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# EVALUATION OF LIFE CYCLE COSTS, BENEFITS, AND PUBLIC PERCEPTIONS OF GREYWATER REUSE SYSTEMS FOR SUPPLEMENTING CONVENTIONAL WATER DELIVERY

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# EVALUATION OF LIFE CYCLE COSTS, BENEFITS, AND PUBLIC PERCEPTIONS OF GREYWATER REUSE SYSTEMS FOR SUPPLEMENTING CONVENTIONAL WATER DELIVERY

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ABSTRACT

The water utility industry is under enormous pressure to meet the challenges of increasing demands due to population growth, lifestyle changes, and depleting freshwater resources. The current and predicted future deficit scenarios challenge water supply managers to come up with a sustainable and reliable alternative source while making the supply infrastructure smarter and resilient. One such alternative source is the greywater that is available at the point of consumption itself. With certain limitations, there have been studies performed to evaluate the life cycle costs and expected monetary benefits of decentralized greywater reuse systems, but the public and health bureaus are apprehensive about the risk of diseases that may arise due to the placement of greywater treatment technologies very near to spaces of human interaction. In an attempt to address these knowledge gaps, the proposed study will evaluate the economic, reliability and public perception related implications of greywater reuse systems in order to evaluate the best combination of physical infrastructure and policy alternatives that will enable greater adoption of these systems and in turn enhance water supply sustainability. The specific goals of this study are to: (a) comparatively evaluate the life cycle costs and expected monetary benefits of decentralized greywater reuse systems considering a utility-scale implementation; (b) evaluate the supply reliability improvement when decentralized greywater reuse systems are installed to complement existing water supply systems; (c) evaluate the public perceptions towards greywater reuse systems and other factors that may increase its adoption. Overall, the proposed study will contribute to the body of knowledge in assessing the potential merits

and limitations of decentralized greywater reuse and determining interventions that will help address the limitations to enable greater adoption of these systems.

DEDICATION

I dedicate this dissertation to my mother, Suneetha Yerri, and my father, Mallikarjuna Reddy Yerri, who has always loved me unconditionally and whose good examples have taught me to work hard for the things that I aspire to achieve. You have been my source of inspiration and strength throughout this journey and in my life. I will forever be grateful for the unconditional love and support you always showered upon me.

I would also like to dedicate this to my good friend, Phalguni Yamuna Moganti for her continuous support throughout this study. I will always be grateful to you for tolerating me and helping me during this journey.

I dedicate this to my younger self who was lost in confidence and was constantly reminded of being “not good enough”. I thank him for believing in himself, taking up the responsibility, chasing his dreams by not losing hope, and not giving up.

Lastly, I dedicate this to *The New Beginnings…*

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My deepest gratitude goes to my parents for their prayers, love, and endless support, I will forever be indebted to you. I would like to thank all my friends and well-wishers for their continuous support and words of encouragement. To my good friend, Phalguni, thank you for your many sacrifices, you were always by my side supporting, motivating, and encouraging, I could not have made it this far without you. I would also like to thank the nonbelievers who always had doubts about what I can do, this only gave me more motivation to succeed.

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Lastly, I would like to thank Cristiano Ronaldo and Tom Brady for inspiring me and showing me that “*it’s not how you start that’s important, but how you finish*”.

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# CHAPTER ONE

# INTRODUCTION

## Motivation for this Study

Continuous supply of clean drinking water is crucial for economic prosperity, security, and health of communities. Clean drinking water supply is dependent both on the availability of freshwater resources and the reliability of the large infrastructure that facilitates the flow of water from its source to demand locations. On the other hand, drinking water infrastructure (i.e., buried pipelines, pump stations, and etc.) is critically deteriorated due to aging and inadequate investment that went into its maintenance (ASCE, 2017). It is estimated that $335 billion of investment is required in the next 20 years to revamp the drinking water infrastructure to be able to continuously meet the water supply reliability targets (EPA, 2013). Furthermore, it is estimated that 15-25% of treated drinking water is lost through pipeline leakages in the U.S. (Shukla et al., 2020). Figure 1-1 depicts a typical cast iron water distribution main that is under service. It can be noticed how deteriorated the pipeline in Figure 1-1 is, and the resulting chances of contamination and structural issues can be very serious. Finally, the centralized form of our current water infrastructure delivery makes it highly likely that the downstream supplies (i.e., services) will be interrupted if an upstream pipeline or other infrastructure component fails. In a nutshell, we are facing severe water scarcity issues in several regions, losing tremendous amounts of treated drinking water through pipeline leakages, facing increased vulnerability to water contamination and main breaks due to deterioration, and risking supply interruptions due to the centralized form of water delivery.

Due to these pressing water supply challenges, there is an increased interest in the diversification of water supply portfolio using alternatives such as greywater (Yu et al., 2015), which will not depend so much on distribution infrastructure that may deteriorate over time. If greywater is captured and reused closer to the source location, such diversification could also minimize the burden on both drinking water and sewer infrastructures.


Figure 1-1. A Typical Deteriorated Water Main under Service (Source: Murphy Pipeline Contractors, https://www.murphypipelines.com/)

Greywater is the residential or industrial wastewater that has not come in contact with toilet and – in most cases – kitchen sink and dishwasher waste too (Al-Jayyousi, 2003). With adequate treatment, greywater can be used for various non-potable end uses such as toilet flushing, outdoor irrigation, and laundry, which together account for more than 45% of a typical household freshwater demand (Liang and Dijk, 2008). Several previous studies attempted to evaluate the economic implications of different greywater reuse adoption scenarios (Zadeh et al., 2012, Friedler, 2008, Penn et al., 2012) and compared the cost of greywater recycling systems for individual (i.e., onsite) and shared (i.e., satellite) scales using various greywater treatment technologies. Irrespective of the reported merits and limitations, there is a general consensus on the need to include water reuse in broader water supply planning, especially in states with water security issues.

Transitioning from a more traditional way of supplying water to this new way is expected to face several societal and organizational hurdles with respect to consumers and municipalities (Geels, 2002). There is always the health and acceptability related risks associated with decentralized reuse systems by the consumers. Hence prior to the implementation/legalization of greywater treatment, public perception is of the utmost importance and the success of such reuse schemes depends on public acceptance. To ensure the proposals of greywater recycling schemes receive a good opportunity for public review in the decision-making process, it is essential to determine and understand public attitudes and perceptions towards greywater reuse. Water utilities or private suppliers establish a level of service based on how much deviation the consumers can accept from the desired performance (Haider et al., 2016). Acceptance, in this case, is generally measured through interviews and surveys after providing services over a given assessment period. Multiple surveys have been conducted by the researchers in the past to study public perception, acceptance, and trends. Some of the main drawbacks observed in the literature are that surveys are focused on specific demographic locations drawing biased results, smaller sample sizes, respondents provided with lack of information, establishing conclusive evidence of a statistical relationship between greywater reuse and specific socio-demographic variables such as income and age. The proposed research is focused on making a significant contribution to the body of knowledge by addressing these specific challenges.

**Research Objective and Scope**

The ***objective*** of this dissertation is to evaluate the economic, reliability, and public perception related implications of decentralized greywater reuse to develop recommendations on the best combinations of physical infrastructure schemes and policy incentives that would enable greater adoption of such systems. To achieve this objective, this Ph.D. study is divided into three phases: (i) comparatively evaluate the life cycle costs and expected monetary benefits of decentralized greywater reuse systems considering multiple greywater treatment technologies; (ii) evaluate the reliability improvement offered by on-site greywater treatment systems that are installed to complement the existing water supply systems; and (iii) evaluate public adoption preferences and determine effective incentives for increased adoption of greywater reuse.

The ***broader impact*** of this dissertation includes: (a) cost-benefit analyses presented in this study would help future policy making in water supply planning and also drive research into technology development and infrastructure planning for the purpose of enhancing the benefits of greywater reuse in comparison to its cost; (b) sensitivity analyses performed in this study identifies the influential factors that make adoption of greywater reuse more or less viable, economically, which provides the consumer and policymakers greater insight towards the greywater reuse systems evaluation; (c) the public perception portion of this study determines the effectiveness of different knowledge media to educate public and change their perceptions on greywater reuse systems, which can be used by water utilities and policymakers; (d) the framework used in this study to perform comparative reliability analysis can be used by the water utilities and infrastructure planners to evaluate the reliability improvement for alternative supply scenarios during rehabilitation planning; (e) dissemination of research findings in the form of journal publications and conference proceedings/presentations. While some of these activities are directed towards the scientific research community, others are directed towards stakeholders and direct beneficiaries such as utility owners and consultants. A few of these impacts have already been realized; for example: (1) a research article based on phase-I and phase-II of this study has already been published in the Journal of Resources, Conservation & Recycling (Impact factor >7); and (2) a research article summarizing phase-III is being prepared for submission to the Journal of Resources, Conservation & Recycling.

## Current State of the Knowledge and Points of Departure

This section presents a review of the state-of-the-art knowledge and practices in the field of greywater reuse systems. Several research studies along with the commercially available greywater technologies are reviewed with their merits, demerits and suitability studied.

### ***State-of-the-art Knowledge***

<u>*Life Cycle Costs Vs Benefits of decentralized greywater reuse systems*</u>

Several previous studies attempted to evaluate the economic implications of different greywater reuse adoption scenarios. Friedler and Hadari (2006) studied the economic feasibility of on-site greywater reuse in the urban sector with rotating biological contactor (RBC)- and membrane bioreactor (MBR)-based systems. In their analysis, the RBC-based system became economically feasible when the building size reached 7 floors or above whereas the on-site MBR-based system proved to be economically unrealistic, becoming economically feasible only when the building size exceeded 40 floors.

Friedler (2008) carried out economic analyses of greywater reuse treatment using rotating biological contactor (RBC) technology in Israel focusing on multi-story residential buildings. A survey conducted as part of the same study indicated high public support for greywater reuse adoption. Zadeh et al. (2012) compared the cost of greywater recycling systems for the individual (i.e., onsite) and shared (i.e., satellite) scales in urban areas using membrane bioreactor (MBR) and vertical flow constructed wetlands (VFCW) technologies by considering 15-year design life. While no land requirement limitations were considered in their study, the results indicated that VFCW is more economically and environmentally viable than MBR. This study also suggested that MBR technology is more suitable for multi-story buildings in urban areas where land acquisition costs may be significant. In other studies, it has been shown that onsite grey-water reuse for toilet flushing alone can reduce the daily household water consumption by 26%, and the use of treated greywater for garden irrigation further reduces the freshwater demand to an overall 41% (Penn et al., 2012).

The model/framework developed in the previous studies to perform the economic evaluation of the greywater system focused mainly on the single house scale, paying much attention to different treatment systems and their performance, while the effects of greywater reuse practice on the satellite scenarios and consequent effects on urban wastewater conveyance systems and treatment plants were scarcely discussed. Also, some of the studies did not consider the evaluation of greywater reuse benefits (Zadeh et al., 2012) and some studies did not capture savings due to freshwater withdrawal aspects as part of the evaluation of the benefits (Friedler, 2008, Friedler and Hadari, 2005, Penn et al., 2012).

*Reliability Improvement Assessment with Greywater Systems*

Most of the published research focused on the analysis and decision process for improving the mechanical reliability of water distribution networks (WDNs). A reliability simulation model for the water supply network that focuses on the failures of pipes and pumps was proposed by Wagner et al. (1988a, b). The model was divided into two parts: a simulation section and a hydraulic network solver. The simulation part known as the Monte Carlo simulation generates failure and repair events according to specified probability distributions. In another model to estimate the reliability of WDNs, Quimpo and Shamsi (1991) used the exponential distribution method to describe the break rate for each pipe. This model uses the minimum path approach to calculate the reliability of the water network. The method involves a hydraulic simulation to determine the flow through all the pipes in the network. The results are visualized using contour lines which demonstrate equal reliabilities and these lines represent reliability surface plots. This method of calculating the reliability of the system totally relies on the connectivity between the demand point and the water source. Hydraulic capacity is not taken into context in their research study. Ciaponi et al., (2012) described a procedure for reliability analysis of

WDNs considering failure states that are a result of the unavailability of system components. Several scenarios with various possibilities of component failures are considered as working states in their model. Assuming that the failed component can be isolated for repair, reliability is determined as the ratio of the actual volume of water delivered during the component failure period to the required volume as per demand. The probability of the failed state is determined using historical break rate data. This research by Ciaponi et al. (2012) is restricted to the unavailability of pipes only and assumed that any failed pipe can be isolated for repair. While these studies focused only on the reliability evaluation of the conventional WDNs, Piratla and Goverdhanam in 2015 attempts to test the hypothesis that the use of on-site greywater reuse significantly improves the reliability in WDNs. Two supply scenarios are considered for the comparative reliability analysis in their study. The first is the business-as-usual or the "centralized" scenario and the second is the "decentralized" scenario where existing municipal water supply systems are complemented with on-site greywater reuse systems. It is assumed in this study that each consumption point will have a treatment unit along with some storage capacity. Ciaponi's method is adapted in this study to estimate and compare WDN reliability for two different supply scenarios (i.e. centralized and decentralized). One of the main drawbacks of this study is that life cycle costs and benefits of the on-site greywater reuse systems are not contemplated in the analysis.

*Public Perception Towards Greywater Reuse Systems*

Multiple surveys have been conducted by researchers in the past to study public perception, acceptance, and trends of greywater reuse. Little et al., in 2000 conducted a study with an objective to determine if health risks and greywater use were positively correlated and whether or not the greywater permitting process could be made more accommodating. A survey conducted by Smith and Hyde in 2015 concluded that aesthetics and smell of recycled water are extremely important and that the quality is very influential upon whether people will be encouraged or discouraged from reusing recycled greywater, especially for toilet flushing. One of the limitations of this study is that the respondents of the questionnaire were not given information/guidance in regard to the greywater reuse applications. In a research study conducted by Shafiquzzaman et al. (2015), a questionnaire survey was developed to evaluate the feasibility of greywater reuse focusing on arid environments. Researchers of this study recommended governments to develop strategies, codes of practice, and standards for providing financial assistance to the consumers after conducting a more detailed survey of a broader range and number of respondents. In a survey conducted in Sydney, Australia in 2004, more than 90% of the participants were willing to reuse treated greywater for gardening and toilet flushing (Marks, 2004). Public concerns about the greywater reuse in terms of environmental and health risks were investigated by Domenech and Sauri in the city of Barcelona, Spain in 2010. Their survey results conclude that about 84% of the respondents were informed about the benefits of the greywater system and felt convinced that the system has no or very low health risk. Studies conducted by Al-Jayyousi, 2003; Abusam, 2008; Buyukkamacia and Alkanba, 2013, conclude the necessity to support and encourage greywater reuse through clear guidelines and technical specifications, and incentives for sustainable greywater reuse. It has been reported by Dolnicar and Schafer (2006), Friedler et al. (2006b), Hurliman and McKay

(2007), Kantanonleon et al. (2007) and Marks (2004) that the highest acceptability of greywater reuse schemes is for non-potable uses. Dolnicar and Schafer (2006) identified reduced levels of acceptance as the recycled water got closer to human contact. Alhumoud and Madzikanda (2010) identified that public support was greater for areas that are water-stressed and areas with unreliable water supply. A study by De Sena (1999) and Parkinson (2008) identified that misinformation, lack of knowledge or instinctive repugnance as accounting for objections in reuse programs.

Some of the limitations of these surveys are that they are focused only on specific locations. For example, surveys by Little et al., in 2000 focused on population in Arizona USA, Khong in 2009 in Berkeley, California, USA, Marks in 2004 in Sydney, Australia, Domenech and Sauri in 2010 in City of Barcelona, Spain. Some of the conclusions of these surveys could be skeptical as the perceptions of the population is drawn from a single demographical location. Results from the surveys conducted in California could be biased as the state is well known for being very environmentally conscious. Concerns over a small sample size for the recorded survey responses can be observed in some of the studies. A study conducted by DuBose, K in 2009 considered the lack of information provided to respondents about the treatment systems, financial and other factors to be its primary limitation of the survey.

***State-of-the-art Practice***

With immense pressure on water resources, various greywater technologies are being used worldwide. Some greywater systems are home-built, do-it-yourself piping and storage systems, but there are also a variety of commercial greywater systems available that filter water to remove hair, lint, and debris, and remove pollutants, bacteria, salts, pharmaceuticals, and even viruses from greywater. Greywater systems that are currently being used by the consumer can be divided into three main categories: diversion systems, physical treatment systems, and biological treatment systems. A variety of diversion systems are commercially available in the market and are mostly used when the greywater codes do not allow greywater to be stored. RBC and MBR are the most widely used biological treatment systems in the industry.

Internationally, there is diversity in the approaches to and stringency of greywater regulations, from being legal with few restrictions to being prohibited in all circumstances (Prathapar et al., CSBE 2003). In other cases, there are no clear policies on greywater and its use may instead be indirectly regulated by building, plumbing, or health codes that are written without consideration of greywater reuse. For example, a country may have wastewater regulations that do not distinguish between black and greywater, e.g. Oman, Jordan (Maimon et al. 2010) or have a plumbing code that prohibits the discharge of non-potable water through outlets such as faucets, such as in Canada’s National Plumbing Code (CMHC 1999). The United States does not have a national greywater policy, leaving the regulation of greywater to the states. About 30 of the 50 states have greywater regulations of some kind (Sheikh 2010). These regulations vary widely. North Carolina has stringent greywater regulations and only allows the reuse of water if it is treated to the same standards that are required for treating sewage water (Sheikh 2010). The state of Arizona has a more flexible greywater policy than many states and is often seen as a leader in terms of the promotion of greywater reuse in the United States.

## Dissertation Organization

This dissertation is organized into five chapters as described in the following paragraphs.

Chapter two presents the development of formulations for a variety of cost and benefit categories associated with the adoption of on-site and satellite greywater reuse alternatives. These formulations are integrated to develop a Microsoft Excel-based life cycle cost vs. benefit analysis tool that can be used for any given network. The model is demonstrated using a modified real-world water distribution network. The outcomes of this phase revealed under what circumstances satellite or onsite water reuse systems offer more sustainability benefits than the business-as-usual centralized supply scenario. Such a comparative analysis of sustainability merits is imperative for understanding the critical bottlenecks to greater adoption of satellite or onsite water reuse systems. This chapter has been published as a peer-reviewed journal article in the *Journal of Resources, Conservation and Recycling.*

Chapter three presents the development of a computational water supply reliability model adapted from a previously proposed theoretical framework that can be applied to both centralized and decentralized supply scenarios for performance evaluation. New formulations for the physical schemes of decentralized reuse systems are developed and appropriately integrated with the conventional water supply schemes. The computational reliability assessment model was developed using the MATLAB programming platform in conjunction with a hydraulic network solver, specifically EPANET 2.2 and is demonstrated on benchmark networks adapted from a real-world water distribution network. The main goal is to evaluate water supply reliability improvement offered by a variety of decentralized reuse systems and subsequently determine the factors that enhance the reliability improvement. This chapter has been published as a peer-reviewed journal article in the *Journal of Resources, Conservation and Recycling*.

Chapter four presents the development of a hybrid behavioral change theory model and a survey to understand consumer preferences with respect to greywater reuse adoption and other factors that increase its adoption. This hybrid model consists of the constructs from Theory of Planned Behavior (TPB), Norm Activation Model (NAM), descriptive norm, and environmental knowledge. This survey was conducted in two different demographic locations, one being an "Impacted Location" like California where the participants are more familiar with the water shortage issues and where the strategies to encourage and adopt greywater systems are already implemented, and the other will be a "Potential Location" like Florida where the water shortage and disposal constraints of the state have not been vulnerable until the recent times. Quantitative and qualitative analysis is performed on the survey response data to understand the public perceptions and attitudes towards water reuse and to investigate their correlations with demographic factors. A statistical method called Structural Equation Modeling is performed to determine the factors influencing public perception towards greywater reuse treatment systems and also to determine the correlation between the greywater reuse adoption behaviors and socio-demographic variables. This chapter will be soon submitted for publication consideration to the *Journal of Resources, Conservation and Recycling*.

Chapter five summarizes the contributions of this dissertation study, highlights the study limitations, and presents directions for future study in the important area of greywater treatment and reuse, and public perception towards it.

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# CHAPTER TWO

# DECENTRALIZED WATER REUSE PLANNING: EVALUATION OF LIFE CYCLE COSTS AND BENEFITS[1]

The objective of this study is to comparatively evaluate the life cycle costs and expected monetary benefits of decentralized greywater reuse systems. Specifically, added life cycle costs and estimated life cycle monetary benefits of satellite and onsite greywater reuse systems are evaluated in comparison with the prevailing centralized systems. Centralized systems refer to the traditional form of water delivery where one centralized treatment plant treats and distributes potable water to a large service area through a water distribution network while a sewer network collects used water for treatment at a centralized wastewater treatment plant before the wastewater effluent is disposed into the environment. Satellite greywater reuse systems collect raw greywater at neighborhood or district level for treatment and re-distribution for non-potable uses within the same neighborhood or district. Onsite greywater reuse systems collect raw greywater for treatment on the premises of where it is produced after which it is re-distributed for permitted non-potable use on the same premises. Infrastructure needs and associated life cycle cost information for both types of greywater reuse systems are appropriately modeled or synthesized from literature. The skeletal layout of a real-world water distribution network is adapted for performing the cost-benefit analysis in this study. Finally, sensitivity of the cost-benefit tradeoff associated with satellite and onsite greywater reuse adoption scenarios is evaluated for various uncertainties associated with technological evolution, policy incentives, and planning schemes. Given that several states in the U.S. are expected to face water shortages in the near future, this study will provide guidance to water utilities and policy makers in planning of future water supply alternatives.

[1] Standalone Published Research Article: **Yerri, S.**, & Piratla, K. R. (2019). *"Decentralized water reuse planning: evaluation of life cycle costs and benefits"*. Resources, Conservation and Recycling, 141, 339-346.

## Introduction

Continuous supply of clean drinking water is crucial for economic prosperity, security, and health of communities. Clean drinking water supply is dependent both on the availability of fresh water resources and reliability of the large infrastructure that facilitates the flow of water from its source to demand locations. Both freshwater resources and supply infrastructure are currently in critical condition in many regions of the world. The detrimental consequences of climate change impacts are already widespread in areas such as California that has witnessed, not very long ago, a sustained drought (one of the most extreme on record) characterized by low precipitation and high temperatures (Shukla et al., 2015; Asner et al., 2016). Several other regions globally face similar freshwater shortages and many more anticipate such shortages in the near future.

On the other hand, drinking water infrastructure (i.e., buried pipelines, pump stations, and etc.) is critically deteriorated due to aging and inadequate investment into its maintenance (ASCE, 2017). As a result, significant amount of treated drinking water is lost through leakages and increasing numbers of water mains are failing every year (ASCE, 2017). It is estimated that $335 billion of investment is required in the next 20 years to revamp the drinking water infrastructure to be able to continuously meet the water supply reliability targets (U.S.EPA, 2009). The condition of sewer infrastructure is not very encouraging either having received a mere D+ grade in the latest ASCE report card (ASCE, 2017). Due to these pressing water supply challenges, there is an increased interest in the diversification of water supply portfolio using alternatives such as greywater (Yu et al., 2015). If determined to be acceptable at large scale, such diversification would significantly alleviate stresses on the already scarce freshwater supplies. If greywater is captured and reused closer to the source location, such diversification could also minimize the burden on both drinking water and sewer pipeline infrastructures.

Greywater is the residential or industrial wastewater that has not come in contact with toilet and – in most cases – kitchen sink and dishwasher waste too (Al-Jayyousi, 2003). In many regions, greywater is directly reused for outdoor irrigation and/or toilet flushing, while in some regions it is captured and discharged to groundwater aquifers. With adequate treatment, greywater can be used for various non-potable end uses such as toilet flushing, outdoor irrigation, and laundry, which together account for more than 45% of a typical household freshwater demand (Liang and Van Dijk, 2008). The scale at which raw greywater should be captured, treated, and distributed back is dependent on land use type, population density, and economies of scale. The type of current water supply infrastructure in urban areas can be characterized as *centralized*, for freshwater is captured and treated at one location for distribution to a larger municipal region. In addition to the *centralized*, two scales of decentralized greywater reuse infrastructure can be envisioned; they are *satellite* and *onsite*. In the *satellite* scenario, raw greywater from a number of dwellings in one or multiple sub-divisions is collected at one satellite treatment plant for treatment and redistribution within the region it is collected from. On the other hand, in the *onsite* scenario, raw greywater from each dwelling is collected, treated and re-supplied using a small-scale treatment unit located within the dwelling.

The three scales of decentralization – centralized, satellite, and onsite – require different types of infrastructures and as a result, the economic, environmental and societal implications vary. Several previous studies attempted to evaluate the economic implications of different greywater reuse adoption scenarios. Zadeh et al. (2012) compared the cost of greywater recycling systems for individual (i.e., onsite) and shared (i.e., satellite) scales in urban areas using membrane bioreactor (MBR) and vertical flow constructed wetlands (VFCW) technologies by considering 15 year design life. While no land requirement limitations were considered in their study, the results indicated that VFCW is more economically and environmentally viable than MBR. This study also suggested that MBR technology is more suitable for multi-story buildings in urban areas where land acquisition cost may be significant. Friedler (2008) carried out economic analyses of greywater re-use treatment using rotating biological contactor (RBC) technology in Israel focusing on multi-story residential buildings. The economic analyses revealed that greywater reuse can be economically viable where water utility prices continue to increase and suggested that an RBC-based reuse system with 15 year return period would be cost-effective for buildings of seven or more stories. A survey conducted as part of the same study indicated high public support for greywater reuse adoption. In other studies, it has been shown that onsite greywater reuse for toilet flushing alone can reduce the daily household water consumption by 26%, and the use of treated greywater for garden irrigation further reduces the freshwater demand to an overall 41% (Penn et al., 2012).

One study investigated the policy aspects of greywater reuse and reported the inconsistencies across various states, especially in plumbing codes; for example, while seven states in the U.S. allow even indoor non-potable reuse of treated greywater, nine states do not even identify “greywater” in their regulations (Yu et al., 2013). Irrespective of the reported merits and limitations, there is a consensus on the need to include water reuse in broader water supply planning, especially in states with water security issues. This study presents a life cycle cost analyses approach for comparatively evaluating two scales of greywater reuse adoption. The cost-benefit analyses presented in this study would help future policy making in water resources planning and drive research into technology development and infrastructure planning for enhancing the benefits of greywater reuse in comparison to its cost.

**Methodology**

This section describes various categories of added costs and benefits considered in this study, which are listed in Table 2-1. A 50-year period is considered for the life cycle analysis (Zhang et al., 2006). Furthermore, sensitivity analyses are performed to identify influential factors that make adoption of greywater reuse more or less viable, economically.

Table 2-1. Various categories of added costs and expected benefits

| | | |
|---|---|---|
| Added Costs | Capital costs:<br>1. Treatment unit:<br>a) Treatment technology<br>b) Chlorination unit<br>2. Storage tanks<br>3. Plumbing adjustments<br>4. Pumps<br>5. Dual Piping (only for satellite scenario)<br>6. Treatment facility set up (only for satellite scenario) | Operational costs:<br>1. Consumables<br>2. Energy costs:<br>a) Treatment<br>b) Collection and distribution<br>3. Maintenance:<br>a) Inspection<br>b) Labor<br>4. Repairs<br>5. Land use |
| Benefits | 1. Savings in drinking water treatment and pumping costs<br>2. Savings in freshwater withdrawal<br>3. Savings in wastewater collection and treatment costs | |

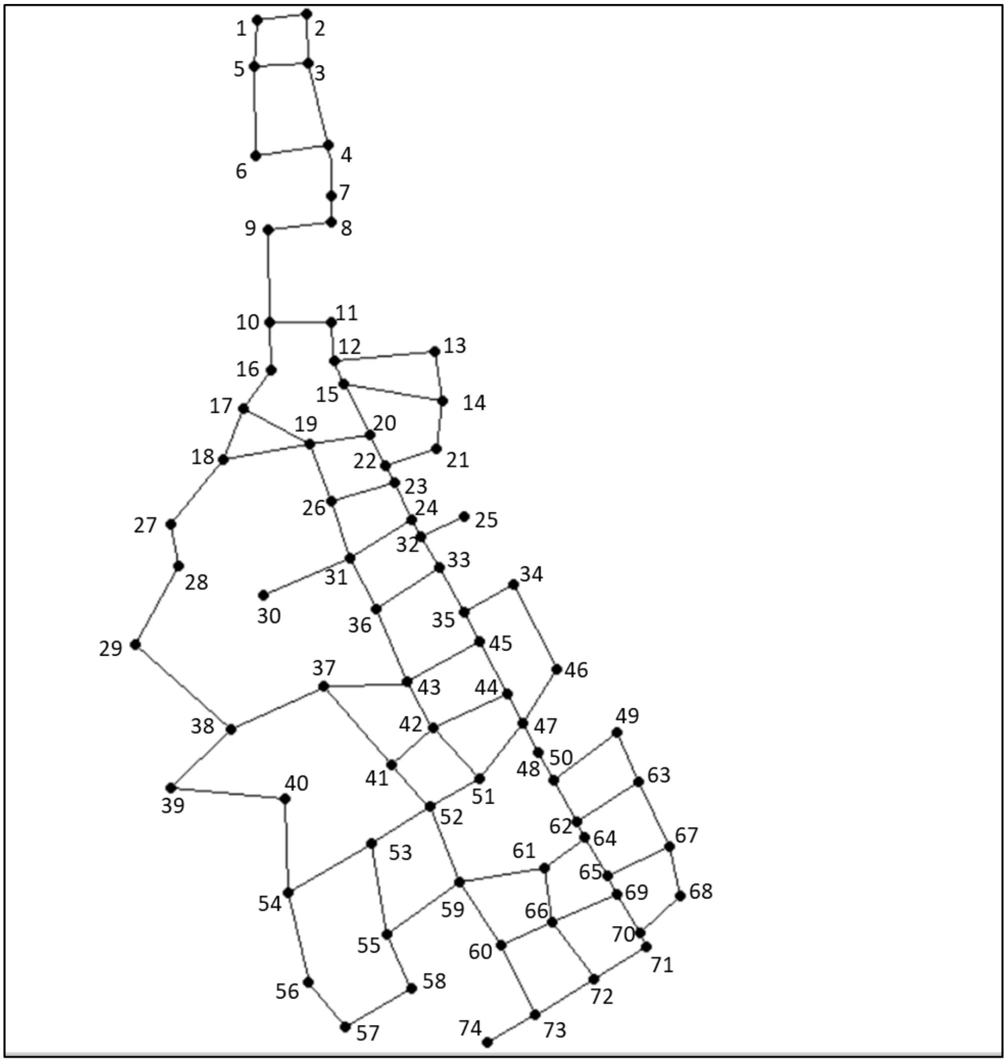


Figure 2-1: Layout of the Case Study Network

A section of a real-world water distribution network is chosen in this study to perform cost-benefit analysis for satellite and onsite greywater reuse scenarios. The skeletal water distribution network is appropriately modified by combining multiple nodes in order to characterize the water consumption features of multi-story buildings; the modified network is depicted in Figure 2-1. The modified study network consists of 74 demand nodes that are connected with 93 pipe links of diameters varying between 101.6

mm (or 4 inches) and 762 mm (or 30 inches), and with pipe lengths varying between 47.2 m to 420 m. Each node is assumed to be a 5-story building with 10 residential units – five two bed one bath units and five three bed two bath units. The type and number of raw greywater sources in both types of units is shown in Table 2-2. The breakdown of household potable water usage considered in this study is shown in Table 2-3.

Table 2-2. Type and number of raw greywater sources at each demand node

| | 2-bedroom unit | 3-bedroom unit | Total # of greywater sources per node |
|---|---|---|---|
| Wash basin | 2 | 3 | 25 |
| Shower | 1 | 2 | 15 |
| Washing machine | 1 | 1 | 10 |
| Bathtub | 1 | 1 | 10 |

Various end uses of treated greywater are permissible depending on the state environmental regulations and treatment level; these include but not limited to outdoor irrigation, industrial cooling, toilet flushing, vehicle washing, food crop irrigation, and other non-potable household water needs. It is believed that primary and secondary treatment levels are sufficient for end uses where there is no direct human contact with treated greywater, but advanced treatment is required for end uses which may require human contact (Yu, 2015). Only toilet flushing is considered the intended end use of treated greywater in this study, given that it accounts for a considerable portion of typical household water demand, as can be seen from Table 2-3. Treatment technologies are appropriately matched to this intended end use. Irrigational end use is considered as an additional end use in the sensitivity analysis. The following paragraphs describe the two scales of decentralization evaluated in this study along with associated added costs and expected benefits.

Table 2-3. Percentage distribution of household water usage (Adapted from Carragher et al., 2012)

| Appliance | Water Demand (%) |
|---|---|
| Tap | 19.30 |
| Bathtub | 1.07 |
| Irrigation | 4.20 |
| Leak | 5.60 |
| Toilet Flushing | 17.15 |
| Washing Machine | 21.64 |
| Shower | 29.48 |
| Dishwasher | 1.56 |

***Scales of Decentralization***

**Satellite:** In this scenario, raw greywater is separated from wastewater at the source to be collected and treated at a satellite treatment facility located not very far from the source nodes. Collected raw greywater and treated greywater are stored in separate tanks near the treatment unit. The study area shown in Figure 2-1 is divided into four zones with each zone having 18 or 19 demand nodes and one satellite treatment unit, as depicted in

Figure 2-2. The treated greywater is supplied through a networked pipeline system for toilet flushing and other reuse purposes.

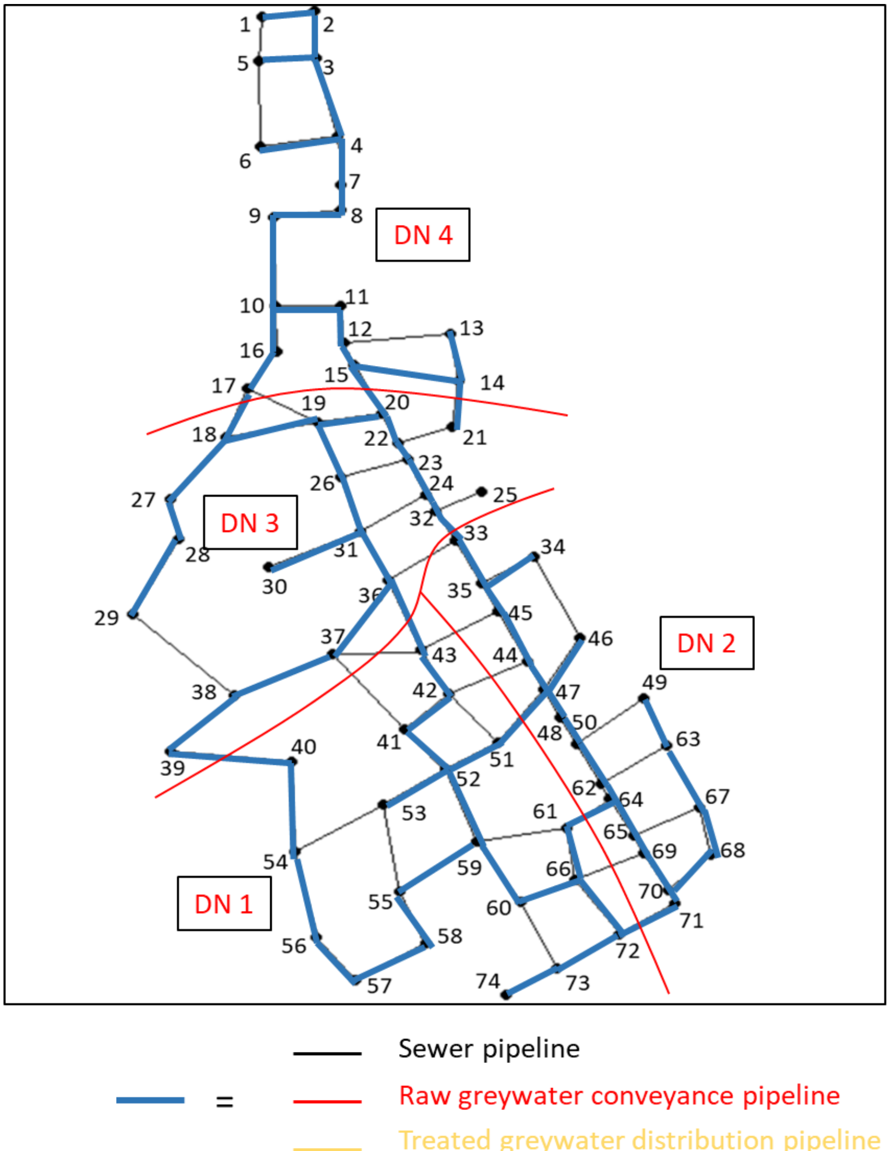


Figure 2-2: Satellite Scenario Schematic

Overall, one treatment unit and related housing facility, two storage tanks, two pumps (one for collection of raw greywater and another for supply of treated greywater), dual piping, and in-house plumbing adjustments are required for each zone in the satellite scenario.

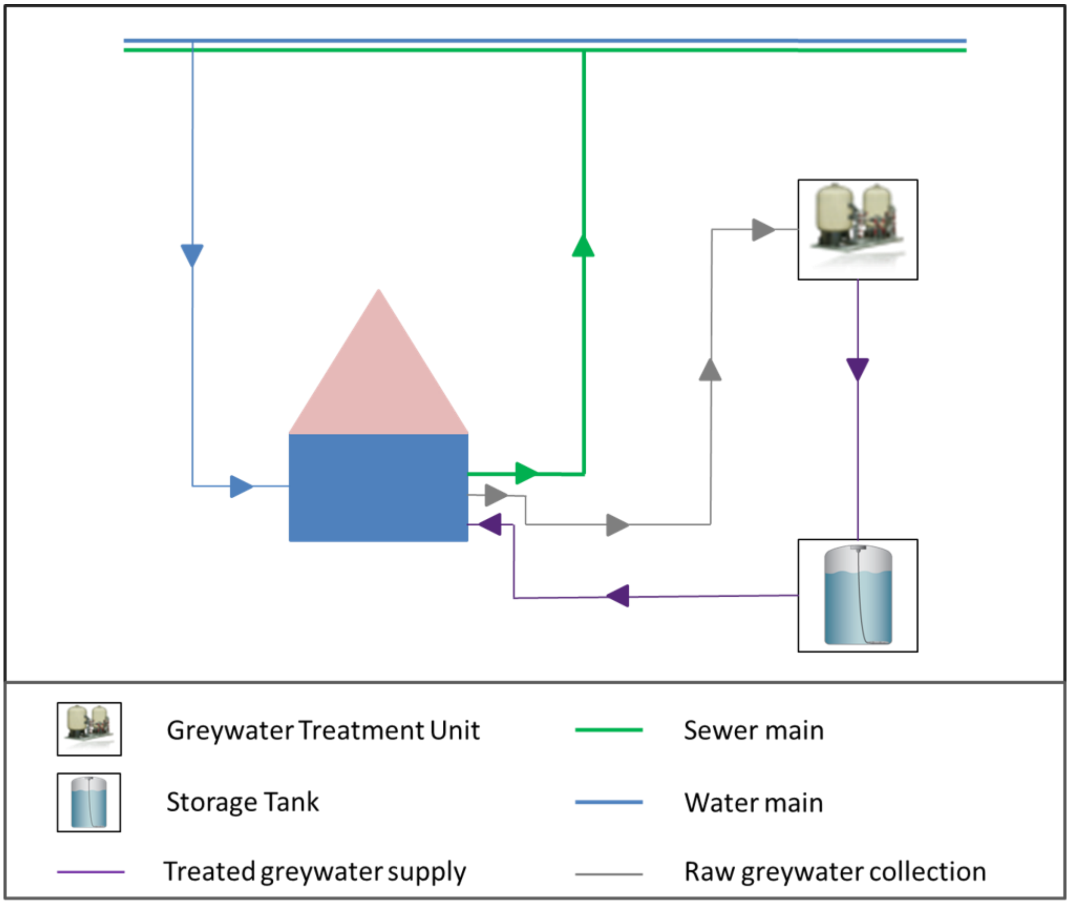


Figure 2-3: Onsite Scenario Schematic

**Onsite:** In this scenario, raw greywater is separated from wastewater and delivered for treatment at the same location as where it is produced. The treated greywater is pumped to an overhead tank for the purpose of storage and reuse as permitted. Required plumbing adjustments are made in the houses to separate raw greywater from wastewater, collect raw greywater, and supply treated greywater. Overall, one treatment unit, one storage tank, one pump and necessary plumbing adjustments are required at each demand node in the onsite scenario. A schematic representation of the onsite scenario is presented in Figure 2-3.

Literature suggests that simple technologies and sand filters have been shown to achieve only a limited treatment of the greywater whereas membranes were reported to provide good removal of the solids; although they could not efficiently tackle the organic fraction (Pidou et al. 2007). Membrane bioreactors (MBR) were reported to be able to achieve good microbial removal without the need for disinfection (Pidou et al. 2007). Rotating biological contractors (RBC) were also reported in the literature to be suitable for greywater treatment for toilet flushing and outdoor irrigation related reuse (Friedler and Hadari, 2006). Based on cost considerations presented in previous studies, RBC technology is determined to be economical for smaller quantities of greywater treatment (i.e., <154.7 $m^3$/day), whereas MBR is economical for larger quantities of greywater treatment (i.e., >154.7 $m^3$/day). As a result, it turned out that MBR is economical than RBC for the satellite scenario whereas the economical option for the onsite scenario could be RBC (<154.7 $m^3$/day) or MBR (>154.7 $m^3$/day) depending on the quantity of raw greywater collected and treated at each node.

*Added Costs*

The added costs include the capital, operational, maintenance, and repair costs as mentioned in Table 2-1.

Capital Costs

Capital costs include the purchase and installation costs of treatment units, plumbing adjustments, pumps, and storage tanks. Capital costs for these components are estimated using Equations 1-7, some of which are adopted from the literature (Friedler and Hadari, 2006) while others are appropriately formulated (Equations 4, 6 and 7) in this study:

$$C_{MBR} = 18{,}853 + 17{,}945 \times Ln(Q) \quad (1)$$

$$C_{RBC} = 3{,}590 \times Q^{0.6776} \quad (2)$$

$$C_{ST} = 2 \times 144 \times V^{0.484} \quad (3)$$

$$C_{PB} = C_{PF} \times (E_F \times F) \times ((D_S \times S_{GS}) + (D_S \times S_{TS}) + E_{ST}) \quad (4)$$

$$C_P = N_P \times 594 \times Q^{0.0286} \quad (5)$$

$$C_{DP} = 2 \times D_{T,P} \times (UC_P \times C_I) \quad (6)$$

$$C_{TP} = 0.5 \times C_{MBR\ or\ RBC} \quad (7)$$

Where,

$C_{MBR}$= Cost for MBR treatment technology ($/ ($m^3$/d))

$C_{RBC}$= Cost for RBC treatment technology ($/ ($m^3$/d))

$C_{ST}$ = Cost of each storage tank ($/$m^3$)

$C_P$ = Pump cost ($/ ($m^3$/d))

Q = Volume of treated greywater per day ($m^3$)

$C_{ST}$ = Cost of each storage tank ($/$m^3$)

V = Volume of each storage tank ($m^3$)

$C_{PB}$= Plumbing costs ($)

$C_{PF}$= Cost of pipe per foot ($/ft); ¾" plumbing pipe size is considered in this study

$E_{ST}$= Storage tank elevation (ft)

$D_S$= Distance between each greywater source (ft)

$S_{GS}$ = Sum of greywater sources

F = Number of floors at each node

$S_{TS}$ = Sum of greywater sources for toilet use

$E_F$ = Elevation difference between each floor (ft)

$N_P$ = Number of pumps considered

$C_{DP}$ = Cost of dual piping ($)

$D_{T,P}$ = Sum of distance between treatment plant and nodes (m)

$UC_P$ = Unit cost of pipe ($/m)

$C_I$ = Installation cost of unit pipe ($/m)

$C_{TP}$ = Cost of treatment plant facility ($)

$C_{MBR\ or\ RBC}$ = Cost of MBR or RBC treatment technology ($)

It should be noted that Equations 1-5 are applicable to satellite and onsite scenarios while Equations 1, 3-7 are applicable to only satellite or onsite scenarios. Furthermore, some of these equations had to be modified appropriately from satellite to onsite scenario; for example, only one storage tank is considered to be used in the onsite scenario and accordingly Eq. 3, which characterizes the satellite scenario, has been modified to $C_{ST} = 144 \times V^{0.484}$.The distance between greywater sources in a typical housing unit is assumed to be 5 ft while the elevation difference between consecutive floors is assumed to be 10 ft for purposes of calculating plumbing adjustment needs and associated costs. Costs of plumbing were adjusted for satellite scenario to reflect the fact that there would not be an overhead storage tank at the demand location. Furthermore, cost of dual piping is only applicable to satellite scenario because there is no need for additional water mains in the onsite scenario. It should be noted that a chlorination unit is estimated to cost about $1670/unit (Friedler and Hadari, 2006).

Operational, Maintenance and Repair Costs

This category includes all the costs associated with disinfectant consumables, electricity, and labor required for maintenance and repairs. Liquid Chlorine is considered the choice of disinfectant and its consumption is estimated using 0.003 kg/ $m^3$ of treated greywater (Friedler and Hadari, 2006). Electricity consumption for treatment and storage is estimated using 1.5 $kWh/m^3$ of treated greywater, while it is considered 0.475 $kWh/m^3$ for supply of treated greywater (Friedler and Hadari, 2006). A $20/hr of labor cost for maintenance, assuming one labor hour worth of work per week per node, is considered. Furthermore, half an hour per week of labor time for inspection purposes is budgeted. The repair costs are reasonably assumed to be 5% of total energy costs. Assuming a 50 year life cycle period, present value of the various annualized operational and maintenance expenses are appropriately calculated. Based on an estimated requirement of 15,000 $m^2$ of area for housing a MBR treatment plant with a capacity of 1900 $m^3$/day (Gander et al., 2000), a land use cost of $8000/month/treatment facility is appropriately budgeted for the satellite scenario. The operational, maintenance and repair costs are calculated using the following equations:

$$C_D = 62.11Q \tag{8}$$

$$C_{ET} = 365Q \times E_C \times C_{UE} \quad (9)$$

$$C_E = 365Q \times E_{CD} \times C_{UE} \quad (10)$$

$$C_L = 12 \times R_H \times M_W \quad (11)$$

$$C_{Ins} = IP \times MS \times D_{MS} \quad (12)$$

$$R_C = 0.05 \times (C_E + C_{ET}) \quad (13)$$

$$PWF = \frac{1-(\frac{(1+I)}{(1+A)})^T}{(A-I)} \quad (14)$$

Where,

$C_D$= Disinfectant cost ($)

Q = Volume of treated greywater ($m^3$/h)

$C_{ET}$= Annual electricity cost for treatment ($/year)

$E_C$= Electricity consumption (kWh/$m^3$)

$C_{UE}$= Unit electricity cost ($/kWh)

$C_E$= Annual electricity cost for conveyance and distribution ($/year)

$E_{CD}$= Energy required for conveyance and distribution (kWh/$m^3$)

$C_{UE}$= Unit electricity cost ($/kWh)

$C_L$= Annual labor costs ($/year)

$R_H$= Hourly wage rate ($/h)

$M_W$=Maintenance sessions per month

$C_{Ins}$ = Annual inspectional costs ($/year)

IP = Inspection personnel charges ($/hr)

MS = Number of maintenance sessions per year

$D_{MS}$ = Duration of each maintenance session (hr)

$R_C$ = Annual repair costs ($/year)

PWF= Present worth factor,

I=Annual Inflation,

A= Annual percentage increase in material (consumables, electricity) cost,

T= Time period (years)

It should be noted that Eq. 8 is adopted from the literature (Friedler and Hadari, 2006) while other equations are appropriately formulated in this study. Furthermore, Eq. 14 is used for calculating present worth factor of consumables and electricity.

***Expected Benefits***

The direct benefits of greywater reuse are the reductions in both the amount of potable water withdrawn from the water distribution network and the amount of wastewater released to the sewer network. There would be a direct monetary benefit associated with these in the form of reduced utility bills. Furthermore, reduced amount of freshwater would be withdrawn from freshwater aquifers contributing to water sustainability. An indirect benefit that has not been estimated in this study is the deferred capital expenditure in rehabilitating water and sewer infrastructure systems due to the reduced burden they would experience as a result of decentralized greywater reuse systems. The direct benefits of reduced utility bills and the value of reduced freshwater withdrawal from water aquifers are considered as benefits in this study. These benefits are estimated using the following equations:

$$S_{WTP} = U_{UC} \times G_T \times 365 \times PWF \quad (15)$$

$$S_{WW} = U_{WW} \times G_T \times 365 \times PWF \quad (16)$$

$$S_{WWTP} = U_{WWTP} \times G_T \times 365 \times PWF \quad (17)$$

Where,

$S_{WTP}$= Cost of savings from water treatment and pumping, $

$U_{UC}$= Utility unit cost, $/m$^3$

$G_T$= Treated greywater used for toilet flushing, m$^3$

PWF= Present worth factor

$S_{WW}$= Cost of savings from water withdrawal, $

$U_{WW}$= Water withdrawal unit cost, $/m$^3$

$S_{WWTP}$= Cost of savings from wastewater treatment and pumping, $

$U_{WWTP}$= Wastewater treatment and pumping unit cost, $/m$^3$

**Demonstration**

Cost-benefit analyses of satellite and onsite scenarios for a 50-year life cycle period are presented in this section. Figure 2-4 illustrates the cost-benefit comparison between the satellite and onsite scenarios. It can be observed from Figure 2-4 that the added costs are much greater than the expected monetary benefits in both satellite and onsite scenarios. It can also be observed from Figure 2-4 that the satellite scenario is more expensive than the onsite scenario over the life cycle period. It can be further observed from Figures 2-5 and 2-6 that dual piping, operational energy and land use accounted for majority of added costs in the satellite scenario whereas treatment units and operational energy accounted for most of added costs in the onsite scenario, respectively.

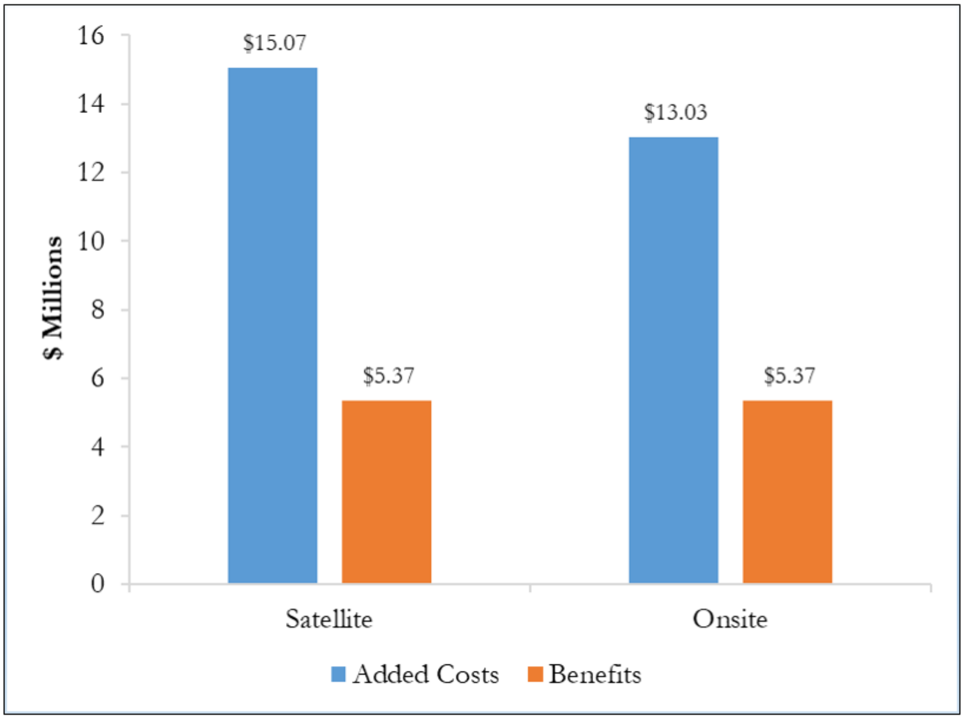


Figure 2-4: Cost-Benefit Comparison in the Baseline Case

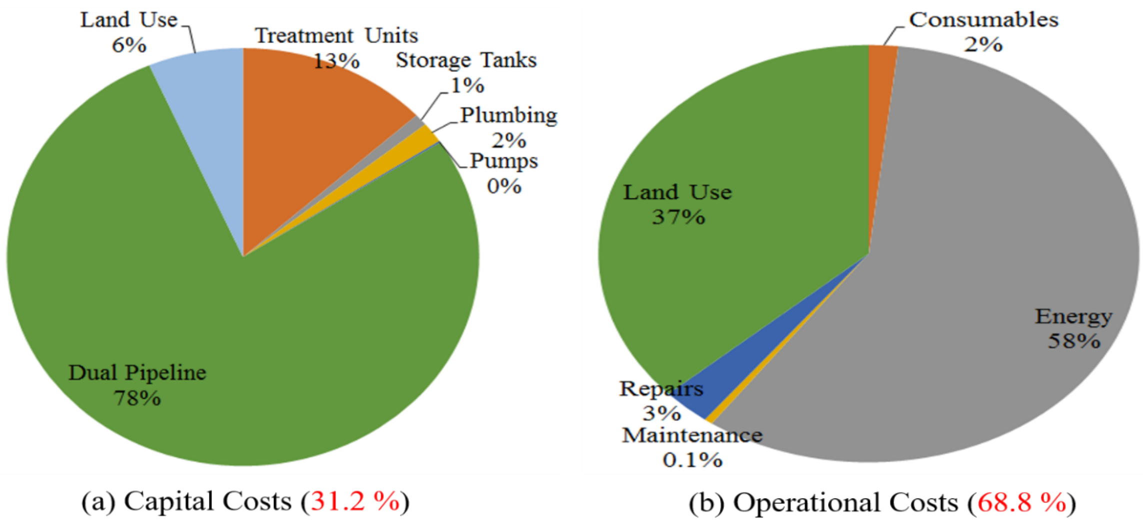


Figure 2-5: Distribution of Life Cycle Costs in the Satellite Scenario

The treatment units related capital costs and operational energy costs in the onsite scenario accounted for about 91% of the life cycle costs, which highlights the need for making these modular treatment units cheaper and energy efficient for them to be more economically feasible. Similarly, energy efficient treatment, collection and supply of greywater along with reduced dual piping and treatment facility costs would make the satellite scenario more economically feasible. The monetary benefits in both scenarios remained same because the estimated reduction in water withdrawal from the drinking water system and wastewater outflow into the sewer system are assumed to be dependent on the percentage of treated greywater that could be re-used at each demand node, which is same for both scenarios.

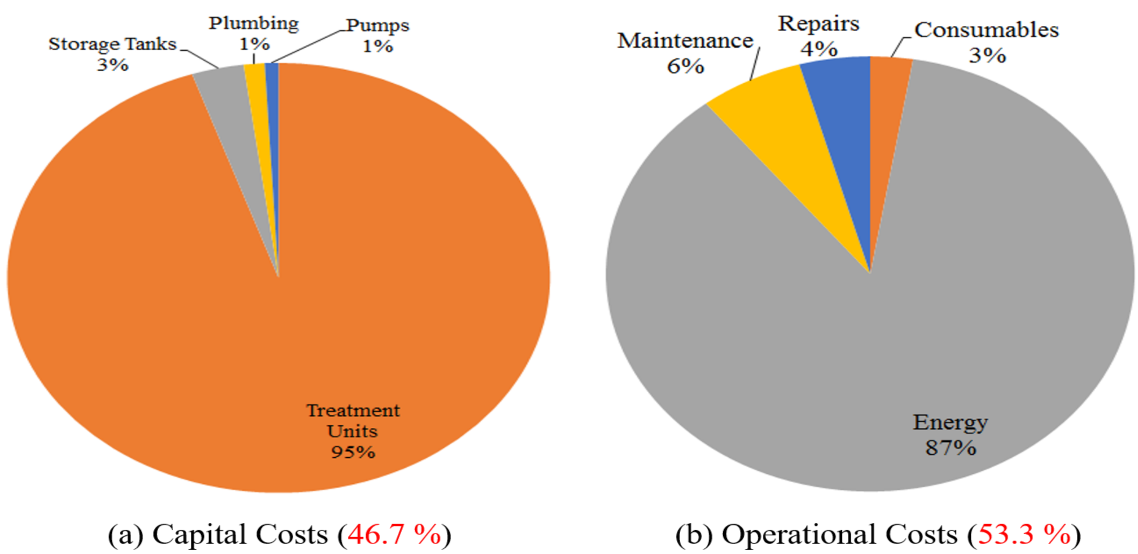


Figure 2-6: Distribution of Life Cycle Costs in the Onsite Scenario

**Sensitivity Analysis**

A number of reasonable assumptions were made in performing the cost-benefit analyses of the satellite and onsite scenarios. The sensitivity of the cost-benefit tradeoff to potential uncertainties associated with the parametric assumptions made in this study is further investigated. A number of sensitivity analyses are consequently devised, as shown in Table 2-4.

Table 2-4. Description of the sensitive analysis parameters

| # | Description | Parameter | Base Case | Range |
|---|---|---|---|---|
| 1 | Cost of treatment unit (TC) | Treatment unit cost ($) | 100% | [-30% to 0%] |
| 2 | Value of freshwater withdrawal (WW) | Benefit ($/m$^3$) | 0.077 | [0.054 to 0.1] |
| 3 | Added irrigational use (IU) | Total % use of treated GW | 17.15% | [17.15% to 37.15%] |
| 4 | Unit energy price (UE) | ($/kWh) | 0.12 | [0.084 to 0.156] |
| 5 | Unit utility cost (UU) | ($/m$^3$) | 0.311 | [0.22 to 0.4] |
| 6 | Varying raw GW sources (VS): BT+WM+S | % of GW treated | 100% | 52.18% |
| | BT+S | | | 30.54% |
| | BT+Tap+S | | | 40.19% |
| | BT+WM+Tap | | | 32.35% |
| | Tap+S | | | 39.13% |
| | WM+Tap | | | 31.29% |
| | Tap+WM+S | | | 60.77% |
| | WM+S | | | 51.12% |
| | BT+WM | | | 22.70% |
| Raw GW Source Acronyms: BT-Bath tub; WM-Washing machine; S-Shower; Tap-Bathroom sink; | | | | |

Variation in the following parameters is studied in the sensitivity analyses: (a) treatment technology costs, (b) value of reduced freshwater withdrawal, (c) added irrigational use of treated greywater, (d) unit energy prices, (e) unit utility cost, and (f) raw greywater sources. Furthermore, sensitivity of the cost-benefit tradeoff is analyzed when greywater is collected from one region but treated and reused in multiple regions. The sensitivity analysis is presented in two parts. In part-A, parameters a-f are briefly described and the results of the sensitivity of total costs and benefits to variation in these parameters are presented. In part-B, benefits of sharing greywater between different regions are described.

***Part-A***

***(a) Cost of treatment units (TC)***

Small-scale treatment technologies are continuously evolving and it is reasonable to anticipate that their costs would decline and quality (and reliability) would go up with time. Treatment related capital costs entail the purchase price of modular treatment units and the chlorination units. A decrease in the treatment cost of up to 30% is considered in the sensitivity analysis, as shown in Table 2-4.

***(b) Value of reduced freshwater withdrawal (WW)***

The value in reduced freshwater withdrawal is considered in this study as one of the benefits associated with greywater reuse adoption. This benefit is estimated using a literature suggested unit value of 0.077 $\$/m^3$ (VNRC, 2013). This value in reality could vary significantly depending on the type of the region and the associated water security issues. Consequently, the sensitivity of the cost-benefit tradeoff to variation in this unit value is investigated. A possible variation of ±30% is considered in the sensitivity analysis, as shown in Table 2-4. Change in the value of reduced freshwater withdrawal would not affect the added costs for both satellite and onsite scenarios, but only affect the benefits.

***(c) Added utility of treated greywater for irrigation (IU)***

In the baseline case, only household toilet flushing is considered allowable utility of treated greywater. Because the total amount of raw greywater collected is more than the demand for toilet flushing, there would be surplus amount of treated greywater produced. To maximize the benefit resulted from greywater reuse, an additional re-use utility in the form of irrigational use is considered with additional demand of up to 20% of treated greywater, as shown in Table 2-4. Only the resulting benefits would vary, but the added costs remain the same when an additional irrigational re-use option is considered. Clearly, the benefits associated with the adoption of greywater re-use would improve with greater utility of the treated greywater, as permitted by the state and federal regulations, and could also become comparable to the added costs.

***(d) Unit energy price (UE)***

Energy prices fluctuate in response to various physical, political and market forces, but their prediction is vital to economic infrastructure planning. The sensitivity of life cycle costs to variation in energy prices is investigated by considering a possible variation of ±30% from its base value of $ 0.12/kWh, as shown in Table 2-4.

***(e) Unit utility cost (UU)***

The sensitivity of the benefits associated with adoption of greywater reuse systems to variation in water and sewer utility rates is investigated by considering possible variation of ±30%, as shown in Table 2-4. It should be noted that both water utility and sewer utility rates are simultaneously increased or decreased by same percentage in each of the sensitivity analysis simulations.

***(f) Varying greywater sources (VS)***

Considering toilet flushing as the only utility of treated greywater, it may not be necessary to collect and treat all of the available raw greywater. Consequently, the raw greywater sources that would be tapped for collection in a typical residential unit have been varied to determine how the cost-benefit tradeoff in both onsite and satellite scenarios changed. Specifically, nine combinations of greywater sources are considered, as shown under in Table 2-4. The treatment, plumbing, and pumping costs are expected to vary when the number and type of raw greywater sources vary. The baseline case considered all the feasible raw greywater sources, namely bath tub (BT), washing machine (WM), shower (S) and tap (T). The sensitivity analysis simulations randomly consider one of the nine possible combinations identified in Table 2-4 for this parameter. The percentage of feasible raw greywater collected in each of the nine combinations is also presented in Table 2-4.

***Multi-Variate Analysis:***

Firstly, a reasonable range of variation is defined, as shown in Table 2-4, for each parameter to study the sensitivity of both added life cycle costs and benefits to such variation. Secondly, principles of Monte Carlo simulation method are used to generate random samples for parametric values from the defined respective ranges to carry out the sensitivity analysis. To maintain the precision and accuracy of the results, 10,000 simulations of random parametric values are generated and studied as part of the sensitivity analysis. In each simulation, multiple parameters are simultaneously varied in a random manner within the chosen range. Thirdly, standardized coefficients in multi-variate regression analysis are calculated to determine the relative influence of each parameter on both added life cycle costs and benefits. Minitab software has been used for the regression analysis (Zhang et al., 2018). The input variables for the regression analysis include all the six parameters studied in the sensitivity analysis whereas the response or output variables are added life cycle costs or benefits. The standardized regression coefficients offer a good measure of the influence of the input variables on the response variables irrespective of the scale of the input variables, and therefore they are considered appropriate for comparing the relative importance of multiple input variables of different scales (or units).

Table 2-5. Standardized coefficient values for Onsite and Satellite scenarios

| Parameters | Onsite | | Satellite | |
|---|---|---|---|---|
| | Added costs | Benefits | Added costs | Benefits |
| Reduced cost of treatment unit (TC) | **363610** | 5768 | **220100** | 3461 |
| Value of freshwater withdrawal (WW) | -4042 | **150649** | 16985 | **148714** |
| Added irrigational use (IU) | 1958 | **1799515** | 11673 | **1803826** |
| Unit energy price (UE) | **713214** | -2143 | **712290** | -380 |
| Unit utility cost (UU) | 123 | **1318485** | 11018 | **1320147** |
| Varying Raw GW sources (VS) | **1966532** | -5560 | **1610277** | -1656 |

Table 2-5 presents the standardized coefficients for all the parameters when added costs and benefits are separately considered as response variable for the onsite and satellite scenarios. The results from Table 2-5 suggest that varying sources (VS) has largest standardized coefficient value, followed by unit energy (UE) cost and treatment unit cost

(TC) for added costs, and therefore it can be inferred that these three are the most influential parameters in that order. Similarly, most influential variables for benefits are found to be irrigational use (IU), change in unit utility (UU) cost and freshwater withdrawal (WW) in that order. It can be noted that the influential variables and their relative influence for both onsite and satellite scenarios remain the same.

Furthermore, based on the analysis of the 10,000 simulations in the sensitivity analysis, various optimal configurations have been identified in Table 2-6. As expected based on the results from the multi-variate sensitivity analysis, least cost configurations in both onsite and satellite scenarios are driven by least parametric values for the three most influential parameters - greywater sources, treatment unit costs, and unit energy costs per Table 2-4. Similarly, highest cost configurations in both onsite and satellite scenarios are driven by highest parametric values for the same three influential parameters. Varying raw greywater sources is significant in determining the added costs, as it directly affects treatment unit cost, treatment technology costs, and plumbing costs. On the other hand, least (and highest) benefits for both onsite and satellite scenarios are driven by least (and greatest) parametric values for irrigational use, unit utility cost, and value of reduced freshwater withdrawal. It is interesting to note that three of the optimal configurations presented in Table 2-6 have greater expected benefits than added costs.

Table 2-6. Least/Greatest Cost/Benefit configurations for Onsite and Satellite scenarios

| | Onsite Scenario | | | | Satellite Scenario | | | |
|---|---|---|---|---|---|---|---|---|
| | Least Cost | Greatest Cost | Least Benefit | Greatest Benefit | Least Cost | Greatest Cost | Least Benefit | Greatest Benefit |
| Added life cycle cost ($ million) | 4.51 | 14.65 | 7.97 | 7.52 | 9.95 | 16.77 | 7.97 | 7.52 |
| Benefits ($ million) | 6.62 | 8.81 | 3.84 | 14.96 | 8.40 | 11.42 | 3.84 | 14.96 |
| Change in treatment costs (%) | -30 | -1 | -12 | -26 | -28 | -3 | -12 | -26 |
| Freshwater withdrawal ($/m$^3$) | 0.074 | 0.09 | 0.055 | 0.097 | 0.076 | 0.077 | 0.055 | 0.097 |
| Irrigational use (% use of treated GW) | 25.24 | 31.31 | 17.35 | 36.91 | 35.24 | 31.91 | 17.22 | 37.12 |
| Unit energy cost ($/kWh) | 0.084 | 0.156 | 0.14 | 0.15 | 0.084 | 0.156 | 0.14 | 0.15 |
| Unit utility cost ($/m$^3$) | 0.29 | 0.27 | 0.22 | 0.4 | 0.23 | 0.36 | 0.22 | 0.4 |
| Varying sources (% raw GW collected) | 0.227 | 0.6077 | 0.3235 | 0.3054 | 0.227 | 0.6077 | 0.3235 | 0.3054 |

***Part-B:***

***Zonal planning for greywater reuse:***

Because surplus amount of treated greywater is produced considering toilet flushing alone as the utility, the satellite scenario planning has been optimized to enable fewer treatment units treat and deliver water to the entire network. In the baseline case, the entire study area is divided into four zones (labeled 1, 2, 3 and 4), as shown in Figure 2-2, assuming each of these zones would house one satellite treatment unit where raw greywater from all the individual nodes in that zone is collected, treated and re-supplied. Two modifications are considered to this baseline zonal planning case: (a) satellite treatment units are only located in zones 1 and 3, and (b) satellite treatment units are only located in zones 2 and 4. The benefits with such modifications result from reduced capital and operational expenses associated with the treatment units, raw greywater collection pipelines, and pumps that would otherwise be needed in each of the four zones.

Figure 2-7 illustrates the variation in added costs with different zonal planning alternatives. It can be observed from Figure 2-7 that added costs have roughly diminished by half when compared to the baseline case and that having satellite treatment units in zones 2 and 4 would be little cheaper than having them in zones 1 and 3. The resulting benefits remain the same in these modified zonal planning cases because the utility of treated greywater does not change in all the zones.

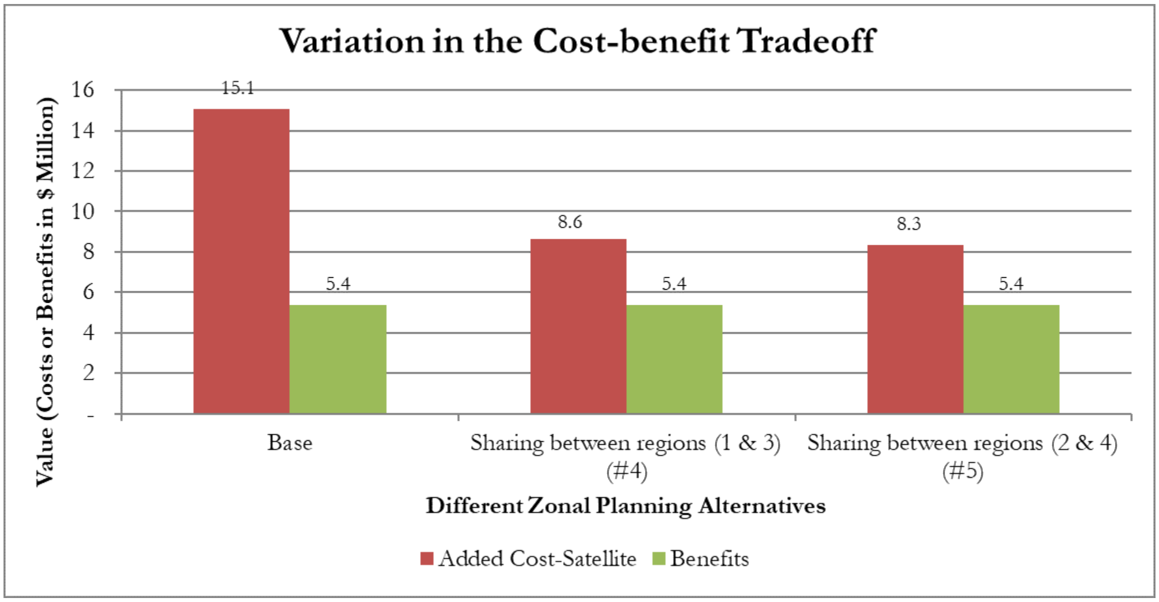


Figure 2-7: Variation in the Cost-benefit Tradeoff with Change in Treatment Unit Costs

**Discussion**

It can be understood from Figure 2-4 that added costs in both satellite and onsite scenarios are at least 140% greater than the benefits, thereby leaving a considerable gap for greywater reuse adoption to be economically viable. Over 90% of the added life cycle costs for onsite scenario are accounted by treatment related capital costs (~44.4%) and operational energy costs (~46.4%). On the other hand, about 90% of the added life cycle costs in the satellite scenario are accounted by operational energy costs (~39.9%), land use costs (~25.5%), and dual piping capital costs (~24.3%). Clearly, operational energy costs accounted for a significant portion of the added life cycle costs for both onsite and satellite scenarios and consequently, greater energy efficiencies in treatment and pumping operations would have the greatest impact on the economic viability of greywater reuse systems, as can be noted from the results of sensitivity analyses where unit energy (UE) costs were found to be influential. Furthermore, it is observed that collecting and treating only a portion of the raw greywater produced in a typical household is sufficient and economical to meet the toilet flushing needs. Specifically, treating raw greywater collected from bath tubs and washing machines (i.e., least cost scenarios in Table 2-6 where bath tubs and washing machines are considered as raw greywater sources) would be the cheapest option for both satellite and onsite scenarios in order to meet the toilet flushing needs.

Reducing the capital costs of treatment units would significantly diminish the added life cycle costs for onsite scenario. On the other hand, sharing of treated greywater collected from only few zones is found to be cheaper for satellite scenario. Additionally, financial incentives provided to manufacturers of greywater reuse systems and associated infrastructure components as well as to house owners in terms of tax credits and low interest loans would further bring down the added life cycle costs for the owner.

In terms of benefits, adding irrigational reuse utility resulted in greatest rise in expected benefits – as can be seen from Table 2-5 – followed by rising utility rates. As the utility rates go up, the anticipated benefits go up and tend to bridge the gap with added costs. Further allowances of using treated greywater for purposes such as vehicle washing in residential settings or cooling onsite power-generation units in industrial settings may produce greater benefits.

**Conclusions and Recommendations**

An easy-to-use life cycle cost model that can be adapted to any study area is presented in this study. The life cycle cost model has been used to perform comparative analysis of added life cycle costs and expected monetary benefits for satellite and onsite greywater reuse systems. Such cost-benefit comparison is imperative for understanding the critical bottlenecks to greater adoption of satellite or onsite water-reuse systems. The methodology and the results of this study will support water utilities, especially those in water-scarce/drought-prone regions, in the planning of future water supplies. Studies such as this may also be used in educational programs to develop awareness among policy makers and consumers regarding the benefits of greywater reuse systems and their decentralization.

Future work should consider dynamic household water usage patterns to account for possible temporal variation in the availability of raw greywater as well as the demand for treated greywater. Other potentially feasible treatment technology options such as activated carbon, reverse osmosis, advanced oxidation, and soil aquifer treatment processes should be evaluated for their economic merits.

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# CHAPTER THREE

# EVALUATION OF WATER SUPPLY RELIABILITY IMPROVEMENT ENABLED BY ON-SITE GREYWATER REUSE SYSTEMS[1]

Water utilities are under enormous pressure to provide a continuous supply of potable water under the presence of an increasing supply-demand deficit. The deteriorating condition of our centralized water distribution infrastructure exacerbates this uncertainty due to the growing number of main breaks and the associated supply interruptions. Distributed water supply systems leveraging treated household and industrial greywater or blackwater are currently being explored as a sustainable alternative in many arid regions to reduce their dependence on conventional freshwater resources. While the sustainability benefits of such alternate water resources have been established, the reliability improvement benefits have seen limited research. To address this need, the objective of this study is to evaluate the reliability improvement when on-site greywater reuse systems complement existing centralized water distribution infrastructure. This study presents a computational water supply reliability model adapted to suit both centralized and on-site supply scenarios. This model is applied to a small water distribution system to evaluate the reliability improvement benefits and further assess their sensitivity to a variety of adoption scenarios and infrastructure characteristics. The results reveal that when on-site greywater reuse systems supplement existing water supply systems, the supply reliability improved up to 195% and 65% for the least cost and the reasonable design scenarios, respectively. However, the reliability improved only up to 31% and 23% for the least-cost and reasonable scenarios, respectively, when the centralized system was merely retrofitted with on-site freshwater storage. The subsequent sensitivity analyses found that the improvement in supply reliability decreased with the increase in

[1] Standalone Published Research Article: Momeni, A., **Yerri, S.**, Piratla, K. R., & Madathil, K. C. (2022). Evaluation of water supply reliability improvement enabled by on-site greywater reuse systems. *Resources, Conservation and Recycling*, *182*, 106326.

system age and pipeline failure growth rate, whereas it increased with an increase in maximum usable reclaimed water, treatment efficiency, and the pipeline roughness coefficient. Overall, the results encourage the adoption of on-site greywater reuse systems from the perspective of infrastructure supply reliability.

**Introduction**

Water, which plays an essential role in the well-being of individuals, communities, and our economy, has multiple purposes ranging from human consumption to industrial cooling, transportation, and irrigation. However, the warmer temperatures due to climate change have been linked to decreasing freshwater in many regions across the globe (Karl et al., 2009). These water security crises are being met with increased reliance on alternate water sources such as reclaimed water and desalination where appropriate. Further, the water distribution infrastructure that supplies the treated freshwater to residential and industrial consumers is old and has deteriorated to the extent that many water utilities are concerned about the reliability of their supply due to an increasing number of pipeline breaks and the resulting supply interruptions. Reliability in this industry is conceived as the ability to continuously meet consumer demand for water both during regular operations and failure events. In 2009, the U.S. Environmental Protection Agency (EPA) projected that an investment of approximately $335 billion over 20 years is needed to upgrade the existing drinking water infrastructure in the United States (Hughes, 2010). With the limited financial resources made available to water utilities, it is unlikely that our water infrastructure will be improved and modernized in the short term.

Alternative water resources with the potential to address the concerns about freshwater scarcity would also minimize reliance on the distribution infrastructure if they are made available at the point of consumption. The resulting benefits to the water utilities include improved supply reliability, a reduced burden being placed on our outdated distribution infrastructure, and a potential deferment of capital improvement investments. One such alternative water source that has proven practical is the use of reclaimed water, specifically the reuse of greywater, wastewater that has not come in contact with toilet, kitchen sink, or dishwater waste (Al-Jayyousi, 2003).

These reuse systems have been found to be beneficial for sustainable water management as well as resulting in a meaningful decrease in water consumption (Vuppaladadiyam et al., 2019; Yerri and Piratla, 2019), and their use has resulted in a decrease in domestic water consumption of approximately 40% (Atanasova et al., 2017; Vuppaladadiyam et al., 2019). More importantly, it has been reported that minimal investment is required for a sustainable local greywater reuse application if it is well serviced (Prodanovic et al., 2017). While there have been previous studies demonstrating the sustainability benefits of greywater reuse systems (Yerri and Piratla, 2019), there have not been many studies focusing on the supply reliability benefits that greywater reuse systems offer due to reduced reliance on water distribution systems. The most notable studies along the lines of system reliability associated with greywater reuse analysis are (1) review on chemical analysis of filtration and disinfection of greywater reuse (Al-Mefleh et al., 2021; Hess et al., 2021), (2) review on the characteristics of efficient greywater reuse (Maimon & Gross, 2018), (3) high-level qualitative assessment of the greywater reuse application (Vuppaladadiyam et al., 2019). To address the limitation on a robust, numerical assessment of a greywater reuse scenario, this study evaluates the supply reliability benefits offered by on-site greywater reuse systems when they complement existing water distribution systems. The sensitivity of the reliability improvement to various systemic variables is also analyzed.

## Methodology

The methodology is described through (i) the characterization of a typical water distribution system (or centralized) and the complementary on-site greywater reuse (or decentralized) adoption scenarios; and (ii) the formulation of the reliability for both the centralized and decentralized greywater reuse scenarios along with a set of formulae to only account for nodally-retrofitted on-site freshwater storage tanks for comparative analysis.

### *Characterization of Centralized and Decentralized Water Supply Scenarios*

A centralized water supply, depicted in Figure 3-1a, is the typical scenario where water is supplied to end users through a distribution network after it has been treated at a centralized water treatment plant (Small water systems, 2020). Used water is first collected through a sewer collection system and then pumped to a centralized wastewater treatment plant where certain pollutants are removed before the effluent is released into nearby water bodies.

In the decentralized supply scenario, as depicted in Figure 3-1b, the centralized supply systems are complemented by on-site greywater reuse systems. In this scenario, it is assumed that each consumption point will have a treatment unit along with some storage capacity. Greywater produced at a given dwelling is collected, treated on-site and then stored for appropriate reuse. The remainder of the water demand at the dwelling will be met through the centralized system. Past research has investigated the decentralized supply scenario, focusing on its cost-benefit tradeoff in comparison with the centralized scenario based on aspects of their life cycles (Yerri and Piratla, 2019). The decentralized scenario explored here is based on the following criteria:

1. Reclaimed water is sent to a local reservoir after treatment.
2. Mass balance equations for decentralized systems are written using one-hour time steps to determine the amount of usable reclaimed water.
3. Reclaimed water is preferred over the centralized supply for meeting the non-potable demand.
4. The centralized or existing supply system is used to meet the remainder of the non-potable and potable demand at each node.

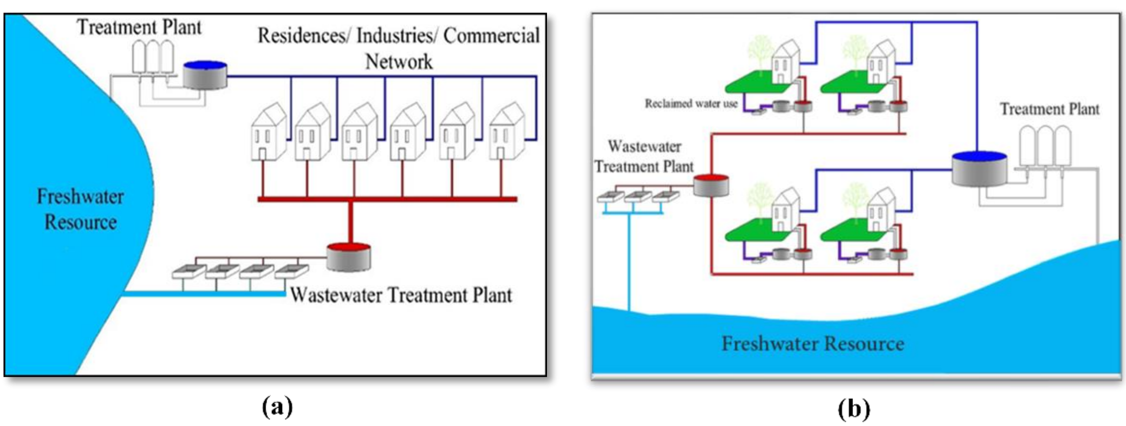



Figure 3-1. Depiction of (a) Centralized and (b) Decentralized Water Supply Scenarios (Goverdhanam, 2014; Piratla & Goverdhanam, 2015)

***Reliability Formulation***

Reliability has several definitions in the context of water supply systems, with most referring to the system's ability to successfully perform under normal and abnormal operational conditions (Giustolisi, 2020; Piratla & Ariaratnam, 2011; Walski, 2020). Abnormal operational conditions in such systems refer to either a demand upsurge (i.e., unusually large withdrawals) or mechanical failure of infrastructure components (i.e., pipe failure or pump breakdown), with reliability of the former commonly referred to as hydraulic reliability and the latter as mechanical. While a completely reliable system is capable of full functionality despite various possible failure scenarios, designing such a system is usually not possible. The reliability assessment model used in this study was adopted from the methodology found in Ciaponi et al. (2012), which considers only the mechanical failure scenarios that are more prevalent in water utilities due to an aging pipeline infrastructure. This section discusses the probabilistic reliability formulation of the centralized and decentralized supply scenarios. New formulations for the physical schemes of decentralized reuse systems are developed and appropriately integrated with the conventional water supply schemes. Additionally, an on-site freshwater storage scenario is formulated and investigated for reliability improvement. The computational reliability assessment model was developed using the MATLAB programming platform in conjunction with a hydraulic network solver, specifically EPANET 2.2. In this study, a 24-hour cyclic pattern has been studied to correspond with the customary practice of daily tank scheduling in most industrial settings.

*Reliability Formulation for the Centralized Supply Scenario*

The reliability of the centralized supply system is estimated using the formulation presented in Equations 1 through 3 based on a pressure-driven demand (PDD) approach of hydraulic analysis. The widely used hydraulic solver EPANET 2.2, which is equipped with the pressure-driven demand option for hydraulic analysis, was used here to accurately estimate the nodal supply ($C_{i,j}$) in a failure event. All single pipeline failure scenarios along with a no-failure scenario are considered as possible working states (*k*) in the reliability assessment:

$$R = \sum_{k=1}^{WS} W_k * RR_k \quad [1]$$

$$RR_k = \frac{\sum_{i=1}^{TS} \sum_{j=1}^{N} ATS_{i,j}}{\sum_{i=1}^{TS} \sum_{j=1}^{N} D_{i,j}} \quad [2]$$

$$ATS_{i,j} = \begin{cases} D_{i,j} & if\ C_{i,j} \geq D_{i,j} \\ C_{i,j} & if\ C_{i,j} < D_{i,j} \end{cases} \quad [3]$$

where $i$ = hourly hydraulic time steps from 1 to $TS$ (=24), $j$ = node indices from 1 to $N$, $N$ equals the number of nodes in the water distribution network (WDN), $TS$ = total number of hydraulic time steps in the demand pattern, $D_{i,j}$ = demand at node $j$ in time step $i$ (*GPM*), $C_{i,j}$ = supplied flow at node $j$ in time step $i$ in gallons per minute (*GPM*), $ATS_{i,j}$ = actual total supply at node $j$ in time step $i$ (*GPM*), $W_k$ = probability of realizing the working state $k$, $RR_k$ = WDN performance in working state $k$, $R$ = global reliability of WDN, and $WS$ = number of working states the WDN can possibly experience considering single pipeline mechanical failures.

*Reliability Formulation for the On-site Storage Centralized Supply Scenario*

Equations 4 through 13 represent the formulation set associated with the on-site freshwater cylindrical storage-included centralized supply scenario considering a PDD analysis in EPANET 2.2. This set of formulae is dynamically conducted for each time step to update the base demand at each demand node according to the on-site storage tank operational status. Therefore, the global reliability of the system in this scenario is yielded below as *R*:

$$R = \sum_{k=1}^{WS} W_k * RR_k \qquad [4]$$

$$RR_k = \frac{\sum_{i=1}^{TS} \sum_{j=1}^{N} ATS_{i,j}}{\sum_{i=1}^{TS} \sum_{j=1}^{N} D_{i,j}} \qquad [5]$$

$$ATS_{i,j} = \begin{cases} D_{i,j} & if\ C_{i,j} \geq D_{i,j} \\ \min\left[C_{i,j} + \frac{ST_{i,j}}{t}, D_{i,j}\right] & if\ C_{i,j} < D_{i,j} \\ \min\left[\frac{ST_{i,j}}{t}, D_{i,j}\right] & if\ ST_j = const. for\ 8\ hours \end{cases} \qquad [6]$$

$$ST_{i,j} = \begin{cases} \frac{ST_j^{min} + ST_j^{max}}{2} & if\ i = 1 \\ \mathrm{ST}_{i-1,j} - \min\left[\mathrm{ST}_{i-1,j}, \left(\mathrm{D}_{i-1,j} - \mathrm{C}_{i-1,j}\right) * \mathrm{t}\right] & if\ i > 1\ and\ C_{i-1,j} < D_{i-1,j} \\ \mathrm{ST}_{i-1,j} + \min\left[\mathrm{ST}_{i-1,j}, \left(\mathrm{C}_{i-1,j} - \mathrm{D}_{i-1,j}\right) * \mathrm{t}\right] & if\ i > 1\ and\ C_{i-1,j} \geq D_{i-1,j} \end{cases} \qquad [7]$$

$$C_{i,j} = \begin{cases} D_{i,j} & if\ C_{i,j} \geq D_{i,j} \\ \mathrm{C}_{i,j} & if\ C_{i,j} < D_{i,j} \end{cases} \qquad [8]$$

$$c_{i,j} = \begin{cases} \mathrm{C}_{i,j} - D_{i,j} & if\ C_{i,j} \geq D_{i,j} \\ 0 & if\ C_{i,j} < D_{i,j} \end{cases} \qquad [9]$$

$$d_{i,j} = \frac{ST_j^{max} - ST_{i,j}}{t} \qquad [10]$$

$$ST_j^{max} = \frac{\pi\Delta_j^2}{4} * L_j^{max} \quad [11]$$

$$ST_j^{min} = \frac{\pi\Delta_j^2}{4} * L_j^{min} \quad [12]$$

$$D_{i,j} = BD_{i,j} + d_{i,j} \quad [13]$$

where $i$ = hourly hydraulic time steps from 1 to $TS$ (=24), $j$ = node indices from 1 to $N$, $N$ = the number of nodes in the water distribution network (WDN), $TS$ = the total number of hydraulic time steps in the demand pattern, $D_{i,j}$ = the dynamically updated demand in EPANET 2.2 at node $j$ in time step $i$ including on-site storage tank demand (*GPM*), $BD_{i,j}$ = the static demand at node $j$ in time step $i$ (*GPM*) without regard to the on-site storage tank demand, $C_{i,j}$ = the supplied flow at node $j$ in time step $i$ (*GPM*) without regard to the on-site storage tank, $c_{i,j}$ = the water supply to the storage tank at node $j$ in time step $i$ (*GPM*), $d_{i,j}$ = the demand of the storage tank at node $j$ in time step $i$ (*GPM*), $ST_{i,j}$ = the on-site storage tank volume at node $j$ in time step $i$ (*US gal*), $ST_j^{max}$ = the on-site storage tank maximum volume at node $j$ (*US gal*), $ST_j^{min}$ = the on-site storage tank minimum volume at node $j$ (*US gal*), $L_j^{max}$ = the on-site storage tank maximum level at node $j$ (*ft*), $L_j^{min}$ = the on-site storage tank minimum level at node $j$ (*ft*) (equals zero), $\Delta_j$ = the on-site storage tank diameter at node $j$ (*ft*), $ATS_{i,j}$ = the actual total supply at node $j$ in time step $i$ (*GPM*), $W_k$ = the probability of realizing the working state $k$, $RR_k$ = the WDN performance in working state $k$, $R$ = the global reliability of WDN, $WS$ = the number of working states the WDN can possibly experience considering single pipeline mechanical failures.

It is also postulated that on-site storage tanks are purposed to be fully exhausted according to the system demand in lieu of the centralized supply provided that they are not operational for more than eight hours. This will guarantee a cyclic pattern in filling and drafting the tanks to maintain the standard water quality.

*Reliability Formulation for the Greywater Reuse Decentralized Supply Scenario*

Reliability in the decentralized supply scenario, which uses on-site greywater reuse systems to complement centralized water distribution systems, is estimated using Equations 14 through 20. Similar to the centralized scenario, the pressure-driven demand analysis in EPANET 2.2 solver is used to estimate the nodal supply ($C_{i,j}$) in a failure event. All single pipeline mechanical failure scenarios are considered as possible uncertainties in the reliability formulation:

$$R = \sum_{k=1}^{WS} W_k * RR_k \qquad [14]$$

$$RR_k = \frac{\sum_{i=1}^{TS} \sum_{j=1}^{N} ATS_{i,j}}{\sum_{i=1}^{TS} \sum_{j=1}^{N} D_{i,j}} \qquad [15]$$

$$ATS_{i,j} = \begin{cases} D_{i,j} & if\ C_{i,j} \geq D_{i,j} \\ D_{i,j} & if\ C_{i,j} \geq \left(D_{i,j} - d_{i,j}\right)\ and\ (X_{i,j} + C_{i,j}) \geq D_{i,j} \\ C_{i,j} + X_{i,j} & if\ C_{i,j} \geq \left(D_{i,j} - d_{i,j}\right)\ and\ (X_{i,j} + C_{i,j}) < D_{i,j} \\ C_{i,j} + d_{i,j} & if\ C_{i,j} < \left(D_{i,j} - d_{i,j}\right)\ and\ X_{i,j} = d_{i,j} \\ C_{i,j} + X_{i,j} & if\ C_{i,j} < \left(D_{i,j} - d_{i,j}\right)\ and\ X_{i,j} < d_{i,j} \end{cases} \qquad [16]$$

$$d_{i,j} = \alpha * D_{i,j} \qquad [17]$$

$$S_{i,j} = \beta_i * C_{i,j} \qquad [18]$$

$$X_{i,j} = \min\left[\left(T_{i,j}/t\right), d_{i,j}\right] \qquad [19]$$

$$T_{i,j} = \begin{cases} 0; & if\ i = 1 \\ S_{i-1,j} + T_{i-1,j} - (X_{i-1,j} * t); & if\ i > 1 \end{cases} \quad [20]$$

where $i$ = hourly time steps from 1 to TS (=24), $j$ = node indices from 1 to $N$, $N$ = number of nodes in the WDN, $TS$ = total number of time steps in the demand pattern, $D_{i,j}$ = demand at node $j$ in time step $i$ ($GPM$), $C_{i,j}$ = flow supplied at node $j$ in time step $i$ ($GPM$), $ATS_{i,j}$ = actual total supply at node $j$ in time step $i$ ($GPM$), $k$ = working state associated with the considered failure and non-failure scenarios at each pipe one at a time, $W_k$ = probability of realizing the working state $k$, $RR_k$ = performance of WDN in working state $k$, $R$ = global reliability of WDN, $WS$ = number of working states the WDN can possibly experience, $d_{i,j}$ = maximum portion of the demand at node $j$ in time step $i$ that can be met with treated greywater ($GPM$), $S_{i,j}$ = volume of treated greywater sent to storage at the end of time step $i$ at node $j$ ($m^3$), $T_{i,j}$ = volume of treated greywater available at the beginning of time step $i$ at node $j$ ($m^3$), $X_{i,j}$ = flow from treated greywater reservoir at node $j$ in time step $i$ needed to meet the non-potable demand of node $j$ ($GPM$), $\alpha$ = percentage of demand that can be met with treated greywater, $\beta_i$ = percentage of WDN supplied water converted to treated greywater, and $t$ = duration of one time step ($hr$).

*Probability of Realizing a WDN Working State*

This section presents the probabilistic aspects of a scenario where a mechanical failure has caused a partial disruption in the centralized WDN system. This failure, which results in the system having a certain working state $k$, causes the unavailability of a component in the WDN. For example, if link $l$ is the only one that has failed in a WDN's working state *k*, the probability of realizing working state *k* is estimated as follows (Ciaponi et al., 2012; Gargano & Pianese, 2000; Piratla & Goverdhanam, 2015; Quimpo, 1994):

$$W_k = P(l) = P(0) * \frac{U_l}{A_l} \quad [21]$$

$$U_l = 1 - A_l = \frac{MTTR_l}{MTTF_l + MTTR_l} \quad [22]$$

$$MTTF_l = \frac{365}{\lambda_l L_l} \quad [23]$$

$$MTTR_l = \frac{1}{\mu_l} \quad [24]$$

$$\lambda_l = \lambda_{l,y} = \lambda_{l,y_0} * e^{A(y-y_0)} \quad [25]$$

where $MTTR_l$ = average time needed to repair link *l*, $MTTF_l$ = average time that link *l* fails, *P(l)* = probability of only link *l* failing in the WDN, *P(0)* = probability of all links functioning without failure in the WDN, $U_l$ = unavailability of link *l* in the WDN, $A_l$ = availability of link *l* in the WDN, $\lambda_l$ or $\lambda_{l,y}$ = estimated failure rate of link *l* in current year *y* (number of failures/km/year), $\lambda_{l,y0}$ = estimated failure rate of link *l* in its installation year $y_0$ (# of failures/km/year), *A* = coefficient of failure growth rate (*1/year*), $\mu_l$ = repair rate for links of type *l* (*#/day*), and $L_l$ = length of link *l* (km).

*Reliability Assessment Assumptions*

The reliability assessment of the centralized and decentralized scenarios is conducted for a period of 24 hours based on the following baseline assumptions:

1. The maximum percent demand ($\alpha$) that can be met using reclaimed greywater after adequate treatment is 25% (a value of zero percent for α represents a no-reuse scenario, whereas a value of 100% represents a potable reuse scenario).
2. The percentage of MWDN supplied water converted to treated greywater ($\beta$) is 24.5%, indicating that 24.5 *US gal* of reusable water is produced for every 100 *US gal* of water supplied by the centralized distribution system. This value is assumed to be the product of a nominal 75% efficiency of the treatment system and the average percentage of daily water consumption by greywater-producing fixtures (~33%).
3. The estimated growth rate coefficient ($A$) (refer to Eq. 16) for evaluating the probability of pipe failure is 0.075.
4. The current age of the system is 50 years (represents a typical water supply system in service).
5. The Hazen-Williams Coefficient of roughness ($RC$) of all pipes is 90 (it is equivalent to a value of head-loss coefficient of $K \approx 1.34$, where $RC$ is inversely proportional to $K^{1/1.85}$).

**Optimal Design of the MWDN**

This section discusses the bi-objective optimization procedure used to obtain the optimal pipe sizes and pump characteristics for the MWDN. A genetic algorithm-based optimization approach is used to design the MWDN considering cost (Wu et al., 2010) and resilience (Todini, 2000) as two objectives. Pipe sizes and pump characteristics are the decision variables considered while a minimum operational pressure of 30 psi and a maximum of 100 psi are the constraints in the design algorithm. A crossover faction ranging from 0.65 to 0.85 and a mutation rate of 0.08 were used in the genetic algorithm. Specifically, the following discrete options for pipe diameters (*D in inches*), pump head ($H^p$ *in ft*), and pump flow ($F^p$ *in GPM*) parameters were considered in the optimization scheme:

$$D \in \{3, 4, 6, 8, 10, 12, 16, 20, 24, 30, 36, 42, 64\} \quad [26]$$

$$H^p \in \{10, 11, 12, 13, \ldots, 250\} \quad [27]$$

$$F^p \in \{1500, 1501, 1502, 1503, \ldots, 15000\} \quad [28]$$

The cost objective is characterized as the installation and operational costs of pipelines and pumps based on Eq. 17 (Wu et al., 2010), with the resilience objective being characterized as the energy redundancy available in the system using Eq. 18 (Todini, 2000):

$$C = \sum_{x=1}^{r} L_x(-19.2 + (5.26 * D_x) + 0.28 * {D_x}^2) + 0.00625 \sum_{i=1}^{p} H_i^p * F_i^p) \quad [29]$$

$$RI = \frac{\sum_{j=1}^{n} q_j(h_j - h_j^*)}{\sum_{k=1}^{m} Q_m H_m + \sum_{i=1}^{p} \frac{P_i}{\gamma} - \sum_{j=1}^{n} q_j h_j^*} \quad [30]$$

Where *RI* = resilience index, $q_j$ is the actual demand (*GPM*) at node *j*, $h_j$ = operational pressure (*psi*) at node *j*, $h^*_j$ = minimum required pressure (*psi*) at node *j*, *n* = number of demand nodes in the system, $Q_m$ = system supply (*GPM*) from reservoir *m*, $H_m$ = head (*ft*) at reservoir *m*, *m* = number of reservoirs, $P_i$ = power of pump *i* (*kW*), $\gamma$ = specific gravity of water, *i* = number of pumps in the system, *C* = aggregate cost estimation (*$*) of the pipe and pump installation, $L_x$ = length (*ft*) of pipe *x*, $D_x$ = diameter (*in*) of pipe *x*, $H^p_i$ = design head (*ft*) at pump *i*, and $F^p_i$ = design flow (*GPM*) at pump *i*.

## Demonstration: Results and Discussion

The modified sectional layout of a real-world WDN (hereafter referred to as an MWDN) depicted in Figure 3-2 is used to investigate the potential improvement in supply reliability achievable through on-site greywater reuse systems when they complement existing WDNs. The MWDN is initially designed for pipe and pump sizes determined using a multi-objective genetic algorithm optimization scheme considering initial cost and resilience as objectives. The resulting design solutions are used for the reliability assessment. Results in this study are presented in three categories: (i) least-cost and reasonable design solutions for the MWDN; (ii) supply reliability improvement for the decentralized scenario relative to the centralized; and (iii) sensitivity of the improvement in supply reliability to a variety of parametric assumptions. After optimizing both pipe sizes and pump characteristic curves for the MWDN considered here using the genetic algorithms in MATLAB, Pareto front plots depicting the resilience-cost tradeoff are developed and presented in Figure 3-3. Of the optimal solutions, two design scenarios are targeted for further consideration in the reliability analysis: (i) the least-cost design scenario (LC), and (ii) the rational design scenario (RS). The least-cost solution is the optimal solution with the lowest cost that meets the design constraints, whereas the rational solution is the one that results in the minimum value of cost divided by the resilience objective values, providing a solution that offers the highest resilience at lowest cost. The LC and RS solutions for the MWDN highlighted in Figure 3-3 are further considered in the reliability analysis.

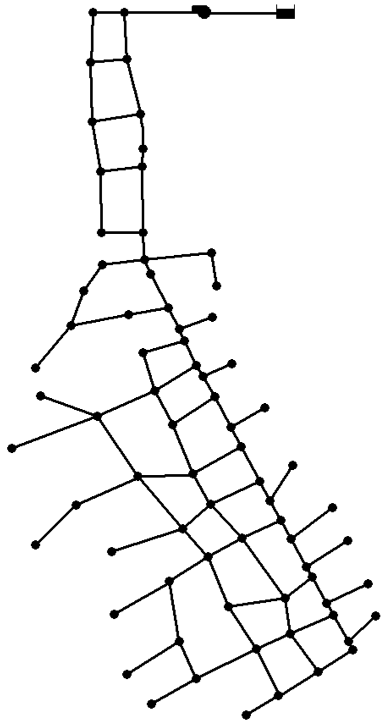


Figure 3-2. Skeleton Layout of Modified Water Distribution Network

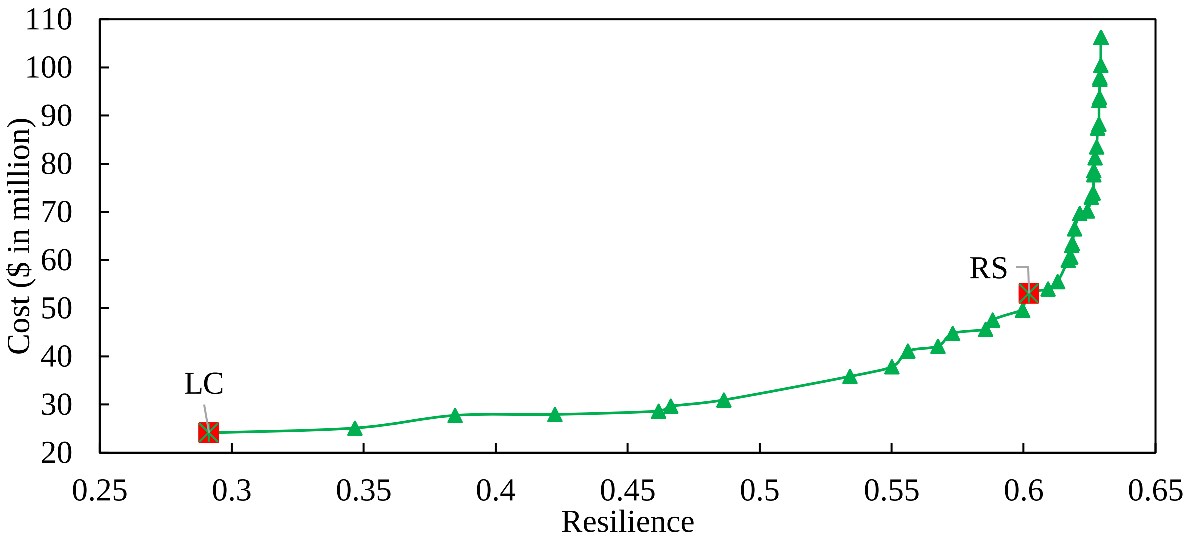


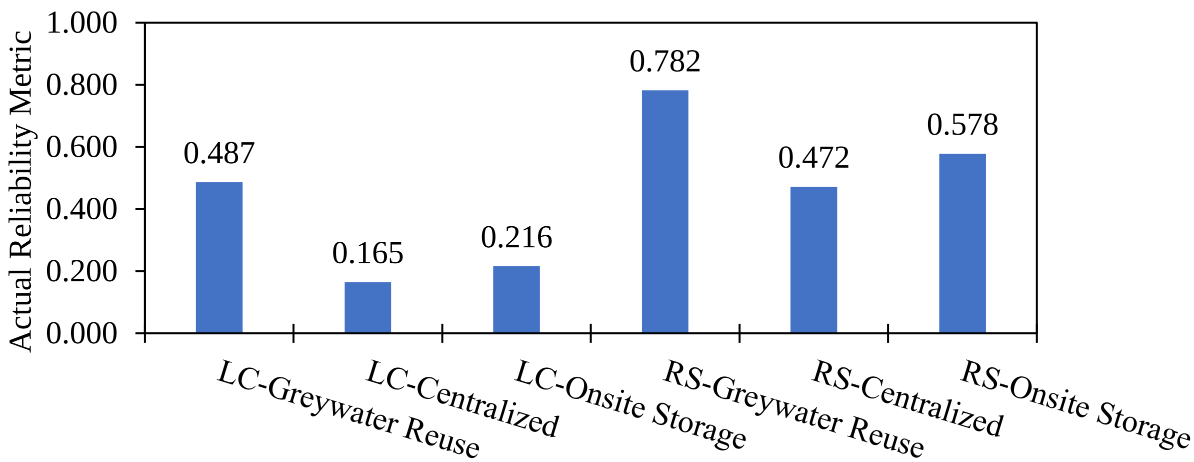

Figure 3-3. Pareto-front Plot for the Non-dominant Solutions in the MWDN (LS: Least Cost and RS: Reasonable Solution)

**Reliability Assessment Results**

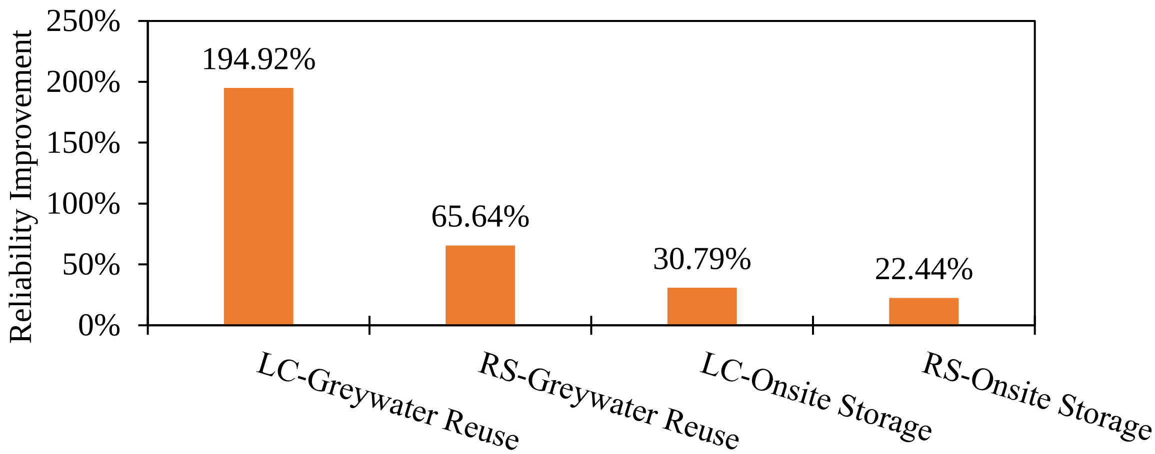
Figure 3-4 illustrates the percentage reliability improvement for the on-site storage-included centralized scenario and decentralized scenario compared to the basic centralized scenario considering the least cost (LC) and rational solution (RS) designs in addition to presenting the actual reliability values for all the cases.

As the figure shows, the supply reliability is enhanced when either on-site greywater reuse or on-site storage tank systems complement existing centralized water distribution systems. The reliability improvement in the LC design case was found to be 194.92% and 30.79% for greywater reuse and on-site storage scenarios respectively, compared to 65.64% and 22.44% in the RS case, for greywater reuse and on-site storage scenarios respectively.

These values demonstrate that decentralized greywater reuse system improves the reliability of the entire system more considerably than freshwater on-site storage-only scenario. It is observed that the superiority of decentralized greywater reuse in the reliability improvement compared to mere on-site storage system lies in the fact that the system demand remains constant and equal to the nodal (i.e., household) demand in the greywater reuse scenario, since the greywater reuse reservoir does not depend on WDN centralized supply, whereas the on-site storage system increases the nodal demand (i.e., the household base demand plus the on-site freshwater storage tank demand); This means that the WDN supply cannot simultaneously account for both the on-site storage tanks and household demand and more importantly maintain the required minimum pressure at the demand node at different time steps.




**(a)**




**(b)**

Figure 3-4. Baseline Scenario Results for Least Cost (LC) and Rational Scenario (RS) Solutions: (a) Reliability Improvement, and (b) Actual Reliability Values

Therefore, the reliability of the system is still mostly reliant on the performance of the centralized supply. This, thus, sheds light on the fact that a substantial amount of the reliability improvement associated with the greywater reuse system stems from the nature of the greywater recycling process rather than the mere practice of storing water. It is also found that the greywater reuse reliability improvement is more emphatic in the LS scenario (~194%) than the RS scenario (~66%) where the centralized supply system is more susceptible to failures due to lower system resilience. However, this reliability improvement comes at an expense associated with the capital cost, installation cost, and operational costs of the on-site greywater reuse systems. A previous study estimated the added cost for the adoption of an on-site greywater reuse scenario to be approximately $13 million for a network layout similar to the one used in this study and with the same total demand of 11,365 cubic meters per day (Yerri et el., 2019). Furthermore, this previous study reported that the capital costs account for about 44.4%, operational costs about 46.4%, and installation costs about 9.2%. These added costs have been reported to be at least 140% greater than the anticipated monetary benefits from the potential reduction in water and sewer utility bills (Yerri and Piratla, 2019). While there seems to be a considerable difference between the estimated additional costs and the anticipated monetary benefits, these systems may be considered viable given the improvement in the supply reliability enabled by on-site greywater reuse systems.

Furthermore, considering the sustainability benefits of these on-site greywater reuse systems, additional financial incentives in the form of tax credits and low-interest loans may further bridge the cost-benefit difference, making these systems more viable. This study further analyzes the sensitivity of the percent reliability improvement to each of the assumed parameters by systematically varying the parameters and repeating the comparative reliability analysis. To exemplify the reliability assessment analysis, Table 3-1 illustrates a granular breakdown of a sample working state (i.e., failure at the third pipe) for all time steps (i.e., 24 hours) in all three considered baseline scenarios associated with water flow turnaround at a sample demand node (#44). As can be found in Table 3-1, the total reliability metric of each time step for on-site storage and greywater reuse systems has improved compared to the basic centralized system as the outstanding portions of the nodal demands are met up with the supply from either freshwater on-site storage or the treated water from the recycled greywater reuse reservoir.

However, it can be observed that flows are only supplied to the on-site storage tanks only when the centralized system is able to provide more-than-nodal-demand supply in order to be stored in the tanks, whereas treatment process (i.e. flows into and from the decentralized greywater reuse system) is constantly taking place regardless of the performance of the WDN supply; it specifically means that treated water can be available at the beginning of each time step (except for the first time step) while there is no guarantee that freshwater is universally available at the on-site storage tanks. Therefore, available treated water at each time step can meet up the demands at nodes in case the main centralized WDN supply turns up insufficient. In other words, the availability of treated water at each time step independent of the performance of the centralized WDN is the primary factor in the greater reliability improvement in the decentralized greywater reuse system compared to the mere incorporation of on-site freshwater storage tanks, where reliability improvement is still dependent on the centralized system performance.

Table 3-2. Granular flow analysis at Node #44 under failure of pipe #3

| Time Step (hr) | Regular Centralized Scenario | | On-site Storage-Included Centralized Scenario | | | | Greywater Reuse Decentralized Scenario | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | WDN Supply to Node (*GPM*) | Total Working State Reliability | WDN Supply to Node (*GPM*) | WDN Supply to Tank (*GPM*) | Tank Supply to Node (*GPM*) | Total Working State Reliability | WDN Supply to Node (*GPM*) | Flow from Treated | Flow to Greywater | Total Working State Reliability |
| 0 | 15.5 | 0.001 | 15.5 | 14.7 | 0.0 | 0.001 | 15.5 | 0.0 | 3.8 | 0.001 |
| 1 | 12.5 | 0.001 | 12.5 | 0.0 | 0.0 | 0.001 | 12.5 | 0.0 | 3.1 | 0.001 |
| 2 | 13.0 | 0.001 | 13.0 | 0.0 | 0.0 | 0.001 | 13.0 | 0.0 | 3.2 | 0.001 |
| 3 | 13.0 | 0.001 | 13.0 | 0.0 | 0.0 | 0.001 | 13.0 | 0.0 | 3.2 | 0.001 |
| 4 | 22.0 | 0.001 | 22.0 | 0.0 | 0.0 | 0.001 | 22.0 | 0.0 | 5.4 | 0.001 |
| 5 | 43.2 | 0.0005 | 43.2 | 0.0 | 19.3 | 0.002 | 43.2 | 5.4 | 10.6 | 0.0014 |
| 6 | 25.2 | 0.0004 | 26.8 | 0.0 | 10.1 | 0.0014 | 25.2 | 10.6 | 6.2 | 0.0011 |
| 7 | 20.2 | 0.0004 | 21.1 | 0.0 | 0.0 | 0.0004 | 20.2 | 6.2 | 5.0 | 0.001 |
| 8 | 25.2 | 0.0004 | 25.4 | 0.0 | 0.0 | 0.0004 | 25.2 | 5.0 | 6.2 | 0.0011 |
| 9 | 38.0 | 0.0004 | 7.0 | 0.0 | 0.0 | 0.0004 | 38.0 | 6.2 | 9.3 | 0.0012 |
| 10 | 38.0 | 0.0004 | 26.0 | 0.0 | 0.0 | 0.0004 | 38.0 | 9.3 | 9.3 | 0.0012 |
| 11 | 34.3 | 0.0004 | 36.0 | 0.0 | 0.0 | 0.0004 | 34.3 | 9.3 | 8.4 | 0.0012 |
| 12 | 40.8 | 0.0005 | 44.2 | 0.0 | 0.0 | 0.0005 | 40.8 | 8.4 | 10.0 | 0.0013 |
| 13 | 43.2 | 0.0005 | 48.5 | 0.0 | 0.0 | 0.0005 | 43.2 | 10.0 | 10.6 | 0.0015 |
| 14 | 44.0 | 0.0006 | 44.0 | 11.9 | 0.0 | 0.001 | 44.0 | 0.0 | 10.8 | 0.0006 |
| 15 | 45.5 | 0.0006 | 50.0 | 0.7 | 0.0 | 0.001 | 45.5 | 0.0 | 11.2 | 0.0005 |
| 16 | 44.7 | 0.0005 | 49.1 | 0.0 | 7.4 | 0.001 | 44.7 | 11.2 | 10.9 | 0.0013 |
| 17 | 28.7 | 0.0004 | 31.2 | 0.0 | 5.2 | 0.0011 | 28.7 | 10.9 | 7.0 | 0.0013 |
| 18 | 28.0 | 0.0004 | 18.8 | 0.0 | 0.0 | 0.0001 | 28.0 | 7.0 | 6.9 | 0.0011 |
| 19 | 43.7 | 0.0005 | 27.4 | 0.0 | 0.0 | 0.001 | 43.7 | 6.9 | 10.7 | 0.0014 |
| 20 | 37.5 | 0.0007 | 37.5 | 17.4 | 0.0 | 0.0007 | 37.5 | 0.0 | 9.2 | 0.0007 |
| 21 | 25.0 | 0.0009 | 25.0 | 12.0 | 0.0 | 0.0009 | 25.0 | 0.0 | 6.1 | 0.0026 |
| 22 | 19.0 | 0.001 | 19.0 | 0.0 | 0.0 | 0.001 | 19.0 | 0.0 | 4.7 | 0.001 |
| 23 | 15.5 | 0.001 | 15.5 | 0.0 | 0.0 | 0.001 | 15.5 | 0.0 | 3.8 | 0.001 |

**Sensitivity Analyses**

This section reports the results from the comprehensive sensitivity analyses, seen in Table 3-2, intended to determine the sensitivity of the reliability improvement of on-site greywater reuse systems to a variety of parametric assumptions in the reliability modeling approach used here.

Table 3-2. Sensitivity Analysis: Parametric Variation

| Model Parameter | Baseline Value | Values for Sensitivity Analysis | | | |
|---|---|---|---|---|---|
| Maximum usable reclaimed water ($\alpha$) | 0.25 | 0.5 | 0.75 | 1.0 | -- |
| Percentage of WDN supplied water converted to treated greywater ($\beta$) | 0.245 | 0.2 | 0.3 | 0.4 | 0.5 |
| Roughness coefficient *(RC)* | 90 | 50 | 70 | 110 | 130 |
| System age $(y_0\text{-}y)$ | 50 | 30 | 40 | 60 | 70 |
| Failure growth rate *(A)* | 0.075 | 0.05 | 0.1 | 0.15 | -- |
| On-site Storage Capacity (*ST*)* | 29.376 | 23.44 | 35.16 | 43.95 | -- |

*The analysis for this parameter (in *US gal*) only accounts for the on-site storage centralized scenario.

***Maximum Usable Reclaimed Water (α)***

Figure 3-5 illustrates the effect of *α,* which denotes the maximum percentage of total demand that can be met by treated greywater, on the estimated reliability improvement. No significant change in reliability improvement is observed when *α* is increased from 25% to 100% (i.e., reclaimed water can be used to meet all the demand) for the LC solution. Similarly, the reliability metric remains unchanged for the RS solution as *α* is increased. This result suggests that the improvement in supply reliability is not limited by how much treated greywater can be used. The reason lies in the fact that there is a maximum amount of greywater that can be collected and recycled given the fact that greywater only accounts for a specific percentage of the household demand. This means that although 100% of the demand can be met by the recycled greywater (i.e., $\alpha$), it cannot be of much use if there is not enough greywater produced by the household to be recycled (i.e., $\beta$) from the very beginning.

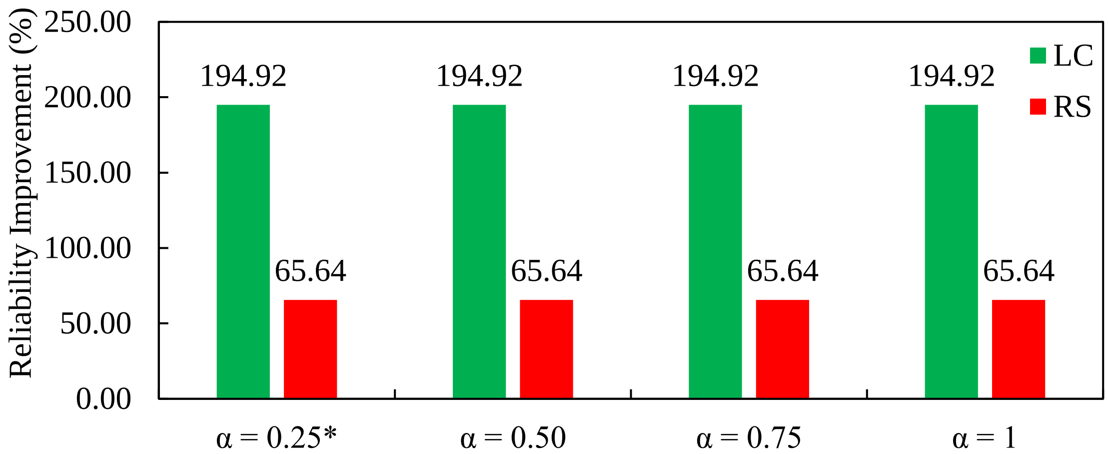



Figure 3-5. Sensitivity of Reliability to the Variation of α in the Least Cost (LC) Solution and Reasonable Scenario (RS) Solution (* denotes the baseline scenario)

***Percentage of WDN Supplied Water Converted to Treated Greywater (β)***

Figure 3-6 illustrates the effects of $\beta$ on the estimated reliability improvement for both the LC and RS design solutions. A negligible increase in reliability of 2 to 3 percent can be observed when $\beta$ is increased from 0.2 to 0.5 for both the RS and LC solutions. This result suggests that as the percentage of WDN supplied water converted to treated greywater increases, the reliability improvement also increases slightly. However, this slight increase in reliability improvement suggests that the percentage of WDN supplied water converted to treated greywater ($\beta$) is also not a significant limiting factor. It can be inferred that the higher availability of household greywater to be recycled (i.e., $\beta$) does not necessarily guarantee higher utility and subsequently higher reliability since recycled greywater can only be used up to meet a portion (i.e., $\alpha$, which is 25%) of the household demand. It is possible that a combined increase of $\alpha$ and $\beta$ will prove to be more significant than the individual increments, which is presented later in the sections of this study.

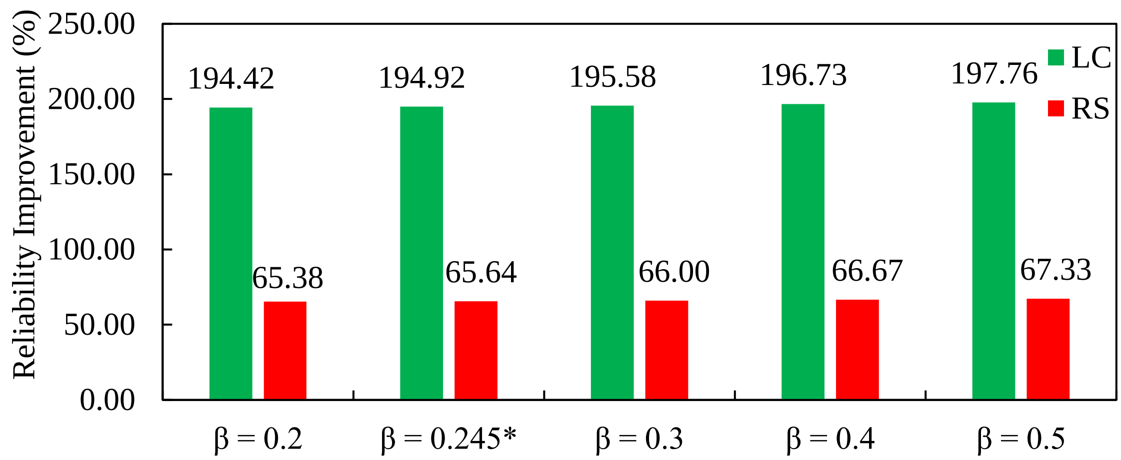



Figure 3-6. Sensitivity of Reliability to the Variation of ß in the Least Cost (LC) Solution and Reasonable Scenario (RS) Solution (* denotes the baseline scenario)

***Simultaneous Variations in α and β***

Figure 3-7 showcases the reliability improvement in the system as both α and β are increased at the same time. Such type of increase improves the capability of the decentralized system to contribute more to the required supply at each node when necessary. As can be observed, the reliability improvement rises from 194.92% to 210.38% in the LC and from 65.64% to 78.89% in the RS scenarios. This observation suggests that as more greywater is produced and is able to be recycled and used, the overall reliability of the system rises. It is comparable to the observations in the individual increases in the previous sections, where little improvements were obtained due to the mutual dependency of $\alpha$ and $\beta$.

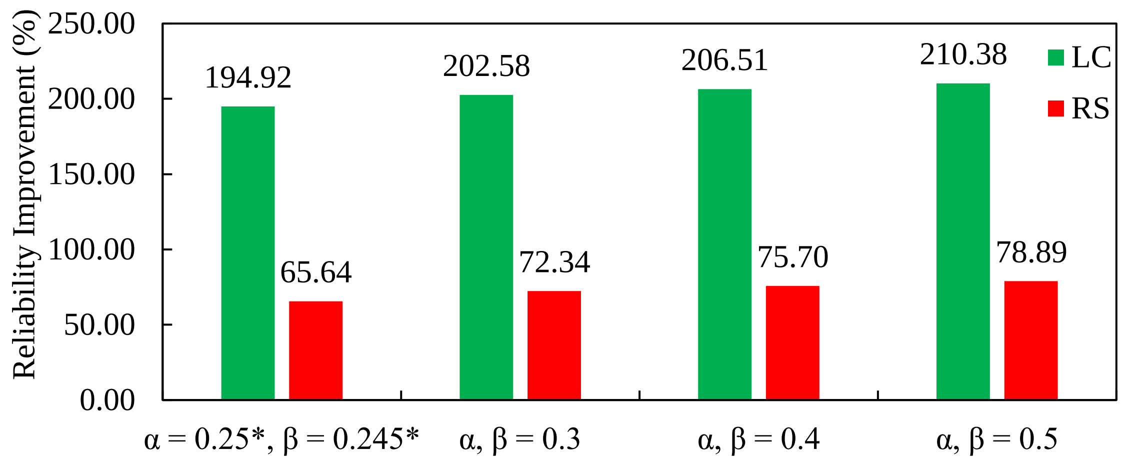



Figure 3-7. Sensitivity of Reliability to the Variation of both $\alpha$ and $\beta$ in the Least Cost (LC) Solution and Reasonable Scenario (RS) Solution (* denotes the baseline scenario)

***The Roughness Coefficient (RC)***

Sensitivity analysis was conducted for roughness coefficient (*RC*) values ranging from 130 to 50 (i.e., smoother pipe surface to rougher pipe surface). Figure 3-8 shows that a decrease in RC results in a steady increase in the reliability improvement from 144.91 % to 300.95% in the LC solution and from 41.44% to 120.23% in the RS solution.

It was also observed that the reliability of centralized MWDN decreased as the pipelines became rougher, which, in turn, results in an improvement in reliability when supplemented with on-site greywater reuse systems.

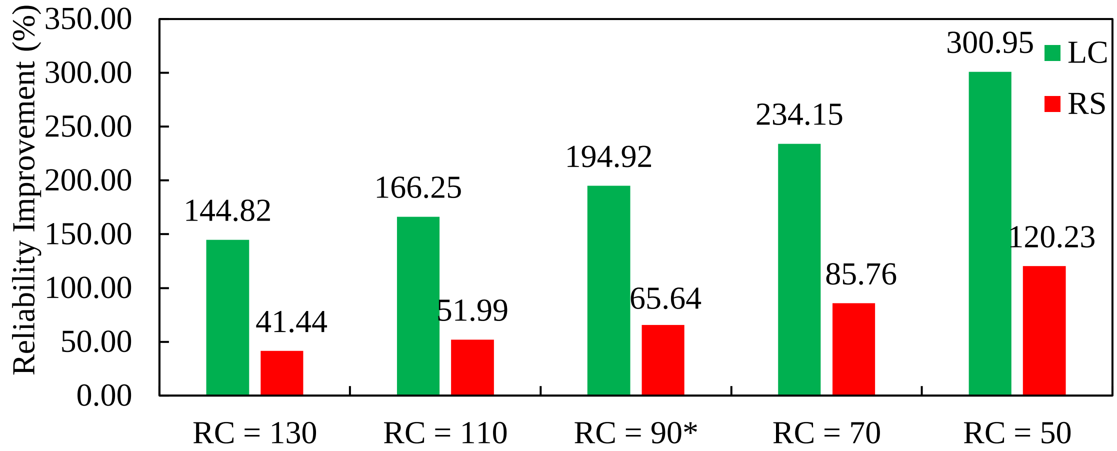



Figure 3-8. Sensitivity of Reliability to the Variations of Roughness Coefficient in the Least Cost (LC) Solution and Reasonable Scenario (RS) Solution (* denotes the baseline scenario)

***Age of the System (y-y0)***

The age of the system is another critical factor that has a significant impact on the performance of

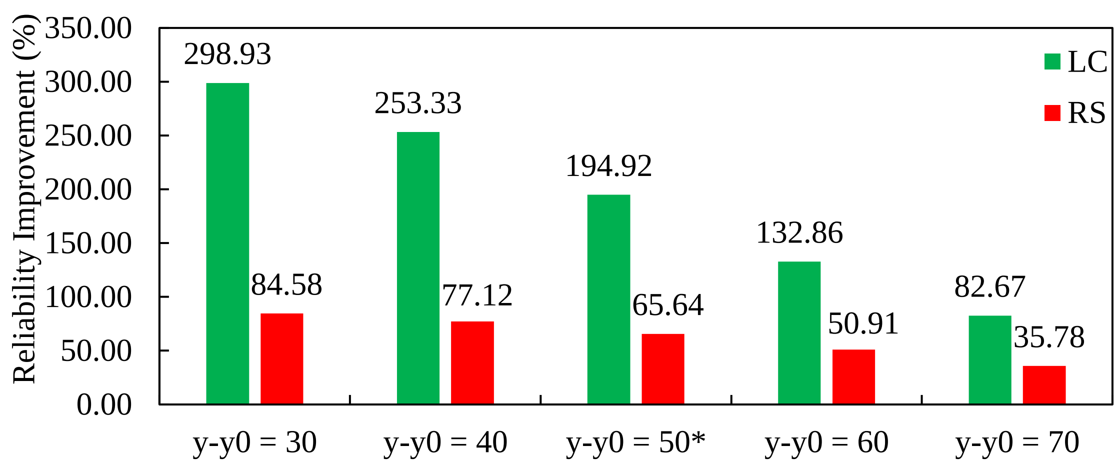



Figure 3-9. Sensitivity of Reliability to the Variations of System Age in the Least Cost (LC) Solution and Reasonable Scenario (RS) Solution (* denotes the baseline scenario)

water distribution systems, with the probability of failure of various components in the infrastructure increasing as the system ages. Figure 3-9 illustrates the impact of the age of the system on reliability improvement for ages ranging from 30 to 70 years. For the LC solution, a significant decrease from 298.93% to 82.67% in the reliability improvement percentage was found when age of the system increased from 30 to 70 years. Similarly, for the RS solution, there is a sharp decrease from 84.58% to 35.78% in reliability improvement observed with an increase in age. This substantial decline indicates that as the pipeline system ages, it becomes much less reliable and more susceptible to failures. Although a decentralized supply system was found to contribute positively to the reliability of the system, its impact decreased as the system aged.

***Pipeline Failure Growth Rate (A)***

The growth rate coefficient (*A*) determines the growth of the break rate of a pipe in a water distribution network: as the value of *A* increases so does the probability of the failure of a single pipe. Figure 3-10 illustrates the effect of the growth rate coefficient on the estimated reliability improvement. As this figure shows, the reliability of the water supply for the centralized and decentralized scenarios of the benchmark designs significantly decreased with an increase in the failure growth rate. Furthermore, reliability improvement was found to decrease considerably from 274.94% to zero and from 80.77% to zero for the LC and RS scenarios, respectively, as the value of failure growth rate (A) increased from 0.05 to 0.15. This trend suggests that the presence of on-site treatment plants to supplement a centralized supply may not have a considerable impact when the availability of the centralized system is compromised because of a large number of main breaks.

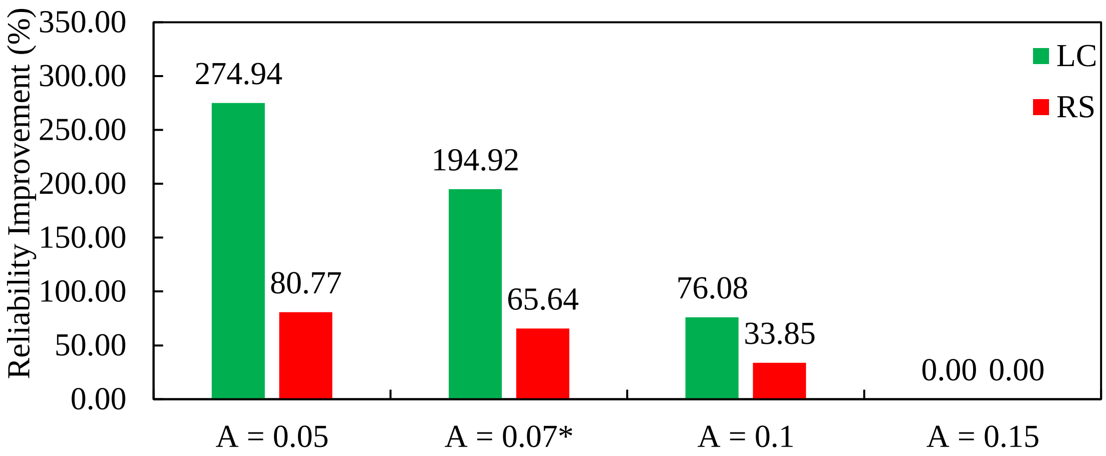



Figure 3-10. Sensitivity of Reliability to the Variations of Failure Rate in the Least Cost (LC) Solution and Reasonable Scenario (RS) Solution (* denotes the baseline scenario)

***On-site Storage Capacity (ST)***

On-site storage capacity is the only parameter associated with the centralized supply scenario where all the demand nodes are retrofitted with on-site freshwater storage tanks. However, the reliability of the system can vary in accordance with the maximum volume of the on-site tanks. For this purpose, this section considers three different storage capacities, and Figure 3-11 summarizes their reliability improvement compared to the regular centralized supply scenario. It is observed that since the system demand far exceeds the capacity of the tanks, the incremental increase or decrease in the storage volume cannot fully account for the nodal demands, and thus the reliability of the system experiences marginal changes (from 30.35% to 30.71 in the LC and from 24.52% to 24.67% in the RS scenarios).

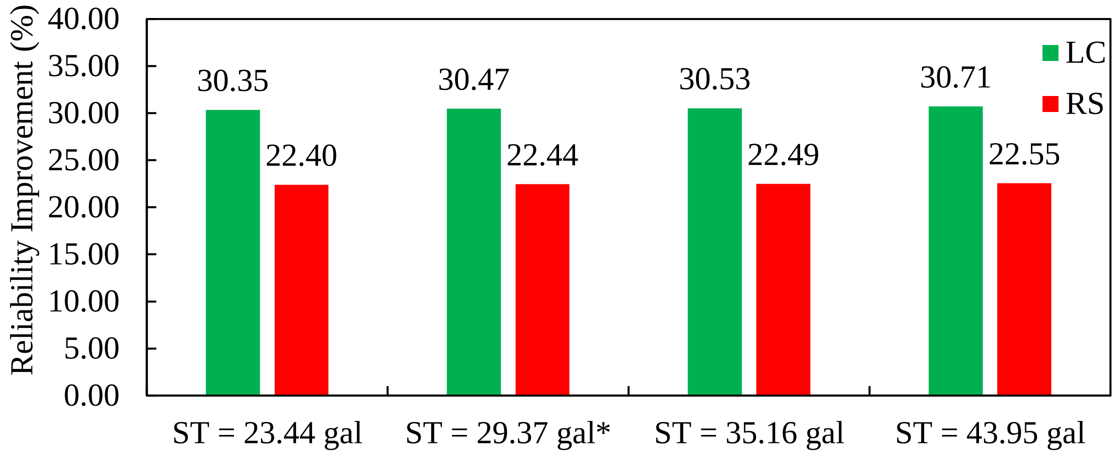



Figure 3-11. Sensitivity of Reliability to the Variations of On-site Storage Capacity in the Least Cost (LC) Solution and Reasonable Scenario (RS) Solution (* denotes the baseline scenario)

As presented before, in both LC and RS baseline scenarios, indeed the presence of the on-site storage system displays a considerable improvement in the reliability of the system compared to the basic centralized scenario; however, it is herein observed that tanks of much larger sizes must be put in place to elicit more significant improvements compared to the on-site storage baseline scenario. However, extremely large on-site tanks are unlikely to be cost-effective.

Sensitivity analyses revealed that the reliability improvement decreased with an increase in the age of the system ($y$-$y_0$) and the failure growth rate ($A$), whereas it almost remained unchanged with an increase in the maximum usable reclaimed water ($\alpha$) and the percentage of WDN supplied water converted to treated greywater ($\beta$) and improved as the roughness coefficient ($RC$) increased. Also, the reliability improvement marginally increased as the on-site storage tank capacity ($ST$) rose, which highlights the importance of an optimal on-site freshwater storage tank size. Overall, the results encourage the adoption of on-site greywater reuse systems based on infrastructure supply reliability, when all three scenarios of basic centralized, on-site storage-included centralized, and greywater reuse decentralized scenarios are tested against each other.

This study numerically demonstrated a significant improvement in the reliability of a WDN when either on-site freshwater storage system or greywater reuse system is incorporated into a conventional centralized system. The essential broad implications of the findings in this study include: (1) the greywater reuse system improves the system reliability more significantly as the WDN is more susceptible to component failures, (2) it is expected that the greywater reuse system contribute more significantly as other layout-varied less-looped networks are studied, and (3) the economic significance of incorporating a greywater reuse system is a harbinger of WDNs that will be less dependent on a centralized supply system, where energy loss due to system leaks or pipe break can be reduced.

**Conclusions and Recommendations**

This study investigated the improvements in water supply reliability resulting from decentralized water sources, involving on-site greywater reuse systems supplementing the centralized water distribution supply. These reuse systems collect and treat greywater on-site for near immediate use as permitted locally. The comparative reliability analysis conducted in this research found significant improvement in supply reliability for the decentralized scenario compared to the centralized scenario, concluding that a decentralized supply complements an existing water supply in terms of the system's capability to meet demands under various uncertainties. Although the magnitude of reliability improvements observed is specific to the benchmark network studied in this research, it can be concluded that having an additional water source on-site results in some improvement in supply reliability for the majority of water distribution systems. It is important to note that individual variations in the amounts of the produced greywater to be sent for recycling and the treated water available at a node do not affect the reliability of the system. Rather, the reliability improvement was found to rise more meaningfully through simultaneous increase in both $\alpha$ and $\beta$. In another case, it was found that the supply reliability improvement decreased when the centralized system is older and resulting in increasing number of main breaks. In contrast, for a given age of a system, the supply reliability improvement was found to increase when the centralized water distribution pipelines became rougher.

While this study found a definite improvement in water supply reliability with on-site greywater reuse systems, it comes with the added expense associated with the capital and operational costs of these systems. A previous study estimated that these added costs outweigh the anticipated monetary benefits in the form of reduced water and sewage utility bills by more than 140% (Yerri and Piratla, 2019). While this cost-benefit monetary gap is significant, supply reliability improvement benefits of on-site greywater reuse systems as demonstrated in this study may make such systems viable for utilities with significant reliability concerns. Furthermore, financial incentives in the form of tax credits or low-interest loans may further address the monetary cost-benefit gap, thus helping to encourage the adoption of on-site greywater reuse systems. As such, the effects of financial incentives and other factors on homeowners' interest in the adoption of greywater reuse systems need to be studied in the future. Further, a more comprehensive multi-variate sensitivity analyses would reveal the combined effects of the infrastructural parameters on the extent of supply reliability improvement. Finally, future research should also investigate the extent of supply reliability improvement with partial greywater reuse adoption where only a few households choose to install greywater reuse systems as opposed to the assumption made in the current study that all the consumption points would have an on-site greywater reuse system.

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# CHAPTER FOUR

# EVALUATING USER WILLINGNESS TO ADOPTING GREYWATER REUSE TECHNOLOGIES: EXPLORING A HYBRID BEHAVIORAL CHANGE THEORY[1]

A current practical solution to support environmental sustainability, particularly in water-stressed and water-scarce places, is the use of greywater as an alternative supply of water. One of the most important factors affecting the success of grey water reuse is public acceptance. Utilizing a hybrid model created using elements from the theory of planned behavior, norm activation model, descriptive norms, and environmental knowledge, this study investigated public willingness to adopt greywater reuse systems. A total of 502 people from the states of Florida and California in the U.S. participated in the study. These two states were chosen because Florida has the potential and need to build greywater treatment systems, while California is thought to be a place where these systems are widely used. According to the findings, 77 percent of the variation in respondents' behavioral intentions may be explained by the hybrid model. The main predictors of behavioral intention to adopt greywater reuse systems are discovered to be awareness of consequences and personal norm. This study used comparative tests to study how behavioral intentions varied between dichotomous groups. It is determined that gender has little bearing on intentions, but whether a person owns or rents a home has a significant impact. Additionally, compared to other age groups, those between the ages of 31 and 44 tend to be more likely to employ greywater reuse systems. Contrarily, California's mean behavioral intention is just somewhat greater than Florida's. The results of this study provided more insight into the ramifications of beliefs as well as implications for creating efficient behavior modification interventions to support the adoption of greywater reuse.

[1] Standalone Research Article: *"Evaluating User Willingness to Adopting Greywater Reuse Technologies: Exploring a Hybrid Behavioral Change Theory"* (under preparation for submission to a journal).

## Introduction

Access to clean water in urban areas has become a crucial global concern as the World Water Organization anticipated that by 2025, more than 67 percent of the world's population will experience water shortages (Grey and Connors, 2009). Additionally, it is predicted that 3 billion people will experience water stress by 2025 (Qureshi and Hajra, 2010). With ongoing population increase, urbanization, and industrialization, the demand for water is obvious. Will the available water resources be able to meet these ever-increasing water demands? What alternatives will there be to meet these expanding demands? To find actions and techniques that will help to reduce these problems, these questions must be raised. To combat the effects of the world's water shortage challenges, it is crucial to develop and implement new and inventive methods of water conservation and reuse. One such alternative is reusing treated greywater.

Reusing greywater can advance sustainable growth and resource preservation without sacrificing public health or the environment. Greywater, as defined by Casanova et al. (2001), Ledin et al. (2001), Ottoson and Stenstrom (2003a), can be characterized as wastewater that does not contain any contributions from washer water. Reusing greywater is a widespread method in regions with severe water shortage problems. Greywater that has been recycled can be used for a variety of tasks, including irrigation and toilet flushing. Greywater reuse minimizes wastewater discharge in addition to water savings, which lowers the cost of ultimate treatment (Santos et al., 2012). It is also concluded that the supply reliability is improved when existing water supply systems are supplemented with on-site greywater treatment systems (Momeni et al., 2022). Greywater reuse solutions have been the subject of numerous studies, and all of these studies show that this practice is not only beneficial but also a sustainable strategy to manage water pollution and its impacts on the environment (Alderlieste and Langeveld, 2005; Chong, 2005; Yerri and Piratla, 2019).

Considering the hazard caused by discharging of untreated greywater into the environment in some developing countries such as Ghana, Uganda, Nepal, Mali and lack of treatment facilities as reported by (Alderlieste and Langeveld, 2005; Katukiza et al., 2014; Oteng-Peprah et al., 2018b; Shresta, 1999) it is prudent to explore greywater treatment and reuse at the household levels. Only a few states in the US with water scarcity or shortages have allowed the use of greywater treatment systems, despite the sustainable aspects of the practice and other advantages. However, questions of perceived health dangers linked with greywater reuse remain a barrier to this practice. It has long been understood how crucial it is to comprehend how the public would react to and adopt water reuse technologies. Hence prior to the implementation/legalization of greywater treatment, public perception is of the utmost significance and the success of such reuse programs depends on public acceptability. Therefore, the aim of this study is to determine the factors that may favor a successful socio-technical transition to greywater reuse that is explored and integrated with a special focus on public acceptance at a household level. This study also determines the effectiveness of knowledge mediums and acts as a reference model and provides guidance to water providers and public policymakers, which leads a step closer to sharing the knowledge on environmental and cost benefits associated with greywater reuse. The study's overarching goal is to shed light on how the public views and accepts the reuse of greywater. Understanding this will serve as a foundation for developing interventions aimed at encouraging greywater treatment and reuse at the household level.

**Literature Review**

The literature has long advocated taking psychological factors into account when forecasting and analyzing consumer behavior. Numerous authors have addressed and improved on issues pertaining to the psychological component for comprehending the elements influencing people's choices. Numerous studies have been done to look at consumer behavior particular to different industries, such as information systems (Loiacono et al., 2007, Rensel et al., 2006), energy consumption (Srivastava et al., 2019, Li et al., 2019), transportation (Liu et al., 2017), etc. The most popular and prominent theory for recognizing behavioral changes is the theory of planned behavior (TPB), which is occasionally combined with the Norm Activation Model (NAM) (Bamberg and Möser, 2007). The TPB model has been successfully used to evaluate various pro-environmental behaviors (Botetzagias et al., 2015, De Leeuw et al., 2015, Fielding, K.S et al., 2008, Oteng-Peprah, M. et al., 2020).  The NAM has been used extensively in the past to explore pro-environmental behaviors in a variety of contexts, including public transportation (Bamberg and Möser, 2007), energy use (Van der Werff and Steg, 2015), carbon footprint (Vaske et al., 2015), and acceptance of responsible technology (Toft et al., 2014).

TPB also used in a study published in 2017 by Kang et al that focuses on studying how Hispanic consumers' views of drought and water resources influence their perceptions and behavior about sustainable water usage. One of the drawbacks of this study is that it concentrated on one significant minority group (Kang et al., 2017). The importance of attitude, perceived behavioral control, and subjective norms in the prediction of intention, lends credence to the notion that the TPB is a good model for analyzing pro-environmental behavior (Lam 1999, Oteng-Peprah et al., 2020). Personal norms were found to be a significant factor influencing a variety of pro-environmental behaviors, such as recycling, using public transportation, and conserving energy and water (Zhang et al., 2013; Seyranian et al., 2015). (Thomas and Sharp, 2013). A number of earlier research have shown how awareness of the consequences affects pro-environmental actions in many contexts, such as using green power (Clark et al., 2003), owning and using a car (Flamm, 2009), reusing water (Saphores et al., 2012), and managing land (Price and Leviston, 2014). In addition, environmental knowledge (Hines et al., 1987, Gifford et al., 2014, Latif et al., 2013, Varela-Candamio, L., et al., 2018; Liu et al., 2017) and descriptive norms (Gardner, B., & Abraham, C., 2010; Rai, V., & Beck, A. L., 2015) are considered to be good indicators of pro-environmental behavior.

The researchers have performed a number of surveys in the past to investigate trends, acceptance, and public image. Smaller sample sizes, respondents receiving incomplete information, and the absence of solid proof of a statistical association between greywater reuse and particular socio-demographic variables like income and education are some of the major limitations mentioned in the research. Studies that used a hydrid model are scarce, if not nonexistent, even if a few studies from the past used the TPB technique to determine the beliefs in implementing greywater treatment systems. This study aims to fill this knowledge gap and address the shortcomings by conducting an empirical analysis of data obtained using a theoretically designed survey instrument, specifically by developing a hydrid model taking into account the constructs from the Theory of Planned Behavior (TPB), the Norm Activation Model (NAM), as well as descriptive norms and environmental knowledge to investigate the behavioral intention (BI) towards adopting greywater reuse systems. Designing effective interventions to encourage the adoption of greywater reuse treatment systems requires understanding the ideas that underlie intentions and behavior. Establishing the extent to which attitudes, norms, PBC, AC, AR, and environmental concern affect intentions to embrace greywater reuse can help determine the kinds of information that will be most helpful and effective in interventions aimed at promoting the use of greywater treatment systems. The study also aims to investigate the behavioral intention to adopt greywater reuse treatment systems in relation to location, gender, income, and age.

**Hypotheses Development**

The purpose of this study is to comprehend the major assumptions that underlie public perceptions and adoption behaviors for greywater reuse systems. Based on the literature review and theoretical underpinnings, we created a comprehensive model that illustrates the relationship between behavioral intention (BI), which in turn influences pro-environmental behavior, and attitude (ATT), subjective norms (SN), perceived behavioral control (PBC), personal norms (PN), awareness of consequences (AC), ascription of responsibility (AR), descriptive norm (DC), and environmental knowledge (EK). Theoretically, behavioral intentions (BI) are positively influenced by each component and are related to one another (TPB and NAM). However, prior research on utilizing these models to anticipate the public's pro-environmental activities provides a variety of explanations for their influence on behavioral intentions (BI). The majority of studies that take into account personal norm (PN) show that it significantly affects behavioral intention (BI) (Harland et al., 1999, Arvola et al., 2008, Kaiser, 2006, Klockner, 2013, Schwartz, 1977). Contrary to the aforementioned assertion, relatively few studies likewise came to the conclusion that personal norm had a weaker association with behavioral intention. (Liu et al., 2017, Tommasetti et al., 2018, Doswellet al., 2011). The findings from research that modified hybrid models to include both TPB and NAM components indicated that subjective norms (SN) do not directly influence behavioral intention (BI) [Lauper et al., 2016, Park and Ha, 2014, Wall et al., 2007). Results from earlier studies indicate that personal norms (PN), attitude (ATT), and perceived behavioral control (PCB) are reliable predictors of pro-environmental activities, even though the role of each construct on behavioral intention varies from study to study. (Oteng-Peprah et al., 2020). Hence to clarify and gain confidence on the indicators the following hypotheses is developed in this study.

Hypothesis 1: The individual's intention (BI) to use a greywater treatment system increases as their attitude (ATT) toward greywater treatment and reuse improves.

Hypothesis 2: Individuals' intentions (BI) to use the greywater treatment system rise as the subjective norm (SN) toward greywater treatment and reuse becomes more positive.

Hypothesis 3: The individual's intention (BI) to adopt the greywater treatment system increases as the perceived behavioral control (PBC) toward greywater treatment and reuse becomes more positive.

It is anticipated that the individual's views, the pressure they feel from others to embrace greywater treatment systems, and their internal sense of moral obligation to use greywater treatment systems will all have an effect on their desire to do so. Personal norm is the central construct of the Norm Activation Model (NAM) and reflects the feeling of moral obligation towards adopting greywater treatment systems. When an individual behaves in a way that is consistent with their personal norms, it can make them feel proud, whereas when they behave in a way that is inconsistent with their personal norms, it can make them feel guilty. Accordingly, it was hypothesized that:

Hypothesis 4: The individual's intention (BI) to adopt the greywater treatment system rises as their personal norm (PN) regarding greywater treatment and reuse becomes more positive.

When people are aware of the negative effects of their actions or inactions on others and themselves, they are more likely to become involved in environmental concerns and employ greywater treatment systems. Greywater treatment system users are supposed to feel a larger moral commitment to use them than those who do not acknowledge the good environmental effects of their use. Similar to this, people who accept responsibility for environmental issues would feel more obligated to contribute to their solution by implementing greywater treatment systems than those who do not. Consequently, it was postulated:

Hypothesis 5: Individuals' intentions (BI) to use the greywater treatment system rise as understanding of the benefits of greywater treatment and reuse (AC) grows.

Hypothesis 6: The individual's intention (BI) to adopt the greywater treatment system increases as the degree of responsibility (AR) for greywater treatment and reuse increases.

Peer effects and reliable information sources have been shown to be important in removing non-financial barriers to pro-environmental action (Bollinger and Gillingham, 2012, Rai and Robinson, 2013, Graziano and Gillingham, 2015, Noll et al., 2014). Adoption of novel technologies like greywater systems is marked by elevated perceptions of risk because such technologies have not yet been extensively tested. Greywater system installation by neighbors can calm fears about perceived risk and give inspiration and assurance (Rai and McAndrews 2012). These observations of other people's behavior can help develop descriptive standards by forming impressions of which behaviors are typical. It was hypothesized that: Given the established relative relevance of peer impacts in the choice to install greywater treatment systems:

Hypothesis 7: The individual's intention (BI) to adopt the greywater treatment system increases as the descriptive norm (DN) toward greywater treatment and reuse becomes more positive.

If a person lacks sufficient understanding of the issue or available solutions, they are less likely to consciously care about the environment or take intentional environmental-friendly acts. As shown by earlier research, knowledge has been found to predict behavior (Levine

& Strube, 2012). Higher degrees of environmental knowledge are probably to have a favorable effect on a person's intention to use greywater treatment systems.

Hypothesis 8: The individual's intention (BI) to adopt the greywater treatment system increases as environmental knowledge (EK) about greywater treatment and reuse becomes more favorable.

Research hypotheses and paths for the current study are presented in Table 4-1.

In this study, a research model was built to evaluate the direct relationships between the components and the aforementioned research hypotheses. The causal effect hypotheses and their respective routes are shown in Figure 4-1.

Table 4-1: Research Hypotheses

| Code | Description | Path |
|---|---|---|
| H1 | Attitude (ATT) has a positive effect on Behavioral Intention (BI) | ATT → BI |
| H2 | Subjective Norm (SN) has a positive effect on Behavioral Intention (BI) | SN → BI |
| H3 | Perceived Behavioral Control (PBC) has a positive effect on Behavioral Intention (BI) | PBC → BI |
| H4 | Personal Norm (PN) has a positive effect on Behavioral Intention (BI) | PN → BI |
| H5 | Awareness of consequences (AC) has a positive effect on Behavioral Intention (BI) | AC → BI |
| H6 | Ascription of responsibility (AR) has a positive effect on Behavioral Intention (BI) | AR → BI |
| H7 | Descriptive Norm (DN) has a positive effect on Behavioral Intention (BI) | DN → BI |
| H8 | Environmental Knowledge (EK) has a positive effect on Behavioral Intention (BI) | EK → BI |

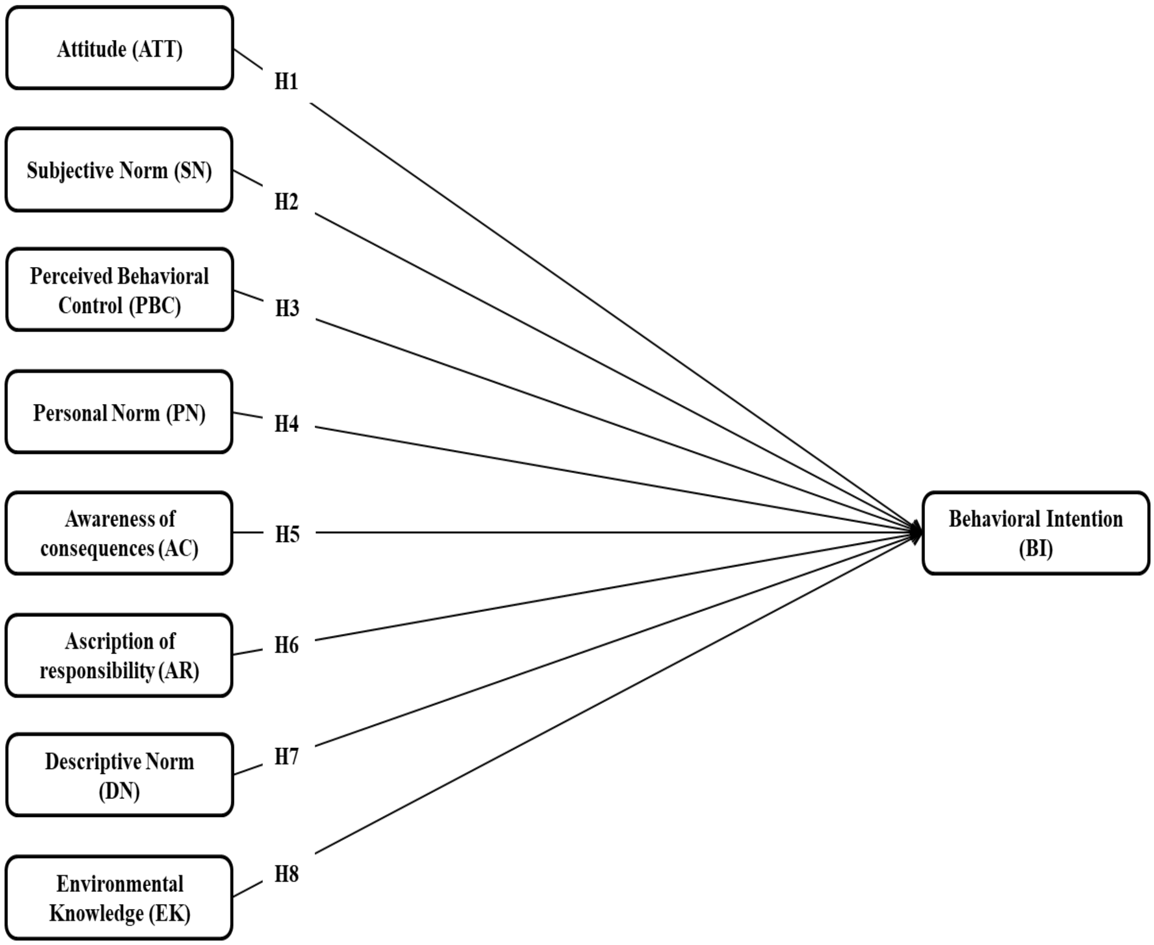


Figure 4-1: Research Model with Relative Paths

## Methods

### *Data Collection and Sample*

Various researchers have undertaken numerous studies on pro-environmental behavior in the past. These investigations used samples with sizes ranging from 200 to 7000. Some of these studies, which had sample sizes under 400, came to the conclusion that even if the survey population was big and diverse enough to produce statistically significant and significant results, future research with a larger sample size and a more evenly distributed distribution across different demographic factors might be able to provide more in-depth and less biased insights. (Srivastava et al., 2019; Park and Ha, 2014). While studies with a sample size of more than 500 appear content with the sample's representation of their model (Wall et al., 2007; Lauper et al., 2016; Fang et al., 2019; Oteng-Peprah et al., 2020). A random sample of people from California, where greywater treatment systems are widely used, and Florida, which has the potential and need to adopt greywater treatment systems, were given access to an online survey in order to gather data. A total of 502 replies were included in the sample, 350 of which were from California and 152 from Florida. Participants ranged in age from 19 to 71 and included 251 men and 251 women. According to age distribution, 17% of respondents were between the ages of 19 and 31; 24% were between the ages of 32 and 44; 20% were between the ages of 45 and 57; and 39% were between the ages of 58 and 72.

***Questionnaire***

A 32-item questionnaire was constructed as a measurement scale for the research based on the hypothesized model developed from a thorough examination of the relevant literature on the public perception towards pro-environmental behavior and greywater reuse systems. There were two sections to the official questionnaire. The goal of the first section was to learn about the respondents' demographic characteristics, such as their age, highest level of education, gender, if they owned a property, and how well they understood the overall effects of the environment. All the measurement scales were nominal. The second part measured the respondents' perception of each construct in the model. In order to ensure the reliability and validity of measurement scales for the constructs, established scales from the literature discussed in the earlier sections were adapted to measure the key variables of this research.  In the previous studies 5-point scales (Wall et al., 2007), 6-point scales (Chuttur, 2009), and 7-point scales (Park and Ha, 2014; Fang et al., 2019) are the most used measurement scales. According to the original TPM proponent Ajzen's work, the theory does not specifically specify whether responses to the scales should be assessed in a unipolar manner. (e.g., from 1 to 7, or from 0 to 6) or in a bipolar fashion (e.g., from -3 to + 3) (Ajzen, 1991) and the author also suggests using 7-point linker scale in the TPB questionnaire guide (Ajzen, 2005). Hence the questionnaire adopted a 7-point Likert scale ranging from 1 (strongly disagree) to 7(strongly agree). Tables 4-2 (a-c) shows the constructs and questions included in this questionnaire.

Table 4-2 (a): Constructs and Measurement Items for Theory of Planned Behavior

| Construct | Measurement Items |
|---|---|
| Attitude (ATT) | 1. Using treated greywater is safe for non-potable usage<br>2. Installing greywater technology at residence helps with water conservation<br>3. Installing greywater reuse technology at residence is important<br>4. Installing greywater reuse technology at residence is beneficial |
| Subjective Norm (SN) | 1. Most people who are important to me think that I should be using treated greywater or installing a greywater treatment system<br>2. Most people who are important to me do not care if I use treated greywater or install a greywater treatment system<br>3. Most people who are important to me approve me using treated greywater or installing a greywater treatment system |
| Perceived Behavioral Control (PBC) | 1. Most people who are important to me think that I should be using treated greywater or installing a greywater treatment system<br>2. I believe I have the ability to use treated greywater or have a greywater treatment system installed<br>3. I feel encouraged to use treated greywater or install a greywater treatment system if financial incentives/benefits are given<br>4. I feel encouraged to use treated greywater or install a greywater treatment system if quality assurance given by a credible information source<br>5. I feel encouraged to use treated greywater or install a greywater treatment system if the certification of the system was easy and quick<br>6. I feel encouraged to use treated greywater or install a greywater treatment system if the permitting process is simplified<br>7. I feel encouraged to use treated greywater or install a greywater treatment system if I am aware that it is sustainable and helping to conserve the environment |

Table 4-2 (b): Constructs and Measurement Items for Norm Activation Model

| Construct | Measurement Items |
|---|---|
| Personal Norm (PN) | 1. I feel a strong personal obligation to use treated greywater or install a greywater treatment system at my residence<br>2. I would feel guilty if I didn’t use treated greywater or install a greywater treatment system at my residence<br>3. I feel good about myself when I use treated greywater or install a greywater treatment system at my residence |
| Awareness of consequences (AC) | 1. When I use treated greywater or install greywater treatment at my residence, I cut down water and sewer utility bills<br>2. I don’t believe that environmental and water scarcity problems can be solved by installing a greywater treatment system at my residence<br>3. Using treated greywater is a major way to conserve water and save the environment |
| Ascription of responsibility (AR) | 1. Because my personal contribution would be negligible, I do not feel responsible to install a greywater treatment system at my residence<br>2. Because I use water, at least somewhat, I am responsible for the adoption of greywater treatment systems<br>3. The local or federal government, not me, is responsible for the adoption of greywater treatment systems |

Table 4-2 (c): Other Constructs and Measurement Items

| Construct | Measurement Items |
|---|---|
| Descriptive Norm (DN) | 1. People who are important to me think greywater treatment and reuse is important<br>2. People who are important to me are willing to adopt greywater treatment systems<br>3. People who are important to me support installation of greywater treatment systems |
| Environmental Knowledge (EK) | 1. Carbon dioxide contributes to the creation of the greenhouse effect<br>2. Overusing fertilizer and pesticide will damage the environment<br>3. Chlorofluorocarbons (CFC) emission from refrigerators is one of the causes to ozone depletion |
| Behavioral Intention (BI) | 1. I plan to install a greywater treatment system at my residence<br>2. I will make an effort to get a price quote on a greywater treatment system<br>3. I will practice greywater reuse if my house were pre-plumbed to support the installation of the greywater treatment system |

**Methodology**

Some of the previous studies employed regression models to investigate the influence of psychological variables on pro-environmental behaviors, which do not allow for discerning the possible interactions between the predictor variables (Abrahamse and Steg, 2011; Botetzagias et al., 2014). Hence, as suggested by few studies, a quantitative statistical strategy is employed called Structural Equation Model (SEM) is employed to address the research objectives (Oteng-Peprah et al., 2020; Botetzagias et al., 2015). SEMs are a very popular analysis method that are frequently used to test models in a variety of social and behavioral science domains. (Klockner, 2013). To conduct the SEM, many scholars such as Liao et al., (2007), Llorens et al., (2007), Sit et al., (2009), Wu et al., (2007), Yu et al., (2010) have proposed a two-stage modeling process, whereby the confirmatory factor analysis (CFA) need to be examined first before testing the structure model. The structural model shows the relationships among the latent variables themselves, while the measurement model (CFA model) is used to determine the relationships between manifest or observable variables and latent or unobserved variables (Ho, 2006). Individual CFAs were conducted for each of the components, as recommended by Hair et al. (2006), and then the measurement model of the study offered details and evaluation based on the Goodness-Of-Fit (GOF) indices and evidence of construct validity. The extraction method used in this investigation was maximum likelihood estimation (MLE), one of the most used estimate techniques that enables assessment of individual direct effects and correlation between error terms. Based on skewness and kurtosis, the distribution's normalcy was confirmed. The normal distribution of the data is the key presumption when utilizing MLE.

Generally, skew and kurtosis that fall between the ranges of -1 to +1, -2 to +2, or even 3 indicate that the data is regularly distributed (Schumacker & Lomax 2010). Byrne (2013) recommended that a cut-off threshold for the kurtosis of less than 7 be used. The data that is regularly distributed and skewed between -3 and +3 could be evaluated.

By taking into account the amount of factor loading (standardized regression weights), Average Variance Extracted (AVE), and Composite Reliability (CR) among sets of items in the construct, the convergent validity may be assessed. The extracted average variance of 0.5 or higher and factor loading estimates with values greater than 0.5 demonstrate acceptable convergence among the construct's elements (Hair, et al., 2006). To demonstrate sufficient internal consistency, the composite reliability (CR) should be 0.6 or above (Bagozzi and Yi., 1988). By comparing the square root of the AVE for two constructs and their correlations, discriminant validity may be evaluated. When the correlation between each pair of constructs is less than the square root of the AVE for each construct, there is evidence of discriminant validity (Fornell and Larcker, 1981; Hair, et al., 2006). Additionally, correlations between the variables should not be higher than 0.85. (Kline 2010). It is important to look at Cronbach's alpha coefficient of internal consistency to make sure the elements create a trustworthy scale. With a value range of 0 to 1, Cronbach's alpha indicates the degree of reliability. According to Nunnally and Bernstein, Cronbach's alpha shouldn't be less than 0.7 for a credible scale. (Nunnally & Bernstein, 1994). According to Quaddus and Hofmeyer (2007), the value of R-squared (R2), which reflects the percentage of variance in the dependent variable explained by its predictors, should be above 0.10 in order to confirm the accuracy of the structural model. The data were analyzed using the Statistical Package for Social Scientists (SPSS) and AMOS software, which also looked at the research study's hypotheses.

### *Data Screening*

In all, 502 data samples were gathered for this investigation. Prior to performing the data analysis, it was crucial to consider the accuracy of the data submitted into the data file as well as the output that would result in correlations without distortions (Tabachnick & Fidell, 2007). Since there was no missing values in the data, no method is employed to treat the missing data. Outliers were assessed using the standardized z-score and Mahalanobis D2 distance for univariate and multivariate outliers, respectively, because they could impact the normality of the data and skew the statistical findings. As no outliers were found, all observations were retained for the analysis.

### *Assessment of the Data Normality*

In order to determine whether the data for the constructs had a normal distribution, the normality test was carried out as the primary presupposition of maximum likelihood estimation. The normal distribution is assessed through univariate distribution. The outcome showed that all items and variables had skew and kurtosis between 3 and 7, respectively (Schumacker & Lomax 2010, Byrne 2013). Therefore, it may be said that a normal distribution accurately described the entire data set of the items. The findings are presented in accordance with Hoyle and Isherwood's suggestions (2013).

## Results and Discussion

### *Measurement Model*

To ensure accuracy in the process, the operationalization of constructs is considered a very important step (Hair, 2006). The strength of the regression paths from the factors to the observed variables (the factor loadings) are of major relevance since it is more particularly interested in how much the observed variables are generated by the underlying latent constructs (Mueller and Hancock, 2019). As mentioned earlier the extracted average variance of 0.5 or higher and factor loading estimates with values of at least 0.5 indicate appropriate convergence of the construct's elements (Hair, et al., 2006). Using AMOS 20.0, the findings from assessing each construct's uni-dimensionality are shown. To measure the nine first-order latent variables that were developed for this study (Table 4-2), 32 items were used. Factor loadings of the items are presented in Table 4-3.

In Table 4-3, model 1 factor loadings represent the results of assessing the standardized loadings of the model’s items. It is observed that the factor loadings of PBC7 was 0.332, below the cut-off of 0.5. Thus, this item was removed from the model. To make sure that the factor structure remained stable, the updated model was tested once more. As a result, the model 2 factor loadings in Table 4-3 represent the second standardized factor loadings for all 31 remaining items. These loadings were greater than 0.5 and ranged from 0.823 to 0.955. As a result, no additional item was eliminated due to inadequate factor loading.

Table 4-3: Standardized Factor Loadings of the Items

| Construct | Item | Model 1 Factor Loading | Item Deleted | Model 2 Factor Loading |
|---|---|---|---|---|
| Attitude (ATT) | ATT1 | 0.865 | | 0.865 |
| | ATT2 | 0.902 | | 0.901 |
| | ATT3 | 0.908 | | 0.908 |
| | ATT4 | 0.934 | | 0.934 |
| Subjective Norm (SN) | SN1 | 0.929 | | 0.929 |
| | SN2 | 0.843 | | 0.843 |
| | SN3 | 0.939 | | 0.939 |
| Perceived Behavioral Control (PBC) | PBC1 | 0.873 | | 0.838 |
| | PBC2 | 0.859 | | 0.823 |
| | PBC3 | 0.859 | | 0.869 |
| | PBC4 | 0.852 | | 0.864 |
| | PBC5 | 0.83 | | 0.845 |
| | PBC6 | 0.844 | | 0.857 |
| | PBC7 | 0.332 | Deleted | |
| Personal Norm (PN) | PN1 | 0.94 | | 0.94 |
| | PN2 | 0.912 | | 0.913 |
| | PN3 | 0.919 | | 0.919 |
| Awareness of consequences (AC) | AC1 | 0.91 | | 0.91 |
| | AC2 | 0.856 | | 0.856 |
| | AC3 | 0.911 | | 0.911 |
| Ascription of responsibility (AR) | AR1 | 0.927 | | 0.927 |
| | AR2 | 0.888 | | 0.889 |
| | AR3 | 0.891 | | 0.891 |
| Descriptive Norm (DN) | DN1 | 0.894 | | 0.894 |
| | DN2 | 0.943 | | 0.943 |
| | DN3 | 0.955 | | 0.955 |
| Environmental Knowledge (EK) | EK1 | 0.908 | | 0.907 |
| | EK2 | 0.888 | | 0.889 |
| | EK3 | 0.873 | | 0.873 |
| Behavioral Intention (BI) | BI1 | 0.938 | | 0.938 |
| | BI2 | 0.93 | | 0.93 |
| | BI3 | 0.916 | | 0.916 |

In addition to providing the tool needed to examine reliability, the SEM is distinguished by its ability to assess the construct validity of a given measurement theory and its overall model fit (Hair, et al., 2006; Ho, 2006). There are several goodness-of-fit indices available for measuring overall CFA, evaluating individual construct CFA, and evaluating proposed structural models. The Goodness-Of-Fit (GOF) indices provide the tools to assess the degree of coincidences between the proposed model's covariance matrix and a sample covariance matrix (Kline, 2010).

In this study, model fit was evaluated using a variety of absolute fit measures, including the Tucker-Lewis Index (TLI), Normed Fit Index (NFI), Incremental Fit Index (IFI), and Comparative Fit Index (CFI). These measures included the Chi-square statistic, Relative Chi-square (2/df), Goodness-of-Fit statistic (GFI), Adjusted Goodness-of-Fit statistic (AGFI), Root Mean Square Error of Approximate GFI values greater than 0.90 signify an excellent match (Hoyle, 1995). Another absolute fit metric is Root Mean Square Error of Approximation (RMSEA), which should be lower than 0.1 to indicate a satisfactory fit (Schumacker and Lomax, 2010). However, RMSEA values between 0.03 and 0.08 indicate a model with a superior match (Hair, et al., 2006; Ho, 2006). Values for the incremental fit indices TLI, NFI, IFI, and CFI range from 0 (poor fit) to 1. (Perfect fit). There is a decent fit between the model and the data when the values are 0.90 and above (Bagozzi and Yi., 1988; Byrne, 2013; Hair et al., 2006; Ho, 2006).

The model indicated that some of the items showed a high discrepancy of covariance between their related errors, indicating the presence of redundant items in the model. The modification index value of covariance between the errors of PBC1 and PBC2 was 85.781. The modified CFA model was conducted, and the results indicate that the modified overall measurement model provided an adequate fit of the data with the remaining 31 items. The results of the goodness of fit indices of the measurement model are represented in Table 4-4.

Table 4-4: Goodness of Fit Indices of the CFA Model

| Fit index | Modified | Recommended | Source |
|---|---|---|---|
| df | 397 | | |
| CMIN | 741.679 | | |
| p-value | 0.000 | > 0.05 | |
| $\chi^2$/df | 1.868 | ≤ 5.00 | Bagozzi and Yi (1988) |
| GFI | 0.914 | ≥ 0.90 | Hoyle (1995) |
| AGFI | 0.893 | ≥ 0.80 | Chau and Hu (2001) |
| CFI | 0.980 | ≥ 0.90 | Bagozzi and Yi (1988); Byrne, |
| TLI | 0.976 | ≥ 0.90 | Hair et al., (2006); Ho, (2006) |
| IFI | 0.980 | ≥ 0.90 | Hair et al., (2006); Ho, (2006) |
| RMSEA | 0.042 | ≤ 0.10 | Schumacker and Lomax, 2010 |

The GFI value was 0.914, which is higher than the advised level of 0.9. Following correction for the degrees of freedom in relation to the number of variables, the adjusted GFI (AGFI) was 0.893, which was higher than Chau and Hu's suggested cut-off limit of 0.80. (2001). It showed that 89.3% of the variances and covariance in the survey data are predicted by the model. The model had an excellent data fit based on the CFI, TLI, and IFI indices having values more than the cutoff value of 0.9 (0.980, 0.976, and 0.980, respectively) (Bagozzi and Yi., 1988; Byrne., 1998; Hair et al., 2006; Ho., 2006). Additionally, the root-mean-square error of approximation (RMSEA) was 0.042, below the Schumacker and Lomax-recommended cut off of 0.1. (2010). Additionally, the Relative CMIN/df was 1.868, less than 5, indicating that the model fit the data well (Bagozzi and Yi., 1988). No modifications are needed because the modified CFA model appropriately fits the data.

Along with the model fit, the scale's reliability, convergent validity, and discriminant validity were investigated. To determine how much variation is shared amongst the model's latent variables, researchers have frequently utilized the Fornell-Larcker (1981) criterion. The Average Variance Extracted (AVE) and Composite Reliability metrics can be used to evaluate the convergent validity of the measurement model in accordance with this criterion (CR). For the amended CFA model with 31 remaining items, Table 4-5 shows the Cronbach alpha and convergent validity results.

Analysis of the standardized loadings presented in Table 4-5 for the model's items revealed that all 31 of the remaining items had factor loadings more than 0.5, ranging from 0.823 to 0.955. This offers proof that the model theory, according to which the objects are connected to the respective constructions, is correct.

In accordance with Nunnally & Bernstein's recommended cutoff of 0.5, Table 4-5 also demonstrates that the AVE, which measures the overall amount of variance in the indicators that the latent construct accounts for, was over this threshold and varied between 0.722 and 0.867. The composite reliability value, which measures how well the construct indicators (items) reflect the latent construct, was above Bagozzi and Yi's (1988) suggested value of 0.6 and varied between 0.919 and 0.951. The Cronbach's Alpha value, which expresses how error-free a measure is, was higher than the 0.7 cutoff point recommended by Nunnally and Bernstein (1994), ranging from 0.919 to 0.950. Therefore, it was determined that the obtained Cronbach's Alpha for all constructs was sufficiently error-free.

Table 4-5: Results of Reliability and Convergent Validity

| Construct | Item | Factor Loading | Average Variance Extracted (AVE) | Composite Reliability (CR) | Cronbach Alpha |
|---|---|---|---|---|---|
| Attitude (ATT) | ATT1 | 0.865 | 0.814 | 0.946 | 0.946 |
| | ATT2 | 0.901 | | | |
| | ATT3 | 0.908 | | | |
| | ATT4 | 0.934 | | | |
| Subjective Norm (SN) | SN1 | 0.929 | 0.818 | 0.931 | 0.930 |
| | SN2 | 0.843 | | | |
| | SN3 | 0.939 | | | |
| Perceived Behavioral Control (PBC) | PBC1 | 0.838 | 0.722 | 0.940 | 0.941 |
| | PBC2 | 0.823 | | | |
| | PBC3 | 0.869 | | | |
| | PBC4 | 0.864 | | | |
| | PBC5 | 0.845 | | | |
| | PBC6 | 0.857 | | | |
| Personal Norm (PN) | PN1 | 0.94 | 0.854 | 0.946 | 0.946 |
| | PN2 | 0.913 | | | |
| | PN3 | 0.919 | | | |
| Awareness of consequences (AC) | AC1 | 0.91 | 0.797 | 0.922 | 0.920 |
| | AC2 | 0.856 | | | |
| | AC3 | 0.911 | | | |
| Ascription of responsibility (AR) | AR1 | 0.927 | 0.815 | 0.929 | 0.928 |
| | AR2 | 0.889 | | | |
| | AR3 | 0.891 | | | |
| Descriptive Norm (DN) | DN1 | 0.894 | 0.867 | 0.951 | 0.950 |
| | DN2 | 0.943 | | | |
| | DN3 | 0.955 | | | |
| Environmental Knowledge (EK) | EK1 | 0.907 | 0.792 | 0.919 | 0.919 |
| | EK2 | 0.889 | | | |
| | EK3 | 0.873 | | | |
| Behavioral Intention (BI) | BI1 | 0.938 | 0.861 | 0.949 | 0.949 |
| | BI2 | 0.93 | | | |
| | BI3 | 0.916 | | | |

To determine how truly different a construct is from other constructs, the discriminant validity was investigated. When it comes to discriminant validity, Kline advises that the correlations between the measurement model's variables shouldn't be more than 0.85. (2010). The discriminant validity of the measurement model is shown in Table 4-6. The other entries in the table are correlations, whereas the diagonals in the table indicate the square root of the average variance that was extracted.

The intercorrelations between the ten constructs ranged between 0.225 and 0.790, which were below the threshold of 0.85 as recommended by Kline (2010). The correlations were also lower than the average variance extracted by the indicators, as shown in Table 4-6, suggesting high discriminant validity between these components (Kline 2010). Upon examining the goodness to fit of data, convergent validity, and discriminant validity of the measurement model, it can be concluded that the measurement scale to assess the constructs and their relative items was reliable and valid.

Table 4-6: Discriminant validity of Measurement Model

| | ATT | SN | PBC | PN | AC | AR | DN | EK | BI |
|---|---|---|---|---|---|---|---|---|---|
| Attitude (ATT) | **0.902** | | | | | | | | |
| Subjective Norm (SN) | 0.528 | **0.905** | | | | | | | |
| Perceived Behavioral Control (PBC) | 0.762 | 0.539 | **0.849** | | | | | | |
| Personal Norm (PN) | 0.665 | 0.689 | 0.751 | **0.924** | | | | | |
| Awareness of consequences (AC) | 0.772 | 0.576 | 0.773 | 0.723 | **0.893** | | | | |
| Ascription of responsibility (AR) | 0.418 | 0.225 | 0.417 | 0.368 | 0.419 | **0.903** | | | |
| Descriptive Norm (DN) | 0.550 | 0.724 | 0.606 | 0.734 | 0.584 | 0.264 | **0.931** | | |
| Environmental Knowledge (EK) | 0.610 | 0.435 | 0.604 | 0.590 | 0.663 | 0.333 | 0.465 | **0.890** | |
| Behavioral Intention (BI) | 0.737 | 0.670 | 0.757 | 0.782 | 0.790 | 0.362 | 0.655 | 0.659 | **0.928** |

***Descriptive Analysis***

In this analysis, covariance matrix method was used to calculate the descriptive function so that all of the variables could be included in the analysis. Table 4-7 displays the means and standard deviation of the constructs, assessed on a 7-point Likert scale.

Table 4-7: Results of Descriptive Statistic for Variables

| Constructs | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Attitude (ATT) | 5.364 | 1.190 | 1.3 | 7 |
| Subjective Norm (SN) | 4.196 | 1.238 | 1 | 7 |
| Perceived Behavioral Control | 5.143 | 1.163 | 1.2 | 7 |
| Personal Norm (PN) | 4.518 | 1.396 | 1 | 7 |
| Awareness of consequences (AC) | 5.027 | 1.264 | 1 | 7 |
| Ascription of responsibility (AR) | 4.394 | 1.380 | 1 | 7 |
| Descriptive Norm (DN) | 4.450 | 1.247 | 1 | 7 |
| Environmental Knowledge (EK) | 5.328 | 1.278 | 1 | 7 |
| Behavioral Intention (BI) | 4.642 | 1.408 | 1 | 7 |

As indicated in Table 4-7, the mean was applied as a measure of central tendency, which indicated that the mean values of all constructs are above the mid-point of 4 out of 7-point Likert scale. The highest mean rating of 5.364 is observed for Attitude (ATT), whereas the lowest mean rating of 4.196 is observed for Subjective Norm (SN). Among the examined variables, Behavioral Intention (BI) had the largest standard deviation (SD) from the mean (1.408). This standard deviation revealed that respondents' perceptions of Behavioral Intention varied quite a bit (BI). In other words, this variable showed the most difference amongst the survey respondents. Contrarily, Perceived Behavioral Control (PBC), with a standard deviation of 1.163, had the lowest variation from the mean. The mean of all variables and the error bars showing their standard deviations are well-illustrated in Figure 4-2.

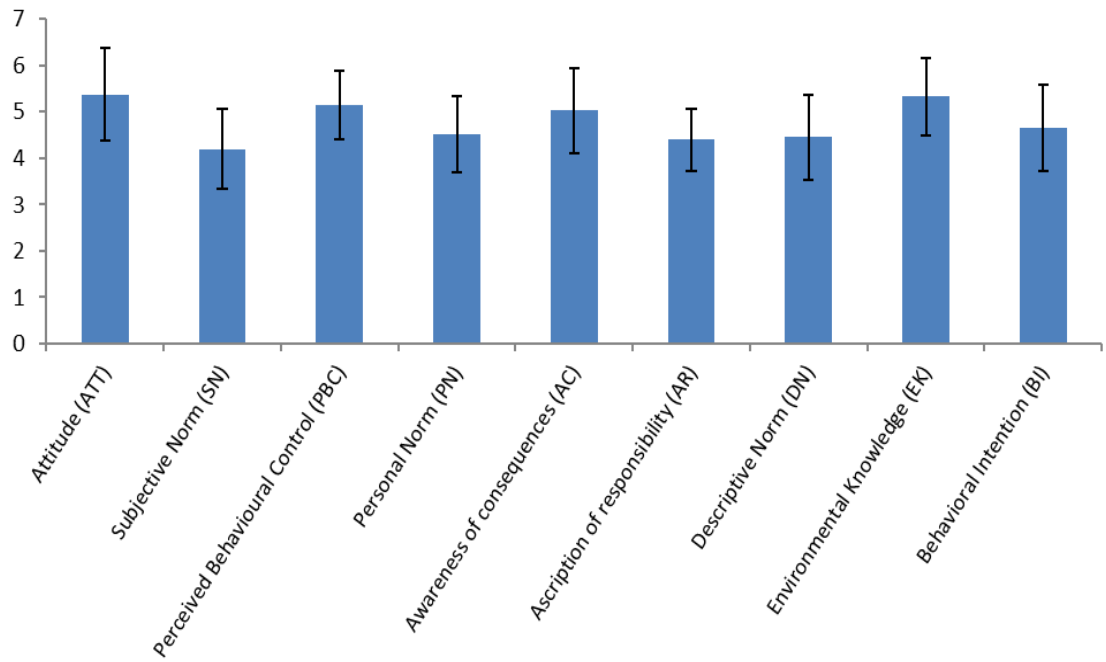


Figure 4-2: Means and Standard Deviation of Variables

***Structural Model***

In this study, the structural model was estimated to examine the research hypotheses using AMOS. In the structural model, the causal effects from Attitude (ATT), Subjective Norm (SN), Perceived Behavioural Control (PBC), Personal Norm (PN), Awareness of consequences (AC), Ascription of responsibility (AR), Descriptive Norm (DN) and Environmental Knowledge (EK) (independent variables) on Behavioural Intention (BI) (dependent variable) were examined (i.e., H1 thru H8 respectively). Figure 4-3 portrays the structural model with causal effects and the standardized regression weights.

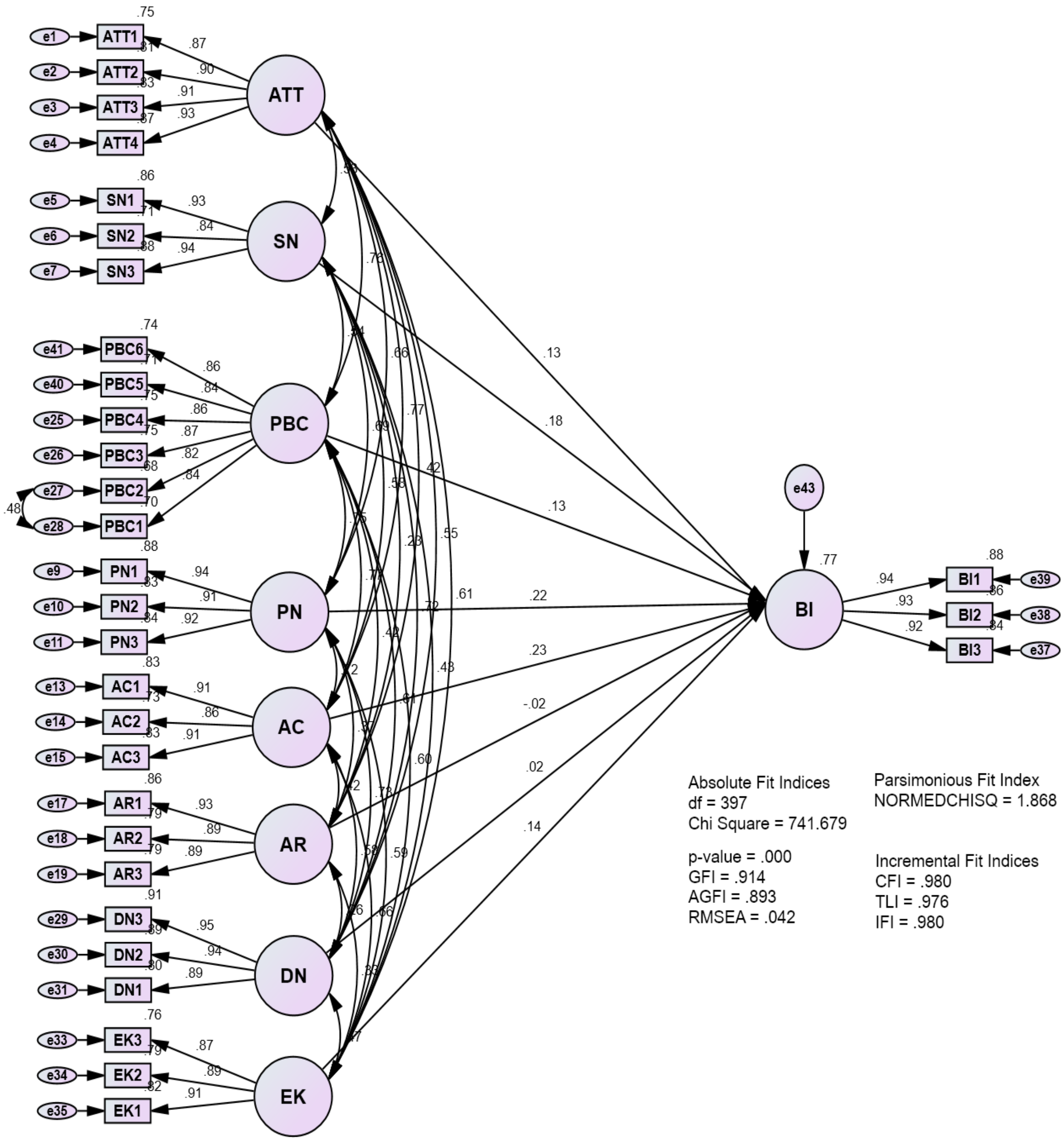


Figure 4-3: Structural Model with Causal Effects and the Standardized Regression Weights

An examination of goodness-of-fit indices indicates adequately fitted the data: $\chi^2$ = 741.679, df = 397, p-value = 0.000, GFI = 0.914, AGFI = 0.893, CFI = 0.980, TLI = 0.976, IFI = 0.980, RMSEA = 0.042 and $\chi^2$/df = 1.868. Although the chi-square statistic is statistically significant, this is not deemed unusual given the large sample size (Bagozzi, Yi, and Phillips 1991).

The $R^2$ value for Behavioural Intention (BI) was 0.77. This indicates the error variance of Behavioural Intention (BI) is approximately 23 percent i.e., 77 percent of variations in Behavioural Intention (BI) are explained by its 8 predictors. Overall findings showed that the scores of $R^2$ value satisfy the requirement for the 0.10 cut-off value (Quaddus and Hofmeyer 2007). The path coefficients and the results of examining hypothesized causal effects are displayed in Table 4-8.

Table 4-8: Hypothesized Causal Effects of the Variables

| Path | Unstandardized Estimate | | Standardised Estimate | Critical Ratio (c.r.) | P-value | Hypothesis Result |
|---|---|---|---|---|---|---|
| | Estimate | S.E. | Beta | | | |
| ATT → BI | 0.173 | 0.063 | 0.132 | 2.758 | 0.006 | H1) Supported |
| SN → BI | 0.196 | 0.047 | 0.175 | 4.172 | 0.000 | H2) Supported |
| PBC → BI | 0.153 | 0.062 | 0.130 | 2.446 | 0.014 | H3) Supported |
| PN → BI | 0.212 | 0.053 | 0.215 | 4.025 | 0.000 | H4) Supported |
| AC → BI | 0.266 | 0.062 | 0.234 | 4.261 | 0.000 | H5) Supported |
| AR → BI | -0.015 | 0.028 | -0.015 | -0.527 | 0.598 | H6) Rejected |
| DN → BI | 0.025 | 0.05 | 0.022 | 0.508 | 0.611 | H7) Rejected |
| EK → BI | 0.156 | 0.043 | 0.136 | 3.655 | 0.000 | H8) Supported |

As shown in Table 4-8, the two paths of Ascription of responsibility (AR) to Behavioural Intention (BI) and Descriptive Norm (DN) to Behavioural Intention (BI) have p-value less than the standardized significant level of 0.05, hence these hypotheses have been rejected. This indicates that the individual's personal belief about whether the individual is responsible for the consequences of their behavior and the individual's perception that others' engagement in greywater treatment adoption do not have any effect of their intention to adopt greywater treatment systems. All other paths were found as statistically significant and therefore support the hypotheses H1, H2, H3, H4, H5, and H8. These findings suggest that a person's intention to adopt greywater treatment systems is significantly influenced by their attitude, perception of social pressure, belief in their ability to exercise free will, sense of personal responsibility, perception of the environmental costs of their behavior, and environmental knowledge. The findings also showed that Awareness of Consequences (AC), which has a standardized path coefficient of 0.234, is the best predictor of Behavioural Intention (BI). Personal Norm (PN), which had a normalized path coefficient of 0.215, was the second-best predictor. The results of path analysis in relation to the above hypotheses is further discussed below:

H1. Attitude (ATT) has positive effect on Behavioral Intention (BI): The critical ratio (c.r.) and p-value of Attitude (ATT) in predicting Behavioral Intention (BI) were 2.758 and 0.006 respectively, which indicate that the regression weight for Attitude (ATT) in the prediction of Behavioral Intention (BI) is significantly different from zero. Thus, supporting H1. Further, the standardized estimate of Beta was 0.132, indicating a positive relationship.

H2. Subjective Norm (SN) has positive effect on Behavioral Intention (BI): The regression weight for Subjective Norm (SN) in the prediction of Behavioral Intention (BI) is significantly different from zero. Thus, H2 was supported. Further, the standardized estimate of Beta was 0.175, indicating a positive relationship.

H3. Perceived Behavioral Control (PBC) has positive effect on Behavioral Intention (BI): The regression weight for Perceived Behavioural Control (PBC) in the prediction of Behavioral Intention (BI) is significantly different from zero. Thus, H3 was supported. Further, the standardized estimate of Beta was 0.130, indicating a positive relationship.

H4. Personal Norm (PN) has positive effect on Behavioral Intention (BI): The regression weight for Personal Norm (PN) in the prediction of Behavioral Intention (BI) is significantly different from zero. Thus, H4 was supported. Further, the standardized estimate of Beta was 0.215, indicating a positive relationship.

H5. Awareness of consequences (AC) has positive effect on Behavioral Intention (BI): The regression weight for Awareness of consequences (AC) in the prediction of Behavioral Intention (BI) is significantly different from zero. Thus, H5 was supported. Further, the standardized estimate of Beta was 0.234, indicating a positive relationship.

H6. Ascription of responsibility (AR) has positive effect on Behavioral Intention (BI): The results indicated that there was no any significant direct relationship between Ascription of responsibility (AR) and Behavioral Intention (BI); path coefficient = -0.015, cr = -0.527, p-value= 0.598. Thus, H6 was rejected.

H7. Descriptive Norm (DN) has positive effect on Behavioral Intention (BI): The results indicated that there was no any significant direct relationship between Descriptive Norm (DN) and Behavioral Intention (BI); path coefficient = 0.022, cr = 0.508, p-value= 0.611. Thus, H7 was rejected.

H8. Environmental Knowledge (EK) has positive effect on Behavioral Intention (BI): The regression weight for Environmental Knowledge (EK) in the prediction of Behavioral Intention (BI) is significantly different from zero. Thus, H8 was supported. Further, the standardized estimate of Beta was 0.136, indicating a positive relationship.

Figure 4-4 depicts the results of examining the causal effects in the structural model with the standardized coefficients.

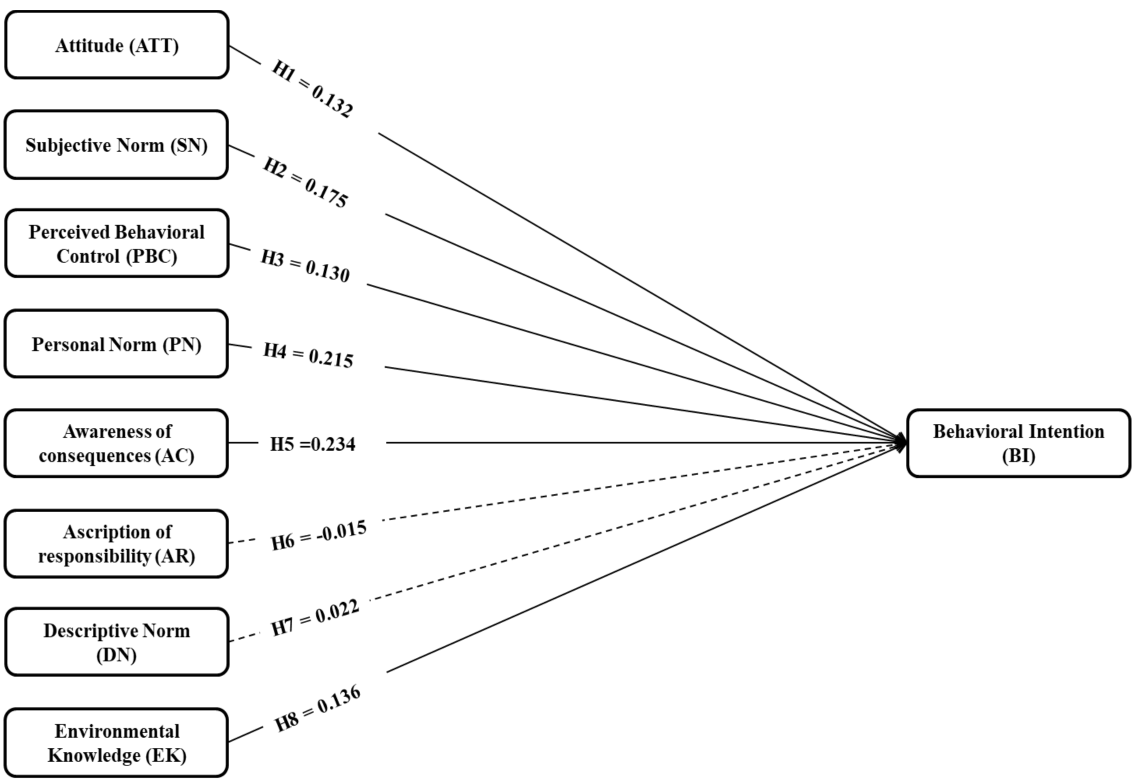


Figure 4-4: Examined Causal Effects Hypotheses and Path Diagram

**Comparative Tests**

Using an independent sample T-test, the mean difference in behavioral intention (BI) between the dichotomous categories of gender, location, and house type is examined.

In order to determine the average difference in behavioral intention (BI) between the age groups, one-way ANOVA and the Post-Hoc test were also used (19-31, 32-44, 45-57, 58-72). Two-way ANOVA was used to assess the mean behavioral intention (BI) difference between the income and location combination groups. In this study, the mean difference in behavioral intention (BI) between the two groups of gender (i.e., male & female), location (i.e., California & Florida), and house type (i.e., own & rent) was examined using a parametric comparison test known as the independent sample T-test. The analysis of the Behavioral Intention (BI) mean difference between the two groups of gender, location, and housing type is shown in Table 4-9 along with the findings of Levene's test of equality of variance and independent sample T-test.

Table 4-9: Mean Difference of Behavioral Intention (BI) between the Groups of Gender, Location & House Type

| **Demographic** | **Levene's test** | | **Independent Sample T-test** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **F** | **p** | **Group#1** | **Group#2** | **Δ** | **T** | **df** | **p** | **Effect Size** |
| Gender | 0.119 | 0.730 | Male=251 | Female=251 | 0.02 | 0.18 | 500 | 0.854 | 0.016 |
| | | | 4.654 | 4.631 | | | | | |
| Location | 0.347 | 0.556 | California=350 | Florida=152 | 0.13 | 0.94 | 500 | 0.344 | 0.091 |
| | | | 4.681 | 4.552 | | | | | |
| House Type | 0.028 | 0.867 | Own=307 | Rent=195 | -0.31 | -2.47 | 500 | 0.014 | 0.227 |
| | | | 4.519 | 4.836 | | | | | |

Δ = mean difference; df = degree of freedom; N = 502; $p<0.05$

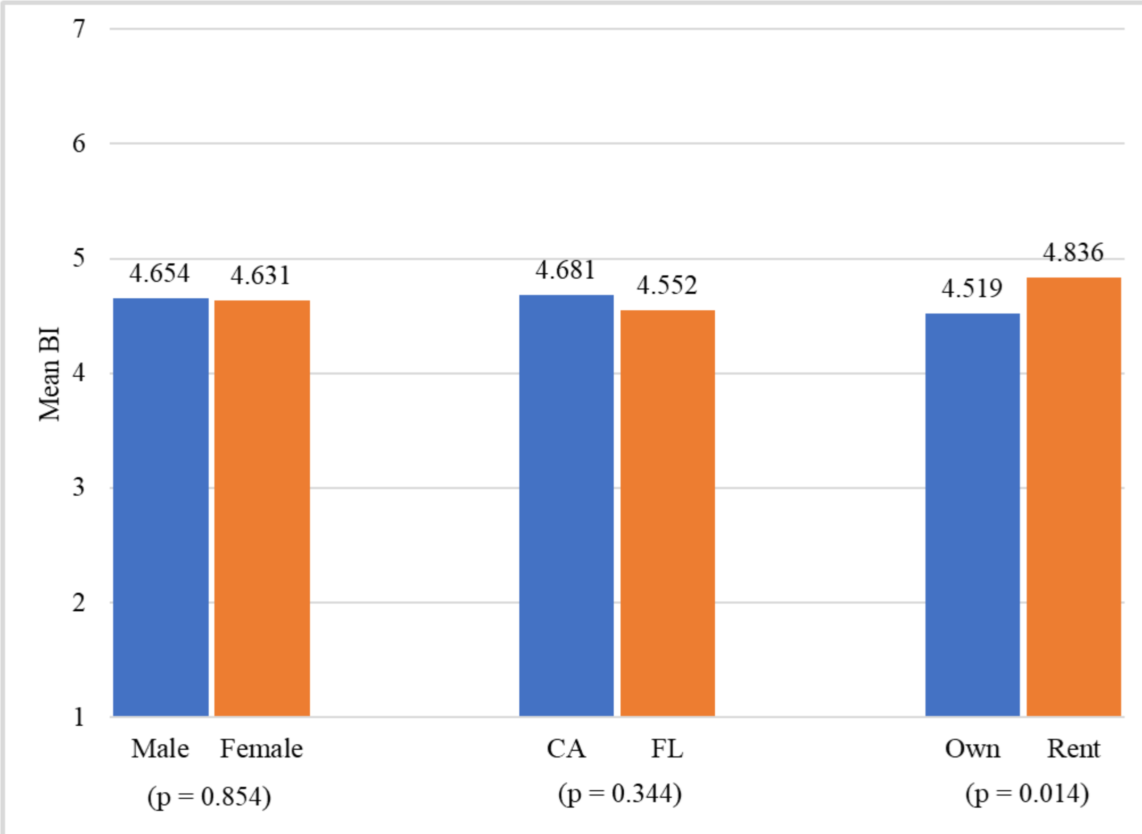


Figure 4-5: Behavioral Intention Mean Differences between the Dichotomous Groups of Gender, Location, and House Type

The findings of the independent sample T-test revealed that men's mean behavioral intentions (BI) were somewhat higher than women's (4.654 vs. 4.631), but the mean difference was not statistically significant because the p-value was higher than the 0.05 cutoff. The effect size is 0.016, indicating that there is only a minor (1.6 percent of a standard deviation) difference in the mean behavioral intention (BI) between male and female. The mean value of Behavioral Intention (BI) in California (4.681) is slightly higher than in Florida (4.631). The effect size is 0.091, indicating the mean difference of Behavioral Intention (BI) between California and Florida is small and equal to 9.1% of a standard deviation. The results of the independent sample T-test also indicate that the mean value of Behavioral Intention (BI) for rented houses (4.836) is significantly higher than for owned houses (4.519). The effect size is 0.227, indicating the mean difference of Behavioral Intention (BI) between rent and own is high and equal to 22.7% of a standard deviation. Figure 4-5 represents the Behavioral Intention (BI) mean differences between the dichotomous groups of gender, location, and house type.

***One Way ANOVA Test***

The one-way ANOVA test is performed as a comparative parametric test in this study. If Levene's p-value is greater than the cutoff of 0.05, the population variances are regarded as being identical. Table 4-10 shows the results of Levene's test for examining the equality of variance and One Way ANOVA for examining the mean difference of Behavioral Intention (BI) between the groups of Age.

Table 4-10: Mean Difference of Behavioral Intention (BI) between the Age Groups

| Demographic | Levene's test | | | ANOVA | | |
|---|---|---|---|---|---|---|
| | F | df | p | F | df | p |
| Age | 1.616 | 3, 498 | 0.185 | 10.932 | 3, 498 | 0.000 |

Levene's test findings are provided in Table 4-10, and they reveal that equality of variance was assumed for age groups because the p-value of 0.185 is higher than the 0.05 cutoff. Therefore, One Way ANOVA was used to investigate the mean behavioral intention (BI) difference between the age groups. The results of One Way ANOVA indicated that the mean value of Behavioral Intention (BI) is significantly changed between the age groups.

***Post-Hoc Tests***

The outcomes of the post-hoc Tukey test for each behavioral intention (BI) measure compared to each other in regard to the age groups are shown in Table 4-11.

Table 4-31: Results of Post-Hoc Tukey Test to Examine Mean Difference in Behavioral Intention (BI) between the Age Groups

| Mean Value of Age | | | | | Standard Error | p |
|---|---|---|---|---|---|---|
| 19 - 31 (n=86) | 32 - 44 (n=122) | 45 - 57 (n=98) | 58 – 72 (n=196) | Mean Difference (Δ) | | |
| 4.806 | 5.122 | | | -0.316 | 0.193 | 0.356 |
| 4.806 | | 4.693 | | 0.113 | 0.202 | 0.944 |
| 4.806 | | | 4.246 | 0.559** | 0.177 | 0.009 |
| | 5.122 | 4.693 | | 0.429 | 0.186 | 0.096 |
| | 5.122 | | 4.246 | 0.875*** | 0.158 | 0.000 |
| | | 4.693 | 4.246 | 0.446* | 0.169 | 0.043 |

As shown in Table 4-11, the results of Tukey test indicated the mean value of Behavioral Intention (BI) for 19 thru 31 years old (4.806) was significantly higher than the mean value of Behavioral Intention (BI) for 58 thru 72 years old (4.246). The Tukey test results also indicated that the mean value of Behavioral Intention (BI) for 58 thru 72 years old (4.246) is significantly lower than 32 thru 44 years old (5.122) and 45 thru 57 years old (4.693). Figure 4-6 represents the Behavioral Intention (BI) mean differences between the age groups with a confidence interval of 0.95.

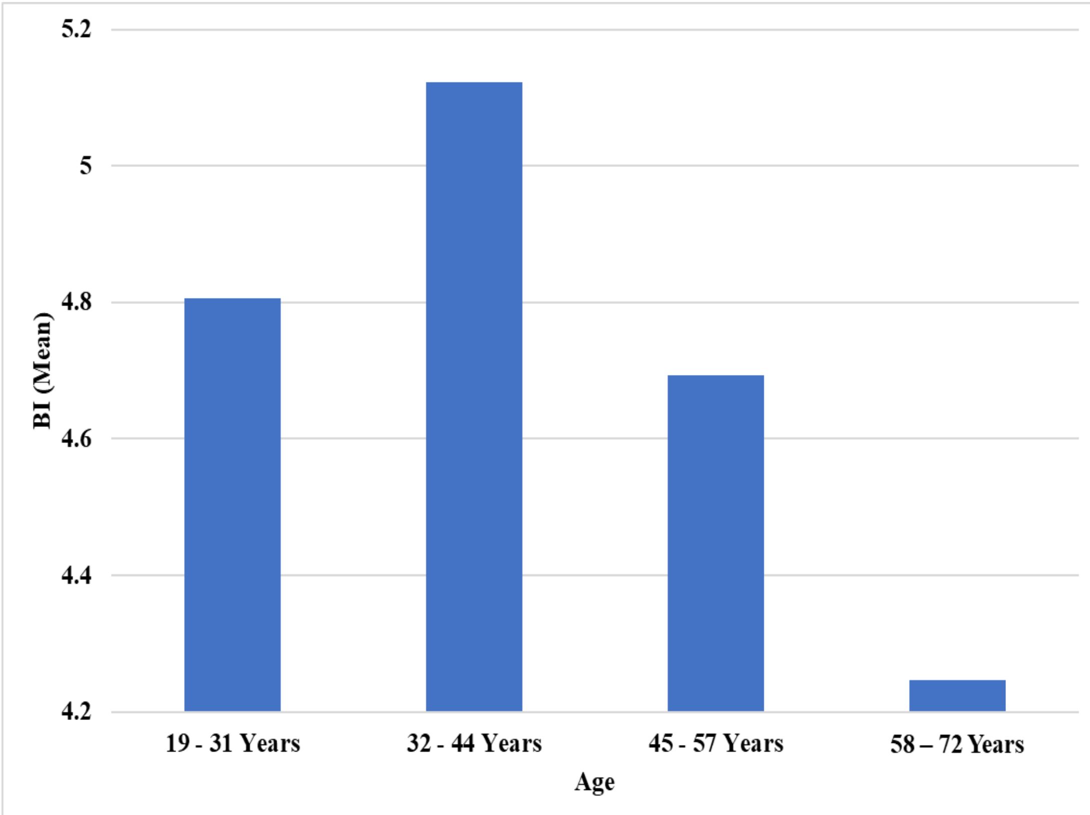


Figure 4-6: Behavioral Intention Mean Values between Age Groups

***Two-Way ANOVA Test***

Using two independent variables, the two-way ANOVA compares the mean differences between groups. The two-way ANOVA test was carried out to compare the mean value of Behavioral Intention (BI) between the two groups of location (i.e., California and Florida) among three groups of income (i.e., Less than $50K, $50K thru $100K and More than $100K). Partial Eta Squared ($\eta^2$) is used to interpret the effect size or magnitude of changes in the mean value over the interaction between the two independent variables. Partial Eta Squared of 0.01 refers to small changes, 0.06 refers to medium changes and

0.14 refers to large changes in the mean value of a variable over a specific period of time (Haase, 1983).

Table 4-12: Mean Difference of Behavioral Intention (BI) between the Combination Groups of Location and Income

| | | N | Mean | F | df | p | η2 | Magnitude |
|---|---|---|---|---|---|---|---|---|
| Location * Income | | | | 0.709 | 2, 496 | 0.493 | 0.003 | Small |
| California | Less than $50K | 139 | 4.568 | | | | | |
| | Between $50K & $100K | 103 | 4.826 | | | | | |
| | More than $100K | 108 | 4.690 | | | | | |
| Florida | Less than $50K | 76 | 4.346 | | | | | |
| | Between $50K & $100K | 47 | 4.679 | | | | | |
| | More than $100K | 29 | 4.886 | | | | | |

As shown in Table 4-12 the value of the F tests in two-way ANOVA table was not statistically significant because of having p-value of 0.493, above the threshold of 0.05. Therefore, it can be stated that the mean value of Behavioral Intention (BI) is almost the same between the combination groups of Location and Income. In the other words, the Behavioral Intention (BI) mean value difference between the interaction groups of location and income is very small and statistically insignificant. Figure 4-7 represents the means plots of Behavioral Intention (BI) mean differences between the combination groups of location and income.

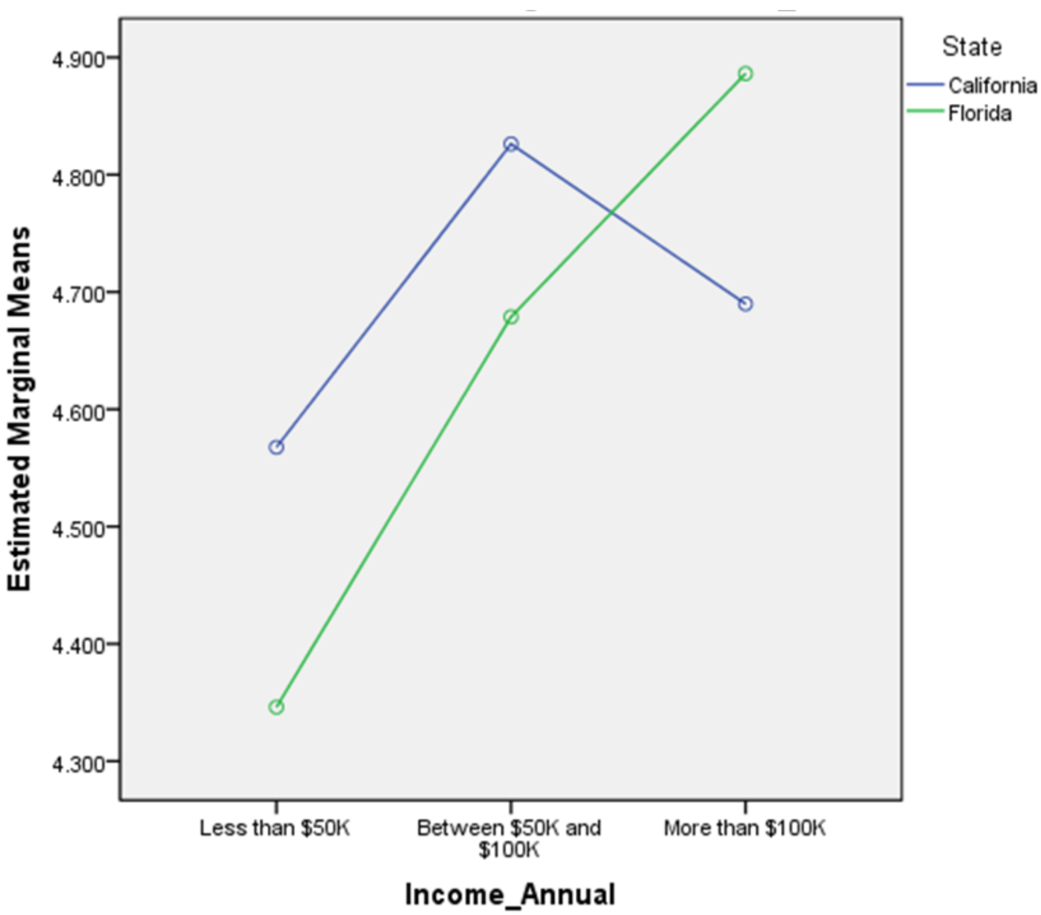


Figure 4-7: Means Plot of Behavioral Intention Mean Values between the Combination Groups of Location and Income

**Conclusions**

The current research made important contributions to the understanding of the public perception of greywater treatment and reuse. It is one of the first to employ the full framework provided by the TPB and NAM as predictors of behavioral intention but also incorporated descriptive norms and environmental knowledge in the model and also to investigate the public perception between two locations. Hypotheses developed in this study is tested by conducted the path analysis using AMOS. The results indicate that

Awareness of Consequences (AC) and Personal Norm (PN) are the first and second strongest predictors of Behavioral Intention (BI) respectively, i.e., an individual’s sense of severity of his or her own actions on the wellbeing of others and the sense of moral obligation have strongest influence on the individual’s intention to adopt greywater reuse treatment systems. However, the individual’s subjective judgment of his or her level of accountability for the results of their actions (Ascription of Responsibility) and the individual’s perspective of the conduct of those around them, specifically it refers to the view of what those near to the individual believe, feel or do tend not have any influence over the individual’s intention to adopt greywater reuse systems. Whereas all other constructs Attitude (ATT), Subjective Norm (SN), Perceived Behavioral Control (PBC), Personal Norm (PN), Awareness of consequences (AC) and Environmental Knowledge (EK) had significant positive effects on Behavioral Intention (BI). It was also observed that the individuals renting a home is influenced substantially more to adopt greywater reuse systems than individuals who owned homes. Also, a significant different in behavioral intention is observed between the age groups 19 to 57 and 58 to 72, the latter is observed to be less motivated to adopt greywater reuse treatment systems.

The results of the current study, in addition to earlier pro-environmental studies, offer convincing evidence of the factors that influence people's adoption and reuse of greywater systems. As a result, they can offer recommendations to the stakeholders and organizations that want to encourage greywater treatment and reuse at the household level. Encouragement of environmental groups to support initiatives that aid in environmental protection and raise knowledge of greywater reuse and treatment are some of the recommendations. Additionally, environmental organizations frequently encourage participation in public demonstrations, mailing postcards and letters to government officials, and signing petitions. This conveys a strong normative message from a variety of sources, which affects people's motivation to participate in greywater treatment and reuse. In order to persuade people to employ greywater reuse systems, campaigns might target particular behavioral goals and drivers. Campaign messages emphasizing the environmental advantages of greywater treatment and reuse, such as the reduction of environmental risks and pollution from untreated greywater, as well as further water conservation, may help shift people's perceptions and lead to actual behavioral change. Since personal norm is the strongest influencer of behavioral intention, greywater treatment systems and reuse could be promoted by creating awareness among the individuals that they could participate and contribute to making a change, where adopting the greywater system could be seen as a moral responsibility. This can be accomplished by making an appeal to people about the risks associated with the discharge of untreated greywater into the environment, which can contaminate freshwater resources and subsequently have an impact on aquatic life, and the fact that their adoption of this system can reduce or change this environmental hazard. The intricacy of the system's quality certification procedure may be streamlined and optimized, for example, by making it easily accessible online, which would change people's attitudes toward greywater reuse systems. Policies like financial incentives, tax credits, or the provision of a free system to decrease the financial load on the individual will be readily adopted. The new study's hybrid model methodology gave researchers a more thorough knowledge of how the public perceives the adoption of greywater treatment and reuse systems and the factors affecting that behavior.

The results of the current study have a drawback in that they are specific to California and Florida; however, these results can be normalized as the locations based on the state of greywater treatment system deployment. The results are therefore transferable to numerous additional places with comparable implementation settings. Nevertheless, there is a need for future research to include screening tests to distinguish between respondents who currently have a greywater treatment system at their home and those who do not, and then test the model to determine the respondents' behavioral intentions. Also, since this study employed an internet/online based survey, despite having sample selection criteria (location, age), there is a risk of sample selection bias as certain groups are under or over-represented in the gathered sample, resulting in a lack of significance with various factors. For example, there are 39% of the respondents were aged between 58 and 72 compared to 17% aged between 19 and 31. Future studies ought to employ more complex methodologies, like asking family members' perspectives while varying their level of knowledge about retrofitting. In this study, financial aspects of greywater treatment systems installation are not included in the survey, and since it has the potential to influence behavioral intention, it is encouraged to examine how much it costs to install greywater treatment systems and how that affects people's intentions to adopt. Furthermore, future studies can evaluate using various statistical methods and test the hybrid model presented in this study as opposed to using structural equation modelling. Another interesting avenue for future research involves in studying the mediation effects of the constructs and their influence on behavioral intention.

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# CHAPTER FIVE

# CONCLUSIONS

## Summary of Research

The water utility industry is under enormous pressure to meet the challenges of increasing demands due to population growth, lifestyle changes, and depleting freshwater resources. The current and predicted future deficit scenarios challenge water supply managers to come up with a sustainable and reliable alternative source while making the supply infrastructure smarter and resilient. One such alternative source is the greywater that is available at the point of consumption itself. With certain limitations, there have been studies performed to evaluate the life cycle costs and expected monetary benefits of decentralized greywater reuse systems, but the public and health bureaus are apprehensive about the risk of diseases that may arise due to the placement of greywater treatment technologies very near to spaces of human interaction. This study addresses these knowledge gaps, and evaluates the economic, reliability and public perception related implications of greywater reuse systems in order to assess the best combination of physical infrastructure and policy alternatives that will enable greater adoption of these systems and in turn enhance water supply sustainability. This study is comprised of three parts: (a) comparatively evaluating the life cycle costs and expected monetary benefits of decentralized greywater reuse systems considering a utility-scale implementation; (b) evaluating the supply reliability improvement when decentralized greywater reuse systems are installed to complement existing water supply systems; (c) evaluating the public perceptions towards greywater reuse systems and other factors that may increase its adoption. Overall, the proposed study contributes to the body of knowledge in assessing the potential merits and limitations of decentralized greywater reuse, and determining interventions that will help address the limitations to enable greater adoption of these systems.

## Major Findings of the Dissertation

This study has made the following contributions to the body of knowledge:

### *Findings from "Chapter Two: Decentralized Water Reuse Planning: Evaluation of Life Cycle Costs and Benefits"*

An easy-to-use life cycle cost model that can be adapted to any study area is presented in this study. The life cycle cost model has been used to perform comparative analysis of added life cycle costs and expected monetary benefits for satellite and onsite greywater reuse systems. Such cost-benefit comparison is imperative for understanding the critical bottlenecks to greater adoption of satellite or onsite water-reuse systems. Key takeaways from this study are: (a) added costs in both satellite and onsite scenarios are at least 140% greater than the benefits, thereby leaving a considerable gap for greywater reuse adoption to be economically viable; (b) operational energy costs accounted for a significant portion of the added life cycle costs for both onsite and satellite scenarios and consequently, greater energy efficiencies in treatment and pumping operations would have the greatest impact on the economic viability of greywater reuse systems, as can be noted from the results of sensitivity analyses where unit energy (UE) costs were found to be influential; and (c) adding irrigational reuse utility resulted in greatest rise in expected benefits followed by rising utility rates.

***Findings from "Chapter Three: Decentralized Water Reuse Planning: Evaluation of Life Cycle Costs and Benefits"***

This study investigated the improvements in water supply reliability resulting from decentralized water sources, involving on-site greywater reuse systems supplementing the centralized water distribution supply. These reuse systems collect and treat greywater on-site for near immediate use as permitted locally. The comparative reliability analysis conducted in this research found significant improvement in supply reliability for the decentralized scenario compared to the centralized scenario, concluding that a decentralized supply complements an existing water supply in terms of the system's capability to meet demands under various uncertainties. Although the magnitude of reliability improvements observed is specific to the benchmark network studied in this research, it can be concluded that having an additional water source on-site results in some improvement in supply reliability for the majority of water distribution systems. It is important to note that individual variations in the amounts of the produced greywater to be sent for recycling and the treated water available at a node do not affect the reliability of the system. Rather, the reliability improvement was found to rise more meaningfully through simultaneous increase in both maximum usable reclaimed water ($\alpha$) and efficiency of treatment plant ($\beta$). In another case, it was found that the supply reliability improvement decreased when the centralized system is older and resulting in increasing number of main breaks. In contrast, for a given age of a system, the supply reliability improvement was found to increase when the centralized water distribution pipelines became rougher.

***Findings from "Chapter Four: Evaluating User Willingness to Adopting Greywater Reuse Technologies: Exploring A Hybrid Behavioral Change Theory"***

The understanding of public perception towards greywater treatment and reuse has been greatly aided by the current research. One of the first models to include descriptive norms and environmental knowledge in addition to the entire framework offered by the Theory of Planned Behavior (TPB) and Norm Activation Model (NAM) as determinants of behavioral intention. The current study thoroughly examines American attitudes about greywater treatment and reuse in terms of beliefs, perceptions, and behaviors. In this study, the disparity in perception across people in various geographical situations is recorded and examined. Locations include California and Florida; they are chosen so that one location (California) is already facing water scarcity and has adopted greywater reuse, and the other location (Florida) has just begun to experience water scarcity and may implement greywater reuse. In none of the prior research investigations has such a comparison of public perception between two sites been found. Structural Equation Modelling, a statistical method is used to analyze data in this study. The results indicate that Awareness of Consequences (AC) and Personal Norm (PN) are the first and second strongest predictors of Behavioral Intention (BI) respectively, i.e., an individual's sense of severity of his or her own actions on the wellbeing of others and the sense of moral obligation have strongest influence on the individual's intention to adopt greywater reuse treatment systems. However, the individual's subjective judgment of his or her level of accountability for the results of their actions (Ascription of Responsibility) and the individual's perspective of the conduct of those around them (Descriptive Norm) tend not have any influence over the individual's intention to adopt greywater reuse systems. It was also observed that the individual's renting a home is influenced substantially more to adopt greywater reuse systems than individuals who owned homes. Also, a significant difference in behavioral intention is observed between the age groups 19 to 57 and 58 to 72, the latter is observed to be less motivated to adopt greywater reuse treatment systems. The findings of this study offers convincing evidence of the factors that influence people's intention to adopt greywater reuse systems and can therefore offer recommendations to the stakeholders and organizations that intend to encourage greywater treatment and reuse at the household level.

**Limitations, Recommendations and Future Direction**

This dissertation provides novel insights in understanding the economic, reliability and public perception related implications of greywater reuse systems. The results presented in this study are promising; they add value to the existing body of knowledge and support further exploration of assessment techniques and behavioral change theories in determining the influencing factors and beliefs of the user to promote greywater reuse system adoption. However, since there are not many studies performed evaluating the cost, reliability, and public perception towards greywater reuse treatment systems, further validation is required to gain confidence in the proposed model.

As presented in *Chapter Two*, only membrane bioreactor (MBR) and rotating biological contactor (RBC) technologies are considered as the treatment technology options. The cost-benefit comparison performed in this study is imperative for understanding the critical bottlenecks to greater adoption of satellite or onsite water-reuse systems. The methodology and the results of this study will support water utilities, especially those in water-scarce/drought-prone regions, in the planning of future water supplies. Studies such as this may also be used in educational programs to develop awareness among policy makers and consumers regarding the benefits of greywater reuse systems and their decentralization. Considering the operational energy costs accounted for a significant portion of the added life cycle costs, policymakers could consider giving discounts on the energy rates to the people installing on-site greywater treatment systems. Furthermore, reducing the capital costs of treatment units would significantly diminish the added life cycle costs for onsite scenario. Initiatives to provide financial rebates or tax incentives to reduce the capital costs would encourage on-site greywater adoption. Future work should also consider dynamic household water usage patterns to account for possible temporal variation in the availability of raw greywater as well as the demand for treated greywater. Other potentially feasible treatment technology options such as activated carbon, reverse osmosis, advanced oxidation, and soil aquifer treatment processes should be evaluated for their economic merits.

As presented in *Chapter Three*, it can be concluded that the greywater reuse system improves the system reliability more significantly as the water distribution network is more susceptible to component failures, however it comes with the added expense associated with the capital and operational costs of these systems. Despite the significance cost-benefit monetary gap, supply reliability improvement benefits of on-site greywater reuse systems as demonstrated in this study may make such systems viable for utilities with significant reliability concerns. Furthermore, financial incentives in the form of tax credits or low-interest loans may further address the monetary cost-benefit gap, thus helping to encourage the adoption of on-site greywater reuse systems. As such, the effects of financial incentives and other factors on homeowners' interest in the adoption of greywater reuse systems need to be studied in the future. Future research should also investigate the extent of supply reliability improvement with partial greywater reuse adoption where only a few households choose to install greywater reuse systems as opposed to the assumption made in the current study that all the consumption points would have an on-site greywater reuse system. Further, a more comprehensive multi-variate sensitivity analyses would reveal the combined effects of the infrastructural parameters on the extent of supply reliability improvement.

As presented in *Chapter Four*, public perception towards greywater reuse systems is evaluated only in California and Florida; however, these results can be normalized as the locations based on the state of greywater treatment system deployment. The results and assessment are therefore transferable to numerous additional places with comparable implementation settings. Also, since this study employed an internet/online based survey, despite having sample selection criteria (location, age), there is a risk of sample selection bias as certain groups are under or over-represented in the gathered sample, resulting in a lack of significance with various factors. For example, there are 39% of the respondents were aged between 58 and 72 compared to 17% aged between 19 and 31. Following are some of the recommendations derived from the results of this study:

- Encouragement of the environmental groups to support initiatives that aid in environmental protection and raise knowledge of greywater reuse and treatment are some of the recommendations. Additionally, environmental organizations frequently encourage participation in public demonstrations, mailing postcards and letters to government officials, and signing petitions.

- Campaign messages emphasizing the environmental advantages of greywater reuse and treatment, such as the reduction of environmental risks and pollution from untreated greywater, as well as further water conservation.
- The intricacy of the system's quality certification procedure may be streamlined and optimized, for example, by making it easily accessible online, which would change people's attitudes toward greywater reuse systems.
- Policies like financial incentives, tax credits, or the provision of a free system to decrease the financial load on the individual.
- Creating greywater adoption awareness to embrace and win the support of significant others, such as family, friends, and neighbors through awareness seminars, commercials, and endorsements.

A direction of future study is to include screening tests to distinguish between respondents who currently have a greywater treatment system at their home and those who do not, and then test the model to determine the respondents' behavioral intentions. Future studies ought to employ more complex methodologies, like asking family members' perspectives while varying their level of knowledge about retrofitting. In this study, financial aspects of greywater treatment systems installation are not included in the survey, and since it has the potential to influence behavioral intention, it is encouraged to examine how much it costs to install greywater treatment systems and how that affects people's intentions to adopt. Furthermore, future studies can evaluate using various statistical methods and test the hybrid model presented in this study as opposed to using structural equation modelling. Another interesting avenue for future research involves in studying the mediation effects of the constructs and their influence on behavioral intention. It should also be noted that the water utilities would resist the implementation of alternative water resources and its usage as the revenue loss for water utilities and increase in inability of paying out the bonds taken for capital projects seem apparent. Currently, this study only aimed to predict the influencing factors towards greywater treatment system adoption, the prediction of adoption rate is still unexplored due to complexity of the user decision making process. Hence, as part of future research, a comprehensive study to predict the adoption rate by introducing the financial aspects and policy changes to the model can be performed. Subsequently, a stochastic model-predictive control problem can be formulated evaluating the life cycle cost-benefit, reliability aspects and predicted adoption of the greywater treatment systems opening the doors between disciplines to overcome the knowledge gap.

In closing, the methods and assessments presented herein show progress in research capturing the costs, reliability, and public perception towards greywater treatment systems and adds to the existing limited existing body of knowledge.