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Understanding Fundamental Phenomena Affecting the Water Conservation Technology Adoption of Residential Consumers Using Agent-Based Modeling

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Abstract: More than one billion people will face water scarcity within the next ten years due to climate change and unsustainable water usage, and this number is only expected to grow exponentially in the future. At current water use rates, supply-side demand management is no longer an effective way to combat water scarcity. Instead, many municipalities and water agencies are looking to demand-side solutions to prevent major water loss. While changing conservation behavior is one demand-based strategy, there is a growing movement toward the adoption of water conservation technology as a way to solve water resource depletion. Installing technology into one's household requires additional costs and motivation, creating a gap between the overall potential households that could adopt this technology, and how many actually do. This study identified and modeled a variety of demographic and household characteristics, social network influence, and external factors such as water price and rebate policy to see their effect on residential water conservation technology adoption. Using Agent-based Modeling and data obtained from the City of Miami Beach, the coupled effects of these factors were evaluated to examine the effectiveness of different pathways towards the adoption of more water conservation technologies. The results showed that income growth and water pricing structure, more so than any of the demographic or building characteristics, impacted household adoption of water conservation technologies. The results also revealed that the effectiveness of rebate programs depends on conservation technology cost and the affluence of the community. Rebate allocation did influence expensive technology adoption, with the potential to increase the adoption rate by 50%. Additionally, social network connections were shown to have an impact on the rate of adoption independent of price strategy or rebate status. These findings will lead the way for municipalities and other water agencies to more strategically implement interventions to encourage household technology adoption based on the characteristics of their communities.

Keywords: agent-based modeling; water conservation; technology diffusion; social networks

1. Introduction

Water is undeniably necessary, supporting 7.4 billion people and over 8.7 billion species of life. However, the growing human population and consequences of climate change have created widespread water scarcity that is only expected to worsen in the coming decades. By 2025, 1.8 billion people around the globe will face water scarcity [1]. Beyond damaging an individual's quality of life, water scarcity also negatively impacts ecosystem health and political and social stability [2]. Climate change adds further pressure to water resources, and government officials and policy advocates have taken two different approaches to address growing water concerns: supply-side management and demand-side management [3]. Supply-side management focuses more on increasing the availability of water through the development and renewal of water infrastructure systems and identifying new water sources [4]. This encompasses the creation of reservoirs, water pumps, and irrigation systems to continue to have adequate water supplies. Supply-side solutions have been effective historically; however, it does not influence water use patterns of the consumer, which is the next necessary step in managing demand growth [4]. Demand-side management is based on the idea that lowering a household's (or other users') usage for water will subsequently reduce water demand. While implementing demand-side management to govern a typically inelastic good is controversial among economists and planners, it has been shown in many studies to be effective in alleviating water scarcity [5–8]. Ref. [6] reviewed different demand-side management tools and explored their potential and effectiveness to save water under varying conditions in developed countries.

At its core, reducing residential water demand can be done by changing behavior or technology [6]. Changing someone's behavior, according to [9,10], is a process including incentives and disincentives, the modeling of behaviors, education, and persuasive communication. These techniques work best with mostly-engaged audiences, are adopted infrequently, and are less likely to save water if people do not trust the water authorities [11]. Despite all of the multifaceted approaches, changing behavior tends to pan out only in the short term while the comprehensive installation of water-efficient appliances in households has been shown to reduce indoor consumption by 35–50% [6]. Change in technology is meant to curb the problems with behavior conservation changes by erecting a more permanent fixture for conservation. In a report of California's water scarcity, [12] found that one-third of the state's water usage could be saved with existing conservation technology. This total equates to more than 2.3 million acre-feet of water. As technology improves, as it has drastically since this report was written in 2003, water savings will only become more prominent. The dire state of water scarcity has diminished the sufficiency of supply-side management. It will eventually become too difficult to track down additional water sources, or there will simply be no more water left to find. Because of this, more research is needed on demand-side approaches. Additionally, although there are two parts to demand-side water management, change in technology will be the most permanent, applicable method heading into the coming decades [13]. Change in behavior is typically ephemeral, while technology is more easily maintained through water policy adoption. However, technology's impact on policy implementation and household adoption patterns still needs to be specified and characterized. Governmental rebate availability, demographic and household characteristics, and external factors are variables that can cause different adoption patterns. Additional costs or potential savings of technology adoption can also be highly variable [14–16]. In addition, the role of "word of mouth" through social network interactions has been shown to be influential to the adoption processes [17]. While some of these influential factors have been researched to promote policy change and growth, there is a deficiency in the existing literature as to how they all intersect and challenge water conservation technology adoption.

To mitigate water scarcity, understanding why—and to what extent—households adopt conservation technology based on the demographic and household characteristic, social interactions, technology cost, water price and other factors is crucial. To this end, the study presented in this paper aimed to investigate the underlying factors and behaviors affecting water technology adoption of residential consumers through the use of Agent-based Modeling (ABM). In the agent-based model of the current study, households are agents categorized into the three adoption states of *non-adopter*, *potential adopter*, and *adopter*, based on the theory of innovation diffusion [18]. The transition of agents between *non-adopter* and *potential adopter* is driven by the adoption utility of households, which is determined by their demographic and household characteristics [19]. Another mechanism triggering this transition is social interactions which influence households' adoption decision-making based on the theory of peer effect [20]. In addition, per the theory of affordability, if the adoption of a new technology is economically affordable for households [21], they would adopt it and thus transition from the *potential adopter* state to the *adopter* state.

Unlike studies that focus on residential water use behaviors [21], conservation technology effectiveness [22,23], and demand projection [24,25], the current study investigated how changes in different mechanisms (such as water price structure) can affect the adoption rate of conservation technology (rather than residential water demand). Hence, the outputs of the ABM developed in this study are the number and type of adopted water conservation technologies under the influence of various factors (e.g., socio-demographic characteristics, social networks, and water policies). In fact, the outcomes of the model developed in this study can supplement the information from residential water demand projection models in order to incorporate the effects of water conservation technology adoption in projecting future demands under various scenarios.

2. Background

Despite there being an immediate need for households to begin conserving water, there is limited knowledge within the scientific community on the reasons people adopt water conservation practices in the first place. Water conservation encompasses both behavioral conservation as well as technology adoption. Because the scope of water conservation is so vast, with both behavioral and technological possibilities, this study focused on water conservation technology adoption conservation as a means of resolving problems with water scarcity. More specifically, we plan to examine the underlying mechanism affecting a household's willingness to adopt water conservation technologies.

Most of the recent literature on residential water conservation management and technology adoption incorporate some of the following features: *water conservation affordability, water price and incentives, education and demographics, household/building attributes*, and *social network influence*. In the following sub-sections, some of the studies on residential water conservation and technology adoption were used for identifying various influencing mechanisms and factors. Although recent studies in this field have contributed thoroughly to water management and the understandings of household influence on water conservation technology, there is currently little to no research assessing all of these mechanisms and factors at once. The remainder of this section summarizes the various mechanisms and factors affecting the water conservation technology adoption of households.

2.1. Water Conservation Affordability

Public acceptance of water conservation technology adoption is integral, but also highly variable [14,16]. The characteristics that influence the potential installation of water conservation technologies are not fully understood. According to [16], cost is one of the largest deterrents or motivations of adopting water-saving technologies. The more expensive a technology, the less likely a household will install it. Income level plays a similar role in influencing the public perception of water-saving technology adoption [26]. Ref. [27] claims that higher-income households are more willing to adopt technologies. Those with less income, conversely, may simply struggle to afford new technologies.

2.2. Water Price and Incentives

Directly reflecting cost and income, external factors such as water pricing and rebate programs play a role in water-saving technology adoption [6]. In a study of 13 California cities, it was found that certain price-based deterrents of water consumption were more influential on conservation than installing water—saving technology [28]. The higher the price of water, the less technology one would adopt; conversely, the lower the price of water, the more technology one would install [28]. Ref. [6] argue that the comprehensive adoption of water conservation technologies can only be implemented by setting effective regulation and incentives. This sentiment is echoed by another study, which supports the implementation of rebate programs particularly for showerheads and cloth washers [29]. However, in older studies, government control and assistance were regarded as counterproductive, which caused more grief than environmental pay-off [30]. Ref. [31] assert that households avoid government programs because they cause increased confusion, provide limited choices, take too much time to install, and do not show the direct conservation effects. To solve this, the greater the financial benefit a government entity or utility employs to encourage water-saving technology adoption, the greater the non-financial resources, such as marketing and education, is needed [27]. While there are conflicting perspectives, it is clear that water pricing and other external factors have potential effects on water conservation technology adoption.

2.3. Education and Demographics

Education and awareness can be just as influential as government financial incentives. Education correlates positively with public acceptance of water-conserving practices [14,16,32]. The development of a greywater reuse program in Barcelona was considered a success due to its awareness efforts and education [33]. For water conservation in general, the more knowledge a household has on conservation practices—whether through behavior or technology—the more that household conserved water [32]. Along with education, researchers have found other demographics that influence a household's willingness to adopt water conservation technology. One example is home ownership status; those who own their home are more likely to consider long-term water conservation solutions such as technology [34,35]. Gender can also make a small impact; since women are commonly heads-of-households, they are more likely to make water conservation technology decisions [19].

2.4. Household/Building Attributes

There are studies that show the specific characteristics of a house itself reflect a particular willingness of the household to adopt water conservation infrastructure. Firstly, the age of a household dictates openness to new technology [36]. The newer the home, the more likely it is to already have water-saving infrastructure [36]. The household size also influences public perception, for those who live in bigger homes may also incur larger water costs and, thus, feel more obliged to invest in water- and cost-saving technology [32]. Installing water conservation infrastructure outside the home can also restore water supplies. Households with larger open spaces are more willing to incorporate technology since outdoor areas significantly contribute to water usage [37].

2.5. Social Network Influence

Recent studies have shown that, both in developing and developed countries, social networks and peer effects are important phenomena in human technology adoption behavior [17,38]. Individual consumer attitudes are modified over time through social influence and interactions [39]. Contextually, households share information and learn from one another. A head-of-household is likely to adopt water-efficient technology based on interactions with someone who has adopted the technology. Technology adopting families educate others on the benefits of technology through their interactions with it. Intuitively, households are more likely to adopt when they know and are connected to other adopters [40]. Through community, people are connected through different means—family, work, neighborhoods. Interactions among households depend on the structure of social networks through which they are connected [41]. Scientifically, however, it is difficult to identify all possible connections based on empirical data [17].

3. Significance

Understanding the underlying mechanism of water conservation technology adoption patterns is relevant because water scarcity is becoming a worldwide epidemic. There are two ways conservation can combat this problem: changing conservation behavior and changing conservation technology. While changing conservation behavior has made significant strides in water preservation, it is not the only piece of the puzzle [12]. It has been discussed that technology improvement is a quicker and more permanent method [6]. However, more research is required to understand the full potential that technology has on water conservation for households. Changing conservation technology in conjunction with behavioral changes can help alleviate water scarcity altogether. As technology improves—as it does every day—there will need to be methods for implementing the technology into households of different demographic, household, and external factors. Households are the agents adopting the technology; therefore, knowing their variability in adoption probability is the next big step in improving the status of drought and water scarcity.

There has yet to be research done that can simultaneously analyze all the demographic, household, external factors (i.e., water pricing structure and rebate policy), and social networks that could influence a household's decision to install water conservation technology. Without this information, government agencies will have no starting point for raising awareness or creating proper policies and regulations to encourage technology adoption. Conservation measures will not be grounded in any knowledge of household influences, making them futile. By focusing on these demographic, household, social and external factors, all aspects of demand-side water management can be evaluated together to solve larger societal and political problems regarding water scarcity and climate change.

4. Methodology

To implement this research, a simulation approach was used. The simulation approach enables replicating many various types of populations, while other methods (such as conducting surveys and interviews) can only reflect one particular population at a time [42]. According to [43], simulation is an effective method for theory development when (i) a theoretical field is new; (ii) the use of empirical data is limited; and (iii) other research methods fail to generate new theories in the field. These traits are consistent with the current study of water conservation technology adoption. The chosen simulation technique for this study is agent-based modeling.

4.1. Agent-Based Modeling

Agent-based modeling (ABM) is a powerful modeling technique that focuses on the individual active components of a system [44]. In ABM, active components (e.g., human entities) are characterized as agents, each with a set of social capabilities and goals, values, and preferences. Agents exist in an environment defined by specific rules/micro-behaviors and can inform or evolve their goals or priorities over time [45]. ABM can account for (1) various rational and behavioral decision-making rules for different agents; and (2) an agent's reactions to other agents' decisions. The use of ABM will enable (1) discovering what factors and micro-behaviors result in technology adoption decisions; (2) juxtapose the preferences of various households with the range of conservation technology alternatives to determine the distribution of expected conservation outcomes; and (3) explore effective intervention strategies to enhance water conservation technology adoption. In addition, the use of ABM will enable the construction of a theoretical space that will include a range of community profiles in terms of demographics, water use, social network structures, and other factors. ABM can replicate many different types of populations, and project diverse, tangible scenarios throughout future years [46,47].

ABM has been successful in studying complex behaviors, policy analysis in infrastructure systems [48,49], and water demand management. Ref. [4,24,50] have utilized ABM as a successful tool to analyze water management systems. Ref. [50] demonstrated that the ABM is a useful methodological approach to dealing with the complexity derived from multiple factors with influence in the domestic water management in emergent metropolitan areas. Ref. [4] developed an ABM framework for assessing the consumer water demand behavior against different degrees of water supply and water supply systems. Their model incorporated both consumers and policy-makers as agents as they adapted their behaviors to different water supply systems and rainfall patterns. Studies such as these have set a precedent that agent-based modeling is a viable research tool for water use and management issues.

ABM has also been successfully adopted in the evaluation of complex phenomena in human-technical systems such as the adoption of environmentally-friendly technologies [38,41,51,52].

For example, Ref. [41] developed an agent-based model for the adoption of residential solar photovoltaic (PV) systems. In addition, other studies, such as one conducted by [38], showed that ABM can be useful in the simulation of the adoption behavior of innovative energy conservation technologies by capturing the underlying mechanisms affecting the decision-making behaviors of households. In another study, Ref. [52] adopted ABM to simulate the technology adoption behaviors related to three water-related innovations among households in Southern Germany. This study demonstrated that ABM enables capturing the effects of various factors and attributes (e.g., geographic attributes, heterogeneous agents, and decision processes). According to the [52], ABM provides a more realistic model of innovation diffusion in comparison with aggregated models such as the Bass model. Ref. [52]'s research evaluated the trends of innovation diffusion under several water strategies and policies by developing an empirically-based ABM. However, their model differs from the one in the current study, in which a theoretically-driven ABM was developed that enables the policymakers to test various intervention strategies to diffuse further water-efficient infrastructure in their application area. In particular, the model in the current study captures the effects of social networks in conjunction with several other socio-demographic factors in understanding household behaviors related to water conservation technology adoption.

In addition, ABM provides a useful tool for conducting exploratory analysis. Exploratory analysis [53,54], utilizes computational models and simulation experiments to conduct scenario analysis and evaluate the behavior of complex systems [47,55]. Exploratory analysis has been utilized in different studies (e.g., [56,57]) for the evaluation of environmental policies. Unlike traditional simulation approaches, exploratory analysis does not aim to predict the behavior of a system and does not intend to optimize a system. Instead, exploratory analysis focuses primarily on considering different policy scenarios based on changes in system behavior and future uncertainty. To this end, ABM enables capturing the adaptive behaviors and complex interactions that affect the patterns of behaviors in a phenomenon of interest [58]. Hence, ABM was selected in this study to conduct exploratory analysis on the evaluation of the underlying mechanisms affecting water conservation technology adoption by residential consumers.

4.2. Theoretical Framework

The ABM in this study was created based on a number of theoretical elements including the theories of Innovation Diffusion, Peer Effect, and Affordability. Demographic and building characteristics, external factors, and social interactions all play a role in whether or not a household adopts water conservation technology. As discussed in Section 2, there have been many studies that analyze the influence of certain demographic, household, and external factors on water conservation technology adoption in isolation; however, theoretically, all of these attributes have the potential to influence a household's willingness to adopt a conservation technology. To this end, the theory of Innovation Diffusion was adopted to capture the coupled effect of income level, education, ownership status, house age, water pricing regimes, rebate availability, technology cost, and social networks concurrently. Based on Innovation Diffusion Theory (IDT), in adopting new technologies, a population can be divided into three groups: *non-adopters*, *potential adopters*, and *adopters* [18]. Non-adopters are individuals who do not consider adopting a new technology. In contrast, potential adopters are individuals who do consider adopting new technologies. Different demographic and household attributes can influence whether an individual is a non-adopter or potential adopter. A potential adopter may become an adopter if the adoption of a technology is economically affordable for it. Based on the similar premise, in this study, households were divided into three categories (i.e., non-adopter, potential adopter, and adopter) in terms of their position for water conservation technology adoption. The transitions of households between these categories depend on their demographic characteristics, household attributes, peer influence, as well as water price and technology price factors. The theoretical framework of these transitions is depicted in Figure 1. Different components of the ABM framework are explained in the following section.

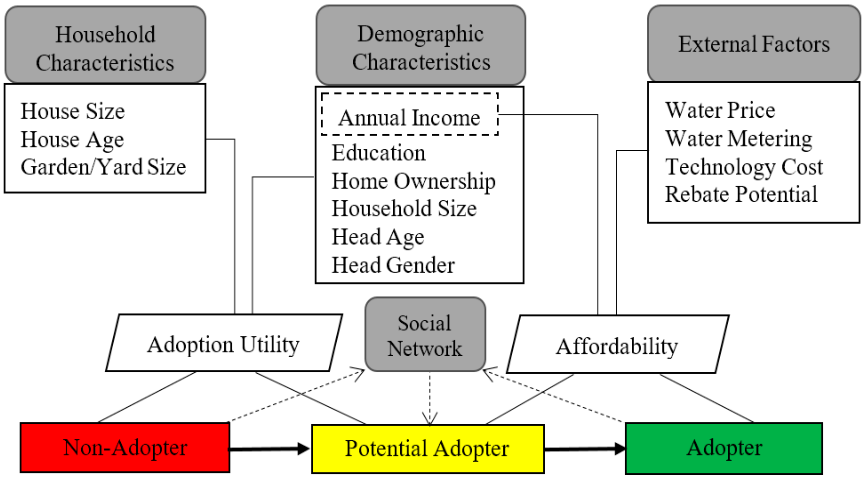

Figure 1. The theoretical framework for the simulation.

4.3. Computational Simulation

The creation of a computational representation for the proposed ABM theoretical framework entails the construction of mathematical models and algorithms to capture the theoretical logic representing the behaviors of households for the adoption of water conservation technology. Anylogic 7.0 was utilized to create a computational ABM. In the ABM framework proposed in this study, an agent (household) is the main target of influence, and the model shows how the agents' behaviors change over a designated period of time. The model incorporates only one agent class, which is the households. The households were divided into three categories (i.e., non-adopter, potential adopter, and adopter), defining their position on water conservation technology adoption. The transitions of households between these categories depend on their demographic and social attributes as well as water price and technology price factors. A household agent, based on its attributes, can transition from one state to another—from non-adopter to potential adopter and from potential adopter to adopter. These transition functions ultimately influence an agent toward or against a particular output. The variables related to the household socio-demographic characteristics, including household income, head education, age and gender, house ownership status, and household size, as well as the household building attributes such as house size and age and garden size, were used to determine one parameter, called *Adoption Utility*, presented in Equation (1):

$$Adoption\ Utility = \sum_{variable} (Coefficient_{variable} \times Value_{variable}) \quad (1)$$

The variables related to the socio-demographic and building attributes of the households, as well as the coefficients of these variables, were abstracted from the study conducted by [19]. The variables and their coefficients are summarized and documented in the Appendix A (Table A1). For example, the Adoption Utility of a household whose head is a female college graduate, without other demographics considered, is calculated as follows: $2.91_{\text{education}} \times 1_{\text{yes}} + 1.21_{\text{gender}} \times 1_{\text{female}}$. If the utility value is greater than or equal to a user-inputted utility threshold, it then triggers the transition from non-adopter to potential adopter. The threshold indicates a measure of sensitivity. A model user can increase the adoption utility threshold in order to increase the importance placed on the demographic and household characteristics. For this particular model, the lowest possible theoretical threshold is 3000, while the maximum threshold is 60,000. The utility threshold is important because it allows the model to simulate a variety of community profiles. Because the utility value and threshold are based on the demographic characteristics and importance of those characteristics, respectively, variations in the threshold values make it possible to explore a range of community profiles. Communities have varying characteristics (e.g., income, education, or even house size distribution). Through the use of the utility threshold, the difference among communities can be reflected in the analysis.

The function rule that triggers the transition from potential adopter to adopter is based on the *Affordability Theory*. Affordability is defined as the ability of households to pay for their water expenditures [59]. A household's annual water expenditures include the annual water bill plus costs of new water conservation technologies adopted until that year. In this model, household *Affordability Index* is measured by the household's annual water expenditures as a percentage of annual income, as shown in Equation (2) [21,59]:

$$Affordability\ Index = 100\left(B + \sum_{T}(C_T - R_T) \times n_T\right)/I \tag{2}$$

where, B is the household annual water bill, I is the household annual income, T is the water conservation technology available for adoption, C_T is the average initial cost of purchasing the technology, R_T is the available rebate for the adoption of the technology, and n_T is the number of the technology in the household.

If the Affordability Index of a household agent is less than the user-defined affordability threshold value, the household agent will transition from potential adopter to adopter. If it exceeds the affordability threshold, the adoption of technology is not affordable, and thus the agent will remain as a potential adopter. In other words, a household adopts the offered conservation technologies until the household's Affordability Index exceeds the affordability threshold value. The affordability threshold value is a function of income, water price, and water technology costs. Since water price might be regulated based on the income profile of communities, the affordability threshold can be location-specific. The affordability threshold ranges from 1–3% according to the studies conducted by the California Department of Public Health, the US Environmental Protection Agency, and United Nations Development Programs [60].

In the affordability measurement process, water price regime is incorporated into the model as an input parameter. Three different water pricing structures were assessed: *fixed price, fixed charge*, and *block prices*. The *fixed price* strategy places a cost on water per unit value. For example, one cubic meter of water costs a household $1.16. A noteworthy component of this pricing strategy is that the cost directly depends on how much water was used. Conversely, *fixed charge* is a pre-established, flat rate ($25.25) per month, regardless of how much water was actually consumed. *Block pricing* is similar to fixed pricing in the sense that the unit rate depends on how much water was used—it is a volumetric pricing strategy. However, instead of charging consumers per unit of water with the same rate, block pricing charges households based on the amount of water they consume. Households who typically use more water are charged at a higher rate than those who use less water. More specifically, households using less than 0.65 m^3/day of water will be charged $0.95 per m^3; households using between 0.65 and 1.5 m^3/day of water will be charged $1.14 per m^3; and households using more than 1.5 m^3/day of water will be charged $1.37 per m^3. These water pricing structures are proposed by [23], and the price values are based on the Miami-Dade Water and Sewer Department's rates [61].

Technology cost was also incorporated into this model as a parameter affecting the affordability index. An agent is able to adopt six main types of water conservation technology: *high-efficiency bathroom faucets, kitchen faucets, shower heads, toilets, washing machines (clothes)*, and *dishwashers*. [23] conducted a study on the cost and efficiency of these technologies, which is documented in Table A2 of the Appendix A, along with the rebate information that the City of Miami Beach Utility offers for each of these technologies [62]. Each technology's water-saving capacity is considered a measure of water demand reduction, as the technology is new and more water-efficient. The rebates can affect the technology cost as well—if household agents feel as though they will receive money back, the costs may be perceived as more affordable according to the established affordability index. This, in turn, impacts the model outputs.

Equations (1) and (2) make up the *Adoption Utility* and *Affordability Index*, which define the adoption state of each household agent (i.e., non-adopter, potential adopter, and adopter). There is another phenomenon that can lead a household agent to transition from the non-adopter state to the potential adopter state and that is the *social network influence* from other agents. According to the theory of *Peer Effect*, household agents can have a connection to each other; through this connection between non-adopter and adopter households, non-adopter agents may communicate with adopter agents, and thus get influenced by them into making decisions regarding the adoption of a new technology [20,63]. The model considers and implements five structures of social networks, the description of which are shown in the Appendix A (Table A3). Once the model has established a network according to the given structural parameters, it proceeds to simulate the social influence between connected agents. Given a user-defined *likelihood of influence*, if the non-adopter agent is connected to an adopter agent, there is a chance that the non-adopter will transition into the potential adopter state. Further details about social network influence modeling can be found in [64].

Figure 2 depicts all the transition rules between the three adoption states of the household agents. As shown in Figure 2, each agent, which is in the non-adopter state initially, can become a potential adopter based on its adoption utility or influence from social networks, and then immediately becomes an adopter if the conservation technology is affordable. Hence, it is possible for a non-adopter to become adopter in one time-step of simulation. However, at the same time step, a non-adopter agent should first become a potential adopter before it turns into an adopter. This is because a direct transition from the non-adopter state to the adopter state is not considered in the theory of innovation diffusion.

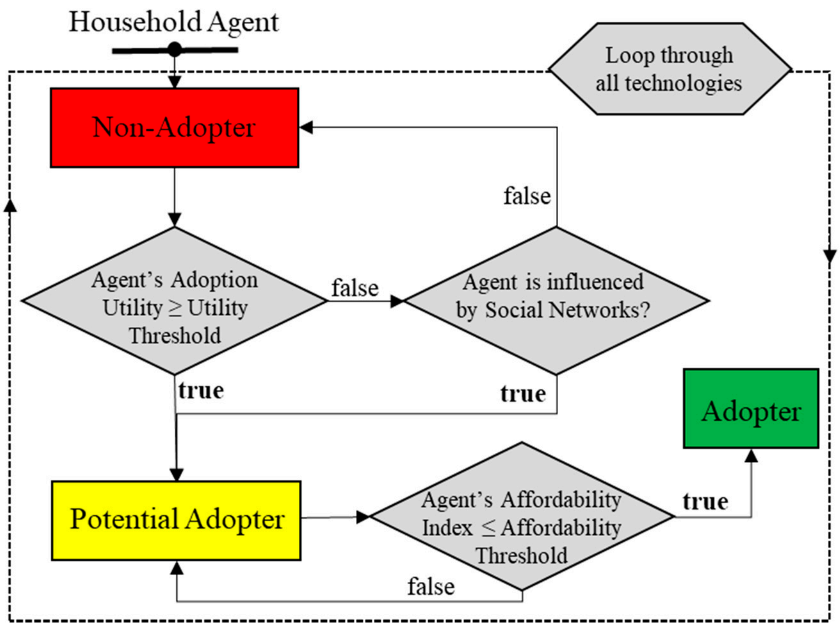

Figure 2. The control-flow diagram for agent transitions between adoption states.

Income growth and household size growth were the last attribute input parameters for the model. All of these inputs will generate a number of outputs, which demonstrate the basis of the type and timing of technology adoption by household agents. The simulation model outputs include the annual percentage distribution of all of the adoption states, the water demand reduction, and the different types of technology adopted over the predetermined time period of simulation which is twenty years.

4.4. Model Initialization and Implementation

In addition to developing a theoretically-driven ABM of household water conservation technology adoption, empirical data was used as values for initial conditions and model parameters to calibrate the ABM. To this end, data from the City of Miami Beach was used in the implementation of the ABM. The City of Miami Beach has more than ten thousand residential water consumers. To reduce the computational complexity of the model, a sample of 280 households that statistically represent the demographic distribution of the population was randomly selected and divided into three zip codes to be modeled. All 280 agents will start out as non-adopters; and, depending on different influences, will transition to potential adopter or adopter. The model then runs using Census data from these three zip codes, as well as individual household water use data provided by the Miami-Dade Utility. The census data includes information regarding median household income, education, average home ownership and average household size. Since some of the data provided by the Census are only average values, a triangular average distribution was used to assign each household a random value (see Figure A1 in the Appendix A). A uniform distribution was also used to assign the household head age, garden size, and house size in square feet. Values of parameters such as head gender and house age were randomly assigned due to the unavailability of data. Moreover, data related to a household's source of water such as the number of showerheads, toilets, and faucets come from a custom distribution. While the model could have been made with hypothetical inputs not based on reality, utilizing real data helps to convey a better narrative about water technology adoption for future policy-making and regulation.

5. Model Verification and Validation

ABMs are often criticized for relying on informal and subjective validation or no validation at all [65]. Validating ABMs developed for complex systems using historical data is difficult and infeasible because of the stochastic nature of human-behavior models [48]. Ref. [52] argued that social-system models cannot be tested for their structure appropriateness in a meaningful way as the interconnections of social processes are vague in the sense that competing theories exist for most phenomena. ABMs are typically validated using internal verification of the features representing the model quality [48,66]. The verification of the ABM developed in this study was conducted through a gradual, systemic, and iterative process. The internal validity of the model was ensured through the use of grounded theories for modeling decision and behavioral processes of households. The theoretical and computational models were built rich in causal factors that can be examined to see what leads to particular outcomes. Each component of the model was checked for completeness, coherence, consistency, and correctness (4Cs) based on the performance of the model outputs. For instance, the model performance was verified by (i) taking the function of one component of the model and making sure it influences the outputs to the degree that is specified in the model; and (ii) running the simulation model with extreme values of each component and verifying the functionality of the model under that situation. Most errors that were discovered through verification had less to do with problems within the theories, and more regarding issues with coding correctly. Thus, most errors in the verification process were fixed relatively quickly and smoothly and then the aforementioned four features (4Cs) of the model were ensured. As there are no aggregated independent data available regarding the adoption of such water technologies in various lifestyles [52], the external validity of the ABM was conducted through the comparison of the model outcomes with the findings of other studies in the area of water conservation technology adoption. This technique has been also applied in a study by [67] for validating multi-agent models. As shown in Table 1, the results of the model reinforce what other studies have already noted. For example, the results of the model showed that the rate of adoption of water conservation technologies under various scenarios can lead to a 3–10% reduction in the overall water demand of the City of Miami Beach; this outcome is consistent with the findings of a study conducted by [68] that analyzed the impacts of the water conservation incentives on water demand in Miami-Dade County through surveys among the households. This study reports that about 6–14% reduction in water demand was achieved during the implementation of two 4-year water conservation incentive programs in this area.

Table 1. The external validation of the model findings.

Aspect of Technology Adoption	Findings of the Model	Examples of Other Studies with Similar Findings
Impact of conservation technology adoption on water demand reduction of the service area	Adoption of water conservation technology under various scenarios potentially could lead to a 3–10% reduction in the overall demand of the City of Miami Beach.	About a 6–14% reduction in water demand has been observed during the implementation of the water conservation incentives program for the residential consumers in Miami-Dade [68]
Effect of water price strategy	Fixed charge strategy of water pricing, which provides cheaper water for households, led to a greater number of adoptions in the model.	"Pricing structure plays a significant role in influencing price responsiveness" [69]. The higher the price of water, the less technology one would adopt; conversely, the lower the price of water, the more technology one would install [28].
Effect of rebate and incentives	Rebate allocation in low-income communities could increase the adoption of the expensive water conservation technologies.	Providing incentives such as rebates for retrofitting households with water-efficient technologies have shown mixed results in terms of reducing water use, especially when compared to price-based approaches [13]
Effect of social networks	Social interactions speeded up the diffusion of water conservation technology. Although the structure of a network was not important in the adoption of technology, it affected the time required for the adoption rate to reach an equilibrium.	"Social network type is not significant in determining mean energy use change, but is when considering the time required the network to reach equilibrium" [40].
Effect of household income level	Income growth mostly influences a household's willingness to adopt water conservation technology.	"We have previously found financial variables to be important supplements to attitude measures in technology adoption modeling" [30].

6. Scenario Setting

After the model was verified and validated, it was used for simulation experimentation and scenario setting. Each of the three water price strategies was analyzed based on the simulation model for different combinations of the model input parameters. The possible scenarios were established based on different combinations of the input parameters in the model, shown in Table 2. Through the combination of various values of the input parameters, 230 scenarios were generated in total. The combinations of these scenarios reflect changes in water pricing structure, rebate status, income growth, household size growth, utility threshold, affordability threshold, and social network structure. Accordingly, under each specific scenario, 100 runs of Monte-Carlo experiments were conducted to determine the mean value of the output parameters (i.e., the number of adoptions and the resulting water savings). In addition, in order to compare the scenarios equally across the analysis, a base scenario was created as the reference point for the comparison. Table 2 also shows the values used for the parameters in the base scenario (see the last column). More details related to which parameters were used and how they were changed in the experimentation process to provide a diverse and all-encompassing series of outputs are presented in the Appendix A (Table A4).

Table 2. The variation of the input parameter values for the scenario setting.

Model Input Parameter	Possible Values	Value in Base Scenario
Water pricing structure	Fixed price; fixed charge; block prices	Fixed price
Rebate status	Rebate; no rebate	No rebate
Income growth (%)	−5; −4; −3; −2; −1; 0; 1; 2; 3; 4; 5	0
Household size growth (%)	−5; −4; −3; −2; −1; 0; 1; 2; 3; 4; 5	0
Utility threshold	10,000; 20,000; 30,000; 40,000; 50,000	30,000
Affordability threshold (%)	1, 1.5, 2, 2.5, 3	1.5
Social network structure	Random (N = 1); distance-based (R = 100); ring lattice (N = 1); scale-free (M = 1); small-world (N = 1, P = 0.1)	Random (N = 1)

7. Results and Discussion

Using the developed agent-based model, the scenario analyses of the simulated data were conducted in order to specify the effects of different factors on the water conservation technology adoption of households. Due to the stochastic nature of the simulation model, the 100 experiments related to each scenario led to varying outcomes, from which the mean value of percent adopter, number of adopted technologies, and overall demand reduction were abstracted and recorded. The results and corresponding discussions were formulated using three different forms of analysis as explained below.

7.1. Socioeconomic Scenario Analysis

Trend analysis across the various generated scenarios of income growth, water pricing strategy, rebate program, and utility threshold showed how much water households saved, how many households adopted, and which technologies were adopted under each scenario. Of these scenarios, certain trends regarding overall demand reduction—due to adoption of the technologies—were discerned and documented in Figure 3. The amount of residential water demand reduction due to the adoption of conservation technology was calculated based on the number and type of technologies adopted over the simulation period (i.e., 20 years). This study did not consider the behavioral aspects related to water conservation. The calculated residential water saving potential is only based on the adoption of conservation technologies. If the water conservation behaviors of the users are considered, the potential for residential water saving could be even more significant. Among the three water price strategies, the fixed charge strategy led to a more overall demand reduction. As shown in Figure 3, allocating rebates could increase its enhancement by 24% (4 m^3/day). The strategy of fixed charge with rebate resulted in a total of 8–12 m^3/day water savings more than the strategy of fixed price without rebate in various income growth rates. This amount means about 46–72% increase in the overall residential water demand reduction amount. In Figure 3, for all water price strategies and rebate status, as the income increased, there was an exponential increase in overall water demand reduction after adoption of new and efficient technologies.

Although increased income led to more water savings derived by the adoption of conservation technologies, it might also lead to higher per capita water usage because higher-income households were shown to consume more water than lower-income households [29]. Hence, the relationship between water usage, the adoption of water conservation technologies, and income is complex. Therefore, the number of technologies adopted were also accounted for in this study, and brought about interesting insights.

Figure 4a shows an exponential trend in the total adoption number of expensive technologies (i.e., toilet, washing machine, and dishwasher) under various water pricing structures and rebate programs. It was discovered that with rebate allocation, the total number of expensive technology adoptions increased by almost 50% regardless of water price strategy or income growth. In Figure 4b, the adoption of inexpensive technologies (i.e., kitchen and bathroom faucet and showerhead) does not increase significantly (less than 10%) under any water price scheme when a rebate is included for affluent households (i.e., positive income growth rates); however, it is significant among the households with negative income growth rates. In other words, the results showed that the effectiveness of rebate programs is dependent on two factors (i) the type of technology (i.e., expensive or inexpensive), for which the rebate is allocated; and (ii) the affluence of the community, in which the rebate program is implemented. Additionally, it can be observed that under the strategy of fixed charge with rebate allocation, the maximum number of inexpensive technologies were adopted, approximately independent of income growth rate. What can be noted, however, is that across all of the other water price and rebate strategies, income growth will lead to the higher adoption of both expensive and inexpensive technologies.

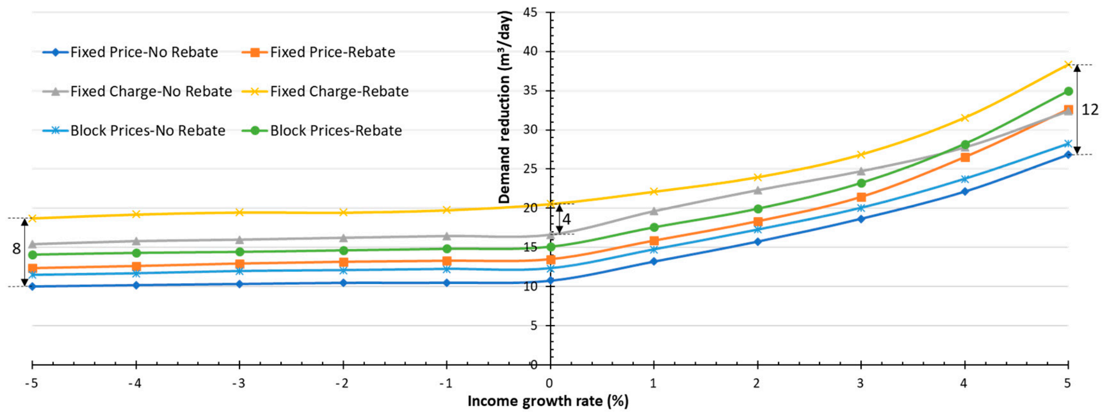

Figure 3. The modeling trends in the overall daily water demand reduction.

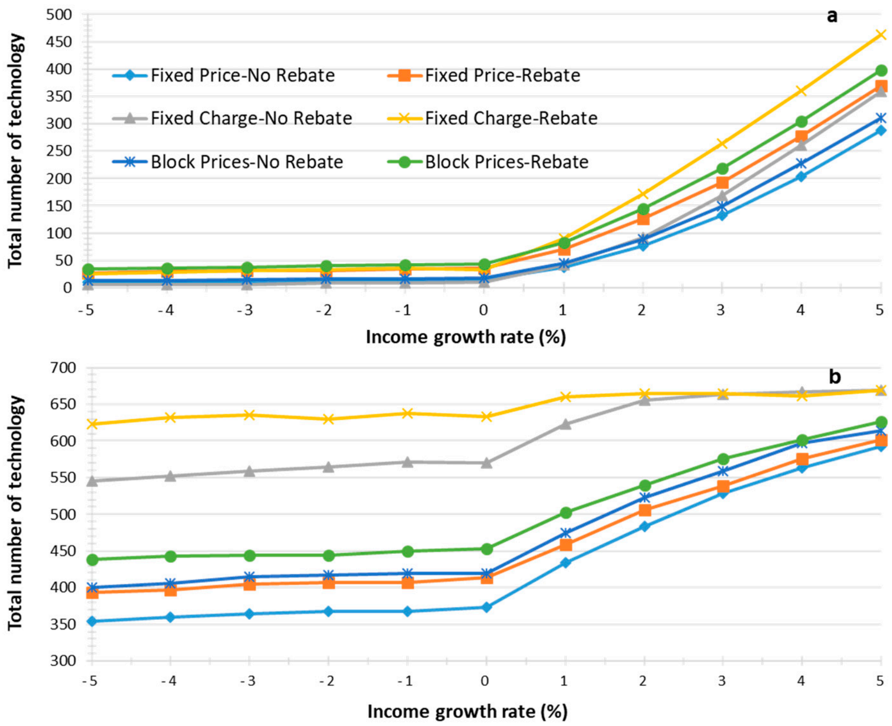

Figure 4. The modeling trends on the total number of adopted technologies (**a**) Expensive technology; (**b**) Inexpensive technology.

The analysis also considered the sensitivity of the results to the utility threshold values. The utility threshold had a negative linear correlation with the adoption rate. Figure 5 shows the mean frequency of adoption states (i.e., adopter, potential adopter, and non-adopter) under various utility threshold values in the base scenario. In this figure, as the threshold increased, the percent adopter decreased, regardless of water price strategy or rebate status. The greater the threshold, the greater the demographic and building characteristics have to be in order to adopt. In contrast, the lower the threshold, the lower importance is granted to these factors. For example, if it is anticipated that demographic and building characteristics will not be important in the adoption of water conservation technology for a specific community (i.e., lower utility threshold), the results show that there is even a potential of a 67% adoption under the base scenario.

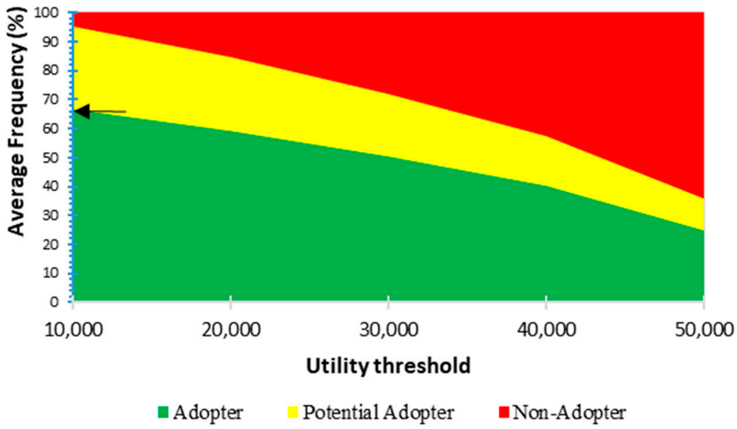

Figure 5. The distribution of adoption states over different utility threshold values.

7.2. Social Network Influence Examination

For all water pricing and rebate potential strategies, five structures of social networking were implemented and tested. Figure 6 demonstrates that among the social network structures, the highest percentage of households transitioned out from a non-adopter state through the scale-free network, followed by distance-based, then small-world networks. In the social networks with the random and ring lattice structures, the smallest household percentage was influenced into adopting water conservation technology. The results also showed that the effect of the social network structure on the adoption of water conservation technology is independent of water price strategy and rebate status. However, the adoption percentage fluctuates across the five social networks under each scenario of price stategy and rebate status.

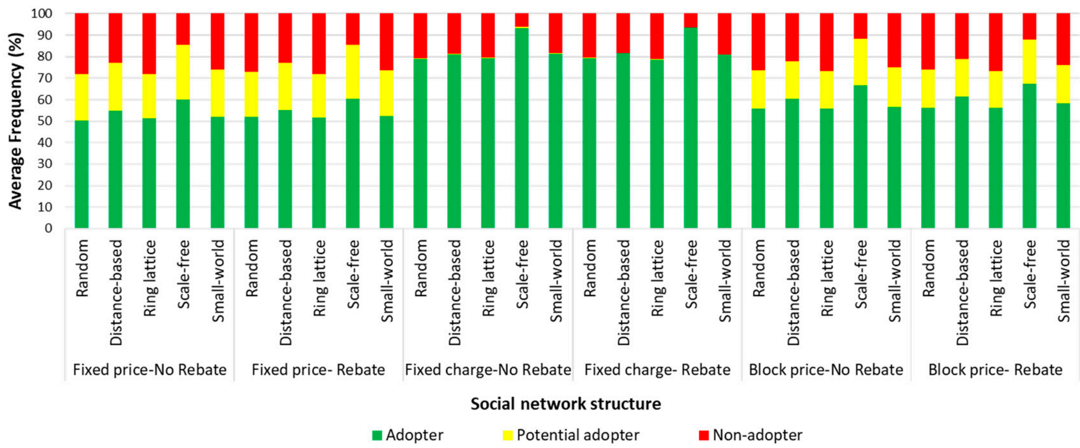

Figure 6. The social network structure influence on the distribution of the adoption states over different scenarios.

Another analysis conducted related to the effects of social network structures was about the rate (speed) of each structure in reaching the adoption equilibrium state. The adoption equilibrium means a steady or stable state where the adoption rate no longer changes [40]. From this point forward, there will be no significant increase or decrease in the adoption rate. The faster a social network structure reaches the adoption equilibrium, the earlier technology diffusion happens [40] and consequently, more water is saved earlier. As shown in Figure 7, whenever a steady state was observed in these graphs, it was identified as the time at which the adoption rate reaches an equilibrium through the influence of social networks. As shown in Figure 7, among the social network structures, the distance-based network reached the equilibrium state most quickly followed by ring lattice then scale-free and small-world networks. The random network has not reached equilibrium over the twenty-year period. So the results indicate that if the peer effect is activated through a distance-based network structure, it can speed up the diffusion of water conservation technology more than other structures.

Under the base scenario, various numbers of connections per agents (N = 0–10) were tested for the random social network structure to evaluate the impact of the increasing connectivity level on the adoption rate of the agents' network. As shown in Figure 8, increasing the number of connections between the households improved their adoption rate significantly. However, it was identified that increasing the connectivity level of agents to more than 5 connections in the random network would have no additional impact on the adoption rate. This level of connectivity (i.e., N = 5) in this network can be characterized as a tipping point, where the effect of connectivity level reaches a stable state.

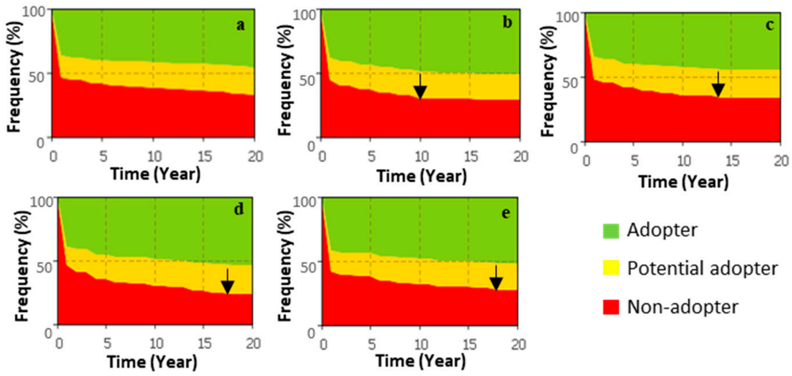

Figure 7. The comparison of the time to reach the equilibrium state across the social network structures (**a**) Random; (**b**) Distance-based; (**c**) Ring lattice; (**d**) Scale-free; (**e**) Small-world.

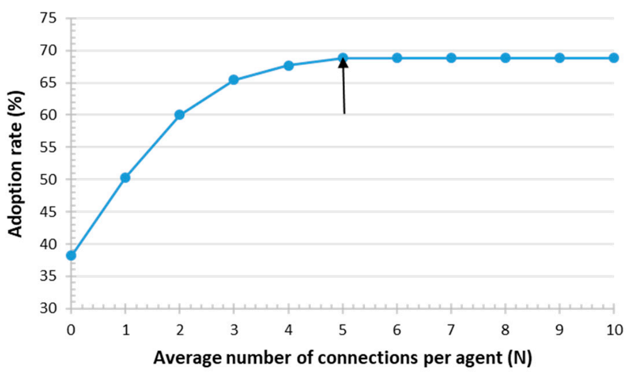

Figure 8. The effect of the connectivity level in social networks on the adoption rate.

The results of this study demonstrated that activating peer effect through social networks in a community can accelerate the diffusion of innovation regardless of the structure of social networks. Educating the public is one of the ways to achieve a greater rate of conservation diffusion [32]. The idea of social marketing can be used to design effective information campaigns in order to encourage water consumers to adopt water conservation technology. Informational programs through various means of social media can increase the knowledge of residents about the benefits of adopting water conservation technologies. For instance, promoting water conservation technology adoption through mass media has the potential to reach a very large number of residential consumers [70]. Based on the results of the current study, future studies can further examine the effects of social media on users' choices of water conservation adoption.

7.3. Scenario Landscape Analysis

The results of the ABM simulation model should be processed to generate the scenario landscape and to identify pathways towards the desired outcomes. Classification and Regression Tree (CART) analysis was used to analyze the simulation data and explain the impact of different factors affecting the water conservation technology adoption. CART is a nonparametric technique for data mining that can select, from among a large number of variables, the most important variables in determining the desirable outcomes based on their interactions [71]. CART operates by recursively partitioning the data until the ending points, or terminal nodes, are achieved using preset criteria. It, therefore, begins by analyzing all explanatory variables and determining which binary division of a single explanatory variable best reduces the deviance in the response variable (final output) to produce accurate and homogenous subsets [72]. The CART analysis has two components: the predictor importance analysis and the regression tree. The predictor importance analysis distinguishes which variables lead the greatest significance for the response variable. The regression tree is a tree-structured representation in which a regression model is fitted to the data in each partition. The importance predictors of each parameter engender a tree diagram that illustrates all possible pathways (combination of different values of the variables) toward or against the final response variable [73].

The predictor importance analysis of CART was conducted to highlight which parameters (mechanisms) fostered the greatest significance to the model outputs. The predictor importance analysis was conducted to determine which parameters (mechanisms) had the greatest effect on the model outputs. The results of this analysis are shown in Figure 9. The results show the importance of each independent parameter (e.g., income growth, water price structure, etc.) in determining different model outcomes: (a) Expensive Technology Adoption (ETA); (b) Inexpensive Technology Adoption; and (c) Overall Daily Water Demand Reduction (ODWDR). As shown in Figure 9 (panel c), the results demonstrated that income growth, affordability threshold, water price structure, and rebate program were the top four most important parameters (in descending order) affecting the total technology adoption (which results in ODWDR). The structure of social networks, utility threshold, and household size growth had less impact on water demand reduction. This order of importance is mostly consistent in the adoption of inexpensive technology. In the adoption of inexpensive technologies, water price was the most important parameter, followed by income growth and utility threshold (panel b). The adoption of inexpensive technologies was more dependent on socio-demographic and house characteristics (which is reflected in the utility threshold) than for expensive technologies. Nevertheless, income growth and affordability threshold, which are economic parameters, influenced the adoption of expensive technologies (panel a).

The simulated data were also utilized for meta-modeling using the regression tree of CART analysis. The scenario landscape was created based on the best fit of the CART model (Figure 10). In Figure 10, each path includes a set of branches representing the specific values of the most important parameters in determining the model outcome based on the predictor importance analysis. Each path leads to a terminal node (shown with bold border) representing the final outcome which is the overall daily water demand reduction (ODWDR). Basically, the scenario landscape of adoption patterns (Figure 10) demonstrates how the results (in terms of residential water demand reduction derived by conservation technology adoptions) would vary under different scenarios (combinations) of the underlying technology adoption mechanisms. As shown in the scenario landscape of adoption patterns

(Figure 10), the residential water demand can be reduced potentially by as much as 5.8–18.3 m^3/day (see the red and green nodes) through the adoption of water conservation technology under different scenarios (which translates to about a 3–10% reduction in the overall water demand of households in the service area).

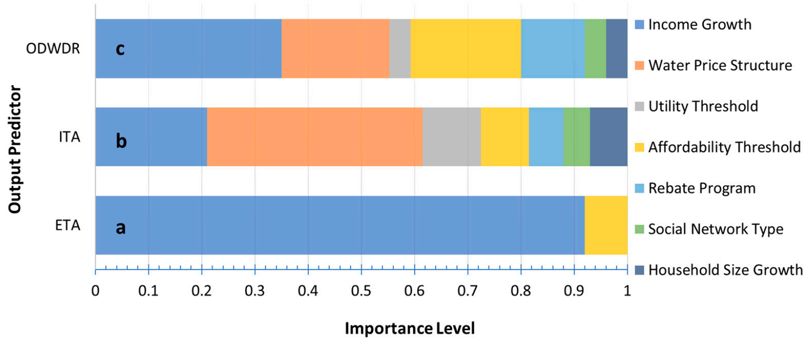

Figure 9. The predictor importance analysis for the model outcomes.

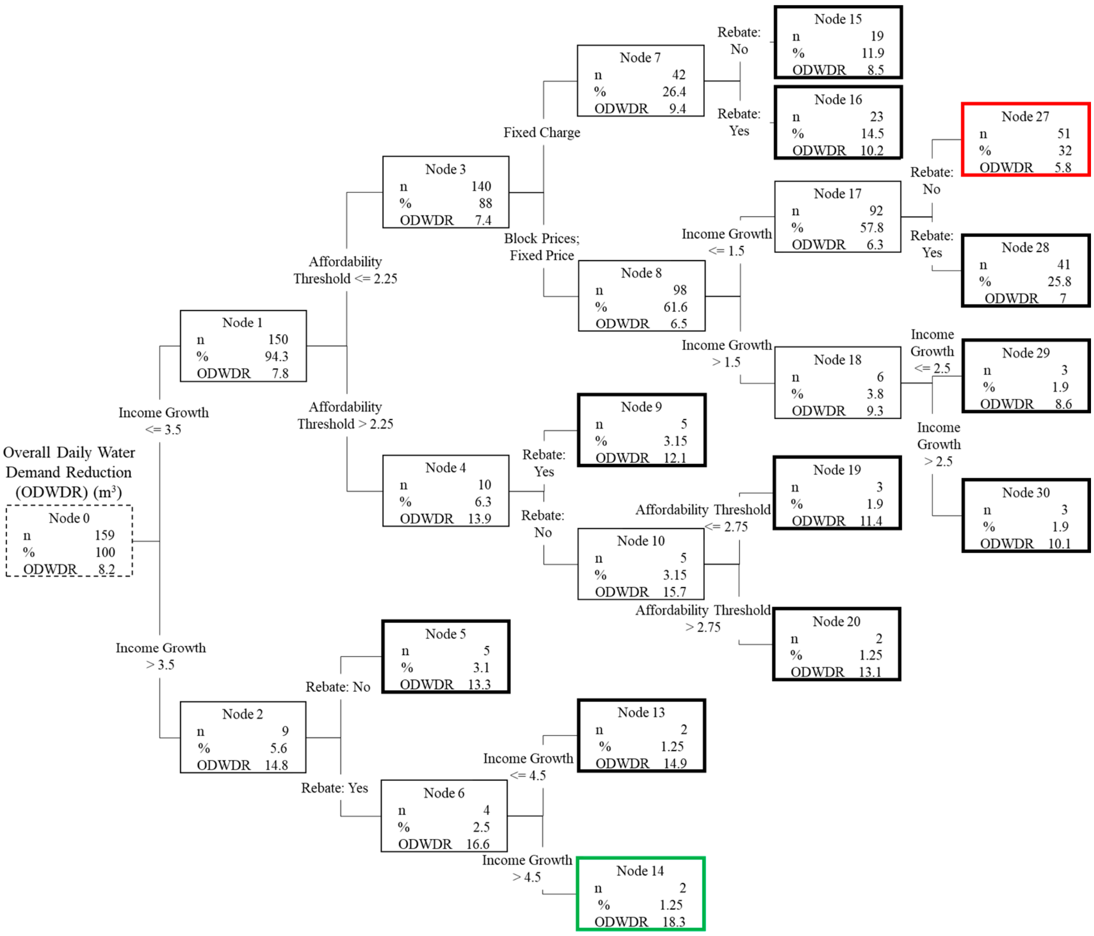

Figure 10. The scenario landscape of adoption patterns using Classification and Regression Tree (CART) analysis.

8. Concluding Remarks

As water scarcity becomes more critical, demand-side management methods for conservation are increasingly necessary. The agent-based model and scenario analysis revealed concrete methods for encouraging household water conservation technology adoption. Firstly, income growth most influences potential adopter households' willingness to adopt, followed closely by water pricing strategy. With no regard to other factors, households adopted enough water conservation technologies to reduce the daily water demand by more than 7 m^3 (almost 8% of the city's daily residential water demand) under the fixed charge water pricing. This reduction was not met under the volume use charging strategies. While fixed charging strategies may lead people to pay less than their water use shows, it can make the adoption of water conservation technology affordable. This is especially true for households that are aware of water shortages, making them potential adopters.

Based on assessing different community profiles from the CART analysis, volumetric water charging strategies are best implemented in more affluent communities where income growth is more likely. Conversely, a fixed charge regime would be best suited for less affluent communities, where income growth is less common. Rebate allocation programs increased the adoption rate—especially for expensive technologies, which had an increase of 50%. The findings suggest that municipalities and water agencies can use rebate allocation programs either with volumetric water pricing strategies or across less affluent communities. This pathway leads to a desired amount of water demand reduction. The adoption of inexpensive technology—i.e., kitchen and bathroom faucet, showerhead—did not increase at all when a rebate was included, and this was especially so in households with high income growth rates. In fact, the adoption of inexpensive technologies is significantly dependent on socio-demographic and household characteristics than for expensive ones. This indicates that targeting households to adopt inexpensive technology needs to involve outreach programs more than rebate policy.

Another important finding was related to the effects of social networks. The adoption percentage fluctuated across all five social networking schemes under each scenario of water price and rebate status. However, the distance-based network, among all network types, reached equilibrium in a shorter period. This means that the peer effect through neighboring social connections can speed up technology adoption potential more so than other social networks.

In terms of water pricing, for households who are already potential adopters, implementing a fixed charge strategy makes the adoption of water conservation technology more affordable. Offering rebates for technologies along with volumetric water pricing will lead communities to adopt enough technology to reach the desired water demand reduction levels. More broadly, if agencies' goals are to increase the rate of technology adoption, they must consider which pricing and rebate policies will be the most successful in their particular community. The planning and governance of water price has a greater importance on household adoption of water conservation technology than any other demographic, household, or social networking factors. The results of this study are important to consider in improving demand-side conservation management strategies. It should be noted that the modeling approach was utilized in this study to explore possible patterns of water conservation technology adoption and examine the underlying mechanisms rather than making predictions. While the research fostered a unique way to evaluate water conservation technology patterns, there are past studies (see Table 1) that, despite using a variety of different methods, found similar findings to the model. This, in turn, served as a point of external validation to the model's results. These results provide a clear course of action for the future development of household water conservation technology adoption programs and provide further evidence that demand-side management strategies will help foster a solution to urban water conservation problems.

9. Limitations and Future Studies

While the findings of this study will help municipalities and water agencies to strategically encourage the household adoption of water conservation technology, they do pose some limitations. Unfortunately, not every demographic characteristic of an individual can have could be accounted for, such as religious identity, race, sexual orientation, or even number of children in the household. That is not to say that all of these demographics would have had an impact on the utility value and household's adoption state, but it could have fostered more inclusive results. These characteristics were not considered due to a lack of information from the Census or water research. In the future, these identities will hopefully become more prominent in mainstream Census and demographic research, allowing for their inclusion in these models. Another important note about this model is that the only dynamic parameters considered were house age and social network influence (peer effect). The other input parameters in the model (such as threshold values) are static, which inhibits the ability of capturing feedback mechanisms. Through a feedback mechanism, households can reflect upon their decisions and change accordingly [63]. For example, the water pricing stays the same over the simulation period (20 years) and does not change based on the rate of adoption. While it is possible for government officials to change water pricing regime after a certain amount of time based on the adoption rate (as a feedback mechanism), this model did not account for them. In the model presented in this study, no feedback mechanism was incorporated as the inclusion of feedback mechanisms in the diffusion of innovations requires new methods of parametrization, calibration, and validation [74]. Hence, it is of great importance to consider the feedback mechanisms in water conservation technology adoption of households in future studies. Future studies can also evaluate additional mechanisms and phenomena affecting the water conservation technology adoption. For example, the impact of implementing water outage policies in a community on the conservation technology adoption behavior of households can be added to the model developed in this study. Despite these limitations, this study presented valuable findings towards better understanding the underlying mechanism of water conservation technology adoption for residential consumers.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The coefficients and values for adoption utility function variables [19].

Variable	Value	Coefficient	Distribution Type
Education:			
High school or less	If Yes = 1, if No = 0	1.92	Real data
Some college	If Yes = 1, if No = 0	2.58	
College graduate	If Yes = 1, if No = 0	2.91	
Advanced degree	If Yes = 1, if No = 0	4.39	
Income			
Less than $40,000	If Yes = 1, if No = 0	0	Real data
$40,000–$75,000	If Yes = 1, if No = 0	1.07	
Above $75,000	If Yes = 1, if No = 0	1.58	
Home ownership	Owner = 1, Renter = 0	1.84	Real data
Head gender	Female = 1, Male = 0	1.21	Random
Resident (head) age	Years	1.01	Histogram
House size	Square feet	1	Uniform (70; 56,000)
Garden size	Square feet	1	Uniform (0; 8000)
House age	Years	0.99	Random (1100)
Household size	Numbers	0.98	Real data

Table A2. The attributes of water conservation technologies in the model [23,62].

Technology	Price ($)	Potential Rebate ($)	Expected Water Savings (Gal/Day/Capita)	Category
Bathroom faucet	15	15	0.57	Inexpensive
Kitchen faucet	15	15	2.8	Inexpensive
Showerhead	100	25	4.85	Inexpensive
Toilet	420	50	1.63	Expensive
Washing machine	670	150	6.91	Expensive
Dishwasher	500	50	0.35	Expensive

Table A3. The attributes and parameters of social network structures [64].

Network Structure	Attribute	Parameter	Parameter values
Random	Assigns each agent a random number of connections within the given average.	Average number of connections per agent (N)	N = 0–10
Distance-based	If the distance between two agents is less than the given maximum connection range (the maximum distance in meters between agents for there to be a connection), then both agents are connected.	Maximum connection ranges (R)	R = 0–500
Ring lattice	Agents are connected according to their closeness to each other while also forming a ring.	Average number of connections per agent (N)	N = 0–10
Small-world	Connections between agents are similar to the ring lattice, while also including some long-distance relationships. The neighbor link probability is the chance that two agents connected to the same neighbor may also connect to each other.	Average number of connections per agent (N); and Neighbor link probability (P)	N = 0–10 P = 0–1
Scale-free	Some agents have multiple connections (considered as hubs), while others have very few connections.	Number of hubs (M)	M = 1–10

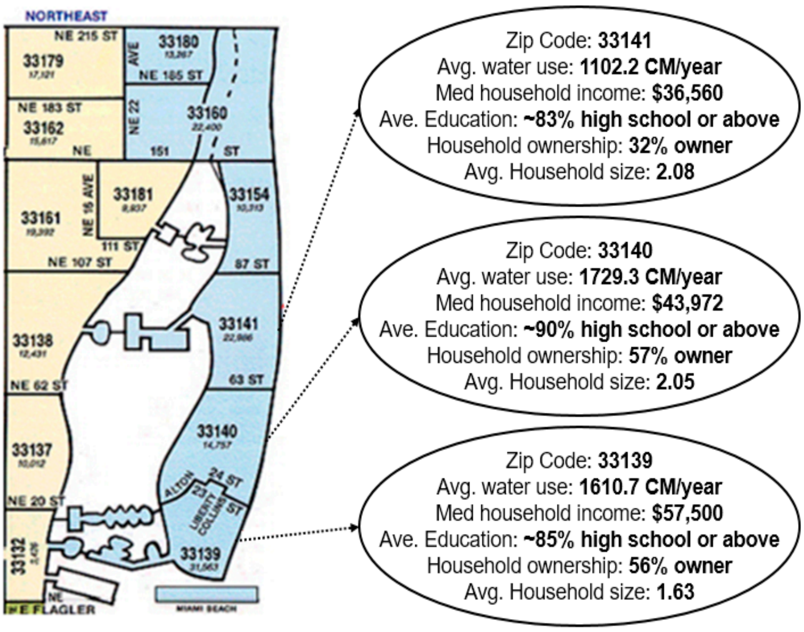

Figure A1. The average demographic and water consumption data of the zip codes used in the model.

Table A4. The variation of parameters for the model experimentation process.

Parameter	Use	Method	Input Unit Changes
Household	Agent	Estimation of consumption; Influence diffusion	No change; 280 agents were used throughout the experimentation process
Water price strategy	Input parameter	Fixed price; fixed charge; block tariffs	Nominal
Rebate status	Input parameter	Rebate; no rebate	Nominal
Social network structure	Input parameter	Random, distance-based, ring lattice, small world, scale-free	Nominal
Likelihood of adoption due to social network	Input parameter	Function of randomTrue (p), given the likelihood p; True/False result	1, 5, 10, 15, . . . , 100%
Income growth	Input parameter	Change in annual income	−5, −4, . . . , 0, 1, . . . , 5%
Household size growth	Input parameter	Change in household size	−5, −4, . . . , 0, 1, . . . , 5%
Utility threshold	Input parameter	Accumulation of attributes influencing the potential for technology adoption (Utility > Threshold)	10,000; 20,000; 30,000; 40,000; 50,000
Affordability threshold	Input parameter	Household ability to pay water expenditures (annual water bill + technology cost)	1, 1.5, 2, 2.5, 3%
Percent adopter	Output parameter	Percentage of agents that adopted at least one water conservation technology	(Changes in the outputs are a reflection of changes in the input parameters)
Demand reduction	Output parameter	m^3 per household	
Kitchen faucet	Output parameter	Number of kitchen faucets adopted	
Bathroom faucet	Output parameter	Number of bathroom faucets adopted	
Shower head	Output parameter	Number of shower heads adopted	
Toilet	Output parameter	Number of toilets adopted	
Washing machine (clothes)	Output parameter	Number of washing machines adopted	
Dishwasher	Output parameter	Number of dishwashers adopted	

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