Decentralized Water Collection Systems for Households and Communities: Household Preferences in Atlanta and Boston

Zhongming Lu[1], Weiwei Mo[2*], Bistra Dilkina[3], Kevin Gardner[2], Shannon Stang[2], Ju-Chin Huang[4], and Maria Christina Foreman[5]

[1]Division of Environment and Sustainability, Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong, China

[2]Department of Civil and Environmental Engineering, University of New Hampshire, Durham, NH 03824, USA

[3] Department of Computer Science, Viterbi School of Engineering, University of Southern California, Los Angeles, CA 90089, USA

[4]Peter T. Paul College of Business and Economics, University of New Hampshire, Durham, NH 03824, USA

[5]Volpe National Transportation Systems Center, U.S. Department of Transportation, Washington, DC 20590, USA

*Corresponding Author: 35 Colovos Road, 334 Gregg Hall, Durham, New Hampshire 03824, Ph: +1-603-862-2808, Email: weiwei.mo@unh.edu

Abstract

Development of sustainable and resilient water infrastructure is an urgent challenge for urban areas to secure long-term water availability and mitigate negative impacts of water consumption and urban development. A hybrid system that combines centralized water infrastructure and household decentralized water facilities, including rainwater harvesting and greywater recycling, may be a solution to more sustainable and resilient water management in urban areas. Understanding household and community preferences for decentralized water facilities is important to inform the design and ultimately the promotion and adoption of such systems. In this study, we conducted a discrete choice experiment, via Amazon Mechanical Turk, to collect data on household choices of different decentralized water facility designs in two U.S. cities, Atlanta, Georgia and Boston, Massachusetts. Based on the responses to the choice experiment, we then developed a latent-class choice model to predict households' preferences of decentralized system design features and examine the influence of socioeconomic and personal characteristics on heterogeneous class membership. We identified six major classes of preferences in Atlanta and Boston, respectively, and evaluated how readily each class is likely to choose a decentralized water facility. Atlanta and Boston have some classes sharing similar preferences for decentralized water systems, but the socioeconomic and personal characteristics of these classes in the two cities are different. We found that the early adoption of decentralized water facilities is positively related to neighbors' adoptions and pressure of water scarcity increases households' willingness to share a decentralized facility. The visualization of spatial distribution of the classes highlighted early demand of decentralized water facilities is likely to emerge in low-property-value communities, which creates a unique opportunity for introducing decentralized water facilities during water infrastructure renovations. Our study provides a framework through citizen engagement to understand social demand and to inform the promotion of decentralized water facilities.

Keywords

Discrete Choice Experiment; Latent-class Choice Modeling; Decentralization; Urban Water Infrastructure; Rainwater Harvesting; Grey Water Recycling

1. Introduction

Water is essential to human wellbeing and prosperity. During the last decade, water scarcity and water shortage has become more prominent, especially in cities with rapid population growth and economic development, which underscores the importance of sustainable water management (Hunt and Watkiss, 2011). Centralized treatment systems are traditionally the dominant form of urban water infrastructure. Water is often withdrawn from remote areas, treated, and distributed to the end users through a vast pipeline network. Similarly, domestic wastewater is collected through a sewer network and treated in a centralized facility before discharge. While the centralized water and wastewater infrastructure systems are efficient in delivering clean drinking water and treating pollutants in wastewater, they often require a large amount of energy for both construction and operation (McDonald et al., 2011; Minne et al., 2012; Muñoz et al., 2010; Srinivasan et al., 2013; Venkatesh and Brattebo, 2011). The dependence of water infrastructure on energy exacerbates the depletion of both resources and increases the vulnerability of water systems to energy system failures (Khalkhali et al., 2018; Mo et al., 2014; Stang et al., 2018). Furthermore, much of the U.S. water infrastructure is aged and approaching the end of its useful life. An estimated 240,000 water main breaks happen per year in the U.S. with an expected cascading replacement cost of more than $1 trillion over the coming decades (AWWA, 2011; Grigg, 2015). Similarly, energy infrastructure is experiencing an increasing number of failures and power interruptions due to extreme weather events and limited maintenance (Miara et al., 2017). Centralized supply networks are especially vulnerable to these system failures and interruptions as they lack diversity in source of supply and system scale. Hence, improving the resilience of water infrastructure while maintaining high-level of water resource availability is a priority as cities plan to renovate aged water infrastructure.

Integrated water management, which includes efficiency improvement, utilization of alternative water resources, and development of hybrid infrastructure systems, has been increasingly recognized as a key to water sustainability in cities (Brown et al., 2009). It was found that residents are willing to pay more for decreased water supply interruptions and improved water quality (Wang et al., 2018). Rainwater harvesting (RWH) is one of the integrated water management approaches that has been promoted in many cities to not only address stormwater runoff issues, but also to provide alternative water sources for domestic uses. Greywater recycling (GWR) is another solution to supplement water supply and reduce the treatment loading placed on wastewater treatment facilities. By combining RWH and/or GWR with centralized water infrastructure, a hybrid system is created that can be more cost-effective, energy efficient, and resilient than upgrading centralized water infrastructure to the same service level (Jeanne et al., 2018; Lu et al., 2013; Makropoulos and Butler, 2010).

Unlike centralized water infrastructure which is usually invested in by public sectors and operated by utility companies, decentralized RWH and GWR systems are usually invested in by property owners, either owned individually or shared with neighbors. Hence, the emergence of hybrid systems relies on accelerated adoption of decentralized water facilities. Incentivizing adoption requires a better understanding of how citizens make choices among different types of water systems as well as the underlying drivers for such choices (Jacobs et al., 2016; Mo et al., 2018; Pearson et al., 2010). Such an understanding can inform where the demand of RWH and GWR systems is high and adoption is likely to occur early in cities (Lu et al., 2017). Current research on RWH mainly focuses on characterizing the way it influences hydrologic processes and the quality of collected rain (Sazakli et al., 2007). GWR is less common than RWH in application, and current research primarily focuses on the technological design of GWR systems (Li et al., 2009). However, the preference and demand for RWH and GWR is less understood to support the planning and promotion of hybrid infrastructure systems. Past analysis in the City of Champaign-Urbana, Illinois indicates that citizens value the benefits of improved water quality and aquatic environment (Londoño Cadavid and Ando, 2013). In this study, we evaluated a set of design features (Table 1) to understand how they affect the decision of choosing RWH or GWR to support holistic planning decisions and policy development.

We chose the random utility theory as our theoretical basis to conduct a discrete choice experiment and develop a statistical model of people's choice of RWH or GWR. The utility is a hypothetical value as a sum of observable features of the choices and an unobserved random component for comparison. The mixed logit model is one common generalized approach to derive and estimate a choice model based on the random utility theory (Hoyos, 2010). The latent-class choice model is one particular form of the mixed logit model, which divides respondents into latent classes and produces class-specific choice models for measuring preference heterogeneity (Boxall and Adamowicz, 2002). Many researches have suggested that people have distinctive flavors regarding services and products (Liao et al., 2014; Lu et al., 2015; Yao et al., 2019). We hypothesize that preference heterogeneity exists among citizens for the choice of RWH or GWR so that the knowledge of early demand and the location of such demand is critical to initialize the promotion. Past studies often focused on one region and convergence studies are rare that can generalize the impacts of socioeconomic and personal characteristics on preference heterogeneity across cities and regions. For the first time we compared the impact of socioeconomic and personal characteristics on preference heterogeneity in choosing decentralized water systems between two U.S. cities: Metro Atlanta, Georgia and Greater Boston, Massachusetts. We hypothesize that residents in the two cities may share similar preferences for decentralized water systems but they can have different socioeconomic and personal characteristics. Hence, such preferences have to be studied on a case-by-case basis. This hypothesis highlights the need for an integrated framework to understand local demand for decentralized RWH and GWR systems.

Our study started with a discrete choice experiment that solicited citizens' choices of decentralized water systems under different design scenarios. Amazon Mechanical Turk, a widely used crowdsourcing platform, was used as a venue to engage citizens (Buhrmester et al., 2011). Using responses from Mechanical Turk, we developed a latent-class choice model that quantifies the heterogeneity of preferences for decentralized water systems within and across two testbed areas. We evaluated the usefulness of Mechanical Turk in citizen engagement. We compared the identified latent classes in the two urban areas, and discussed how early each class is likely to adopt decentralized water systems. We further visualized and analyzed the spatial distributions of latent classes across the two areas, which can inform the spatial characteristics of potential adoptions. This study presents an integrated framework that utilizes citizen engagement to understand social demand and to inform the planning of more sustainable hybrid water infrastructure designs in cities.

2. Methods & Materials

2.1. Discrete Choice Experiment Design

The discrete choice experiment design was developed in two stages. In the first stage, we collaboratively developed a choice experiment draft through literature review and conducted a test on Mechanical Turk, which asked for responses to the choice experiment questions and feedback on the overall experimental design. While this initial draft was generally considered to be easy to understand, an outstanding recommendation was to keep the number of options small in each comparison. Thus, we revised the draft to only include two options in each choice scenario to allow easy differentiation between the options (Que et al., 2017). In the second stage, we conducted a second round of data collection to check the statistical significance of different design features' impact on people's choices. In the final revision, we included 6 features that are most influential on people's choices. The qualitative definitions of each feature's levels are self-evident, and the ranges of system costs and savings were collected from decentralized water system vendors and are considered reasonable for both Atlanta and Boston.

The finalized discrete choice experiment includes a total of twelve choice scenarios. Each scenario contains two upgrade options to install a decentralized water supply system. Each upgrade option is described by six features at different levels. Features include system type, ownership, installation cost, significance of environmental benefits, neighbor's choice, and annual net saving from the upgrade (Table 1). Respondents were asked to choose either a preferred option out of the two or neither. We used the choice design function in the JMP software (SAS Institute Inc, 2012) to design the 12 sets of comparisons (24 options) used in the discrete choice experiment. The software uses D-optimal design to minimize the covariance of features so that each feature can be evaluated independently. This design allows one level of a feature to be paired with all levels of other features for comparison at least one time across the 24 options. The twelve scenarios are available in the Supporting Information (SI).

Table 1. Decentralized water facility design features and levels.

Option Features	Levels	Variable coding for latent-class choice modeling
System Type	Rainwater harvesting; rainwater collection varies seasonally	Categorical variable
	Greywater recycling: water for reuse is constant	
Ownership	The system will be sized for and owned by your own household	Categorical variable
	The system will be owned communally; you will own a share of it, pay for that share and accumulate the benefits shown	
Upfront installation cost you will pay	\$500	Numerical variable, scaled to 0.08333 (\$500/\$6,000)
	\$1,000	Numerical variable, scaled to 0.16667 (\$1,000/\$6,000)
	\$3,000	Numerical variable, scaled to 0.05000 (\$3,000/\$6,000)
	\$6,000	Numerical variable, scaled to 1.0000 (\$6,000/\$6,000)
Environmental benefits (e.g., reduce flooding risk; drought mitigation)	No benefit	Categorical variable
	Insignificant	
	Moderate	
	Significant	
Neighbors' choice	No installation yet	Categorical variable
	Some of your neighbors already installed one	
	Most of your neighbors already installed one	
Your saving per year (e.g., water saving minus electricity for pumping water)	Avg. \$240	Numerical variable, scaled to 0.3333 (\$240/\$720)
	Avg. \$480	Numerical variable, scaled to 0.6667 (\$480/\$720)
	Avg. \$720	Numerical variable, scaled to 1.000 (\$720/\$720)

2.2. Data Collection and Correction

Surveys were published on Amazon Mechanical Turk. The Turk is a crowdsourcing platform that provides a time-effective solution for citizen engagement (Crump et al., 2013). We only allowed respondents from

Metro Atlanta and Greater Boston to complete the surveys through the restriction of registered respondents outside Georgia and Massachusetts, and the screening based on reported zip code and county. Incomplete responses were excluded for data quality control and each respondent who completed the survey was paid one dollar. The surveys were available for four months on the Turk and we collected 697 and 602 useful responses from Metro Atlanta and Greater Boston, respectively. Our sample sizes exceed the minimum number that can enable a 95% confidence level with 5% margin of error to represent the choices of the five-million residents in both cities (Bellera and Hanley, 2007). Census data were compared with our sample statistics to examine the sample bias, which was corrected by reweighting the responses in the analysis.

2.3. Latent-class Choice Modeling.

We developed a latent-class choice model to characterize heterogeneous preferences for decentralized water systems among different social groups. We modeled each individual's choice as a result of system design features and socioeconomic/personal variables. Individuals are classified using socioeconomic and personal variables, and each individual has differential preferences on the six design features (Eq. 1). Table S1 in the SI defines the variables for modeling class membership and choice. We selected the Latent GOLD Choice 5.0 software that uses the expectation-maximization algorithm to develop the latent-class choice model (Vermunt and Magidson, 2005). The software cannot automatically determine an optimal class number. We tested the model for a range of class numbers and each class number with 150 runs to avoid local optimal solutions. We chose the run that yields the lowest Bayesian Information Criterion (BIC) to determine the optimal class number for interpretation. In general, BIC performs better than other Information Criteria to determine the class number (Nylund et al., 2007).

$$P(y_{it} = m|z_i) = \sum_{x=1}^{X} P(x|z_i)P(y_{it} = m|x) \qquad \text{(Eq. 1)}$$

where $P(y_{it}=m|z_i)$ is the probability of an individual i giving response m to choice scenario t; y_{it} is the choice of the individual i in the choice scenario t; m is the nominal dependent variable of the choice (i.e., option 1, option 2, and neither of them); $P(x|z_i)$ is the probability of individual i belonging to a certain class x; z_i represents the socioeconomic and personal characteristics of individual i; x is the latent class membership (i.e., latent variable); X is the number of classes; and $P(y_{it}=m|x)$ is the class-specific conditional probability of individual i giving response m to choice scenario t (Eq. 2).

$$P(y_{it}=m|x)=\frac{\exp(U_{m|x}^{t})}{\sum_{m'=1}^{M}\exp(U_{m'|x}^{t})} \quad \text{(Eq. 2)}$$

where, $U_{m|x}^{t}$ denotes the utility associated with the alternative m in choice set t of individual i belonging to class x (Eq. 3).

$$U_{m|x}^{t}=\beta_{no\_adopt|x}d_{no\_adopt,m}+\sum_{j=1}^{D}\beta_{j|x}d_{j,m} \quad \text{(Eq. 3)}$$

where, $d_{j,m}$ is the value of the j^{th} design feature of alternative m in choice set t (Table 1 Column 3); $\beta_{j|x}$ is the class-dependent coefficient associated with the j^{th} design feature. Each level of a categorical feature has one coefficient and the sum of these coefficients is zero for this categorical feature. We created a dummy variable "$d_{no\text{-adopt, m}}$" to model the option of "neither of them". The value is zero for the two presented options and one for the "neither of them" option, respectively.

The equations for the probability of individual i belonging to a certain class x have the same structure of Eqs. 2 and 3. Similar to Eq.3, a set of class-dependent coefficients are estimated to sum up socioeconomic features and personal characteristics. The class membership is further predicted using a similar equation of Eq. 2. The details of probability functions and the application of expectation–maximization to run the estimate can be found in the Latent GOLD Choice manual (Lu et al., 2015; Vermunt and Magidson, 2005).

2.4. Spatial Visualization

We used a population synthesizer developed by Arizona State University to create complete individual household samples that represent the households living in each census block group in the City of Atlanta and Boston (Choupani and Mamdoohi, 2016). The synthesizer uses census summary statistics of socioeconomic variables and Public Use Microdata Sample (PUMS) to reproduce a complete household sample. The sample only contains the part of socioeconomic variables for each household that are available from PUMS (i.e., age, education, gender, housing type, household size, household income, ownership, and race). We combined these socioeconomic variables and the average personal characteristic values from the survey to estimate the probability of synthetic households belonging to different classes. We visualized class distribution at census block group levels in Atlanta and Boston.

3. Results and Discussion

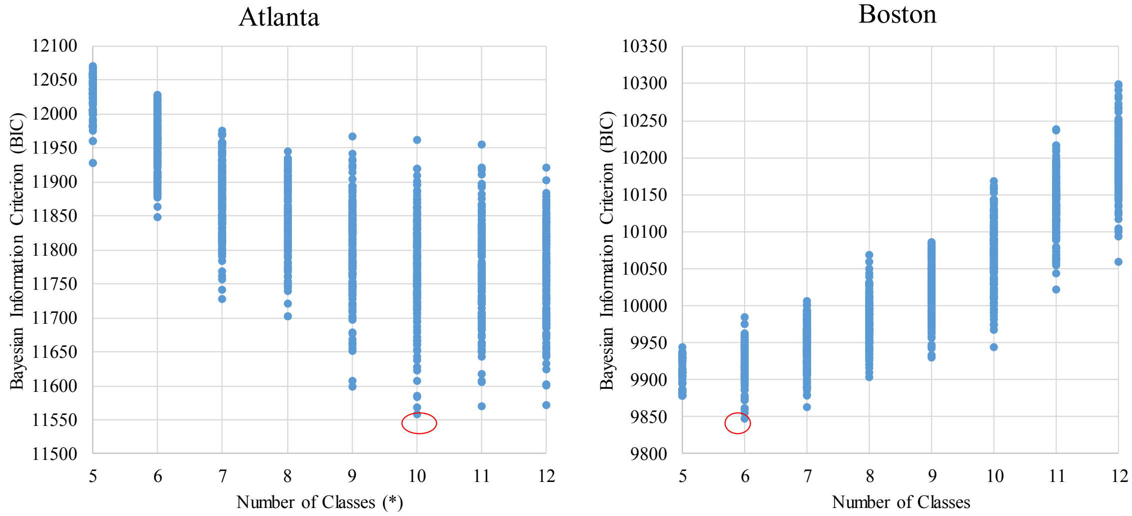
3.1. Summary of Respondents from Mechanical Turk

We first evaluated the sample bias from Mechanical Turk by comparing the socioeconomic characteristics of our respondents with the averaged demographic data obtained from U.S. Census for Metro Atlanta and Greater Boston (Table S2). Most socioeconomic variables have similar distributions between our survey respondents and the census data except age, education, and household head. In our survey responses, the group that is older than 60 years old as well as the group that is high school graduate or less are underrepresented. We have more respondents considering themselves as household heads than that are in U.S. Census. To reduce the sample bias, we used the PUMS data and corrected the weights of individual responses before the latent-class choice modeling.

3.2. Selection of an Optimal Class Number and Summary of the Model Statistics

The summary of model statistics is available in Tables S3&S4. According to the R^2 values, the latent-class choice model explains 48.1% and 45.3% of the variance in the choices of Atlanta and Boston respondents, respectively. Both the impacts of design features on the choice and the difference of these impacts across classes are statistically significant, which can be used to interpret preference heterogeneity in both cities. The socioeconomic and personal variables we defined have significant influences on class memberships. We consider that our latent-class choice models can help examine our hypotheses of preference heterogeneity and differential socioeconomic features of people sharing a similar preference in two cities.

In Atlanta the optimal class number was found to be 10, which has the lowest BIC (Fig. 1). However, we excluded 4 of the 10 classes because the size of each of the four classes is only less than 3% of the sample size (10-20 responses while we have 12 class-specific independent parameters (Eq. 3 and Tables S3&4) to estimate). The small sample size cannot produce reliable estimates for analysis (Nasserinejad et al., 2017). Accordingly, we analyzed the largest 6 classes in Atlanta. The optimal class number was 6 in Boston. The optimal class number verifies our first hypothesis of preference heterogeneity.



*Note: We excluded 4 of the 10 classes that the class size is smaller than 3%.

Figure 1. Use of Bayesian Information Criteria (BIC) to select the optimal class number in Atlanta and Boston

3.3. Latent Classes in Atlanta

We named the six classes based on their stated preferences for decentralized water facility design features in the discrete choice experiment. Figure 2 shows the levels of choice modeling variables and the conditional probability for each design feature level selection based on the assigned class. The conditional probability explains the choice of each class facing different levels of one design feature while holding others the same. The six class names are “undiscerning adopter,” “rational adopter,” “rational late adopter,” “cost-sensitive late RWH adopter,” “cost-sensitive & saving significant GWR to own,” and “neighbor-sharing RWH.” The “undiscerning adopter” does not show any significant difference among various levels of design features. This class has a high probability to choose a decentralized water system without discriminating between system designs. The “rational adopter” class shows minimal rejection to choosing a decentralized water system and the system can be either GWR or RWH. Members in this class prefer low cost, significant environment benefits, high annual saving, and the system that most neighbors install. The “rational late adopter” demonstrates a similar preference for system features except that this class has a higher likelihood of not adopting the decentralized water system. The “cost-sensitive late RWH adopter” is also likely to not adopt the decentralized water system. This class prefers a low-cost RWH system if he/she considers a decentralized water system. The “cost-sensitive & saving-significant GWR to own” class prefers a low-cost, self-owned GWR system with significant savings. The “neighbor-sharing RWH” class shows a strong preference to share RWH with the neighbors, especially when most neighbors choose to have one decentralized water system.

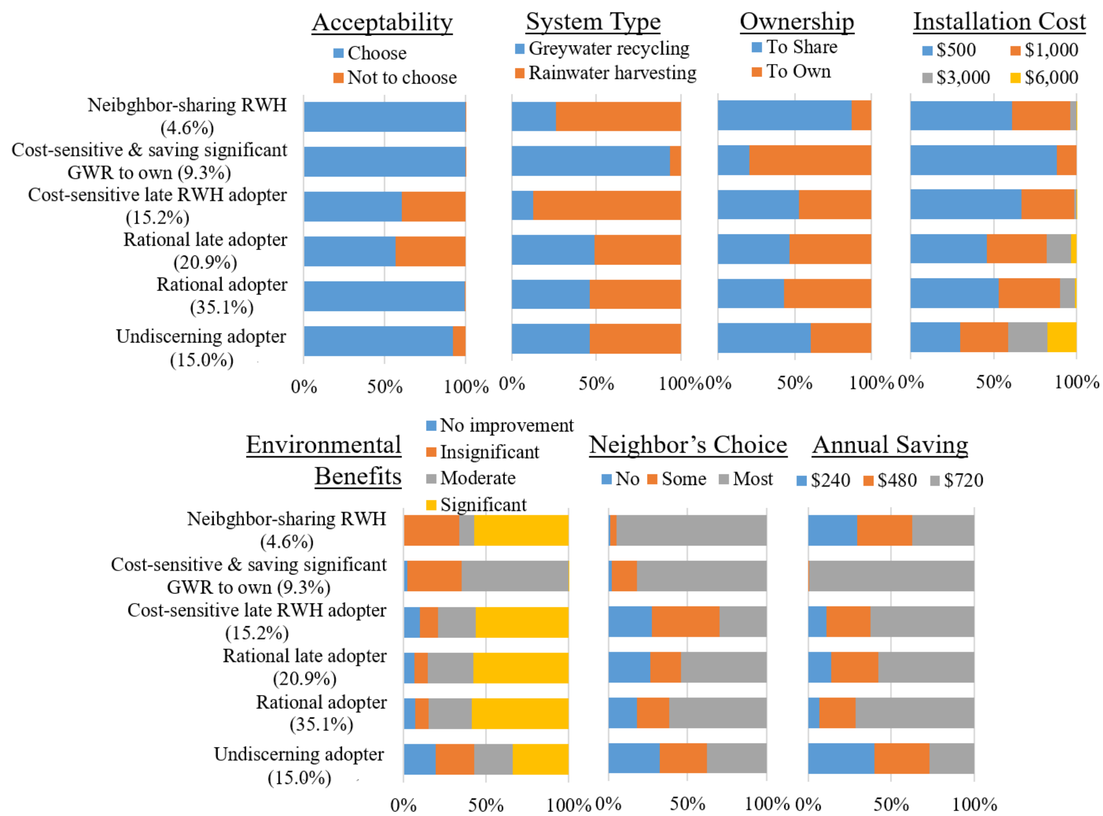


Figure 2. Class-dependent conditional probability of choosing a decentralized water facility associated with various levels of design features in Metro Atlanta.

The “rational adopter” class is the largest class and about 35.1% of the households belong to this class in Metro Atlanta. The “rational late adopter” is the second largest class and about 20.9% of the households belong to this class in Metro Atlanta. The “cost-sensitive late RWH adopter” class favours a less expensive RWH system and about 15.2% of households belong to this class in Metro Atlanta. The remaining 15.0%, 9.3% and 4.6% of total households belong to the “undiscerning adopter,” “cost-sensitive & saving significant GWR to own,” and “neighbor-sharing RWH,” classes, respectively. In general, households in Metro Atlanta prefer a decentralized water system with a low cost, a high saving, and significant environmental benefits.

The system can be either RWH or GWR, and it can be shared with the community or own privately. Neighbors' installations of such systems will be a plus to encourage the adoption.

3.4. Latent Classes in Boston

We similarly named the six classes in Boston: "undiscerning adopter," "cost-effective," "rational late adopter," "cost-sensitive late RWH adopter," "benefit-significant GWR," and "neighbor-sharing, cost-sensitive, and benefit-significant GWR" (Fig. 3). Boston shares some common classes with Atlanta, including "undiscerning adopter," "rational late adopter," and "cost-sensitive late RWH adopter." The other three classes in Boston behave differently than those in Atlanta. The "cost-effective" class in Boston prefers a decentralized water system with a lower cost and a higher annual saving while the similar class "rational adopter" in Atlanta prefers more environmental benefits and neighbor's choice in addition to a low cost and a higher annual saving. The "benefit-significant GWR to own" in Boston prefers a decentralized GWR that has significant environmental benefits and a high annual saving. In Atlanta, the "cost-sensitive & saving-significant GWR to own" class prefers a decentralized GWR that is cheap and saving-significant. Regarding the sharing of a decentralized system, the "neighbor-sharing" class in Atlanta prefers an RWH while the similar class in Boston prefers a low-cost GWR with significant environmental benefits and a high saving.

In Boston, the "cost-effective" class is the largest class with 35.3% of the households belonging to this class. The "undiscerning adopter" is the second largest class with about 25.9% of the households belonging to this class. The "rational late adopter" is the third largest class with about 15.3% of the households belonging to this class. The remaining 11.8%, 6.08%, and 5.62% of total households are the "cost-sensitive late RWH adopter," "benefit-significant GWR to own," and "neighbor-sharing, cost-sensitive, and benefit-significant GWR," classes, respectively. On the whole, Boston residents show the same preferred decentralized water system that has a low cost, a high saving, and significant environmental benefits as Atlanta residents do. The system can be either RWH or GWR and the neighbors' installations of such systems will be an incentive. This consistency of the preferred decentralized water system in Atlanta and Boston reveals a universal preference pattern for technology innovations.

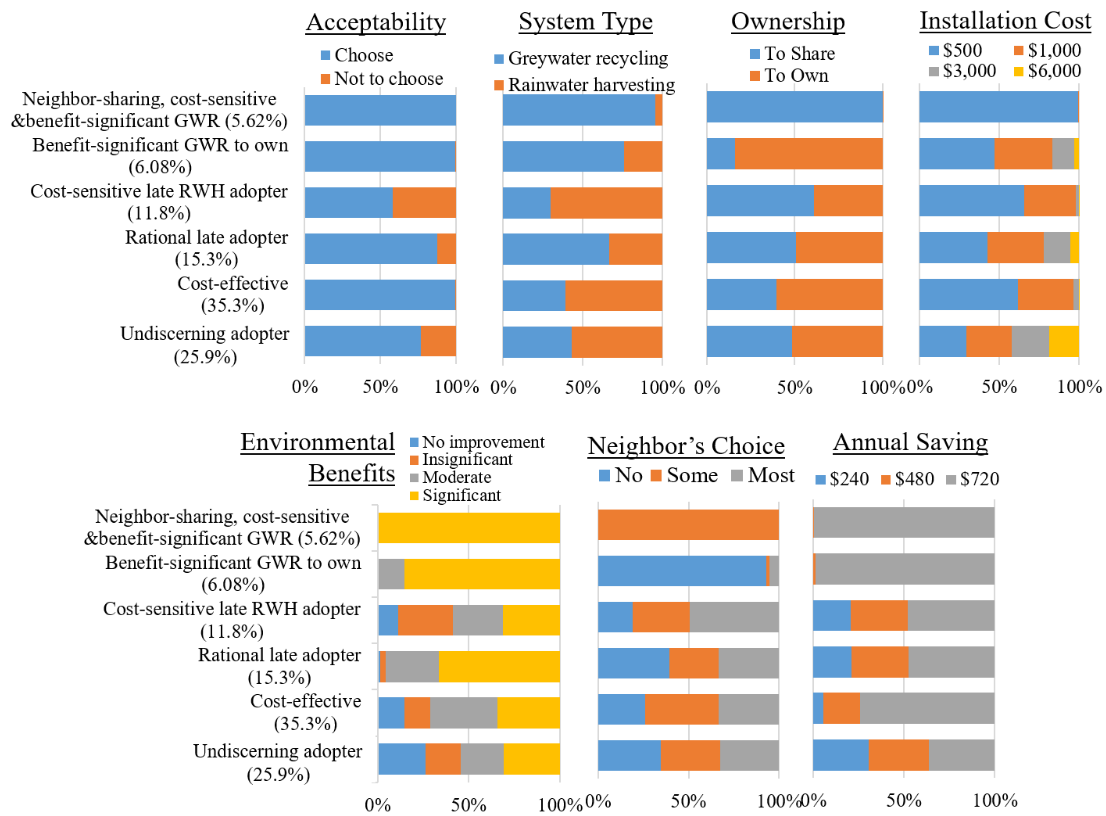


Figure 3. Class-dependent conditional probability of choosing a decentralized water facility associated with various levels of design features in Greater Boston.

3.5. The Impact of Socioeconomic Status on Preferences: Cross-City Comparison

Tables S3&4 summarize the impact of socioeconomic and personal characteristics on class membership. We use "Time to complete the survey" as a measure of personality regarding how fast a person can make decisions (Table S1). The time a respondent spends can reflect the certainty of his/her decision and the inclusion of response time can improve the model performance (Uggeldahl et al., 2016). In Atlanta, the "undiscerning adopter" class members answered surveys faster than other classes. The average household income of this class ranks near the bottom among classes yet 76% of class members plan to purchase or upgrade properties. Moreover, the "undiscerning adopter" class members report more neighbor's installations of RWH and GWR than other classes. The demand of improved properties, the fact that their neighbors have installed similar systems, and the fast decision-making skill can all contribute to the likelihood of a "undiscerning adopter" to install decentralized water facilities. The "rational adopter" class members do not have any overwhelming socioeconomic or personal features that make this class unique. The “rational late adopter” class members spent more time on surveys than other classes and about 72% of the class members indicate having no plan to change their current properties. About 80% of the “cost-sensitive late RWH adopter” class members live in single-family houses and about 90% of the class members do not consider water scarcity to be an issue. The average age of this class is the highest among all classes. The average household income of the “cost-sensitive & saving significant GWR to own” class is the highest among all classes. The majority of the “neighbor-sharing RWH” class members live in multi-family houses and 67% of the members think that water scarcity will probably be a problem. On average, this class knows more about decentralized water systems than others.

In Boston, the “undiscerning adopter” class members answered surveys faster than other classes except the “benefit-significant GWR to own” class. The “undiscerning adopter” class members in Boston also report more neighbor’s installations of RWH and GWR than other classes. The “cost-effective” class members do not have any overwhelming socioeconomic or personal features that make this class unique. The “rational late adopter” in Boston also spent more time on surveys than other classes. The majority of “rational late adopter” and the “cost-sensitive late RWH” classes indicated no plan to change their current properties. The average age of the “cost-sensitive late RWH” adopters is the highest among classes. The “benefit-significant GWR to own” class members are younger than 30 years old and unmarried. However, most class members have household sizes larger than three people. It is likely that the “benefit-significant GWR to own” class members room with others. The majority of the “neighbor-sharing, cost-sensitive, & benefit-significant GWR” class members (about 70%) live in single-family houses and the house size is larger than 1,500 ft^2. About 95% of class members plan to purchase or upgrade properties. On average, the proportion of the “neighbor-sharing, cost-sensitive, & benefit-significant GWR” class members who consider that water scarcity will probably be an issue is the highest among all classes.

Based on Table S3&S4, the impacts of socioeconomic and personal characteristics on class membership are different between the two cities. Table S5 summarized the profiles of the socioeconomic and personal characteristics of “undiscerning adopter,” “rational late adopter,” and “cost-sensitive late RWH adopter” in both cities. While sharing similar preferences on decentralized water systems, we found the socioeconomic and personal characteristics of the three latent classes across the two cities can be very different, which supports our second hypothesis that people sharing a similar preference in two cities may have differential socioeconomic characteristics. For instance, the majority of the “undiscerning adopters” in Boston live in multi-family houses while a large proportion of the “undiscerning adopters” in Atlanta live in single-family houses. This is reasonable because Atlanta is more sprawled than Boston. The overall socioeconomic statistics are also different between Atlanta and Boston including property ownership, house types, household income, among others (Table S2). The perception of water scarcity in Atlanta is slightly stronger than that in Boston (Figure S1). We hence conclude that socioeconomic composition and local development matter for preference heterogeneity analysis. Meanwhile, we found that the impacts of neighbor’s choice and water scarcity perception on class membership were consistent in both cities. If the neighbors install one decentralized system, the individual is more likely to be an “undiscerning adopter”. In other words, the choice of neighbors can accelerate an individual’s decision of choosing a decentralized water system. If an individual believes that water scarcity will probably be an issue, he/she tends to act as a “neighbor-sharing RWH” in Atlanta or a “neighbor-sharing, cost-sensitive & benefit-significant GWR” in Boston.

3.6. Diffusion of Decentralized Water Facilities in Atlanta and Boston

We developed an innovation diffusion curve that approximates how early different classes in Metro Atlanta are likely to choose a decentralized water system (Fig. 4). Franceschinis et al. constructed a psychological factor that measures the degree of innovativeness to link classes to the diffusion of innovation curve (Franceschinis et al., 2017). Our diffusion curve is based on the relative timing when incentives can fulfill expectations of the six classes to install decentralized water facilities. For instance, environmental benefits such as flooding risk reduction and drought mitigation are only significant when the installations of decentralized water facilities reach a certain threshold. The system cost may take a certain period of time to decline when the demand starts to increase. We considered that the “undiscerning adopter” class is the earliest adopter because this class has a high probability to choose a decentralized water system and this class makes decisions much faster without discriminating between system designs. The “rational adopter” follows the “undiscerning adopter” as the early majority but the “rational adopter” needs some environmental benefits, economic savings, and neighbors' adoptions to support decisions. The "rational late adopter" as the late majority will be more willing to adopt a decentralized water system as environmental benefits and annual savings become more significant. We conjecture that the "cost-sensitive late RWH adopter" and "cost-sensitive & saving-significant GWR to own" are inactive groups since they are sensitive to the cost and they may consider a decentralized water system when the price goes down in the future. The "neighbor-sharing RWH" class is the latest adopter because the class depends on its neighbors to collectively share an RWH, which may take a long time among neighbors to reach a consensus.

Similarly, we also developed an innovation diffusion curve that approximates how early the six classes in Greater Boston are likely to choose a decentralized water system (Fig. 4). The "undiscerning adopter" class is considered as the earliest adopter, followed by the early majority "cost-effective" class who needs cost-effective decentralized water systems. The "rational late adopter" class will be the late majority who is more willing to choose decentralized water systems when environmental benefits become significant. The "cost-sensitive late RWH adopter", "benefit-significant GWR to own", and "neighbor-sharing, cost-sensitive & benefit-significant GWR" are the inactive groups because these classes need either a low-cost choice or significant environmental benefits and economic savings.

According to our hypothetical diffusion curves of how early different classes are likely to choose decentralized water systems, the diffusion of decentralized water systems in Boston may be faster than in Atlanta. However, the diffusion also depends on local contextual factors including system cost, environmental benefits, annual saving, and neighbor's choice. The modelling of diffusion will be investigated more thoroughly in a future study.

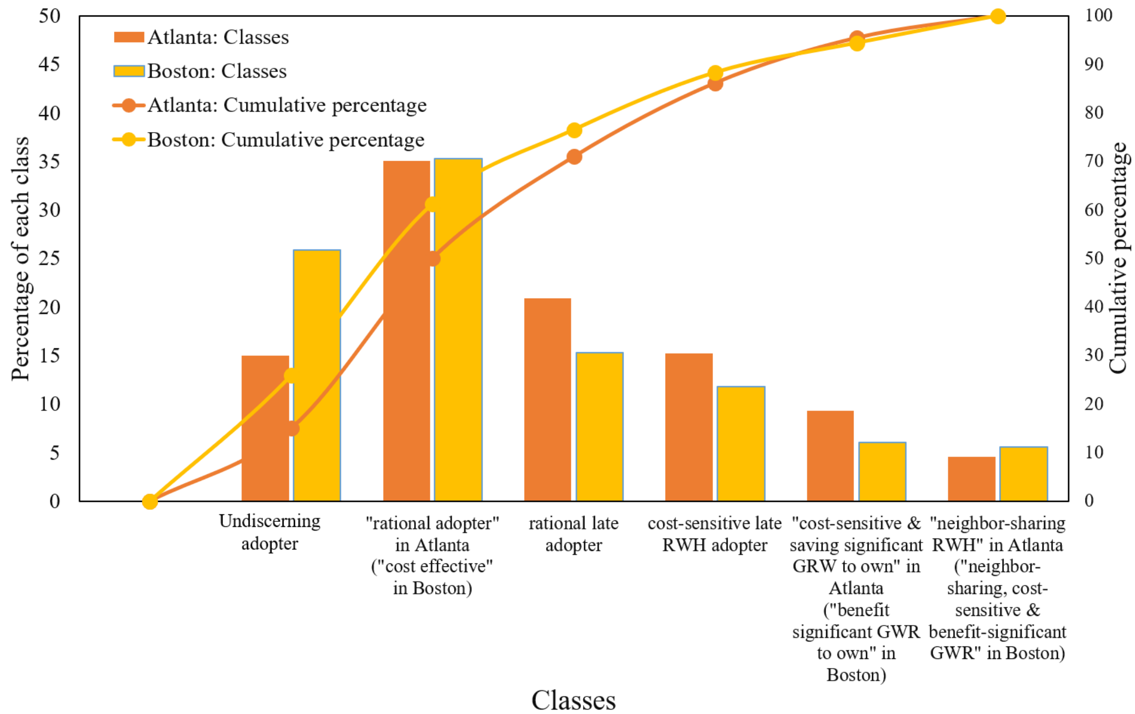


Figure 4. Diffusion curves of decentralized water facilities in Atlanta and Boston.

3.7. Spatial Distribution of Classes in Atlanta and Boston

We analysed the spatial distribution of the different classes of adopters in our two testbed areas in order to gain potential insights for planning purposes. We created a set of synthetic households for each census block group in Atlanta and Boston and used synthetic households' socioeconomic features and the average personal features to predict class memberships. We visualized the percentages of different classes in Atlanta and Boston, respectively (Figs. 5 and 6).

In Atlanta, a higher percentage of households belonging to the "undiscerning adopter" is found in the downtown, indicating incentivizing initial adoptions of decentralized water systems in this area could potentially result in a rapid diffusion. The majority of households residing in the southern part of Atlanta are "rational adopter" while a high percentage of households is "rational late adopter" in the northern part of Atlanta. The diffusion of decentralized water systems is likely to start earlier in the southern part of Atlanta than the northern part. There are several census block-groups across the city that have a higher percentage of households belonging to “cost-sensitive late RWH adopter” and “cost-sensitive & saving-significant GWR to own.” The presence of “neighbor-sharing RWH” is low in the downtown area.

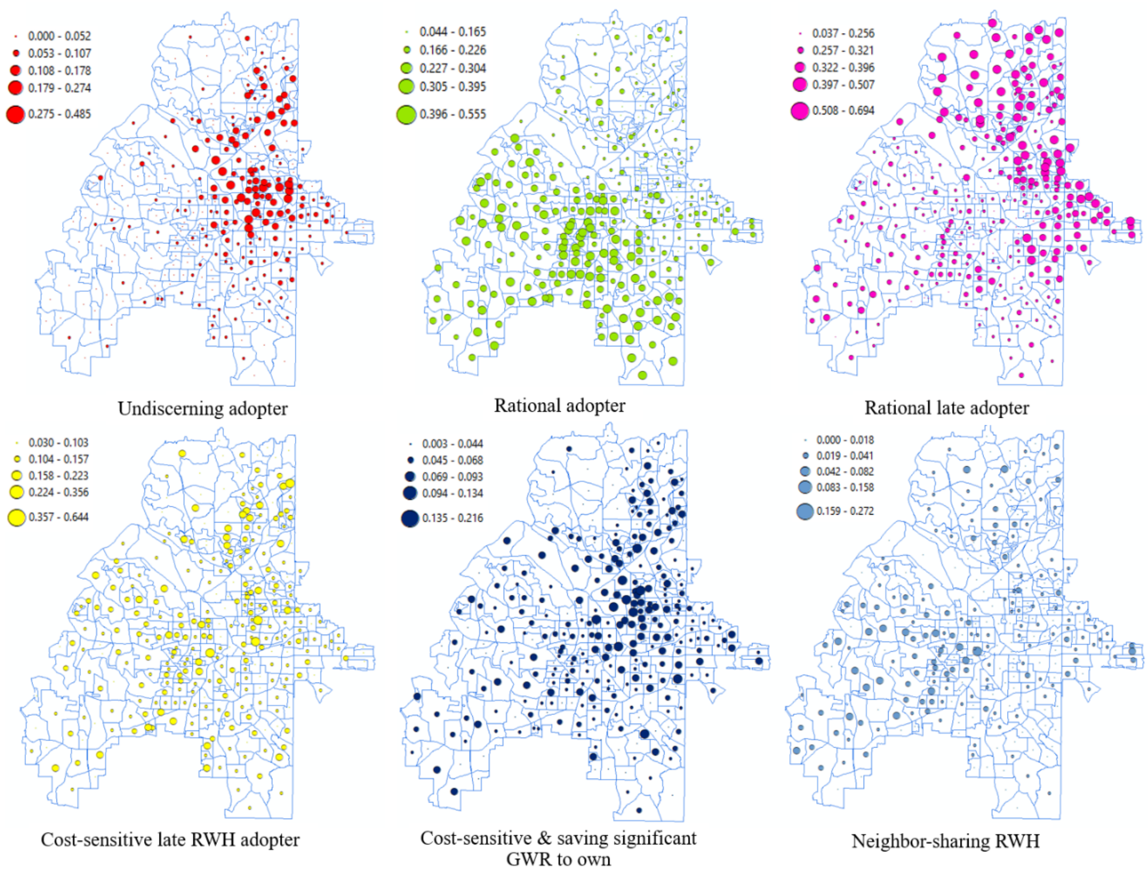


Figure 5. Spatial distribution of latent classes in Atlanta.

In Boston, the “undiscerning adopter” class is more widely distributed than that in Atlanta. In general, the “undiscerning adopter,’’ “cost-effective,” and “cost-sensitive late RWH” members are concentrated in relatively lower-property-value communities in the southeastern part of the city. A high percentage of households belonging to the “rational late adopter” is located in the northwestern part of the city. In Boston, the presence of the two classes “benefit-significant GWR to own” and “neighbor-sharing, cost-sensitive, & benefit-significant GWR” is small.

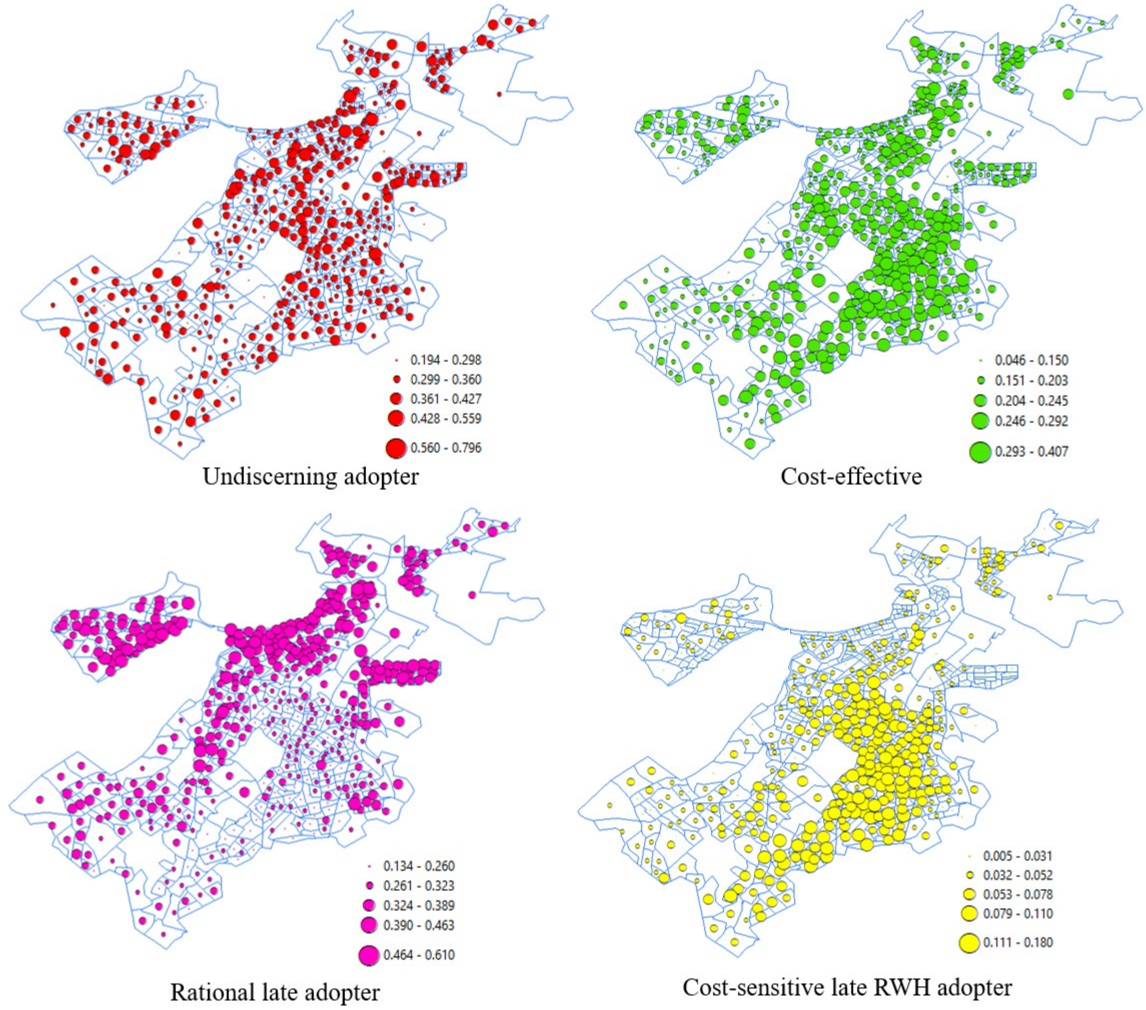


Figure 6. Spatial distribution of latent classes in Boston.

Our visualization included the socioeconomic features available from the census and the average personal characteristics from the survey and indicates significant spatial heterogeneity in decentralized water system demands in both Atlanta and Boston. In Atlanta, an early adoption of decentralized water system can occur in the downtown. In Boston, there are more districts and neighborhoods that can initialize the early adoption of decentralized water systems. In Atlanta, the communities in the downtown and the southern part of the city are poorer than that in the northern part. A higher percentage of households belonging to “undiscerning adopter” and “rational adopter” in the downtown and the southern part of Atlanta indicates that relatively low-property-value communities have higher demands for decentralized water facilities as an acceptable alternative to improve community quality. In Boston, we also found a higher percentage of households belonging to "undiscerning adopter" and "cost-effective" in relatively low-property-value communities and neighborhoods, especially in the southeastern part. The "rational later adopter" are found in wealthier communities which have a low demand for decentralized water systems. We conclude that policy incentives targeting the promotion of decentralized water systems in these high-demanding communities could also create an opportunity for community renaissance through the improvement of community water service and management quality.

3.8. Some Limitations of Preference Analysis

Sample size is one key aspect to develop a reliable preference analysis. In our study, we tested Amazon Mechanical Turk as a platform for collecting responses. Although the cost is lower than traditional methods (e.g., face-to-face, mail, and telephone), the advantage of crowdsourcing was not shown in our study. The number of workers on the Amazon Mechanical Turk is large, which is around 100-200 thousand globally. However, the cohort in the Metro Atlanta and Greater Boston is much smaller and we only received about 600-700 responses, which represent around 0.12‰ of the population in both metro areas. Better participatory approaches that enable the engagement of a representative proportion of citizens to evaluate developing and/or future technologies would benefit research like this and would better inform incentives and strategies for transitioning to more resilient water infrastructure. Participatory technologies will be particularly valuable for developing countries where the need for more sustainable and resilient water infrastructure is much more urgent.

Our spatial visualization provides a reference for initializing the decentralization of water infrastructure. For instance, it can be a good start to promote water decentralization in the downtown of Atlanta and the communities in the southeastern part of Boston, where there is a higher percentage of households belonging to the "undiscerning adopter" class. However, it is not sufficient for supporting policy and economic incentive development. A diffusion of innovation model should be constructed that takes personal features into account, including impact of neighbor behavior and environmental change, to predict the adoption and diffusion of decentralized water systems. The diffusion model will distinguish spatial distributions of RWH versus GWR and predict the ownerships of decentralized RWH and GWR facilities. Moreover, such a model will enable the examination of the impacts from different policy and economic incentives to increase the adoption from a system perspective. The results will be more informative for policy makers and city managers to initialize water decentralization programs.

4. Concluding Remarks

The promotion of decentralized water facilities and the emergence of a hybrid water system relies heavily on citizens' preference and demand. In this paper, we developed a discrete choice experiment to elicit, via Amazon Mechanical Turk, individual choices for designs of decentralized household and community water collection facilities in Metro Atlanta and Greater Boston. Mechanical Turk is one of the commercial crowdsourcing platforms that enable convenient data collection. Given the relatively small cohort size at the target metro regions in Mechanical Turk, we were only able to collect between 600 and 700 responses in Metro Atlanta and Greater Boston, respectively, in four months. Alternative survey technologies to enhance participation and to improve representation of the population is needed and will be investigated in the future.

Using latent-class choice modelling, we found significant preference heterogeneity among residents in both Metro Atlanta and Greater Boston regarding the choice of a decentralized water facility. We identified and discussed the six major classes in both cities. Some classes (e.g., undiscerning adopter) are likely to install a decentralized water facility earlier than others (e.g., cost-sensitive late RWH adopter). Our data analysis showed that comparing to Atlanta, Boston had a larger proportion of households belonging to the "undiscerning adopter" class, suggesting that Boston would be expected to adopt decentralized water facilities at a faster rate once introduced. The two cities share some common traits in classes that show similar preference patterns. Although the socioeconomic and personal factors that determined the groupings of households in the two cities were not identical, we found consistent effects of neighbor's choice and perception of water scarcity on the class memberships. Households are more likely to adopt a decentralized water facility if their neighbors already install one, and if households have the perception of water scarcity, they are willing to share the investment of a decentralized water facility within the community. Our findings suggest support from the public sector to help initialize the adoption of decentralized water facilities will accelerate the diffusion.

The spatial visualization of the distribution of different classes in Figures 5 and 6 highlights the areas of early demand for decentralized water facilities in Atlanta and Boston. In particular, downtown Atlanta and the southeastern part of Boston exhibit higher proportions of households belonging to the “undiscerning adopter” class, indicating a higher chance of success if a government, public utility, or non-governmental organization starts the promotion in these districts.

Acknowledgement

We would like to acknowledge the support of the National Science Foundation under a CRISP Type I Award (#BCS-1638334 and 1638268). The startup support from the Hong Kong University of Science and Technology is also acknowledged. The authors would like to thank anonymous reviewers for the comments and suggestions. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding agencies in any form.

References

AWWA, 2011. Dawn of the Replacement Era: Reinvesting in Drinking Water Infrastructure, Ingenieria del medio ambiente y sanitaria. American Water Works Association.

Bellera, C.A., Hanley, J.A., 2007. A method is presented to plan the required sample size when estimating regression-based reference limits. J. Clin. Epidemiol. 60, 610–615. https://doi.org/https://doi.org/10.1016/j.jclinepi.2006.09.004

Boxall, P.C., Adamowicz, W.L., 2002. Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach. Environ. Resour. Econ. 23, 421–446. https://doi.org/10.1023/A:1021351721619

Brown, R.R., Keath, N., Wong, T.H.F., 2009. Urban water management in cities: historical, current and future regimes. WATER Sci. Technol. 59, 847–855. https://doi.org/10.2166/wst.2009.029

Buhrmester, M., Kwang, T., Gosling, S.D., 2011. Amazon's Mechanical Turk: A New Source of Inexpensive, Yet High-Quality, Data? Perspect. Psychol. Sci. 6, 3–5. https://doi.org/10.1177/1745691610393980

Choupani, A.-A., Mamdoohi, A.R., 2016. Population synthesis using iterative proportional fitting (IPF): A review and future research, in: International Conference on Transportation Planning and Implementation Methodologies for Developing Countries (12th TPMDC) Selected Proceedings, Transportation Research Procedia. ELSEVIER SCIENCE BV, pp. 223–233. https://doi.org/10.1016/j.trpro.2016.11.078

Crump, M.J.C., McDonnell, J. V, Gureckis, T.M., 2013. Evaluating Amazon's Mechanical Turk as a Tool for Experimental Behavioral Research. PLoS One 8, e57410.

Franceschinis, C., Thiene, M., Scarpa, R., Rose, J., Moretto, M., Cavalli, R., 2017. Adoption of renewable heating systems: An empirical test of the diffusion of innovation theory. Energy 125, 313–326. https://doi.org/https://doi.org/10.1016/j.energy.2017.02.060

Grigg, N., 2015. Infrastructure Report Card: Purpose and Results. J. Infrastruct. Syst. 21, 2514001. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000186

Hoyos, D., 2010. The state of the art of environmental valuation with discrete choice experiments. Ecol. Econ. 69, 1595–1603. https://doi.org/https://doi.org/10.1016/j.ecolecon.2010.04.011

Hunt, A., Watkiss, P., 2011. Climate change impacts and adaptation in cities: a review of the literature. Clim. Change 104, 13–49. https://doi.org/10.1007/s10584-010-9975-6

Jacobs, K., Lebel, L., Buizer, J., Addams, L., Matson, P., McCullough, E., Garden, P., Saliba, G., Finan, T., 2016. Linking knowledge with action in the pursuit of sustainable water-resources management. Proc. Natl. Acad. Sci. U. S. A. 113, 4591–4596. https://doi.org/10.1073/pnas.0813125107

Jeanne, C., Sybil, S., Dan, F., Neil, G., Larry, R., Jon, H., 2018. Centralized and Decentralized Strategies for Dual Water Supply: Case Study. J. Water Resour. Plan. Manag. 144, 5017017. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000856

Khalkhali, M., Westphal, K., Mo, W., 2018. The water-energy nexus at water supply and its implications on the integrated water and energy management. Sci. Total Environ. 636, 1257–1267. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.04.408

Li, F., Wichmann, K., Otterpohl, R., 2009. Review of the technological approaches for grey water treatment and reuses. Sci. Total Environ. 407, 3439–3449. https://doi.org/10.1016/j.scitotenv.2009.02.004

Liao, F.H., Farber, S., Ewing, R., 2014. Compact development and preference heterogeneity in residential location choice behaviour: A latent class analysis. Urban Stud. 52, 314–337. https://doi.org/10.1177/0042098014527138

Londoño Cadavid, C., Ando, A.W., 2013. Valuing preferences over stormwater management outcomes including improved hydrologic function. Water Resour. Res. 49, 4114–4125. https://doi.org/10.1002/wrcr.20317

Lu, Z., Crittenden, J., Southworth, F., Dunham-Jones, E., 2017. An integrated framework for managing the complex interdependence between infrastructures and the socioeconomic environment: An application in metropolitan Atlanta. Urban Stud. 54, 2874–2893.

Lu, Z., Noonan, D., Crittenden, J.C., Jeong, H., Wang, D., 2013. Use of impact fees to incentivize low-impact development and promote compact growth. Environ. Sci. Technol. 47, 10744–10752. https://doi.org/10.1021/es304924w

Lu, Z., Southworth, F., Crittenden, J.C., Dunhum-Jones, E., 2015. Market potential for smart growth neighbourhoods in the USA: A latent class analysis on heterogeneous preference and choice. Urban

Stud. 52, 3001–3017. https://doi.org/10.1177/0042098014550956

Makropoulos, C.K., Butler, D., 2010. Distributed Water Infrastructure for Sustainable Communities. Water Resour. Manag. 24, 2795–2816. https://doi.org/10.1007/s11269-010-9580-5

McDonald, R.I., Green, P., Balk, D., Fekete, B.M., Revenga, C., Todd, M., Montgomery, M., 2011. Urban growth, climate change, and freshwater availability. Proc. Natl. Acad. Sci. U. S. A. 108, 6312–6317. https://doi.org/10.1073/pnas.1011615108

Miara, A., Macknick, J.E., Vörösmarty, C.J., Tidwell, V.C., Newmark, R., Fekete, B., 2017. Climate and water resource change impacts and adaptation potential for US power supply. Nat. Clim. Chang. 7, 793.

Minne, L., Pandit, A., Crittenden, J.C., Begovic, M.M., Kim, I., Jeong, H., James, J.-A., Lu, Z., Xu, M., French, S., 2012. Energy and water interdependence, and their implications for urban areas, in: Encyclopedia of Sustainability Science and Technology. Springer, New York, NY, pp. 3449–3471.

Mo, W., Lu, Z., Dilkina, B., Gardner, K.H., Huang, J.-C., Foreman, M.C., 2018. Sustainable and Resilient Design of Interdependent Water and Energy Systems: A Conceptual Modeling Framework for Tackling Complexities at the Infrastructure-Human-Resource Nexus. Sustainability 10, 1–10.

Mo, W., Wang, R., Zimmerman, J.B., 2014. Energy–Water Nexus Analysis of Enhanced Water Supply Scenarios: A Regional Comparison of Tampa Bay, Florida, and San Diego, California. Environ. Sci. Technol. 48, 5883–5891. https://doi.org/10.1021/es405648x

Muñoz, I., Milà Canals, L., Fernández-Alba, A.R., 2010. Life Cycle Assessment of Water Supply Plans in Mediterranean Spain: The Ebro River Transfer Versus the AGUA Programme. J. Ind. Ecol. 14, 902–918. https://doi.org/10.1111/j.1530-9290.2010.00271.x

Nasserinejad, K., van Rosmalen, J., de Kort, W., Lesaffre, E., 2017. Comparison of Criteria for Choosing the Number of Classes in Bayesian Finite Mixture Models. PLoS One 12, e0168838.

Nylund, K.L., Asparouhov, T., Muthén, B.O., 2007. Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. Struct. Equ. Model. A Multidiscip. J. 14, 535–569. https://doi.org/10.1080/10705510701575396

Pearson, L.J., Coggan, A., Proctor, W., Smith, T.F., 2010. A Sustainable Decision Support Framework for Urban Water Management. WATER Resour. Manag. 24, 363–376. https://doi.org/10.1007/s11269-

009-9450-1
Que, S., Awuah-Offei, K., Weidner, N., Wang, Y., 2017. Discrete choice experiment validation: A resource project case study. J. Choice Model. 22, 39–50. https://doi.org/https://doi.org/10.1016/j.jocm.2017.01.006
SAS Institute Inc, 2012. JMP® 10 Design of Experiments Guide.
Sazakli, E., Alexopoulos, A., Leotsinidis, M., 2007. Rainwater harvesting, quality assessment and utilization in Kefalonia Island, Greece. WATER Res. 41, 2039–2047. https://doi.org/10.1016/j.watres.2007.01.037
Srinivasan, V., Seto, K.C., Emerson, R., Gorelick, S.M., 2013. The impact of urbanization on water vulnerability: A coupled human–environment system approach for Chennai, India. Glob. Environ. Chang. 23, 229–239. https://doi.org/https://doi.org/10.1016/j.gloenvcha.2012.10.002
Stang, S., Wang, H., Gardner, K.H., Mo, W., 2018. Influences of water quality and climate on the water-energy nexus: A spatial comparison of two water systems. J. Environ. Manage. 218, 613–621. https://doi.org/https://doi.org/10.1016/j.jenvman.2018.04.095
Uggeldahl, K., Jacobsen, C., Lundhede, T.H., Olsen, S.B., 2016. Choice certainty in Discrete Choice Experiments: Will eye tracking provide useful measures? J. Choice Model. 20, 35–48. https://doi.org/https://doi.org/10.1016/j.jocm.2016.09.002
Venkatesh, G., Brattebo, H., 2011. Energy consumption, costs and environmental impacts for urban water cycle services: Case study of Oslo (Norway). ENERGY 36, 792–800. https://doi.org/10.1016/j.energy.2010.12.040
Vermunt, J.K., Magidson, J., 2005. Technical guide for Latent GOLD Choice 4.0: basic and advanced.
Wang, J., Ge, J., Gao, Z., 2018. Consumers' Preferences and Derived Willingness-to-Pay for Water Supply Safety Improvement: The Analysis of Pricing and Incentive Strategies. Sustain. . https://doi.org/10.3390/su10061704
Yao, R.T., Langer, E.R., Leckie, A., Tremblay, L.A., 2019. Household preferences when purchasing handwashing liquid soap: A choice experiment application. J. Clean. Prod. 235, 1515–1524. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.07.002