and voice their questions throughout the study. After the participants answered each climate control question, they were asked how confident they were in their answer and how helpful the website was in discovering their answer. The metric for each of the inquires was a scale from "Not Very Confident (1)" to "Very Confident (7)". At the conclusion of all tasks, the participant was given a post-survey. The post-survey included a System Usability Scale, as well as qualitative questions on their opinion of the application.

Limitations. The main limitation of this usability evaluation is that the participants were not representative of the target population. As a pilot study, however, this still provided actionable results and suggestions.

RESULTS AND DISCUSSION

The average confidence in the participants' answers to each of the climate control questions prior to utilizing our application were 5.43, 3.86, and 5.00, while the averages after were 3.71, 4.14, and 4.71, respectively. This showed that the overall average confidence after using the website decreased by 0.57.

The system usability scale provided the user-perceived complexity of the website as shown in Figure 5. For the open-ended questions in the survey, participants listed what they thought to be the best features of the application. Many answers were similar in listing the home heat graphics, visualization options, and interactivity. Similarly, they were also asked to list the three areas of the application that need the most improvement. The answers were generally on the same page, emphasizing the need to simplify the graph and improve the instructions for effectively using the website.

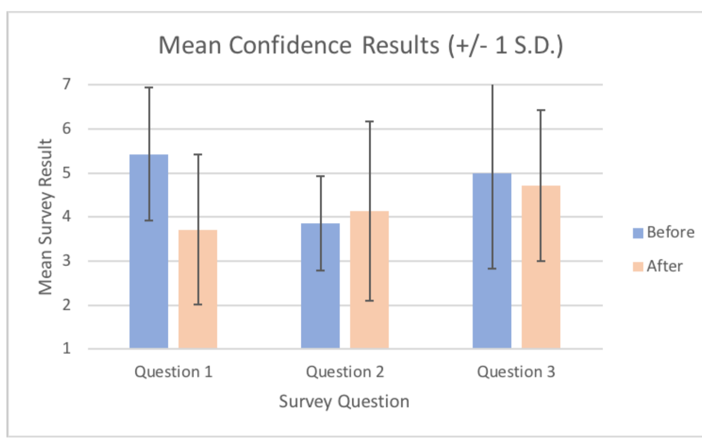

Figure 4. Graphs the average confidence before (blue) and after (orange) and the standard deviation (black lines). Question 1: How would you keep your indoor home temperature below 90 degrees for the least amount of money? Question 2: Describe the best way to cool your home for $50 every five days. Question 3: Define the pros and cons of weatherizing your windows versus turning on your A/C unit.

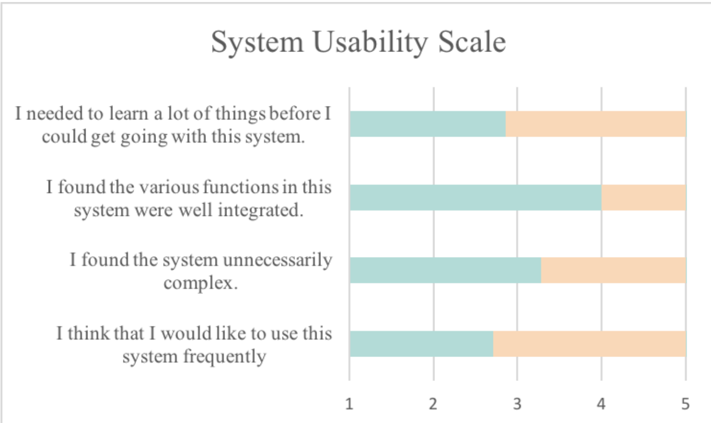

Figure 5. Shows four of the ten averages from the results of the system usability scale.

CONCLUSION

Data visualization has the potential to assist underserved low-income communities in the decision-making process and to compensate for the lack of resources provided to them by officials. Future work on this subject includes running a more extensive case study on the marginalized population instead of pulling from a pool of undergraduate students. It would also be beneficial to implement some of the improvements recommended during the pilot study. Detailed descriptions and learning pop-ups for the different house cooling options would provide more interactivity and possibly help steer the user towards finding a good solution to each of the tasks. Another recommendation was to have the dangerous temperature line correspond to the financial limit of the user. This would help the graph intuitively show the temperature and cost relationship while possibly simplifying the graph.

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