An investigation of the substitution rate and environmental impact associated with secondhand clothing consumption in the United States

by

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B.Sc., Bangladesh University of Textiles, 2012
M.S., Kansas State University, 2018

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Interior Design and Fashion Studies
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Abstract

Due to massive environmental pollution and resource depletion associated with post-consumer clothing waste, secondhand clothing (SHC) consumption is recognized as one of the critical sustainable strategies. However, the environmental benefit of clothing reuse has not been studied rigorously. Moreover, one of the main factors of assessing the environmental benefit of reuse, termed as substitution rate (SR), is also an understudied topic. The SR attempts to estimate how much new clothing is not purchased as a result of a secondhand purchase. This study identified the SR value of SHC consumption for U.S. consumers and examined the influence of various factors associated with it. Using the SR value, the study also assessed the potential environmental benefit of secondhand use of a 100% cotton knit t-shirt.

An online questionnaire survey was administered to 920 U.S. participants who purchased SHC items in the past year. The SR value was calculated using collected data, and a one-sample t-test was used to examine the difference of SR between U.S. consumers and other reported European and African countries in the published studies. A cluster analysis was conducted to explore the typologies of U.S. participants based on their age, gender, race, household income, motivation/barrier of purchasing SHC, and SR value. Besides, Poisson regression analysis was conducted to investigate if/how age, gender, race, household income, and motivation/barrier of purchasing SHC predict SR value. Finally, life cycle assessment (LCA), typically a 'cradle-to-grave' approach of identifying the environmental impact of a product, process, or service in various stages of the corresponding life cycle, of secondhand use of a 100% cotton knit men's t-shirt was conducted to assess the environmental benefit of clothing reuse.

The result indicated that the average SR of various secondhand clothing types for U.S. participants was 67.81% ± 4.96. This finding suggests that, on average, 100 SHC purchases

substitutes between about 63 and 73 new purchases. It was found that the SR value of U.S. participants was significantly higher (M = 67.81, SD = 8.45) than the average 45.13 SR value for other selected European and African countries. Female participants showed lower SR than male participants, and the difference of substitution rate across different gender groups was statistically significant (F [2, 890] = 3.23, $p < .05$). Similarly, younger participants showed higher SR than older participants. Furthermore, this study also found that higher income was associated with a higher SR value. However, age, gender, race, household income, motivation, and barrier were not good predictors of SR value in the regression model. The finding further indicated that the secondhand use of a 100% cotton men's t-shirt resulted in a potential saving of an estimated 1.48 kg CO_2 eq. GHG emission, 1.8 m^3 water consumption, and 1.06 m^2a eq. land use, considering 56.7% SR value for the t-shirt.

This study filled an important data gap as related to the SR value of SHC, especially for U.S. consumers. This study also made an initial attempt to understand the potential environmental impact of SHC consumption in the context of the United States. The study would provide SHC-based brands and retailers with an estimation of the potential environmental benefit of SHC, thereby offering a likely marketing opportunity. Overall, this study lends strong support to the existing body of knowledge that clothing reuse is better than disposing of clothes, and the potential environmental benefit can still be realized with as low as 5% SR value.

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Dedication

To my parents, Delwar Hossain Patwary and Tazmun Nahar

To my wife, Jaysmin Jahan

To my son, Shehbaz Sayyan Patwary

Chapter 1 - Introduction

Background of the Study

The fast-fashion business model, characterized by short lead times for cheap, low-quality products, has caused many environmental and social problems worldwide over the last few decades. From raw materials extraction to the final disposal of garments, every stage of the clothing life cycle has a negative impact on the environment to some degree. The fashion industry is responsible for 8-10 percent of global carbon emission annually (UN Alliance for Sustainable Fashion, n.d.). Between 2005 and 2016, the impact of the global apparel industry on climate change increased by 35 percent and is projected to increase by 49 percent between 2016 and 2030 if business-as-usual prevails (Quantis, 2018). If current practices go on, the industry will have 1.5 times more impact on climate change than what its impact was in 2005 (Quantis, 2018). Furthermore, if 80 percent of people living in emerging economies (i.e., Brazil, China, India, etc.) buy the same quantity of apparel as that of western consumers, the CO2 emission of the fashion industry would increase 77 percent by 2025 (Remy et al., 2016).

One of the biggest problems of fast fashion is the amount of post-consumer clothing waste it generates every year. The global clothing industry produces between 80-100 billion pieces of products each year (Batelier, 2018; Siegle, 2017), and most of them become trash in less than a year (Ellen MacArthur Foundation, 2017). Clothing consumption has nearly doubled in the last 15 years, while consumers keep them half as long as they did 15 years ago (Remy et al., 2016). As a result, clothing ends up in landfills faster than ever. Every year, about 91 million tons of apparel are thrown away (Ellen MacArthur Foundation, 2017), which occupies about 5 percent of the world's landfill space (World Wear Project, 2019). One garbage truck of clothing is burned or landfilled every second, enough to fill 1.5 Empire State Buildings every day (Drew & Reichart, 2019; Ellen MacArthur Foundation, 2017).

The United States alone generated 16.89 million tons of textile waste in 2017 (i.e., 6.3% of total municipal solid waste), of which 66 percent was landfilled (U.S. Environmental Protection Agency, 2019). Between 2000 to 2017, the amount of U.S. textile waste has nearly doubled (U.S. Environmental Protection Agency, 2019a), making it the fastest-growing type of municipal solid waste (Karidis, 2018). An average Americans throw away about 82 pounds of textiles each year (Council for Textile Recycling, 2018). The European Union (EU) sent 6 million tons of clothing to landfills and incinerators in 2015 (The European Clothing Action Plan, n.d.). The average EU consumer generates about 24 pounds of textile waste (European Environmental Agency, 2019). Australians produce more than a quarter-million tons of clothing waste annually (Jones, 2017). Average Australians throw away about 51 pounds of textiles each year (Jane, 2016). China generates 20-26 million tons of textile waste annually, of which only 10-15 percent is collected for re-utilization (Spuijbroek, 2019). Collectively, the world generated 2.01 billion tons of solid waste in 2016, and the amount is projected to be 3.4 billion tons by 2050 (Kaza et al., 2018). If clothing waste increases at the same rate, the world will have nearly 1.7 times more textile waste by the year 2050. It is estimated that global clothing consumption will increase 63 percent by 2030, which will produce an additional 57 million tons of waste annually, reaching an annual total of 148 million tons (Global Fashion Agenda and the Boston Consulting Group Inc., 2017). Therefore, it is evident that the world will produce more clothing waste in the future if business-as-usual continues.

In consideration of these facts, it is widely accepted that the clothing supply chain needs to become circular to design waste out of the system (Ellen MacArthur Foundation, 2017;

European Environmental Agency, 2019). Furthermore, responsible consumption (i.e., purchasing, caring, and disposal) is thought to be vital in dealing with the fast fashion waste problem (Beton et al., 2014; The European Clothing Action Plan, 2019; Quantis, 2018). One of the best sustainable actions consumers might take is using purchased clothing longer (European Environmental Agency, 2019; Patagonia, n.d.; Schmidt et al., 2016). The reason is that longer use of clothing minimizes the need for new purchases and thereby reduces the need for fresh raw materials consumption. Longer use of clothes might come in various forms of reuse, for instance, mending, repurposing, secondhand, swapping, and renting, etc. Keeping clothing items in use until the useful life is over minimizes unnecessary purchases, thereby reducing resource consumption. Extended use also slows down the rate of clothing waste stream to the landfill or incinerator. Hence, reuse is placed on top of the waste hierarchy (i.e., a policy tool representing most favorable to least favorable actions in terms of resource and energy consumption) in both U.S. and EU environmental regulations (European Commission, 2010; U.S. Environmental Protection Agency, 2019b).

The environmental benefit of clothing reuse is reported in many published studies. For instance, Waste and Resource Action Programme (WRAP), a UK nonprofit committed to resource efficiency, identified that if UK people were to use their clothes for an additional nine months, they could see footprint reductions of 22 percent less carbon, 33 percent less water, and a reduction in waste of 22 percent (Waste and Resource Action Programme, 2017). If everyone bought one used clothing item instead of new in 2019, the world would have saved 5.7 billion pounds of carbon dioxide equivalent (CO_2 eq.) emission, 25 billion gallons of water, and 449 million pounds of waste (ThredUp, 2019). Allwood et al. (2006) reported, "Extending the life of clothing so that the demand for new products is reduced by 20% leads to a reduction of about

20% in all measures in the producing country" (p.40). A reduction of demand for 1 kg of virgin cotton fibers through secondhand clothing purchase or reusing might save 65 kilowatt hour (kWh) of electricity. For polyester, it might save up to 90 kWh (Woolridge et al., 2006). Reusing 100 cotton t-shirts might reduce 14 percent global warming burden from its life cycle. In the case of 65/35 polyester/cotton trouser, it might reduce 23 percent (Farrant et al., 2010). Fisher et al. (2011) estimated that reusing (e.g., from a charity shop and eBay) saves approximately 6.6 lbs. CO2 eq. for a cotton t-shirt and 8.8 lbs. for a woolen sweater. Recently, Nørup (2019) did an environmental assessment of textile reuse in different scenarios and reported varied environmental benefits depending on sorting locations.

However, the studies are very limited in providing a comprehensive understating of the benefit of clothing reuse. The reason is that the environmental benefit from reusing textiles and clothing depends on the substitution rate, also known as replacement or displacement rate. Substitution rate refers to how many new clothing items are not purchased because of a consumer's substituting with a second-hand clothing (SHC) item. Farrant et al., (2010) defined substitution rate as "…an estimation of the extent to which SHC replaces the purchase of new clothes" (p.728). If a secondhand purchase substitutes a similar new purchase, it will save all the embedded resources (e.g., water, energy, chemical) consumed and required resources to manage end-of-life waste. Therefore, in order to understand the environmental benefit of reuse, it is necessary to understand, 1) whether reuse substitutes the need for new items, 2) what type of new items reuse substitutes, and 3) how reusing is carried out, meaning what additional resources are consumed in reusing activities. Identifying the substitution rate is challenging because it depends on individual consumers, geographic locations, and types of clothing items (Schmidt et al., 2016; Stevenson & Gmitrowicz, 2012). The data related to the substitution rate is almost nonexistent, and only a few studies investigated the issue (Beton et al., 2014; Nørup et al., 2019). Most of those studies were in the European context, and Nørup et al. (2019) investigated the substitution rate in the African context (only study outside Europe). There is no published study of the substitution rate found in the U.S. context. Therefore, it is crucial to investigate the U.S. substitution rate to understand the environmental benefit of clothing reuse better.

There is a projection that the SHC market will grow 1.5 times the size of fast fashion in the USA and become a $64 billion market by 2028 (ThredUp, 2019). Nearly half of U.S. resale transaction in 2016 was related to clothing (ThreadUp, 2019). A similar trend can also be seen in many European markets, such as Denmark and Germany (Waste and Resource Action Programme, 2019). Between 2006 and 2016, global SHC trade increased by about 106% (Brady & Lu, 2018). Consumers are increasingly accepting secondhand stores as popular channels of clothing acquisition (Imran et al., 2018). Furthermore, they use secondhand routes (such as charity shops, donations, family, and friends) to get rid of their unused clothes (Waste and Resource Action Programme, 2019). Despite this promise of a growing SHC market, little is known about what triggers consumers to engage in SHC consumption and what constraints they face (Baker & Yurchisin, 2014; Ferraro et al. 2016) as well as how these factors might impact substitution rate and environmental impact of SHC. Therefore, it is necessary to investigate how different consumer characteristics and behavior, such as demography, motivations, and barriers, might play a part in determining substitution rate and thereby enhance our understanding of the environmental benefit of SHC consumption.

Statement of the Problem

While reuse is recognized as the superior sustainable action in global waste management strategy (European Commission, 2010; U.S. Environmental Protection Agency, 2019b), the environmental benefit of clothing reuse has not been studied rigorously (Schmidt et al., 2016). The fundamental building block for understanding the ecological benefit of clothing reuse is the substitution rate, which is an extremely understudied topic (Nørup et al., 2019). A few studies have been conducted from the European perspective, but studies are non-existent in the U.S. context. This lack of knowledge of substitution rate limits our comprehensive understanding of the environmental impact of clothing reuse.

Likewise, no previous study has investigated factors that may impact the substitution rate of SHC consumption. Specifically, it is important to understand the influence of consumer motivations and barriers related to SHC purchases. While U.S. secondhand clothing market is continuously growing (Raymond James, 2019; Strähle & Klatt, 2017; ThredUp, 2019) and the overall global economic activity related to SHC is quickly expanding (Brady & Lu, 2018; Guiot & Roux, 2010; Han, 2013), the motivations and barriers of SHC consumption have not been extensively investigated (Baker & Yurchisin, 2014; Ferraro et al., 2016; Laitala & Klepp, 2018). Therefore, it is imperative to get a better understanding of consumer motivations and barriers of SHC consumption, how these factors might impact substitution rate, and what environmental benefits might be realized from SHC clothing reuse.

Statement of the Purpose

The purpose of this research was to understand the environmental benefit of clothing reuse through the lens of secondhand clothing consumption. One of the main factors of understanding the environmental benefit of reuse is the substitution rate. Therefore, this study examined the substitution rate of SHC consumption. In addition, the study examined how different consumer characteristics and motivations/barriers of SHC consumption impacted the substitution rate, thereby providing a better understanding of the environmental benefit of SHC reuse. The specific research objectives were to:

1. Identify the substitution rate of SHC consumption for U.S. consumers
2. Investigate the way U.S. secondhand consumers can be classified in terms of demographic characteristics (i.e., age, gender, race, and income), motivations/barriers of SHC consumption, and substitution rate.
3. Examine the impact of various factors (such as demography, motivations, and barriers) on substitution rate of SHC consumption and
4. Assess the potential environmental benefit of SHC consumption.

Justification of the Study

While reuse is widely recommended as a superior environmentally-preferred alternative to recycling, incineration, and landfilling (Beton et al., 2014; European Commission, 2010; European Environmental Agency, 2019; Sustainable Clothing Action Plan, n.d.; U.S. Environmental Protection Agency, 2019b), studies examining the benefit of clothing reuse are very limited (Schmidt et al., 2016). Likewise, research on the fundamental piece of information that helps assess the benefit of clothing reuse (i.e., substitution rate), is almost non-existent (Norup et al., 2019). While a few studies identified substitution rates in the European and African contexts, no previous research has examined the substitution rate in the U.S. context. As substitution rate varies with individual consumers, geographic locations, and types of items (Stevenson & Gmitrowicz, 2012), it is crucial to identify the substitution rate in the U.S. context.

Without understanding the substitution rate, it is challenging to understand the environmental benefit of clothing reuse comprehensively. Besides, identifying the U.S. substitution rate will improve the existing life cycle inventory (LCI) to better model future environmental impact assessments of clothing reuse.

Furthermore, while previous studies identified the substitution rate, there has not been a comprehensive investigation of the influence of other factors (such as demography, motivation, barrier, etc.) on the substitution rate. As a matter of fact, consumer motivations and barriers of SHC purchase themselves are understudied topics (Ferraro et al., 2016; Baker & Yurchisin, 2014). As a result, little is known about the influence of consumer characteristics (i.e., demography) and behavior (i.e., motivations/barriers) on substitution rate. Therefore, it is necessary to investigate the substitution rate and influence of different consumer factors on it to understand the environmental benefit of clothing reuse better. In this study, SHC consumption would be considered as a form of clothing reuse.

Definition of Terms

Allocation: "Partitioning the input or output flows of a process or a product system between the product system under study and one or more other product systems" (International Organization for Standardization 14040:2006, section 3.17).

Background System: "Those processes, where due to the averaging effect across the suppliers, a homogenous market with average (or equivalent, generic data) can be assumed to appropriately represent the respective process … and/or those processes that are operated as part of the system but that are not under the direct control or decisive influence of the producer of the good….” (EU-JRC-IES, 2010, pp. 97-98). Secondary data is usually used in the background system.

Clothing Supply Chain: “A series of interrelated activities which originates with the manufacture of fibers and culminates in the delivery of a product into the hands of the consumers” (Jones, 2006, p. 1).

Clothing/Fashion/Textile and Apparel Industry: The industry that involves production, distribution, and sale of clothing products, such as active-wear, formalwear, and children-wear, etc. In this study, clothing, fashion, and textile and apparel (TA) industry are used interchangeably.

Cradle to Grave: The cradle-to-grave approach “…begins with the gathering of raw materials from the earth to create the product and ends at the point when all materials are returned to the earth” (Curran, 2006, p.1).

Fast Fashion: “… a business strategy which aims to reduce the processes involved in the buying cycle and lead times for getting new fashion product into stores, in order to satisfy consumer demand at its peak” (Čiarnienė & Vienažindienė, 2014, p. 1012).

Foreground System: “Those processes of the system that are specific to it … and/or directly affected by decisions analyzed in the study” (EU-JRC-IES, 2010, p. 97). Primary data is usually used in the foreground system.

Functional Unit: A functional unit is a “…quantitatively defined measure relating the function to the inputs and outputs to be studied” (Matthews et al., 2015, p.87). An LCA is carried out based on this key piece of information. For instance, if the functional unit of an LCA analysis is ‘one ceramic drinking glass providing one year of service’, then the analysis will consider all the process inputs and outputs related to that information.

Greenhouse gases (GHG): Atmospheric gases occurring naturally or human-induced which are deemed responsible for the greenhouse effect. Few such gases are- carbon dioxide, methane, water vapor, nitrogen dioxide, etc.

Life Cycle Assessment: Life Cycle Assessment (LCA) is a "structured, comprehensive and internationally standardized" (EU-JRC-IES, 2010, p. IV) technique to assess the impact made by a product, process, or service in their entire life cycle. In other words, it refers to the "compilation and evaluation of the inputs, outputs and the potential environmental impacts of a product system throughout its life cycle" (International Organization for Standardization 14040:2006, section 3.2).

Life Cycle Impact Assessment (LCIA): Life cycle impact assessment refers to relating all the inputs and outputs of a product system to the human health, environmental health, and resource depletion. The purpose of the impact assessment is to evaluate the "…magnitude and significance of the potential environmental impacts of a product system" (Beton et al., p.60).

Life Cycle Interpretation: "Phase of life cycle assessment in which the findings of either the inventory analysis or the impact assessment, or both, are evaluated in relation to the defined goal and scope in order to reach conclusions and recommendations" (International Organization for Standardization 14040:2006, section 3.5).

Life Cycle Inventory (LCI): The life cycle inventory is a list of all inputs and outputs relevant to a product system (Matthews et al., 2015). It is a "compilation and quantification of inputs and outputs for a product throughout its life cycle" (International Organization for Standardization 14040:2006, section 3.3). Input might be raw materials, water, and energy while output might be emission to air, water, and soil.

Life Cycle: "Consecutive and interlinked stages … from raw material acquisition or generation from natural resources to final disposal" (International Organization for Standardization [ISO] 14040:2006, section 3.1).

Mid-point and End-point Impact Category: The total environmental impact caused by a product's lifecycle is measured through some impact categories. The list of these categories can be very broad. Therefore, a relevant list of impact categories is used. The shortlist of that (such as human health, environmental health, and resource depletion) is called the end-point category. Different sub-categories informing each of these end-point categories are called as mid-point category (Huijbregts et al., 2016).

Post-consumer textile waste: Any worn-out, unwanted, or damaged clothes that consumers get rid of after using them for a certain time (Koszewska, 2018).

Reuse: "any operation by which products or components that are not waste are used again for the same purpose for which they were conceived" (European Commission, 2008, p.10)

Secondhand Clothing/Apparel: Apparel/clothing item that is in a condition of reuse as their original intended purpose, excluding vintage/antique clothing (Roux & Guiot, 2008; Stevenson & Gmitrowicz, 2012).

Substitution Rate: A "…estimation of the extent to which SHC replaces the purchase of new clothes" (Farrant et al., 2010, p.728).

Waste Hierarchy: A ranking of the least to the most environmentally preferred waste management strategies (U.S. Environmental Protection Agency, 2019b).

The following are the definitions of impact categories used in Life Cycle Impact Assessment.

Global Warming: The effect of greenhouse gas (GHG) emissions on the climate. GHG emissions can be carbon dioxide (CO2), nitrogen dioxide (NO2), methane (CH4), chlorofluorocarbon (CFC), etc. In the hierarchist life cycle impact assessment (LCIA) method, the global warming potential (GWP) of these GHG gases is characterized for a 100-year time horizon with respect to carbon dioxide emission and measured in kg CO2 eq. (Huijbregts et al., 2016).

Stratospheric Ozone Depletion: The effect of ozone-depleting substances (ODSs) on human health. The ODSs have chlorine or bromine group in them and interfere with stratospheric ozone, resulting in damage to human health, such as skin cancer and cataract. The Ozone Depleting Potential of ODSs is measured in kg Chlorofluorocarbon-11 equivalent (CFC-11 eq.), which quantifies how much stratospheric ozone an ODS can deplete in a specific time frame (in case of hierarchist method, it is 100 years) (Huijbregts et al., 2016).

Ionizing Radiation: The effect of radionuclide emission on human health. These types of emissions are typically generated from burning coal, mining, processing, and waste disposal. The radionuclide emission causes human health damage thorough cancers and severe hereditary diseases. The Ionizing Radiation Potential (IRP) of various substances is measured in Kg Cobalt-60 equivalent (CO-60 eq.), which quantifies the collective exposure level of the human population to radionuclide emission within a specific time frame and the resulting human health damage (Huijbregts et al., 2016).

Fine Particulate Matter Formation: The effect of fine solid particles on human health. Any pollution (such as CO_2, NO_2, SO_2, etc.) that generates aerosols (i.e., fine solid particles) have a negative impact on human health, for instance, respiratory disease. Fine particulate matters (PM) having a diameter of fewer than 2.5 micrometers (μm) are mainly associated with respiratory morbidity. The potential of fine particulate matter formation is measured in kg Particulate Matters 2.5 equivalent (PM2.5 eq.) (Huijbregts et al., 2016).

Ozone Formation: The effect of ozone on both human health and the ecosystem. Ozone is formed by the photochemical reaction of NO_x and Non-methane Volatile Organic Compounds (NMVOCs). Ozone causes harm to human health, such as lung damage, asthma, and pulmonary diseases. It also causes harm to the ecosystem, such as reduction of growth and seed production. In order to evaluate the impact, the Photochemical Ozone Formation Potential of various substances is measured in kg NO_x eq. (Huijbregts et al., 2016).

Terrestrial Acidification: The effect of emission-related acidity on plant species. Inorganic substances such as sulfates, nitrates, and phosphates cause a change in acidity in the soil, having a negative impact on plant species. The terrestrial acidification is measured in kg Sulphur dioxide equivalent (kg SO_2 eq.) (Huijbregts et al., 2016).

Freshwater Eutrophication: The effect of nutrients (such as phosphorus, nitrogen) on the freshwater species. The increased level of nutrients into soil and water leads to a greater uptaking by various organisms, resulting in a relative loss of species. The freshwater eutrophication potential of various substances is measured in relation to phosphorus and expressed in kg Phosphorous equivalent (kg P eq.) (Huijbregts et al., 2016).

Marine Eutrophication: The effect of nutrients on the marine ecosystem. When the runoff and leach of plant nutrients are discharged into the marine system, it leads to oxygen deficit resulting in ecosystem disturbance. The marine eutrophication potential of various substances is measured in relation to nitrogen and expressed in kg Nitrogen equivalent (kg N eq.) (Huijbregts et al., 2016).

Toxicity: The effect of toxic substances (such as cobalt, copper, zinc, etc.) on human health, water, and ecosystem. The toxicity is measured in various dimensions, such as human carcinogenic toxicity, human non-carcinogenic toxicity, marine ecotoxicity, freshwater ecotoxicity, and terrestrial ecotoxicity. The human carcinogenic and non-carcinogenic toxicity indicates the impact of toxic substances on the cancerous and non-cancerous effect of the human population. The marine ecotoxicity indicates the impact of toxic substances on seawater organisms. The freshwater ecotoxicity indicates the impact of toxic substances on freshwater organisms. The terrestrial ecotoxicity indicates the impact of toxic substances on land organisms. The toxicity potential of various substances is measured in kg 1,4-dichlorobenzene eq. (1,4 DCB eq.) (Huijbregts et al., 2016).

Water Use: The effect of water use on human and environmental health. The impact associated with water use comes from the change in the original condition of available water in terms of evaporation, incorporation into products, and displacement. The alteration of the original water source leads to water scarcity, resulting in reduced crop yield, biodiversity loss, or human malnutrition. Water use is measured in cubic meter (m^3) (Huijbregts et al., 2016).

Land Use: The effect of land use on the ecosystem. The land occupation, land transformation, and land relaxation lead to relative species loss. The land use is measure in square meter land equivalent ($m^{2)}$ (Huijbregts et al., 2016).

Mineral Resource Scarcity: The effect of mineral use on future resource scarcity. The use of mineral reduces the overall mineral availability in the ore. This situation will require extracting more ores in the future to get the same amount of mineral, resulting in resource scarcity. This scarcity is measured in kg Copper equivalent (kg Cu eq.), which quantifies how much extra ores need to be extracted in the future to get 1 kg of Cu equivalent (Huijbregts et al., 2016).

Fossil Resource Scarcity: The effect of fossil fuel use on future resource scarcity. Fossil fuel refers to coal, oil, and gas. The use of fossil fuel reduces future availability and this scarcity is measured in kg oil eq.

Organization of the Paper

This dissertation includes five chapters. Chapter 1 provides the background of the study, statement of the problem, the purpose of the study, justification of the study, and definition of terms.

Chapter 2 presents a review of the literature and research questions and hypotheses. Review of literature includes a discussion on fast fashion, environmental impact and waste generation, clothing waste management, secondhand clothing market, motivations and barriers towards purchasing secondhand, substitution rate, life cycle assessment, and life cycle studies of clothing reuse.

Chapter 3 provides the research methodology, including research design and data processing and analysis. The research design includes instrumentation and LCA methodology. Instrumentation consists of the motivation of the SHC purchase scale, barriers of SHC purchase scale, substitution rate, demographics, and other items, pretesting and pilot testing of survey, reliability, and validity of the final survey, sample and recruitment. The LCA methodology includes goal and scope definition, inventory analysis and tool, and impact assessment applied.

Chapter 4 reports findings in relation to research questions and hypotheses posed and

Chapter 5 brings a thorough discussion of the findings in relation to available studies investigating relevant issues. The last chapter also includes a presentation of key implications, limitations of the research, recommendations for future studies, and ends with concluding remarks.

Chapter 2 - Review of Literature

This study investigated the potential environmental benefit of SHC consumption (i.e., clothing reuse). In order to investigate the benefit, it is necessary to identify the substitution rate of SHC consumption. Therefore, the study also examined the substitution rate of SHC reuse. Furthermore, the study investigated the influence of other factors (such as consumer demographics, motivations, and barriers of SHC purchase) on substitution rates to understand the environmental benefit of SHC consumption better. This chapter provides a synthesis of the existing body of literature in the areas of 'fast fashion, environmental impacts and waste generation,' 'clothing waste management,' 'secondhand clothing market,' 'motivations and barriers towards SHC purchase,' 'substitution rate,' 'Life Cycle Assessment (LCA),' and 'LCA of clothing reuse.'

Fast fashion, environmental impact and waste generation section discusses how the global fast fashion phenomenon is generating massive amounts of clothing waste and causing environmental problems, which leads to a discussion about what waste management strategies the world currently has in place. In clothing waste management, that issue is discussed elaborately, and the importance of clothing reuse (i.e., SHC) is highlighted. This leads to the discussion of the global SHC market and consumer motivations and barriers related to SHC consumption. The subsequent sections discuses studies related to substitution rate, general LCA method, and LCA of clothing use.

Fast Fashion, Environmental Impacts and Waste Generation

Fast fashion, powered by shorter lead time, cheap, and low quality, has changed the global clothing consumption pattern (Cachon & Swinney, 2011; Daystar et al. 2019). Starting from the late 1980s to the early 1990s, brands and retailers started expanding their overseas production facilities in the global south, mostly in far eastern countries. With the help of cheap labor, brands started bringing an unprecedented number of products to the market all year round. For instance, Zara and H&M, two major fast-fashion brands, offers 24 and 12-16 collections respectively each year (Remy et al., 2016). Through attractive advertisement and promotional packages, brands attract consumers to align their life with the so-called 'latest trend' in terms of "…social status, taste level, general cultural awareness, and personal individuality" (Anguelov, 2015, p.4). They continuously offer consumers attractive price points that often becomes impossible to resist, sometimes leading to compulsive buying (Yurchisin & Johnson, 2004). For instance, the price of clothing dropped 53 percent in the UK market and 3 percent in the U.S. market between 1995-2014 (Remy et al., 2016). In contrast, consumer purchasing power has increased many times in the same timeframe (Trading Economics, n.d.). As a result, fast fashion has become so affordable that western consumers can often purchase an article of clothing at the same price as a Starbucks coffee. Consequently, the demand for fast fashion keeps on increasing (Imran et al., 2019), and the global apparel industry produces a stunning 80-100 billion pieces of products every year (Batelier, 2018; Siegle, 2017). Between 2000 to 2015, global clothing sales have doubled (Ellen McArthur Foundation, 2017), and it is estimated that global apparel consumption will increase 63 percent by 2030 (Global Fashion Agenda & Boston Consulting Group Inc., 2017). While the consumption is rising, the utilization (i.e., the ratio of how long apparel is used to its useful lifetime) is almost linearly decreasing. For instance, consumers keep clothing half as long as they did 15 years ago (Remy et al., 2016). Ellen McArthur Foundation (2017) reported that this global under-utilization value of clothes could be as much as $460 billion a year. Increasing clothing consumption and under-utilization have a significant environmental impact because a lot of resources are consumed in the clothing life cycle.

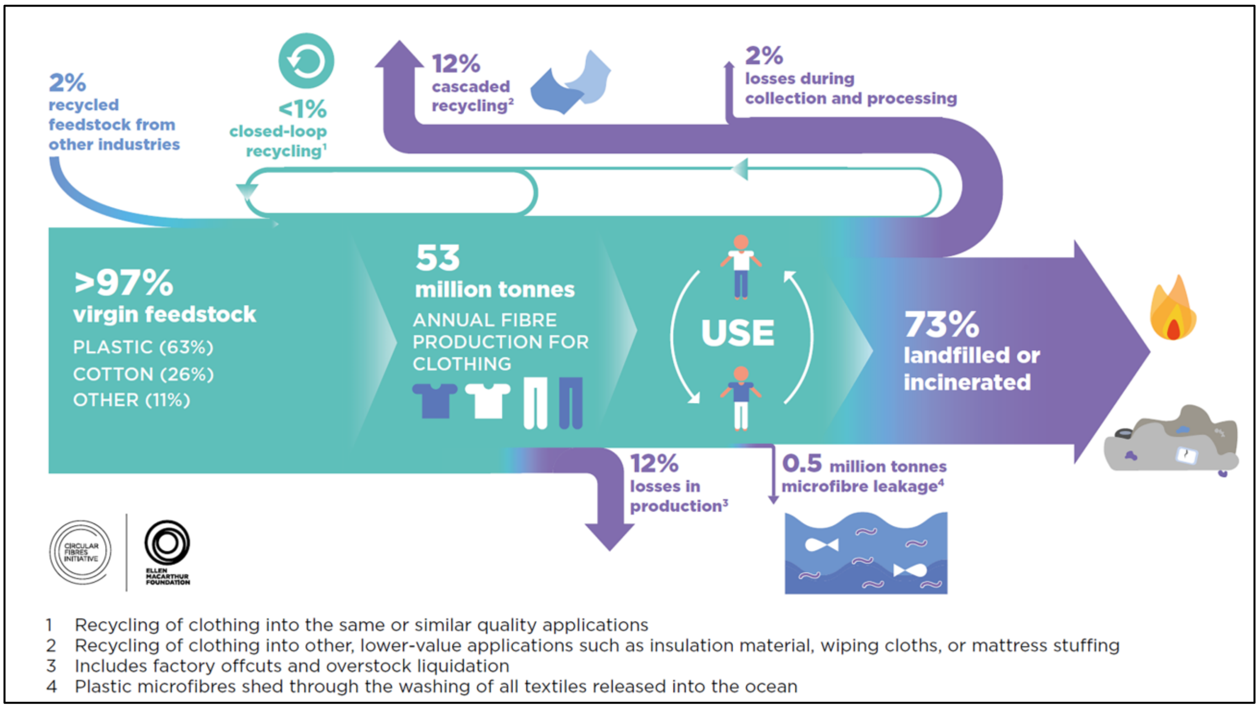
The typical clothing life cycle involves fiber cultivation or extraction, yarn manufacturing, fabric manufacturing, dyeing, printing, finishing, use, and disposal. Each stage of the clothing life cycle has a negative ecological footprint to some degree (Quantis, 2018). Conventional cotton cultivation consumes a massive amount of global freshwater resources. Textile wet process (e.g., scouring, bleaching, mercerizing, dyeing, printing, and finishing) also consumes a huge amount of water. As a result, the clothing industry is now the second-largest consumer of global freshwater resources (UN Economic Commission for Europe, 2018). Cotton cultivation is fertilizer and chemical-intensive, consuming about 24 percent of global insecticides and 11 percent of pesticides (Sweeny, 2015). The substantial amount of harmful chemical use and effluent discharge in the textile wet process contributes to 20 percent of global industrial pollution (UN alliance for sustainable fashion, 2019). Textile yarn, fabric, and wet process are heavily energy-intensive. The clothing industry requires about 13,000 metric tons of oil equivalent (Mtoe) annually (BP, 2014). The material input for producing synthetic textile and other processing, such as electricity, gas, chemicals, etc., depletes about 98 million tons of non-renewable resources every year (Ellen MacArthur Foundation, 2017). Apart from all these environmental footprints of the pre-consumer stage, laundering of clothing items in the consumer use phase causes 20-30% of oceanic microplastic pollution (Henry et al., 2019). All these contributors to environmental pollution in the pre-consumer stage is tied to the clothing waste generation. With each discarded clothing item, all the embedded resources (i.e., water, energy, chemicals, etc.) are also wasted. Similarly, the rate of clothing waste generation directly influences upstream resource consumption. Therefore, slowing down clothing waste generation in important to save valuable resources and reduce environmental impacts.

However, the continuous supply of cheap clothes in the market and massive consumer under-utilization again go hand in hand in creating an enormous amount of waste. Fast fashion consumers dispose of clothes so often that it has become the fastest-growing type of municipal waste in the United States (Karidis, 2018). About 6.3% of U.S. municipal solid waste is now textile waste (U.S. Environmental Protection Agency, 2019). An average U.S. and EU consumer generates nearly 53 pounds of textile waste each year, double the amount of global average of 26 pounds (Council for Textile Recycling, 2018; Ellen MacArthur Foundation, 2017; European Environmental Agency, 2019). This phenomenon is so severe that it can be compared to generating 1.5 Empire State Buildings of textile waste every day (Drew & Reichart, 2019) or one garbage truck of textile waste every second (Ellen MacArthur Foundation, 2017). Global fashion Agenda and the Boston consulting group Inc. (2017) estimated that the world would generate 57 million tons of additional textile waste beginning from 2030 if the business as usual prevails. With the ongoing trend, the municipal waste management system will be overwhelmed by clothing waste, and the global agricultural, industrial, and habitable land will be severely strained (Kaza et al., 2018). Globally, less than 1% of discarded clothes are recycled, and most of the rest goes to landfill, which is the least preferred option in the waste management strategy. A global picture of materials flow for clothing is shown in Figure 2.1, which demonstrates how wasteful today's global clothing industry has become.

Clothing waste is both an environmentally and economically expensive affair. This waste typically goes to either landfill or incinerator (U.S. Environmental Protection Agency, 2019). If it goes to landfill, it mainly generates methane along with other harmful greenhouse gases during decomposition. In addition, the leachate, hazardous liquid from decomposed clothing waste, goes underground to pollute groundwater in the long run (Friis, 2018; Thompson, 2017). Moreover, a major portion of this clothing waste is made of synthetic fibers that can stay in the landfill for hundreds of years (Li et al., 2010). When going to the incinerator, clothing waste produces harmful toxic pollutants (Ibanez et al., 2000).

Figure 2.1.

Global Material Flow for Clothing in 2015



Note. Reused from *A New Textiles Economy: Redesigning Fashion's Future* (p.20), by Ellen MacArthur Foundation, 2017, copyright 2017 by Ellen MacArthur Foundation.

Apart from the environmental issue, managing waste is a very costly process. For instance, the landfill tipping fee (i.e., the price paid for waste disposal in landfill) has increased from $45.82 in

2000 to $51.82 in 2017 per ton in the United States (U.S. Environmental Protection Agency, 2019a). Waste management cost for textiles in the United States was $3.5 billion in 2013 and estimated to be around $4.5 billion by 2020 (Adler & Johnson, 2017). Therefore, consumers need to be cautious in their clothing disposal decision because it has tremendous environmental and economic implications.

However, countless factors influence the consumer decision-making process for discarding clothes. The simplest way it can be viewed is that when consumers do not have an emotional connection with a product, they throw it away, a phenomenon often termed as the lack of 'emotional durability' (Chapman, 2009). Emotional durability might come from the right fit, transparency of production, brand loyalty, and co-creation (Blackburn, 2009). In a study by Daystar et al. (2019), consumers differed in their indication of the useful lifetime of clothing items made from similar materials. This finding suggests that while some products still have a long functional life left, consumers may throw them away based on their subjective (or emotional) perception of the product's life (in terms of appearance, odor retention, etc.). If the sentimental value attached to a piece of apparel is higher, consumers tend to keep it (Ha-Brookshire & Hodges, 2009). Anyway, this decision-making process of which clothing items to keep and which to discard is not a simple one. Before making final decision to discard clothes, consumers go through a process leading to one of three possible choices: 1) keeping it (i.e., reuse, down-cycling, etc.), 2) permanently dispose of it (throwaway, giveaway, etc.) and 3) temporarily dispose of it (loan, rent, etc.) (Jacoby et al., 1977).

The factors influencing the discarding decision can be grouped into three categories: psychological attributes of the decision-maker (personality, attitudes, learning, etc.), the intrinsic value of the product (condition, fit, durability, etc.) and extrinsic context (finances, fashion change, legal, etc.) (Jacoby et al., 1977). Laitala (2014) conducted a critical review of published research focused on consumer clothing disposal behavior from 1980-2013. Her findings shed light on disposal methods, motivations for selection of disposal method, and reasons for clothing disposal, as given below:

1. Disposal methods: key methods of clothing disposal were identified as giving away to friends and family, a donation to charity, repurposing, and selling. Consumers prefer delivering clothing for reuse rather than binning them.
2. Motivations for selection of disposal methods: key motivations identified as the convenience of disposing of, donating as a form of helping others, and social and environmental concern, etc.
3. Disposal reasons: main disposal reasons were categorized into wear and tear, fit or size, fashion, taste, or boredom.

However, there is a research gap in understanding the clothing disposal behavior of consumers. A recent study by Bernardes et al. (2020) reviewed 51 studies concerning clothing disposal behavior. They reported that studies mainly examined how clothing is disposed of, not why they disposed of them. Based on their review, they proposed four future research agendas, 1) investigating the decision-making process of consumers' clothing disposal, 2) examining sustainable disposal behavior, 3) exploring external factors, and 4) improving the current methodology of understanding the issue. Nevertheless, it is challenging to change consumer behavior related to discarding clothes and waste generation. The problem is ingrained into cultural, social, and national practice, and it requires both individual and institutional efforts to bring the desired change. Once the waste is created, the next step is to manage that properly to minimize environmental damage. Therefore, the following section sheds light on the current practice of clothing waste management.

Clothing Waste Management

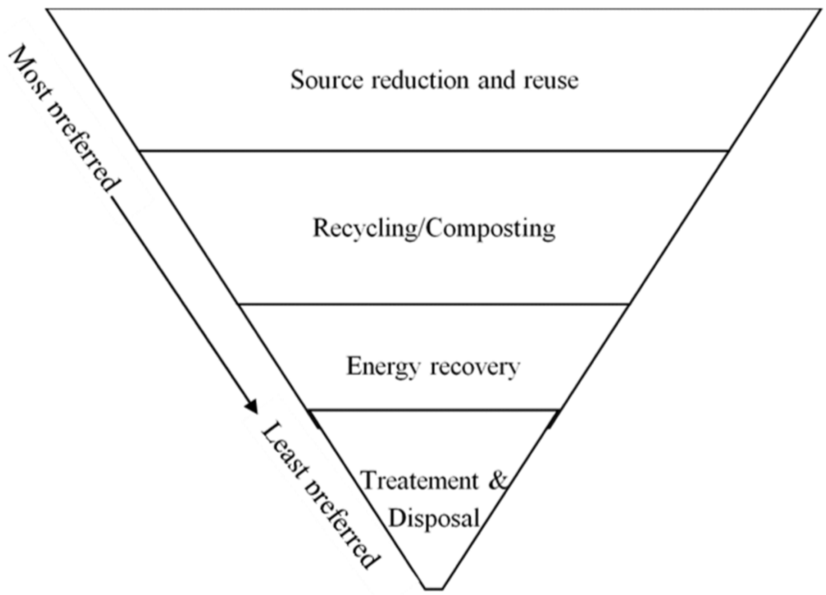
Waste management requires a life cycle approach, which means looking for waste reduction opportunities from raw material extraction to end-of-life (EOL) stages. Throughout the clothing life cycle, there are many opportunities to manage materials sustainably. For instance, using toxic-free and durable materials, conserve water and energy, and treat liquid and solid wastes responsibly. Each of the stages of clothing production can be linked to waste generation in the EOL. A better understanding of the clothing life cycle provides brands and manufacturers with better management options as to which materials to use and how to disassemble (or recycle) at the EOL stage. Keeping the EOL management option in mind during the design phase can save up to 80% of a product's impact in its later life (Thinkstep, 2019). Overall, clothing and textile waste can be broadly categorized into, 1) post-industrial (i.e., waste generated during manufacturing, for example, cutting waste), 2) pre-consumer (i.e., low-quality or rejected item) and 3) post-consumer waste (i.e., worn-out, damaged or unwanted clothes) (Koszewska, 2018). This study strives to identify the environmental benefit of clothing reuse, which is mainly associated with post-consumer waste. To keep the discussion relevant to the study goal, the next section discusses the sustainable strategies of managing post-consumer clothing waste.

The best way to manage post-consumer clothing waste is to reduce the waste generation in the first place, termed as 'prevention' (U.S. Environmental Protection Agency, 2019b). Clothing made with durable materials and having emotional elements (i.e., good fit, evoking a memory, etc.) will potentially lengthen its lifetime, thereby slowing the waste stream. At the same time, sensible consumption is essential. These strategies, that is, using durable materials, adding emotional element and responsible consumption falls into ‘prevention’ strategy and are grounded in ‘slow fashion’ movement (Fletcher, 2010). Slow fashion celebrates “… long heritage, durable pieces, or classic design” (Fletcher, 2010, p.262). It emphasizes a conscious design process with considerations on resource flows and social and environmental impact. Slow fashion consumers, being conscious about the social and environmental impact of clothes, therefore, slows down waste generation (Pookulangara & Shephard, 2013). Waste prevention strategy through sensible consumption and disposal is the first component of the 3R waste hierarchy.

Globally, the 3R waste hierarchy provides the basis of waste management and resource utilization framework. It is incorporated in most countries’ waste management plans, including the United States, EU, Japan, China, and Korea (Sakai et al., 2011). The 3R strategy is integrated into United Nations’ Sustainable Development Goals (SDG) too, for instance, SDG 12, which promotes responsible production and consumption to reduce waste generation through prevention, reuse, and recycling. The components of 3R include reduce, reuse, and recycle. From the perspectives of clothing waste, reduce component focuses on sensible consumption or moving away from fast fashion, and minimizing waste generation. Reuse component emphasizes reusing or extending clothing lifetime in various ways, such as repairing, donating, and buying secondhand, etc. Recycling underpins recovering useful raw materials from disposed clothes and inputting them into a new product (Thompson, 2017). In the context of the United States, the Resource Conservation and Recovery Act (RCRA) and the Pollution Prevention Act mainly guide waste management policy (Sakai et al., 2011). The U.S. Environmental Protection Agency’s waste management hierarchy ranks various waste management strategies from least to most environmentally preferred (U.S. Environmental Protection Agency, 2019b) (Figure 2.2).

Figure 2.2.

U.S. Environmental Protection Agency Waste Management Hierarchy



It ranks reduction of waste at source (i.e., prevention) as the most preferred way of managing waste. This reduction can take the form of reusing donation items, redesigning products, and reducing packaging waste. Recycling is the second most preferred option after reusing. It entails activities related to collecting used, reused, and unused items that could otherwise go to landfill, or incinerator and transforming them into useful products through upcycling or downcycling. The third most environmentally preferred way is energy recovery from burning non-recyclable items in the form of heat, electricity, or fuel. Finally, the least environmentally preferable way is landfilling after the proper treatment of toxics materials embedded into products. The EU waste management framework echoes the same ranking of least preferred to most preferred alternatives (European Commission, 2010).

A closer look at global waste management strategies demonstrates that clothing reuse is a highly preferred way of resource utilization and waste minimization. Reuse is also one of the main pillars of the future textile economy proposed by the Ellen MacArthur Foundation (2017). The recent campaign of circular fashion, which promotes principles like zero-waste design, repair, reuse, and resource recovery, etc. strongly emphasizes the importance of extending clothing lifetime (Koszewska, 2018). Extending clothing life by using functionally and emotionally durable materials is also touted as a sustainable strategy (Blackburn, 2009). It is also often said that the best sustainable action consumer could take is to use the purchased clothes for longer (European Environmental Agency, 2019; Schmidt et al., 2016). Secondhand clothing consumption extends product lifetime, therefore recognized and campaigned as a sustainable strategy. The global market of SHC is steadily expanding due to the environmental consciousness of brands, manufacturers as well as consumers. The next section elaborates on the global secondhand clothing market.

Secondhand Clothing Market

At present, many western countries are experiencing higher consumer demand for secondhand clothing (Strähle & Klatt, 2017). In recent years, SHC trade "…has drawn a bigger spotlight than ever" (Jenss, 2016, p.234), becoming a global trend (Chan et al., 2015) and a hot button issue (Brady & Lu, 2018). Between 2006 and 2016, the value of global SHC trade increased by about 106 percent (Brady & Lu, 2018). It is estimated that the global SHC market will increase almost five times by 2023 in comparison to 2012, with a market value of $51 billion (O'Connell, 2019). At present, about 2-4 million tons of used clothing are traded annually (Common Objective, 2018).

Global economic activities related to secondhand goods have constantly been increasing (Guiot & Roux, 2010; Han, 2013; Herjanto et al., 2016). Both traditional (i.e., Goodwill, Salvation Army, etc.) and online secondhand retail channels (eBay, ThredUP, YCloset, etc.) are experiencing economic growth. For instance, the retail service of Goodwill generated $167,603,000 in revenue in 2018, a 2.4 percent growth from 2017 (Goodwill, 2018). Likewise, The Salvation Army's public sales generated $593,167,000 in revenue in 2018, a 1 percent growth from 2017 (The Salvation Army, 2018). The annual revenue of ThredUp (which is the largest online thrift store) is projected to reach $51 billion by 2023, a 112 percent growth from 2019 (Anderson, 2019). Other online secondhand retailers, such as RealReal and Poshmark, etc. are also experiencing growth in sales volume and revenue generation. A survey of 500 consumers aged 13-45 by Raymond James (a U.S. financial service firm) revealed that 15 percent of these consumers already use apparel resale sites with 40 percent likely to use in the future (Raymond James, 2019). ThredUP (2019) reported that about 56 million women bought secondhand products in 2018, about a 27 percent increase from just 44 million in 2017.

Established brands, retailers, and designers are keen to collaborate with resale outlets to capture the secondhand market. For instance, Stella McCarthy collaborated with RealReal in an initiative to offer consumers $100 store credit who consigns their products on RealReal. This is an initiative of Stella McCarthy to join the secondhand market as well as keeping their items out of landfills. The partnership resulted in a 65 percent increase in RealReal consignor of Stella McCarthy items in 2018 (The RealReal, 2018). Eileen Fisher started a program called "Renew" through which it collects gently worn items through a take-back policy. After collection, they refurbish them, recreate new items from them, and then sell them. They give consumers $5 renew reward cards for each item. This Renew program gives clothing second and third life and extends the product's lifetime (Eileen Fisher, n.d.). Patagonia has a discounted price offer for its secondhand items. H&M has a garment collection program to collect unwanted items from the consumer. They bring those items back into the market through re-wear, reuse, and recycling programs. In 2014, they initiated a *capsule collection* program that used recycled fiber from take-back garments to make denim pieces (H&M, n.d.). Macy and JCPenny are also keen to partner with ThredUP to capitalize on the secondhand market (Loeb, 2019). In a report jointly published by Business of Fashion and McKinsey & Co., 'End of Ownership' was predicted to be the upcoming trend in the fashion arena. More than 40 percent of the consumers surveyed considered pre-owned and rental clothing as more relevant compared to less than 30 percent who did not find it relevant (Imran et al., 2018).

The global trade value of used clothing was $3.79 billion as of 2017 (The Observatory of Economic Complexity, n.d.). Used clothing is the 54th most traded product of the world out of 1,232 products (The Observatory of Economic Complexity, n.d.). Due to the overconsumption of fast fashion items, the developed nations discard tons of unwanted clothes that are exported to developing countries. A snapshot of the global trade of secondhand garments, top exporters, and importers is given in Table 2.1 to provide an overview of the current global secondhand clothing market (The Observatory of Economic Complexity, n.d.).

Table 2.1.

Global Trade Statistics of Secondhand Clothing

	Trade Value (in million dollar)	**Market share (%)**
Top exporters		
United States	682	18
Germany	386	10
United Kingdom	346	9.1
China	271	7.2
South Korea	224	5.9
Top importers		

Pakistan	236	6.2
Malaysia	154	4.1
Ukraine	153	4.1
Ghana	128	3.4
Kenya	125	3.3

From the above discussion, it is evident that the global SHC market is expanding. It is also noticeable that both brands/retailers and consumers are slowly moving towards SHC-based products. Hence, there should be more business models in the future based on used clothing. The question becomes: what triggers consumers to buy SHC and what constraints do they encounter. The next section synthesizes those issues by exploring consumer motivations and barriers associated with SHC purchase.

Motivations and Barriers towards Purchasing SHC

According to Solomon and Rabolt (2004), “motivation refers to the processes that cause people to behave as they do” (p.111). Motivation occurs to satisfy a need. A need arises when there is a discrepancy between a consumer’s current state and an expected ideal state (Solomon & Rabolt, 2004). Consumer motivation is the driving force towards action. This driving force propels consumers to satisfy both physiological and psychological needs through product consumption (Berkman et al., 1997; Schiffman & Kanuk, 2010). Therefore, secondhand clothing (SHC) purchases can be seen through the typology of utilitarian versus hedonic needs. The hedonic need is less focused on the acquisition, instead, it is focused mainly on the experience of shopping (i.e., psychological), for example, excitement, social interaction, self-confidence, and fantasy (Babin et al., 1994; Solomon & Rabolt, 2004). On the other hand, the utilitarian need is focused mainly on the functional or practical benefit (i.e., physiological), such as comfort, protection, and looking good, etc. (Babin et al., 1994; Solomon & Rabolt, 2004). A consumer might engage in secondhand shopping out of purely hedonic motivation or utilitarian motivation, or both at the same time (Bardhi & Arnould, 2005; Guiot & Roux, 2010). For instance, Bardhi and Arnould (2005) identified that consumers go secondhand shopping to exercise 'thriftiness' as well as to have 'fun' (p.226). In that sense, it is more likely that many motivations interact simultaneously to drive consumers to participate in secondhand purchasing. There might exist one or two main motivations (for example, economic or treasure hunting), but other factors may work in the background, leading consumers to buy secondhand.

Apart from hedonistic-utilitarian dichotomy, SHC acquisition can satisfy other needs (Maslow, 1970), often simultaneously, depending on the consumer characteristics and involvement with the product (Solomon & Rabolt, 2004). These needs might be physiological (i.e., covering the body), safety (i.e., protecting the body), social (i.e., acceptance/rejection by others), esteem (i.e., wearing trendy fashion to feel included), and self-actualization (i.e., expression of self) (Solomon & Rabolt, 2004). Consumers traditionally bought SHC items because of financial reasons. The low price of SHC was the primary reason for purchasing secondhand (Xu et al., 2014). Therefore, there was a social stigma attached to secondhand purchases. As low-income consumers used to shop from secondhand stores, a negative social view was attached to it. Also, there were other concerns about using secondhand, for example, contamination, germ, and misfortune (Hansen, 2010). However, social stigma and other concerns about buying secondhand are fading away gradually. Today, consumers buy secondhand for a variety of reasons. For instance, Yan et al. (2015) studied college student's secondhand shopping behavior and found that environmental consciousness, price sensitivity, and style preference were a few factors that motivated them. Some other aspects consumers evaluated besides price were a variety of styles, brand names, and high quality (Napompech & Kuawiriyapan, 2011).

Consumer motivations for secondhand shopping might again be viewed from self-oriented and other-oriented reasons (Park et al., 2017; Reiley & DeLong, 2011). Self-oriented reasons are associated with self-serving in some ways, for example, looking different, unique, and fashionable as well as saving money, nostalgia seeking, etc. On the other hand, other-oriented reasons include concerns for others, for example, supporting a charity, caring for the environment, and reducing waste (Laitala & Klepp, 2018). Along with different motivations of secondhand shopping, some studies reported that demographic and social-psychological characteristics of consumers play a crucial role (Bianchi & Birtwistle, 2010; Reiley & DeLong, 2011). For example, Guiot and Roux (2010) found that younger consumers were utilitarian and more frugal shoppers than hedonic. As such, older consumers were hedonic and focused more on uniqueness.

Guiot and Roux (2010) took a step further and categorized various internal, external, hedonistic, utilitarian, self-oriented, and other-oriented consumer motivations of secondhand shopping under critical, economic, and recreational motivations. Critical motivations involve departing from mainstream consumer culture for moral reasons, for example, to reduce clothing waste from buying secondhand. Consumers with strong critical motivations tend to be ecologically or socially concerned. Economic motivations involve purchasing items with less spending. A consumer with economic motivations focuses mainly on budget, and they enjoy bargain hunting of secondhand shops. Recreational motivations fall under the hedonic shopper category emphasizing shopping experience more than acquiring products. They also proposed a motivation scale based on that classification. Critical motivations included two dimensions, such as 'distance from the system', and 'ethics and ecology'. Economic motivations include 'fair price' and 'qualificative role of price'. Recreational motivations consist of 'treasure hunting', ‘originality’, ‘social contract’ and ‘nostalgic pleasure’. In addition to these three motivations, Ferraro et al. (2016) identified ‘Fashionability’ as another important motivation of secondhand purchases. Fashion motivations involve expressing self, uniqueness, and looking different. SHC helps consumers to stand out and showcase their identity. Consumers often find the right items in secondhand stores that match with their personality as well. In their study, Yan et al. (2015) found that college students who purchase secondhand clothing do so to express a ‘vintage look.’ Furthermore, as the secondhand market is growing, consumers also find it trendy to shop secondhand (Hansson & Morozob, 2016; Ferraro et al., 2016).

As a whole, motivations, and barriers go hand in hand in shaping consumer decisions to purchase secondhand clothing. The primary motivations for purchasing SHC are cheap price, finding desired attributes, environmental and social concern (Laitala & Klepp, 2018; Niinimäki, 2010). The main barriers towards SHC identified by Stevenson & Gmitrowicz (2012) are the quality and durability of items as well as the guarantee available. Hiller Connell (2010) identified two internal and four external barriers to SHC acquisition. Internal barriers include knowledge and attitudes, whereas external barriers include limited availability, lack of economic resource, less-enjoyable secondhand store, and society’s expectation. Anyway, the same factors that act as motivation can alternatively be viewed as a barrier (Laitala, & Klepp, 2018). For instance, economic factors can be argued as motivation (if the price of an item is within a satisfactory range of consumer) or barrier (if not in the satisfactory range). Similarly, the shopping experience is motivation if the experience is enjoyable and a barrier if the store is unappealing (as identified in Hiller Connell, 2010). A comprehensive taxonomy of motivations and barriers towards acquiring secondhand clothes developed by Laitala and Klepp (2018) is given below in

Table 2.2 to provide a perspective of how motivations and barriers are intermingled with one another.

Table 2.2.

Motivations and Barriers Towards Purchasing Secondhand Clothing

Category	**Motivation**	**Barrier**
Economic	Cheap price, good value for money, free hand-me-downs	Expensive, not enough value for money, new clothing is cheap
Quality	Better quality than new fast fashion	Poorer, used, shorter life expectancy, does not last as long
Environment and not-wastefulness	Ethical reuse and recycling, non-wasteful attitudes	Lack of information about production and used chemicals
Social aspects and reputation	Reflect personal ethical view, anti-consumption attitude, avoid mainstream fashion, group belonging	Embarrassing to buy or wear used, lower socio-economic range, negative peers
Hygiene and Health	Harmful chemicals washed out to a larger degree	Unhygienic, odor, unsanitary, dirt, less-stringent legislation for chemicals
Preference	Prefer secondhand	Prefer new, used in unappealing
Uniqueness and style	Unique items, special, nostalgia, individuality	Not one's style
Fashion and trendiness	Vintage trend, brand items	Outdated, not in fashion
The shopping experience, contextual aspects	Exciting, treasure hunt, fun, challenging, social events	Time-consuming, inconvenient, poor-size selection, unorganized, lack of information
Intimacy and transfer of personality	A positive connection to the previous owner, closeness, love	Someone else's clothing, stigma, fading sense of self, transfer of misfortune

It is worth noting that researchers investigated motivations and barriers through different lenses, although they essentially communicated the same thing. For instance, Laitala and Klepp's

(2018) ‘environmental and not-wastefulness’ category falls into Guiot and Roux’s (2010) ‘critical’ category. Similarly, Laitala & Klepp’s (2018) ‘hygiene and health’ falls into Hiller Connell’s (2009) ‘attitudinal barrier’ category. Differently viewed, most of these motivations and barriers can simply be fitted into either the internal (or self-oriented) or external (or other-oriented) category. For instance, consumer motivations concerning economy, distancing from the mainstream, and nostalgia seeking, etc. are self-oriented, whereas environmental and social concern, supporting charity, not-wastefulness, promoting reuse, and recycling falls under the other-oriented category. Similarly, barriers concerning expensive secondhand price, poor quality, social expectation, and personal hygiene, etc. are self-oriented barriers, whereas lack of product’s manufacturing info and lack of secondhand stores to support reuse might fall into other-oriented reasons. Like any other consumer behavior, therefore, the main takeaway is, secondhand clothing consumption is influenced by a host of internal-external, hedonistic-utilitarian, and self-oriented vs other-oriented motivations/barriers as well as driven by many socio-psychological and demographic factors.

These motivations and barriers, shaped by various factors, might impact the substitution rate as related to consumer SHC consumption. However, substitution rate-related study is almost non-existent (Nørup et al., 2019), and no previous research explored the influence of different variables (such as consumer behavior) on substitution rate. This lack of understanding of issues surrounding substitution rate hinders understanding whether and how secondhand purchases can reduce the number of new purchases. It limits the understanding of the environmental benefit of clothing reuse. Therefore, it is important to investigate the substitute rate of SHC reuse. The next section discusses the substitution rate and various associated factors.

Substitution Rate

When consumers purchase SHC, it does not automatically reduce a consumer's need for purchasing a new item. Consumers might purchase SHC because it is cheap, or they enjoy the shopping experience or so on. Consumers who purchase SHC because of financial or ecological reasons make an intentional purchase because their purpose is to save money or reduce environmental impact. In the case of intentional SHC purchase, substitution rates would be higher because the purchase substitutes a new purchase. Whereas consumers who purchase SHC as an additional purchase because of the cheap price do not make a necessary purchase. This type of additional purchase does not necessarily substitute new purchases, leading to a lower substitution rate. Some consumers might purchase SHC as a one-off event or spur-of-the-moment shopping without thinking much. This type of random purchase may or may not save a similar new purchase. Therefore, three situations might arise during SHC purchase that has implications on subsequent purchase: 1) consumer's buying SHC replaces the purchase of a new item (i.e., intentional purchase), 2) consumer's buying SHC does not replace the purchase of a new item (i.e., additional purchase), or 3) consumers buying SHC may or may not replace the purchase of a new item (i.e., random purchase). Therefore, it becomes challenging to estimate the environmental benefit of clothing reuse represented by SHC purchases. As a result, it is necessary to understand how reuse of clothing (SHC) reduces the necessity of buying a new product, a measure termed replacement rate, displacement rate, or substitution rate (Farrant et al., 2010; Stevenson & Gmitrowicz, 2012). In this study, the substitution rate was used, and it was defined as a "…estimation of the extent to which SHC replaces the purchase of new clothes" (Farrant et al., 2010, p.728). Identifying the substitution rate is the main building block for estimating the environmental benefit of reuse. It remains the most important indicator of the environmental impact of reuse regardless of products (Cooper & Gutowski, 2015; Schmidt et al., 2016; Zink et al., 2014).

In the context of clothing, it remains one of the most controversial issues in assessing the benefit of reuse. The reason is that without proper investigating, "it cannot be stated that each item has actually displaced the purchase of a garment made from virgin material" (Woolridge et al., 2006, p. 100). Because there is a lack of representative data, many studies simply assumed a 100% substitution rate in their studies to estimate the environmental benefit of reuse (Allwood, Cullen et al., 2010; Beton et al., 2014 Schmidt et al., 2016; Watson et al., 2016). A 100% substitution rate assumes that for every secondhand purchase, a similar new purchase is substituted, which is not practically correct. Not all consumers entirely rely on secondhand for their clothing needs. Similarly, individual consumer's intention to not buy a new item also varies from purchase to purchase. Therefore, it is an overestimation of how secondhand purchase saves a new purchase and, thus, has introduced uncertainty in any environmental assessment based on that. The lack of data on substitution rate led to studies being completed assuming a 100% substitution rate. In addition, as discussed before, a secondhand purchase is influenced by a lot of internal and external factors, motivation, and barriers. As such, the substitution rate might also be influenced by those things. Hence, more research is necessary to gather data on the substitution rate as well as how different factors influence this rate.

However, very few studies (i.e., only four were found during this review) have tried to estimate the substitution rate of clothing reuse through a direct questionnaire-based survey of consumers. The survey question item was similar; however, the calculations varied slightly in these studies. For instance, Farrant et al. (2010) published the first study on the substitution rate, where they interviewed more than 200 consumers from Sweden, Denmark, and Estonia. They estimated that every 100 SHC purchases would save between 60 to 85 new clothing purchases depending on the location. Stevenson and Gmitrowicz (2012) conducted a questionnaire-based survey with 3,186 consumers about 1,737 textile items in Britain (England, Scotland, and Wales) to estimate the substitution rate. Findings reported an average of 28.5% substitution rate for SHC purchase, meaning that for every 100 secondhand purchases, approx. 28.5 new purchases are saved. Castellani et al. (2015) surveyed 414 consumers in Italy and reported a 47.25% substitution rate, suggesting that for every 100 secondhand purchase, about 47 new purchases are saved. Finally, Nørup et al. (2019) surveyed 3,485 consumers and 14,190 textile items in Angola, Malawi, and Mozambique and reported an average value of 45% substitution for those countries. A summary of the previous studies concerning the substitution rate is given in Table 2.3.

Notably, three of the four studies were conducted in European countries (i.e., Denmark, Sweden, Estonia, England, Scotland, and Italy) and the fourth reported substitution rate for several African countries. Averaging the substitution rates from these studies yields a 45.13% substitution rate. The relatively high number results due to the substantially higher (i.e. 60 percent on the lower range) substitution rate reported by Farrant et al. (2010). When considering only studies of European countries, the average substitution rate value becomes 45.25%. This suggests that every 100 SHC purchase reduces consumers' need for purchasing about 45 new clothing items. Based on the published studies so far, using 45.13% seems the best value for future studies. However, this would be overgeneralization of global data, and therefore more studies are needed to investigate substitution rate in various geographic and demographic contexts (Nørup et al., 2019; Sandin & Peters, 2018) as it varies from product to product, purchase to purchase and consumer to consumer (Stevenson & Gmitrowicz, 2012). Specifically, there has been no substitution rate data estimated from the U.S. and the Asia Pacific, which limits the assessment of the environmental benefit of clothing reuse on a global scale. For such studies to be carried out in the future, global inventory data of the substitution rate will be crucial.

Table 2.3.

Studies Concerning Substitution Rate

Study	Avg. Substitution Rate	Sample size	Location	Survey Question
Stevenson & Gmitrowicz (2012)	28.5%	3,186 consumers and 1,737 textile items	England, Scotland, and Wales	For each item purchased, would you have bought a similar item new if you hadn't found it in a secondhand shop? Responses: Yes; no; maybe.
Farrant et al. (2010)	60%	236 consumers	Copenhagen, Sweden, and Estonia	Would you have bought a similar item new if you hadn't found it in a secondhand shop? Response: Yes, for sure; no; maybe.
Castellani et al. (2015)	47.25%	414 consumers	Italy	The item bought at the secondhand shop substitutes the purchase of a new item? Responses: a. no, it is an item I would not buy if I wasn't in the shop b. Yes, I came to the secondhand shop instead of going to another shop.
Nørup et al. (2019)	63 ± 6% in Angola, 35 ± 1% in Malawi and 37 ± 5% for Mozambique	3,485 consumers and 14,190 textiles items	Angola, Malawi and Mozambique	For each textile item purchased, would you have bought a similar item new if you had not found it in a secondhand shop or market? Responses: Yes; no; maybe.
Average (*SD*)	45.13% (14.07)			

Just as the studies concerning substitution rate are very few, so are studies that cross-analyze how different parameters might impact the rate. It is evident from the previous studies that the substitution rate is very sensitive and may vary with varying types of consumers. For instance, Stevenson and Gmitrowicz (2012) reported that the 35-44 age group had the highest substitution rate, while 55 and beyond had the lowest. This finding suggests that the 35-44 age group made intentional SHC purchases through any critical, economic, or fashion motivations (Ferraro et al., 2016; Guiot & Roux, 2010). When consumers purchase intentionally, it leads to a higher substitution rate. They also found that the substitution rate increased with income, and children's clothing is associated with the highest substitution rate. This finding suggests that higher-income consumers may purchase SHC due to critical motivation (e.g., environmental consciousness, reducing waste), leading to a higher substitution rate value. Regarding the impact of gender on substitution rate, the study found the difference statistically not significant. Examining why they bought items secondhand, 43% of women indicated 'spur of the moment' compared to 34% of men. This finding suggests that women buy more impulsive secondhand clothes than men and might demonstrate a lower substitution rate. Stevenson and Gmitrowicz's (2012) study is the only study reporting the association of socio-demographic characteristics with the substitution rate of clothing reuse. Likewise, there is no study examining the association of consumer motivations of buying secondhand with substitution rate. Therefore, it is imperative to conduct more studies on substitution rate as well as investigate consumer typologies in terms of socio-demographic characteristics, motivations, and any relationship to substitution rate.

The published studies, although very limited, show a pattern of how socio-demographic characteristics and different motivations of consumer's SHC purchase influence substitution rate. For instance, Stevenson and Gmitrowicz (2012) found that older consumers (i.e., 55 & beyond) had a lower substitution rate. The explanation of this may be evident in Guiot and Roux's (2010) study, where older consumers were reported to be more hedonistically motivated and younger consumers more utilitarian and economically motivated when buying secondhand. Looking into what relation might exist between gender and substitution rate, a statistically non-significant result was found from Stevenson and Gmitrowicz (2012). However, their study also found that females exhibited more 'spur of the moment' secondhand shopping than males, indicating more impulsive buying. Therefore, it might be the case that females shop more impulsively, which leads to additional purchase instead of a necessary purchase, resulting in a lower substitution rate. Stevenson and Gmitrowicz (2012) also reported that higher incomes lead to a higher substitution rate. A possible explanation could be that as affluent consumers have options to buy expensive and trendy apparel, any secondhand purchase is very much intentional and a conscious choice, leading to a higher substitution rate. On the other hand, less affluent consumers have economic motivation for secondhand shopping, which naturally leads to a higher substitution rate. A synthesis of these patterns of associations shaped by various consumer behavior and characteristics is shown in Table 2.4.

As stated earlier, understanding the substitution rate is the crucial step towards understanding the environmental benefit of clothing reuse (that is, SHC consumption in this study). Life Cycle Assessment (LCA) is a globally recognized and comprehensive method of assessing the environmental impact of products, processes, or services. The next section discusses LCA in general, and the subsequent section synthesizes studies related to LCA of clothing reuse.

Table 2.4.

Substitution Rate, Consumer Characteristics and Buying Behavior

Consumer Characteristics	Association	Behavior	Reference
Age	Older consumer---lower substitution rate	Hedonic motivation	Guiot and Roux (2010); Stevenson & Gmitrowicz (2012)
	Younger consumer---higher substitution rate	Utilitarian and economic	
Sex	Female---low substitution rate	Additional purchase	Stevenson & Gmitrowicz (2012)
	Male---high substitution rate	Intentional purchase	
Income	Higher income---higher substitution rate	Critical motivation	Stevenson & Gmitrowicz (2012)
	Lower income---higher substitution rate	Economic motivation	

Life Cycle Assessment

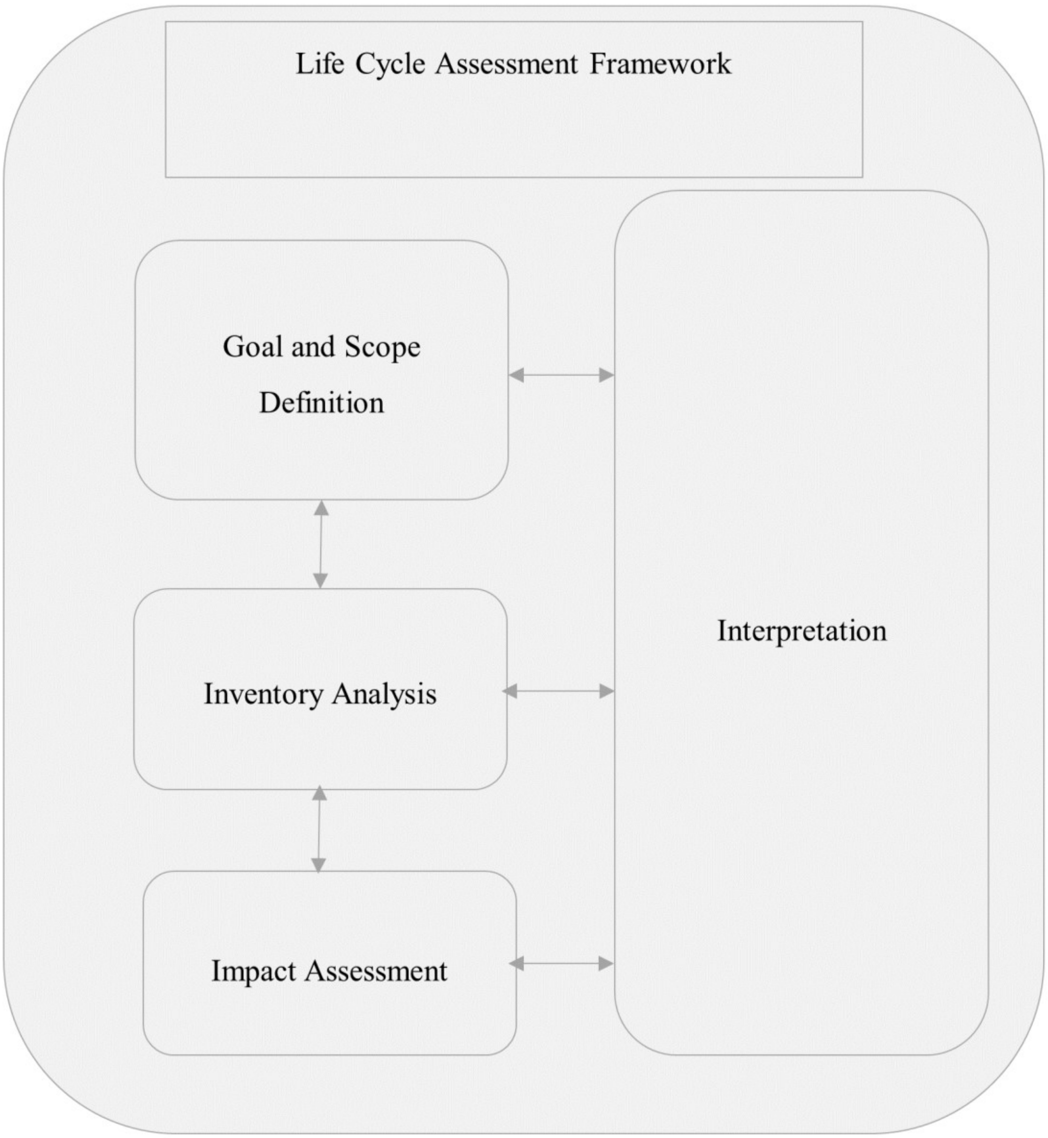
Life Cycle Assessment (LCA) is a "structured, comprehensive and internationally standardized" (EU -JRC- IES, 2010, p. IV) technique to assess the impact made by a product, process, or service in its entire life cycle. The life cycle represents all the stages involved to render a product, process, or service. In a broader sense of sustainability, a product, process or service can have an impact on the environment, society, and economy (Brundtland Commission, 1987). As a result, LCA can be of different types depending on what impact one would like to measure. The main three types of LCA are environmental LCA (E-LCA), social LCA (S-LCA) and Life Cycle Cost (LCC) analysis. Other kinds of LCA can be organizational LCA (O-LCA) and economic input-output LCA (EIO-LCA). Based on the three dimensions of sustainability, namely environmental, social, and economic, different LCA techniques have been formulated to identify impact along those dimensions. As such, E-LCA identifies the ecological impact of a product, process, or service. Likewise, S-LCA identifies the social implications of product, process, or service. The same way, LCC identifies all the costs involved to render a product, process, or service, involving both total costs of rendering and cost associated with externalities (for example, social cost and environmental cost) (Finkbeiner et al., 2010). A holistic approach that involves E-LCA, S-LCA, and LCC of a product, process, or service might, therefore, be termed as life cycle sustainability assessment (LCSA) (Finkbeiner et al., 2010).

International Organization for Standardization (ISO) sets the standard framework for conducting LCA. More specifically, ISO 14040:2006 and ISO 14044:2006 provides a detailed outline of principles, frameworks, requirements, and guidelines of conducting an LCA (ISO 14040:2006; ISO 14044:2006). Both series are a part of the overall ISO 14000 series on the environmental management system. The ISO standards for LCA have four distinct phases: goal and scope definition, inventory analysis, impact assessment, and interpretation (Figure 2.3).

The goal and scope phases need to clearly outline the intent and audience of the study with explicitly communicating the product system, system boundary, and functional unit, etc. The inventory analysis phase involves collecting and documenting all the relevant input-output data in conjunction with the stated goal and scope of the study. The impact assessment phase converts inventory data into specific impact category, for example, converting carbon emission to climate change. Finally, the interpretation phase puts the impact assessment result into perspectives, provides recommendations, and offers insights (Matthews et al., 2015; Tobler-Rohr, 2011).

Figure 2.3.

ISO 14040:2006 Life Cycle Assessment Framework; Both-way Arrow Represents the Iterative Nature of LCA Method



LCA Studies of Clothing Reuse

An understanding of the environmental benefit of reuse is a challenging task. The main reason is that there is no consensus on how to model the LCA system boundary and how to allocate the avoided impact caused by reuse (Sandin & Peters, 2018). In addition, the primary question remains, does reuse trigger consumers not to consume new items? If it does, how much consumption of new items is reduced (the so-called substitution rate discussed above)? Another question to be determined is whether reusing propels so-called rebound effect or not, meaning that if consumers purchase additional new items from the money saved from reuse (e.g., secondhand acquisition) (Cooper & Gutowski, 2017). Previous studies primarily used a mass-based approach for carbon footprint assessment (Castellani et al., 2015). Comprehensive LCA-based approaches are missing in the context of clothing reuse (Gregson et al., 2013). Nevertheless, past studies have provided strong support for the environmental benefit of clothing reuse comparing to other end-of-life (EoL) options (Sandin & Peters, 2018).

For instance, Wooldridge et al. (2006) reported that a reduction of 1 kg virgin cotton consumption through reuse saves about 65 kWh and a reduction of 1 kg polyester consumption saves about 90 kWh, through reducing energy need from product's lifecycle. However, they did not consider the impact of the post-consumer use phase in the models. Therefore, the net environmental savings might have been inflated. Moreover, this study is quite old and carried out in the UK, so the data quality is not as high and generalizable.

Farrant et al. (2010) researched the environmental savings of two apparel items: 100% cotton t-shirt (250 gm) and 65% cotton/35% polyester trouser (400 gm). She reported a 14% reduction of global warming for 100% cotton t-shirt and a 45% reduction in human toxicity category for 65% cotton/35% polyester trouser from a collection of 100 pieces of reused garments. She also reported a substitution rate of 60-85%, depending on the location. This study is the first study using the substitution rate in the LCA modeling of clothing reuse. However, their approach to identifying the substitution rate had later been modified slightly by other researchers.

Fisher et al. (2011) calculated the benefits of various scenarios of clothing reuse in the UK context. They reported that providing a typical cotton t-shirt (produced in China) for direct reuse (i.e., to a charity shop or eBay) results in 3 kg CO_2 eq. saving per t-shirt. Likewise, providing a typical cotton t-shirt (produced in China) for reuse through a preparation network (i.e., an organization that collects, sorts, and prepares) saves about 2.5 kg $CO_{2eq.}$ They considered a 60% substitution rate following Farrant's (2010) study. However, sensitivity analysis showed that benefit could be realized for a substitution rate as low as 25%. Additionally, Fisher et al. (2011) reported the benefit of reusing a woolen sweater. They reported that providing a typical woolen sweater (produced in China) for direct reuse (i.e., to a charity shop or eBay) results in 4.5 kg CO_2 eq. saving per sweater. Likewise, providing a typical woolen sweater (produced in China) for reuse through a preparation network (i.e., an organization that collects, sorts, and prepares) saves about 4 kg CO2 eq. The reuse life of the sweater was considered one year, and the substitution rate was considered as 50 percent.

Watson et al. (2016) reported that the reuse and recycling of exported Nordic textiles have the potential of saving an estimated 190,000 tons of CO_2 eq. GHG emissions and 70 million cubic meters of water by reducing the need for the production of virgin materials. They also pointed out that the best improvement to decrease the environmental impact of the textile life cycle is mostly consumer-oriented, with reuse and recycling reported to have best reduction potential in any midpoint impact categories, including 8% in climate change and particulate formation, 12% in ionizing radiation, 8% in terrestrial acidification and fossil depletion, and 7% in urban land occupation. Reuse and recycle were also reported to have reduction potential in end-point categories, including 8.1%, 5.7%, and 7.7% in human health, ecosystem diversity, and resource availability respectively (Beton et al., 2014). On the other hand, Schmidt et al. (2016) conducted LCA on 100% polyester, 100% cotton, 100% wool, and average Nordic fiber-mix with various scenarios in the context of Nordic countries. They reported reuse as the most favorable route for discarded textiles as well.

Castellani et al. (2015) investigated the avoided impact of a 100% cotton t-shirt (250 gm, produced in India) and 70% wool/30% viscose blended sweater (500 gm, manufactured in China) reused for one year, integrating a 47.25% substitution rate from a direct consumer survey. Their result shows that the highest impacts (that can be avoided) occurred in 'water resource depletion' and 'mineral, fossil and regenerated resource depletion' midpoint category for cotton t-shirt and wool/viscose blended sweater respectively. A summary of potential avoided impact from clothing reuse is given in Table 2.5.

However, there are cases where reuse might not provide an environmental benefit. For instance, if the use of reused garment does not reduce purchasing of new clothes (i.e., low substitution rate), if the preparation of reuse (that is, washing, drying, etc.) is powered by fossil energy, if the avoided production from reuse is environmentally clean and if the reuse triggers rebound effect (Cooper & Gutowski, 2017; Sandin & Peters, 2018). Most of the previous studies did not include collection, sorting, and preparing operations related to reuse, assuming that they are comparatively negligible (Beton et al., 2014, Sandin & Peters, 2018). Likewise, studies did not consider the impact caused by clothing maintenance activities in the reuse phase (Beton et al., 2014; Castellani et al., 2015; Fisher et al., 2011). From the perspectives of natural fiber-made apparel, this might bias the result. The reason is that the clothing care phase is one of the largest contributors to GHG emission for many types of apparel and can contribute significant GHG emissions through washing and drying activities (Allwood et al., 2006; Yun et al., 2017).

Table 2.5.

A Summary of LCA Studies of Clothing Reuse

Study	Items Studied	Functional Unit	Country	LCA type	Key Findings
Woolridge et al. (2006)	Cotton and Polyester	Annual recycled tons; and 1 ton of recycling	UK	Streamlined LCA	A reduction of 1 kg virgin cotton consumption through reuse saves about 65 kWh and a reduction of 1 kg polyester consumption saves about 90 kWh energy.
Farrant et al. (2010)	100% cotton t-shirt 65/35 polyester/cotton trousers	100 garments	Sweden	Cradle to Grave	For 100 garments reuse, 14% decrease of global warming for a cotton t-shirt; and a 45% reduction in human toxicity for 65/35 PC trouser.
Fisher et al. (2011)	Cotton t-shirt and woolen sweater	1 typical item	UK	Cradle to Grave	A typical cotton t-shirt (produced in China) for direct reuse results in 3 kg CO_{2eq} per t-shirt. A typical woolen sweater (produced in China) for direct reuse results in 4.5 kg CO_{2eq} per sweater.
Castellani et al. (2015)	Cotton t-shirt 70/30 wool/viscose sweater	1 unit	Italy	Cradle to Grave	The highest impacts (that can be avoided) occurred in 'water resource depletion' for a cotton t-shirt. The highest impacts (that can be avoided) occurred in 'mineral, fossil, and regenerated resource depletion' for wool/viscose blended sweater.
Watson et al. (2016)	All exported textiles from Nordic countries	75,000 tons	Nordic countries (i.e., Denmark, Finland, Norway, and Sweden)	Unknown	Potential saving of an estimated 190,000 tons of C02 eq. GHG emissions, and 70 million cubic meters of water per year.

A few things that stand out from LCA of clothing reuse are that 1) LCA-based comprehensive studies are limited in the context of clothing reuse, 2) there is a severe lack of substitution rate data which is the fundamental building block of LCA modeling of clothing reuse, 3) studies emphasized more on environmental savings instead of looking into the impact caused by reuse activities, 4) there is no consensus on system boundary, making LCA of clothing reuse studies almost incomparable, 5) most of the studies are in the European context; other geographical locations lack such studies, and 6) however limited the literature are, they provide strong support that reusing is a superior sustainable strategy. Therefore, it is evident that more studies should be carried out in other geographic locations on substitution rate, factors affecting substitution rate, and LCA on clothing reuse, etc. to understand the issue better. The United States is the greatest consumer of fast fashion, the biggest generator of clothing waste per capita, and the largest exporter of secondhand clothes (Brady & Lu, 2018; Council for Textile Recycling, 2018). Therefore, there is no better place than the U.S. to carry out a study of substitution rate, factors associated with substitution rate, and environmental assessment of SHC reuse.

Research Questions

The review of the literature provided a few key pieces of information leading to research questions. First, the substitution rate is important to understand the environmental benefit of clothing reuse. Second, substitution rate varies by consumers, purchased items, and geography; and consumer motivations and barriers might influence it. Third, studies need to incorporate relevant substitution rate data to model the environmental impact assessment of clothing reuse. Based on that, the following research questions were made to meet the research objectives:

Obj. 1. To identify the substitution rate of SHC consumption for U.S. consumers.

RQ 1. How does the substitution rate of U.S. SHC consumers differ from the rates reported for selected European and African countries?

Obj. 2. To investigate the way U.S. SHC consumers can be classified in terms of demographic characteristics (i.e., age, gender, race, and household income), motivations/barriers of SHC consumption, and substitution rate.

RQ 2. What are the typologies of U.S. SHC consumers in terms of age, gender, race, household income, motivations, barriers, and substitution rate?

Obj. 3. To examine the impact of various factors (such as demography, motivations, and barriers) on substitution rate of SHC consumption

RQ 3. Do age, gender, race, household income, motivations, and barriers predict the substitution rate of SHC consumption?

Obj. 4. To assess the potential environmental benefit of SHC consumption.

RQ 4. What potential environmental benefit can be realized from avoiding a new clothing item purchase (i.e., 100% cotton men's t-shirt, 120 gm), assuming an average substitution rate (i.e., 56.7%)?

Chapter 3 - Methodology

Research Design

The research sought to identify the substitution rate of clothing reuse for U.S. SHC consumers, explore the factors associated with substitution rate, and utilize these findings to understand the environmental impact of clothing reuse better. The research employed quantitative approaches, including two components: 1) questionnaire survey and 2) LCA. The questionnaire survey was developed based on published studies with modifications. The questionnaire survey gathered data regarding motivations and barriers towards SHC, substitution rate, and other relevant inventory data for LCA. On the other hand, the LCA estimated the potential environmental impact of SHC consumption, and it followed ISO guidelines (ISO 14040:2006; ISO 14044:2006). To keep the discussion organized, the whole research design was divided into three parts: instrumentation, LCA methodology, and overall data analysis plan. Instrumentation includes motivation and barrier scale as related to SHC purchase, measures of substitution rate, pretesting and piloting the survey, reliability, validity, and final scale development plan, and sampling and recruitment strategy. Because LCA itself has its methodological framework guided by ISO, it is discussed separately. Finally, the overall data analysis plan is presented to provide the rationale of why different analysis approaches were undertaken and how that served the research purpose.

Instrumentation

A few studies were used to develop the survey instrument, specifically, Nørup et al. (2019), Stevenson and Gmitrowicz (2012), Ferraro et al., (2016) and Guiot and Roux (2010), Hiller Connell (2010) and Laitala and Klepp (2018). At the beginning of the survey, there were two control questions: 1) Have you purchased any secondhand clothing within the last 12 months? 2) Are you currently living in the United States? If respondents answered 'yes,' they were qualified to take the survey, and if they answered "no," the survey was ended for them. Moving forward, they encountered questions related to motivations for purchasing SHC. The purpose of these questions was to discover the primary reasons they buy SHC.

The Motivation of the SHC Purchase Scale

The study used Ferraro et al. (2016) scale with few modifications to measure consumer motivations for SHC purchases, Ferraro et al. (2016) developed a motivation scale based on Guiot and Roux's (2010) study. Guiot and Roux (2010) collected qualitative and quantitative data from 708 respondents and proposed an SHC motivation scale. The scale includes three motivations and eight underlying factors. The motivations were critical, economic, and recreation. Critical motivation includes two factors, such as 'distance from the system' and 'ethics and ecology.' Economic motivation includes two factors, such as 'fair price' and 'gratification role of price.' Finally, recreational motivation consists of four factors, such as, 'treasure hunting,' 'originality,' 'social contract,' and 'nostalgic pleasure.' Building on these three motivational categories, Ferraro et al. (2016) added another motivational category, namely 'Fashionability.' Their finding highlighted that SHC offers fashion motivation to consumers by providing a way of creating personal and unique fashion styles. Combining fashionability with Guiot and Roux's (2010) other three categories (i.e., critical, economic, and recreation), Ferraro et al. (2016) used a 9-item 7-point Likert scale ranging from 1 (strongly agree) to 7 (strongly disagree). However, Ferraro et al. (2016) scale ignored a few factors, such as 'social contact' and 'nostalgic pleasure' as identified by Guiot and Roux's (2010) study. Moreover, they included only one item for fashion motivation, which might not be robust enough to bring the necessary insight.

Therefore, this study added an item for 'social contact' factor, which is, 'because I enjoy social interaction while shopping secondhand' as well as an item for 'nostalgic pleasure,' which was, 'because I am attracted more to old things than new ones' (Guiot & Roux, 2010). In addition, the existing item under fashionability motivation of Ferraro et al., (2016), which is, 'because it is fashionable,' was reworded as 'because they are unique.' Furthermore, a new item was included under 'fashionability' motivations, which was, 'it is trendy to buy secondhand.' Therefore, the final scale became an 11-item 7-point Likert scale, with 1= strongly disagree, 7= strongly agree. To give a quick overview, the scale asked participants, 'what is your motivation for purchasing secondhand clothes?' with statements like 'I buy secondhand clothes to avoid large corporate chain' or 'because I enjoy social interaction while shopping secondhand.' The participant indicated their level of agreement from the 7-point Likert Scale. A detailed overview of inclusion, exclusion, and modification of items towards the development of the final scale measuring motivation of the SHC purchase is given in Table 3.1.

Table 3.1.

Development of Motivation for SHC Purchase Scale

Reference Scale	Motivation Category	Factors	Item	Modified/Added	Comment
Ferraro et al. (2016)	Critical	Distance from the system	To avoid large corporate chains	N/A	The 'critical' motivation was proposed by Guiot & Roux, (2010) and have two factors in it, namely 'distance from the system' and ethics and ecology'
		Ecology	To do my bit for the environment	N/A	
		Ethics	To support a charity	N/A	
	Economic	Fair price	For economic purposes	N/A	The 'economic' motivation was proposed by Guiot & Roux, (2010) and have two factors in it, namely 'fair price and 'gratification role of price'.
		Gratification role of price	For a 'thrill of a bargain'	N/A	
	Recreational	Treasure hunting	Because it is like 'treasure hunt'	N/A	The 'recreational' motivation was proposed by Guiot & Roux, (2010) and have four factors in it, namely 'treasure hunting', 'originality', 'social contract', and 'nostalgic pleasure'.
		Originality	Because the stock is surprising	N/A	
		Social contact	Because I enjoy social interaction while shopping secondhand	Yes	This item is from Guiot & Roux, (2010) study.
		Nostalgic pleasure	Because I am attracted more to old things than new ones	Yes	This item is from Guiot & Roux, (2010) study.
	Fashionability	N/A	Because they are unique	Yes	Fashionability motivation is from Ferraro et al., (2016) study. Literature suggests that two factors might exist, 1) uniqueness and 2) acceptance of secondhand shopping among consumers.
			Because it is trendy to buy secondhand	Yes	

Barriers of SHC Purchase Scale

The study used items from Stevenson and Gmitrowicz's (2012) study to measure barriers of SHC purchase with a few modifications. In their study, Stevenson and Gmitrowicz (2012) included 11 statements with the two most often responded items being 'I like to buy new things' and 'concern about quality.' However, they skipped many barriers suggested by earlier studies, such as items pertaining to the internal and external barriers category (Hiller Connell, 2010). Therefore, this study included additional items from Hiller Connell's (2010) findings to Stevenson and Gmitrowicz's (2012) study as well as modify existing items to make it relevant to this study.

A total of seven new items was added, and four items were deleted from Stevenson and Gmitrowicz's (2012) study. The added items belong to a lack of desirable product attributes, store attributes, society's expectation, knowledge, attitude, and intimacy-related barrier categories [as identified by Hiller Connell (2010) and Laitala & Klepp (2018)]. Item 5, 7, 8, and 11 of Stevenson and Gmitrowicz's (2012) study was deleted because they are not relevant for this study. Item 1 was modified to improve relevancy, for instance, 'I like to buy new things' was modified as 'I prefer to buy new clothes.' Item 2, that was, 'concerns about the quality,' was modified as I am concerned about the quality of used clothing.' 'Item 3, that was, 'lack of a guarantee,' was modified as 'I am concerned about the lack of guarantee of used clothing.' Item 4, that was, 'Concerns about durability, was modified as "I am concerned about the durability of used clothing.' Item 6, that was, 'new items are similarly priced,' was rewritten as 'I can buy new clothes with the money that I need to spend for secondhand.' Item 9, which was, 'products not available except as new' was rewritten as 'I can only find my preferred clothing items as new in traditional retail stores.' Item 10, which was, 'don't know where to buy them secondhand,' was modified as 'I don't know where to buy them from.'

To align with the motivation scale discussed above, a similar Likert scale was used for response option (that is, 1= strongly disagree, 7= strongly agree). Therefore, the final scale became a 14-item 7-point Likert scale ranging from 1=strongly disagree to 7= strongly agree. The scale then contained most of the barriers of SHC purchase as identified by previous studies, such as knowledge, attitude, preference, economy, availability, store attributes, lack of desirable product attributes, society's expectation, and intimacy. A detailed overview of inclusion, exclusion, and modification of items towards the development of the final barriers of the SHC purchase scale is given in Table 3.2.

Table 3.2.

Development of Barriers to SHC Purchase Scale

Reference Scale	Barrier Type	Item	Alteration	Comment
Stevenson & Gmitrowicz (2012)	Preference	I prefer to buy new clothes	Modified	Classified by Laitala, & Klepp (2018).
	Lack of desirable product attributes	I am concerned about the quality of used clothing	Modified	Mentioned by Hiller Connell (2010) as an external barrier.
	Lack of desirable product attributes	I am concerned about the lack of guarantee of used clothing	Modified	One of the main reasons identified by Stevenson & Gmitrowicz's (2012) study.
	Lack of desirable product attributes	I am concerned about the durability of used clothing	Modified	One of the main reasons identified by Stevenson & Gmitrowicz's (2012) study.
	Lack of desirable product attributes	These items lack variety	Added	Mentioned by Hiller Connell (2010) as an external barrier.
	Economic	I can buy new clothes with the money that I need to spend on secondhand.	Modified	Mentioned by Hiller Connell (2010) as an external barrier.
	N/A	No transport to get items home	Dropped	Might not be relevant in the USA.
	N/A	Don't know	Dropped	Not relevant
	N/A	Don't need them	Dropped	Not relevant because of the control question applied.
	Availability	I can only find my preferred clothing items as new in traditional retail stores	Modified	Mentioned by Hiller Connell (2010) as an external barrier.

Reference Scale	Barrier Type	Item	Alteration	Comment
	Knowledge	I don't know where to buy them from	Modified	Mentioned by Hiller Connell (2010) as an internal barrier.
	N/A	Secondhand venue opening hours	Dropped	Not relevant.
	Knowledge	I heard there may be environmental benefits, but I do not understand how this is true	Added	Mentioned by Hiller Connell (2010) as an internal barrier.
	Attitude	It is hard to find items with a good fit	Added	Mentioned by Hiller Connell (2010) as an internal barrier.
	Attitude	They are less stylish	Added	Mentioned by Hiller Connell (2010) as an internal barrier.
	Store attributes	Secondhand stores have an unpleasant odor	Added	Classified by Laitala, & Klepp (2018).
	Society's expectation	It is embarrassing to buy or wear secondhand clothes	Added	Classified by both Laitala, & Klepp (2018) as well as Hiller Connell's (2010) study.
	Intimacy and transfer of personality	I don't like to buy someone else's clothing	Added	Classified by Laitala, & Klepp (2018).

Substitution Rate, Demographic and Other Items

Past studies used a simple question to identify the substitution rate of clothing reuse, that is, 'For each item purchased, would you have bought a similar item new if you hadn't found it in a secondhand shop or market?' Typical response options were 'yes,' 'no' or 'maybe.' However, the response options and the calculation method varied slightly across studies. For instance, Farrant et al. (2010) used a specific approach to allocating substitution rates in the range of 100-67-50-33-0%. The highest allocation (i.e., 100% substitution rate) was provided to the respondents who indicated no intention of seeking a new item when successfully finding and buying a similar SHC item. The lowest allocation (i.e., 0% substitution rate) was allocated to respondents for whom purchasing an SHC item does not change their intention to buy a similar new item. This allocation method was purely subjective and therefore modified in later studies. One study varied the response options (i.e., Castellani et al., 2015) by not including a 'maybe' option and considered only a 100% substitution rate as indicated by 'yes' response by consumers. However, other studies (Farrant et al., 2010; Nørup et al., 2019; Stevenson & Gmitrowicz, 2012) included the 'maybe' option and included half of the 'maybe' option in the calculation formula of substitution rate. Nørup et al. (2019) calculated a substitution rate both with and without 'maybe' option and then added them as an error bar. For instance, Norup et al. (2019) found a 63 ± 6% substitution rate for Angola, meaning that the substitution rate is 63% without plugging 'maybe' option in the calculation. Counting the 'maybe' option as 'yes,' the substitution rate will be changed to 69% (i.e., 63 + 6). Similarly, the substitution will be 57% (i.e., 63-6) by counting the 'maybe' option as 'no.' The benefit of using an error bar in the calculation is that it provides a greater understanding of substitution rate data. Using only 'yes and 'no' options might either overestimate or underestimate the data, as discussed above.

Therefore, in this study, Nørup et al. (2019) approach was retained to calculate the substitution rate. However, the 'uncertain' option was used instead of a 'maybe' option in the response category. For some consumers, 'maybe' option might lean more towards 'yes' than 'no' option. Hence, an 'uncertain' option was used, and it was thought to be providing a more neutral tone. An example of how the substitution rate was calculated is given in Appendix A. The formula for calculating the substitution rate is given below.

Substitution Rate, $S =$

$$\frac{\text{total number of items with 'Yes' response} + \frac{1}{2} \text{ of the number of items with 'uncertain' response}}{\text{Total number of items purchased}} \quad (1)$$

In addition to asking substitution rate-related questions, the survey included a few more items to get additional insight about secondhand consumption as well as gather inventory data for LCA modeling. For instance, the survey asked participants how long they intended to keep the secondhand item. This response helped estimate washing and drying-related energy consumption of clothing use phase. Another item asked the respondents if they would buy additional new items from the money saved from purchasing secondhand. This item offered insight about the rebound effect as cautioned by studies (Cooper & Gutowski, 2017; Sandin & Peters, 2018). Finally, there were demographic items involving gender, age, race, and annual household income. These items helped understand the association of these variables with the substitution rate, as discussed in the literature review section.

Pretesting and Pilot Testing the Survey

The survey was pretested with ten U.S. participants. Pretesting the survey is important "…to pinpoint problem areas, reduce measurement error, reduce respondent burden, determine whether or not respondents are interpreting questions correctly, and ensure that the order of questions is not influencing the way a respondent answers" (Ruel et al., 2016, p. 101). The researcher arranged a Zoom interview with pretesting participants. Each participant read the survey items out loud and gave their feedback on wording, clarity, and overall flow. Based on their feedback, the items were modified, reworded, and reorganized. The researcher also tracked the average duration of taking the survey and kept the final survey participation within 10-15 minutes range. Survey duration is important to reduce respondent fatigue and increase participation rates (Stevenson & Gmitrowicz, 2012). Once pretesting was done, the survey was further piloted with 20 U.S. participants to rehearse the coding and data analysis. This helped gauge the '…viability and efficacy of the survey process" (Ruel et al., 2016, p. 116). A summary of the pretesting and pilot testing is provided in Appendix B.

Reliability, Validity and Final Survey

The researcher checked the internal reliability (i.e., inter-item correlation) of the scale. Cronbach's alpha is the common measure to test the internal reliability of scales (Lance et al., 2006). The alpha score of motivation to the SHC purchase scale was 0.85, deemed to be good and reliable (George & Mallery, 2003; Tavakol & Dennick, 2011). The alpha score for barriers to the SHC purchase scale was 0.93, deemed to be excellent and reliable (George & Mallery, 2003; Tavakol & Dennick, 2011). Face validity, content validity, and construct validity were established based on committee members' comments (Presser & Blair, 1994). Face validity refers to eyeballing the items to see if they are aligned with study intention. Content validity is established by robust literature review and expert comments. Construct validity refers to the extent a survey measures the underlying construct of interest, and a good reliability score is a precursor to construct validity. Based on the pretest and pilot test analysis, the survey was modified to ensure content validity. The final survey included motivational scale, barrier scale, substitution rate, demographic and other questions. The final survey is shown in Table 3.3.

Sample and Recruitment

In order to get an adequate sample size appropriate for the planned analysis, it was determined the study needed to secure a sample size between 700 and 1,000 subjects. This sample size was aligned with previous studies investigating the substitution rate (Nørup et al., 2019; Stevenson & Gmitrowicz, 2012) and was sufficient for the statistical analysis methods applied. For example, Green (1991) suggested a sample size of 104 plus predictors for regression analysis. On the other hand, Dolnicar (2002) suggested a sample size of $5*2^k$ (where k is the number of variables) for cluster analysis. The final sample size used in this study was 920, which was robust as per the above suggestion and rested within the 3.24 confidence interval at a 95% confidence level. This indicates that if 50% of participants pick a particular option, we can be 95% certain that between 46.76% (50-3.24) and 53.24% (50+3.24) of the entire population would have picked the same option.

The targeted participants were U.S. consumers who purchased SHC items within the last one-year timeframe from the date of survey participation. The participants were recruited through Amazon Turk (MTurk). Mturk was reported as a valid channel of collecting a representative sample of the U.S. population (Berinsky et al., 2012) and used by previous studies investigating SHC consumers (Park et al., 2020; Zaman et al., 2019). As indicated before, there were two control questions to identify qualified participants, 1) have you purchased any secondhand clothing within the last 12 months? and 2) Are you currently living in the United States? If respondents answered ‘yes,’ they moved forward, and if they answered “no,” the survey ended for them.

Table 3.3.

Final Questionnaire Survey

	Category	Survey Question	Item	Response Option
1.	Control	Have you purchased any secondhand clothing within the last 12 months?	-	Yes, No
2.	Control	Are you currently living in the United States?	-	Yes, No
3.	-	What types of secondhand clothing do you usually purchase? [select all that apply]	-	Dress pants, casual pants, shorts, woven shirt, knit shirt, coat/jacket, dress, skirt, underwear, bra/undershirt, socks, sleepwear, swimwear, children's clothing, other (please specify)
4.	Substitution Rate	Thinking about the last time you purchased this secondhand item, would you have purchased a new item if you hadn't found a secondhand version?	Dress pants, casual pants, shorts, woven shirt, knit shirt, coat/jacket, dress, skirt, underwear, bra/undershirt, socks, sleepwear, swimwear, children's clothing, other (please specify)	Yes, No Uncertain
5.	Use phase	For each secondhand clothing item purchased, how long are you likely to use the item before discarding?	Dress pants, casual pants, shorts, woven shirt, knit shirt, coat/jacket, dress, skirt, underwear, bra/undershirt, socks, sleepwear, swimwear, children's clothing, other (please specify)	a. 1 month b. 6 months c. 1 year d. 2 years e. 3 years f. until the item is no longer wearable g. I don't know

	Category	Survey Question	Item	Response Option
6.	-	What types of clothing do you refuse to purchase secondhand? [select all that apply]	-	Dress pants, casual pants, shorts, woven shirt, knit shirt, coat/jacket, dress, skirt, underwear, bra/undershirt, socks, sleepwear, swimwear, children's clothing, other (please specify)
7.	Rebound effect	Do you save money from purchasing secondhand clothing?	-	yes no I don't know
8.	Rebound effect	If you have saved money from secondhand purchasing, do you immediately spend your saving on additional purchases (clothing or non-clothing)?	-	yes no I don't know
9.	Rebound effect	What type of additional items are you likely to buy with this saved money?	-	new secondhand I don't know
10.	Motivation (Cronbach's Alpha=0.85)	The primary reason I purchase secondhand clothing is:	1. To avoid large corporate chain. 2. To support a charity 3. To find vintage items 4. To express my environmental concern. 5. For the 'thrill of a bargain'. 6. Because the items are cheaper. 7. Because the items are attractive. 8. Because the items are unique. 9. Because it is like a treasure hunt. 10. Because I enjoy the social interaction while shopping secondhand. 11. Because It is trendy to buy secondhand.	7-point Likert Scale 1= strongly disagree 7= strongly agree
11.	-	Are there any other reasons you purchase secondhand clothing that was not mentioned above?	-	Yes___________ No
12.	Barrier (Cronbach's Alpha=0.93)	The main reason I DO NOT purchase secondhand clothing is because:	1. I don't know where to purchase secondhand clothing 2. They are less stylish. 3. It is hard to find items with good fit. 4. Secondhand clothing options lack variety	7-point Likert Scale 1= strongly disagree 7= strongly agree

	Category	Survey Question	Item	Response Option
			5. I can only find my preferred clothing styles as new products in traditional retail stores 6. I can buy new clothing with the money I would spend for secondhand. 7. I am concerned about the durability of used items. 8. I am concerned about 'no return policy' of secondhand stores. 9. I am concerned about the quality of used clothing. 10. I heard there may be environmental benefits, but I do not understand how this is true. 11. Secondhand store has an unpleasant odor. 12. Secondhand clothing are dirty. 13. I prefer to buy new clothes. 14. It is embarrassing to buy or wear secondhand clothes.	
13.	-	Are there any other reasons you do not purchase secondhand clothing that was not mentioned above?	-	Yes___________ No
14.	Gender	What is your gender?		Male Female Other Prefer not to disclose
15.	Age	What is your age?		15-24 25-34 35-44 45-54 55-64 65 and more Prefer not to disclose
16.	Race	What is your race/ethnicity?		White/Caucasian Black/African American Hispanic/Latino American Indian/Alaska Native Asian/ Asian American Native Hawaiian/ Pacific Islanders Others_________ Prefer not to disclose
17.		What is your household income?		Less than $20,000

Category	Survey Question	Item	Response Option
			$20,000-$29,999
			$30,000-$39,999
			$40,000-$49,999
			$50,000-$59,999
			$60,000-$69,999
			$70,000-$79,999
			$80,000-$89,999
			$90,000-$99,999
			$100,000-$109,999
			$110,000-$119,999
			$120,000-$129,999
			$130,000-$139,999
			$140,000-$149,999
			$150,000-$159,999
			$160,000-$169,999
			$170,000-$179,999
			$180,000-$189,999
			$190,000-$199,999
			$200,000 and over
			Prefer not to disclose

LCA Methodology

LCA is typically a 'cradle-to-grave' approach of identifying the environmental impact of a product, process, or service in various stages of the corresponding life cycle. The cradle-to-grave approach "…begins with the gathering of raw materials from the earth to create the product and ends at the point when all materials are returned to the earth" (Curran, 2006, p.1). The International Organization for Standardization (ISO) provides a detailed guideline for conducting an LCA. It includes four distinct steps to conduct an environmental assessment of a product or service, namely 1) goal and scope definition, 2) inventory analysis, 3) impact assessment, and 4) interpretation (ISO 14040:2006; ISO 14044:2006). Each step of LCA is discussed below:

Goal and Scope Definition

Goal

ISO requires that the goal of LCA communicates the following four items, "…1) the intended application, 2) the reason for carrying out the study, 3) the audience and 4) whether the results will be used in comparative assertions released publicly" (Matthews et al., 2015, p.85). The goal of this LCA study was to estimate the potential environmental impact of secondhand consumption of a 100% cotton men's t-shirt. This study estimated the life cycle impact of the item across 18 midpoint categories of the ReCiPe 2016 (v1.02) method. The findings of the study were intended to inform secondhand consumers, academicians, and policymakers. Table 3.4 presents the key aspects of the goal of the study.

Table 3.4.

The Goal of the LCA Study

Component	Objective
The intended application	To improve the current understanding of the environmental benefit of secondhand clothing consumption
The reason for carrying out the study	To investigate the environmental benefit of clothing reuse
The audience	Consumers, academician, and policymakers
Whether the results will be used in comparative assertions released publicly	No

Secondhand Apparel Assessed

In this study, a secondhand men's cotton knit t-shirt (made in Bangladesh) was examined to understand the potential benefit of SHC consumption. A men's t-shirt was selected for analysis given that it was one of the most purchased items in the secondhand category (Nørup et al., 2019; Napompech & Kuawiriyapan, 2011), and substitution rate was found to be relatively higher (45% ± 4%) and consistent for t-shirts (Nørup et al., 2019). The United States imported about 174 million pieces of men's cotton knit shirt (i.e., category 338) from Bangladesh in April 2020, an 18.89% increase from April 2019 (Office of Textiles and Apparel, n.d.). Category 338 includes products like men's t-shirt, tank tops, sweatshirts, pullovers, etc. (https://otexa.trade.gov/correlat/cor338.htm). Therefore, this study would offer a valuable contribution to understanding the environmental benefit of secondhand consumption of men's knit shirts in the context of the United States as well. The features of the clothing item studied are provided in Table 3.5.

Table 3.5.

Secondhand Product Details

Product Features	**Specification**
Mass	120 gm; Size M.
Fiber	100% cotton
Fabric detail	Circular knit, single jersey fabric; batch-dyed with reactive dye
Country of origin	Made in Bangladesh
Brand	Cotton Heritage (USA)
Picture	

Scope

The scope of an LCA study is, "… a collection of qualitative and quantitative information denoting what is included in the study, and key parameters that describe how it is done" (Matthews et al., 2015, p.86). The key elements of the scope of LCA are, 1) the functional unit, 2) the product system, 3) system boundary, 4) the inventory, and 5) the impact assessment category (Matthews et al., 2015). Each element is discussed below:

Functional Unit

A functional unit is a "…quantitatively defined measure relating the function to the inputs and outputs to be studied" (Matthews et al., 2015, p.87). It should clearly bridge the function with the input and output of a product system. It is also important to note that the functional unit should relate the function of the product to be studied, rather than the product itself (Matthews et al., 2015). In this study, the functional unit was ‘secondhand consumption of a 100% cotton men’s knit t-shirt (120 gm) with 56.70% substitution rate’. The substitution rate is the extent of how much new purchase is substituted as a result of buying secondhand. The 56.70% substitution rate for men’s shirts was established based on a survey administered on 920 U.S. SHC consumers (Table 4.2). Based on the 56.7% substitution rate, the potential environmental benefit of secondhand use was calculated by subtracting the second life impact (i.e., one iteration of washing) form the first life impact (i.e., raw materials, production, transportation, and landfill/incineration) and multiply the result by 56.7%. To explain more:

If,

1. First life impact (i.e., raw materials, production, transportation, and landfill/incineration) = X
2. Second life impact (i.e., one iteration of washing) =Y
3. Substitution Rate (SR) = 56.7%

Then, the potential benefit = (X-Y) *0.567

Allocation and Cut-off Criteria

The 100% impact of extracting raw materials, manufacturing, transportation, and end-of-life waste management was allocated to the first life of the clothing, following WRAP (2011), Castellani et al. (2015), and Farrant et al. (2010) study. The impact associated with secondhand consumption are, 1) consumer transport-related impact 2) secondhand store-related impact and 3) consumer care of secondhand clothing. Previous studies either neglected the consumer transported-related impact (i.e., Farrant et al., 2010) or assumed a 10 km passenger car (i.e., Castellani et al., 2015). As for secondhand store-related impact, some secondhand stores launder clothing before selling, some do not. If they do not launder clothing, the only impact comes from electricity consumption from store operation, which was considered negligible (Castellani et al., 2015). If they wash clothing, there would be some impact. However, there is a data gap of this activity of SHC stores, therefore not included in the analysis. Also, Farrant et al. (2010) and Watson et al. (2016) reported that the collection, processing, and transport of SHC was not significant, therefore can be neglected.

Therefore, the main impact of secondhand clothing is laundering activities (washing, drying, and ironing) from the use phase. To fully understand the use phase impact, it is necessary to know how long, on average, consumers use different types of SHC items. In other words, how long the second lives of various clothing items are. It is also important to know how long the first lives of different clothing are. In their modeling, Farrant et al. (2010) and Castellani et al. (2015) assumed the same duration of first and second life, which they recommended for further study. It is also logical to know if a particular clothing item has a third life or not and If it does, then how long that life is.

Due to the above complexity, this study ignored the total use phase-related impact from second life. Instead, the study included one iteration of laundering as the main impact from secondhand, based on the following ground: 1) it is quite challenging to know how many lives a particular clothing item has, and if the care behavior varies with different lives of clothing, 2) it is not logically okay to give credit of first-life care impact to secondhand consumption 3) people may want to wash secondhand clothing before their first use because of dirt, pathogens, or other issues (Laitala & Klepp, 2018). Any flow that contributes less than 1% of the footprint by mass or energy is considered negligible and excluded from the scope of the study.

System Boundary

A ‘product system’ satisfies a need. It is “… a collection of processes that provide a certain function” (Matthews et al., 2015, p.87). For instance, a t-shirt product system is a collection of spinning, weaving/knitting, dyeing, and sewing processes through which a t-shirt is made to satisfy one’s clothing needs. A ‘system boundary’ lists, “…which subset of the overall collection of processes and flows of the product system are part of the study, in accordance with the stated study goal” (Matthews et al., 2015, p.90). The product system and system boundary communicate the product system to be studied.

The system boundary of this study included a cradle-to-grave approach involving cotton cultivation, spinning, knitting, batch dyeing, cut-and-sew, transportation, care phase, and disposal (Figure 3.1, 3.2 and Table 3.6). The care phase shown in Figure 3.1 is the secondhand clothing care phase. The details about allocation and calculation procedures were explained earlier. The transportation involved between the process flows was also considered. The disposal typically has two scenarios: landfill and incineration. In this study, both of these disposal scenarios were modeled according to EPA (2019) textile waste data (i.e., landfill/incineration: 66% / 19%). The processes that fall outside of the system boundary included any accessories/trims/care labels used in the garment, manufacture of capital equipment (for instance, spinning mill or machine), and secondhand shop maintenance-related emission (for example, electricity consumed) (Table 3.7). All the packaging is also outside the system boundary, except what is involved in cotton harvesting and yarn production.

Figure 3.1.

System Boundary

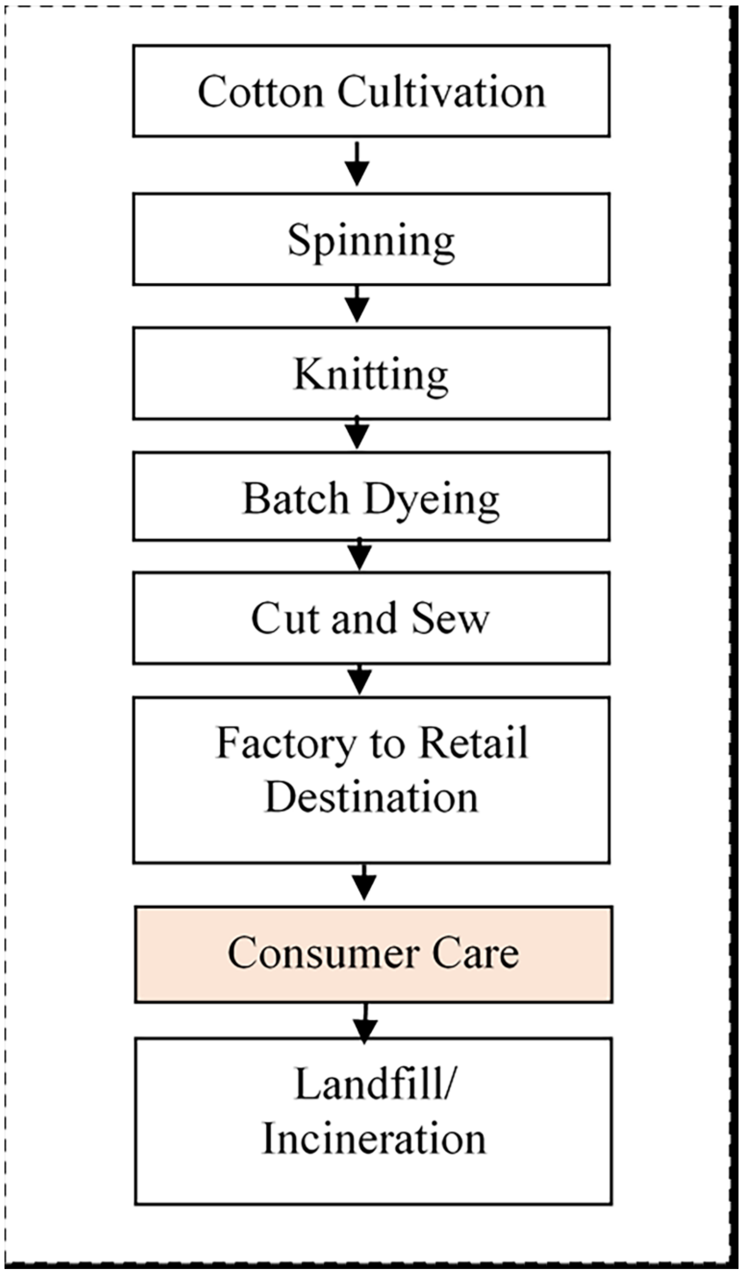


Figure 3.2.

System Boundary Including Geographic Reference

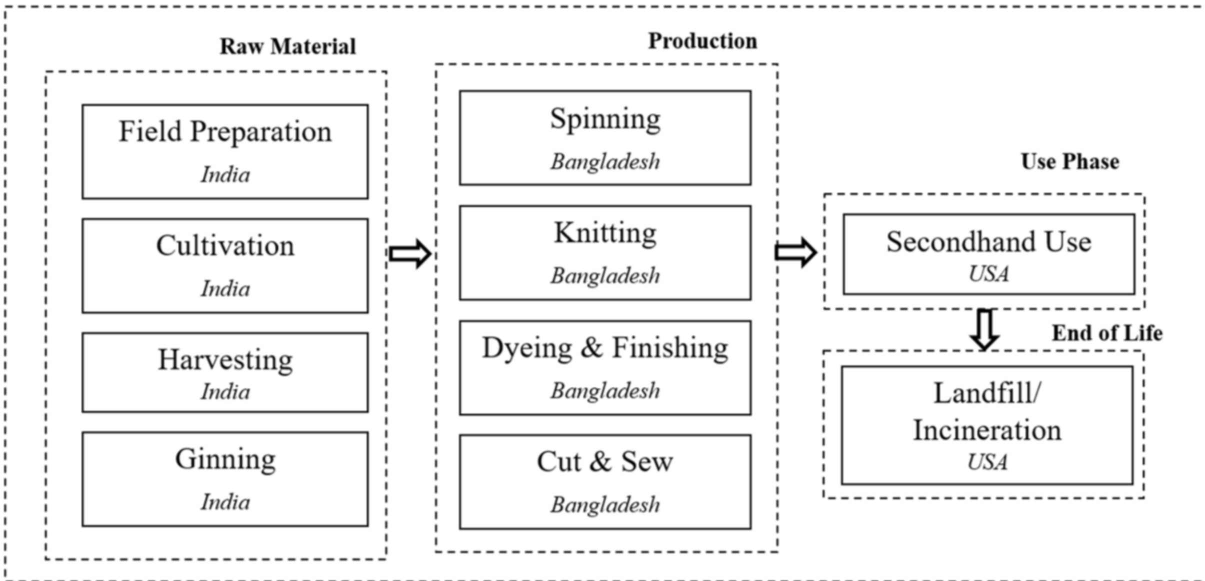


Table 3.6.

The Avoided Versus Added Impact by Secondhand Consumption

Avoided Impact by Secondhand Consumption	**Added Impact by Secondhand Consumption**
Cotton cultivation	Consumer care (secondhand)
Spinning	
Knitting	
Batch dyeing	
Cut and sew	
Transportation of product from factory to retail destination	
Landfill/Incineration	

Table 3.7.

Inclusion and Exclusion of Items in System Boundary

Inside system Boundary	Outside system Boundary
✓ Raw materials ✓ Manufacturing of textiles ✓ Packaging associated with cotton harvesting and yarn production ✓ Water ✓ Chemical ✓ Electricity ✓ Transportation ✓ Use phase ✓ End of life	× Accessories, trims, care label × Packaging × Capital equipment × Store operation-related emission

Inventory Analysis and Tool

The main data source for this study was Ecoinvent v3.4 and published studies (Appendix E). Ecoinvent is the most reliable and exhaustive database containing a higher number of materials, chemicals, and processes entering into the textile life cycle (Beton et al., 2014). In addition, relevant country-specific data (where available) was fed into Ecoinvent inventory. SimaPro v8.5.2.0 (PRé Consultants, 2020) was used to model the LCA. SimaPro is one of the most popular LCA software and used extensively by other researchers (Beton et al., 2014; Roos et al., 2015).

Cotton Cultivation

It was assumed that the cotton fiber used was imported from India, the largest exporter of cotton to Bangladesh (Kasabe, 2018). Bangladesh imports cotton from 42 countries of the world, including India, Central Asian countries, USA, and African countries (USDA Foreign Agricultural Service, 2018). In the fiscal year 2018-19 (Aug-Jul), Bangladesh sourced 26% of its cotton need from India (USDA Foreign Agricultural Service, 2018). The second big cotton sourcing destination for Bangladesh is Uzbekistan (16% share) followed by USA (9%). About 80% of garments made in Bangladesh are cotton-made, and 90% of these used in knitwear (USDA Foreign Agricultural Service, 2018).

Cotton agriculture involves field preparation, cultivation, harvesting, and ginning. Field preparation includes ploughing, harrowing, hoeing, sowing, and currying. Cultivation includes irrigation, weed and pest control, and fertilization. Harvesting and ginning include picking, separating cotton fibers from seeds (i.e., ginning), and transporting. These processes consume water, energy, fuel, and fertilizers, as well as generates wastes and emissions (Shah et al., 2018). Country-specific LCI data of cotton cultivation is very limited. To date, the LCI data of cotton cultivation is reliably available only for the USA and China. There are partial data available in the context of India (Reinhard et al., 2017). Therefore, the global average inventory data from Ecoinvent was used for modeling background data of cotton cultivation, and India-specific data were used to represent cultivation practices using data from Cotton Incorporated (2017), Shah et al. (2018), and Bevilacqua et al. (2014) studies (Table 3.8).

Table 3.8.

Inventory of Cotton Cultivation in India

Parameter	**Unit**	**Value/ kg of cotton**
Cultivated area	ha	0.0015
Urea	kg	0.062
N	kg	0.1489
P_2O_5	kg	0.0489

K_2O	kg	0.0071
Pesticides	kg	0.0012
Irrigation water	m3	2.9759
Electricity	kWh	0.5971
Transport (Lorry 3.5-16t)	tkm	0.326

Note. The inventory was created using Cotton Incorporated (2017), Shah et al (2018), and Bevilacqua et al. (2014) studies. For a detailed inventory, please refer to Appendix E.

Production Stage

The textile production stages include spinning, knitting, dyeing, and cut-and-sew processes. The main resources used in these stages are electricity, heat, water, chemicals, auxiliaries, and dyes (Moazzem et al., 2018). To model these stages, the global average inventory data from Ecoinvent was used, while using country-specific data where available. All the background data for production stages, such as chemicals, auxiliaries, and dyes were used from the Ecoinvent database. The reason is that Bangladesh mainly imports these items from the rest of the world (Moazzem et al., 2018).

The spinning process includes opening/cleaning of fiber from cotton bales, carding, pre-drawing/preparation, combing, drawing, roving, and spinning. These processes transform raw cotton fibers from cotton bales into yarn to be used in subsequent textile knitting and coloration processes. The environmental impact of the spinning process comes mainly from electricity consumption, spinning waste, and spindle oil (i.e., lubricating oil). To produce one kg of cotton yarn, about 1.36 kg of fiber is needed (36% waste) (Cotton Incorporated, 2017). The electricity requirement of producing cotton yarn is 1.76 kWh per kg (Moazzem et al., 2018). The electricity consumption data of India was used as a proxy for Bangladesh. The lubricating oil requirement is 0.0005 kg (Roos et al., 2015), and water consumption is 1.32 liter per kg of cotton ring-spun yarn (Hossain, 2017). The LCI inventory used for modeling the spinning process is given in Table 3.9.

Table 3.9.

Inventory of Yarn Manufacturing

Parameter	Unit	Value/kg of yarn
Cotton fiber	kg	1.36
Electricity	kWh	1.76
Water	liter	1.32
Lubricating oil	kg	0.0005

Note. The inventory was created using Cotton Incorporated (2017), Moazzem et al. (2018), Roos et al. (2015), and Hossain (2017) studies. For a detailed inventory, please refer to Appendix E.

The knitting process involves back-winding, creeling, and knitting. The environmental impact of this stage comes mainly from electricity consumption, lubricating oil, and waste. The inventory for this stage is prepared using Roos et al. (2015), Cotton Incorporated (2017), and Hossain (2017) study. The detailed inventory for the knitting process is given in Table 3.10.

Table 3.10.

Inventory for Knitting

Parameters	**Unit**	**Value/kg of knitted fabric**
Cotton fibers	kg	1.02
Electricity	kWh	1.04
Water	liter	1.04
Lubricating oil	kg	0.1

Knit dyeing (i.e., exhaust dyeing) involves pretreatment (i.e., scouring and bleaching), dyeing, finishing (i.e., softening), drying and compacting. Scouring agent to remove impurities and improve absorbency. Bleaching removes the natural fiber color of fabric and improves whiteness. In the dyeing process, reactive dyes and auxiliary chemicals (such as salt, sequestering agent) are used. After dyeing, fabric goes through the softening, drying, and compacting process. The impact of this process mainly comes from consuming chemicals, auxiliaries, water, and energy, as well as wastewater treatment. Very little Bangladesh-specific inventory data was found related to knit t-shirt dyeing. Therefore, proxy inventory data (India-specific) was used from Murugesh and Selvadass's (2013) study, given in Table 3.11. Murugesh and Selvadass (2013) reported a knit-dyeing inventory of stone and blue color t-shirt. In this study, the average value of those dyeing parameters was used. This data would be very similar to that of Bangladesh because of geographical proximity and similar manufacturing practices.

Table 3.11.

Inventory for Dyeing

Parameters	Unit	Value/kg of dyed fabric
Dyeing		
Cotton fiber	kg	1.1300
Reactive dye 1	kg	0.0011
Reactive dye 2	kg	0.0082
Reactive dye 3	kg	0.0019
Wetting agent	kg	0.0035
Sodium hydroxide	kg	2.8000
Acetic acid	kg	0.0035
Soap, at plant	kg	0.0210
Water	kg	48.4917
Electricity	kWh	0.1330
Heat, from logwood	MJ	19.9480
Softener pad		
acetic acid	kg	0.0008
Water	kg	0.8000
Electricity	kWh	0.0156
Stenter drying		
Electricity	kWh	0.0737
Heat, from logwood	MJ	2.9597
Compacting		

Electricity	kWh	0.1434
Heat, from logwood	MJ	3.3603

Note. Please see Appendix E for a detailed inventory

The cut-and-sew process mainly involves laying, cutting, sewing, ironing, finishing, and packaging. The main resource used in this process is electricity. The finishing process consumes steam and electricity. The resource requirement varies with every product, and it is challenging to gather inventory data for individual apparel items (Moazzem et al., 2018). In addition, the data related to the apparel cut-and-sew process is very limited. Only Jungmichel's (2010) study was found to report Bangladesh-specific cut-and-sew data. Therefore, a Bangladesh-specific inventory was created using Jungmichel (2010) and Ross et al., (2015) study. The inventory for the cut-and-sew process is given in Table 3.12.

Table 3.12.

Inventory Related to the Cut-and-Sew Process

Parameters	**Process**	**Unit**	**Value/kg of knit t-shirt**
Electricity	Relaxing	kWh	0.0408
Electricity	Cutting	kWh	0.0815
Electricity	Sewing	kWh	2.6280
Electricity	Quality check 1, sewing	kWh	0.0741
Electricity	Sucker machine	kWh	0.5557

Electricity	Ironing	kWh	0.0500
Electricity	Quality check 2	kWh	0.3890
Electricity	Finishing	kWh	0.0815

Consumer Care Phase

The consumer clothing care phase involves laundering and drying. The main impact of this phase comes from detergent, water, and electricity consumption. In this study, the use phase of the first life of the t-shirt was not considered. One laundering was modeled for the secondhand t-shirt under the assumption that consumers typically launder SHC after purchasing, thus it should be included as a part of the process. The environmental impact from one second-life laundering was considered as the added impact from secondhand use. An inventory for the consumer use phase was created from several published studies, given in Table 3.13.

Table 3.13.

Inventory Related to the Use Phase

Parameter	Unit	Value/kg	Reference
Detergent	kg	0.02	Schenck, 2013
Water consumption	kg	16.5	EPA, 2018; Yamaguchi et al., 2011
Electricity consumption (washing)	kWh	0.17	Cotton Incorporated, 2017
Electricity consumption (drying)	kWh	0.21	Yamaguchi et al., 2011

Note. The most efficient washer and energy-efficient dryer were considered. Please refer to Appendix E for detailed inventory; assumed the same washing behavior of first-hand use prevailing to the secondhand use.

Secondhand Apparel Preparation

Collection, sorting, and preparation (i.e., washing and drying) were assumed negligible in the previous studies concerning clothing reuse (Farrant et al., 2010; Schmidt et al., 2016; Watson et al., 2016;). Therefore, in this study, the impact of these activities was not modeled. The total energy requirement of collection, sorting, and preparation activities were reported as 5 MJ per kg of textiles (Schmidt et al., 2016), which is negligible in comparison with the textile production. The transportation of used clothes from consumer residence to secondhand shop was assumed as 10 km in previous studies (for example, Castellani et al., 2015), which is also negligible and was not modeled.

Landfill/Incineration

Ecoinvent inventory for the waste scenario of non-durable goods was used to model landfill and incineration. This inventory models landfill/incineration scenario of 1 kg textiles, using relevant mass-based allocation of 2006 U.S.-specific textile waste data. However, the U.S. Environmental Protection Agency (2019) published recent data where it reported that about 66% of textile waste going to landfill and 19% going to incineration. Therefore, in this study, this updated waste management scenario was modeled.

Transportation

The major cotton-producing states within India are Punjab, Haryana, Rajasthan, Gujarat, Maharashtra, Madhya Pradesh, Telangana, Andhra Pradesh, and Karnataka (Ministry of Textiles India, 2019). Bangladesh imports raw cotton from India by road through the Petrapole-Benapole border (Kasabe, 2018; Maritime Gateway, n.d.). An average distance of these states from Dhaka, the capital of Bangladesh, was assumed to be the road transportation associated with cotton import from India to Bangladesh. Using Google Maps, the average distance found was 1,223 miles (Table 3.14). A heavy-duty truck (gross weight, >12t) run by diesel was assumed to transport the cotton from India to Bangladesh. The product was assumed to be manufactured in one of the factories in Dhaka because most of the garment factories of Bangladesh are located within the Dhaka district (Labowitz & Baumann-Pauly, 2015). Once the product was made, it was assumed to be transported to the Chattogram port, which is the largest seaport of Bangladesh. A light-duty vehicle (gross weight, <3.5t) was assumed to transport goods within these processes (i.e., spinning to knitting, knitting to dyeing, dyeing to cut-and-sew and cut-and-sew to delivery port). From there, it was assumed that the item would be shipped to the port of Los Angles in the USA using standard maritime shipping freight and then transported to Manhattan, Kansas by medium and heavy-duty truck (gross weight, 9.75-16.5t). It should be noted that Bangladesh does not have any direct maritime freight route to Los Angles. Typically, the freight first goes to any intermediary port (i.e., Malaysia, China, Hong Kong, or Singapore) and then to U.S. port. Therefore, a shipping route was assumed based on Maersk's (www.maersk.com) typical shipping schedule (i.e., Chittagong [BD]-Tanjung Pelepas [MY]-Xiamen [CN] - Los Angeles [USA]). Maersk is the largest oceanic shipping line of the world and a leading logistics provider in Bangladesh (Marine Insight, 2020). The transportation-related inventory used in this study is presented in Table 3.15.

Table 3.14.

Indo-Bangla Cotton Import Route

Route	**Distance (in miles)**
Punjab-Dhaka	1,304
Haryana-Dhaka	1,217
Rajasthan-Dhaka	1,308
Gujarat-Dhaka	1,489
Maharashtra-Dhaka	1,153
Madhya Pradesh-Dhaka	1,020
Telangana-Dhaka	1,135
Andhra Pradesh-Dhaka	1,033
Karnataka-Dhaka	1,347
Average Distance	**1,223**

Table 3.15.

Transportation-related Life Cycle Inventory

Transportation Scenario	**Distance (mile)**	**Mode**

Raw Materials to Spinning	1,223	heavy-duty truck (>12t)
Spinning to fabric	10	light-duty vehicle (<3.5t)
Fabric to dyeing	10	light-duty vehicle (<3.5)
Dyeing to cut-and-sew	10	light-duty vehicle (<3.5t)
Cut-and-sew to delivery Port (i.e., Chattogram port)	159	light-duty vehicle (<3.5t)
Chattogram (BD)- Tanjung Pelepas (MY)- Los Angles (US)	9,288 nautical miles[1]	Maritime shipping
Port of Los Angles to- Manhattan, Kansas	1,526	Medium and heavy-duty truck (gross weight, 9.75-16.5t)

Note. See Appendix E for a detailed inventory. Sea distance was estimated using https://sea-distances.org/ (BD-MY=1390, MY- CN=1782, CN-LAS=6,116; total= 9,288 nautical miles.)

Impact Assessment

The purpose of the impact assessment is to evaluate the "…magnitude and significance of the potential environmental impacts of a product system" (Beton et al., p.60). ISO 14040 requires individuals to list impact categories, the methodology of impact assessment, and interpretation (Matthew et al., 2014). In this study, the ReCiPe 2016 method (v1.02) - hierarchist perspectives - was used for impact assessment (Huijbregts et al., 2016). ReCiPe method includes a standardized set of characterization factors that reduces confusion in interpretation (Beton et al., 2014). It includes 18 midpoint and 3 endpoint indicators to estimate environmental impact. In this study, only midpoint indicators were used because the midpoint characterization has relatively greater relation to environmental flows, provides lower uncertainty, and can offer a broad set of impact indicators (Hauschild & Huijbregts, 2015). On the other hand, endpoint categories provide a relatively higher level of uncertainty (Hauschild & Huijbregts, 2015). The midpoint and endpoint categories as well as their units of measure are presented in Table 3.16.

Table 3.16.

Midpoint and Endpoint Indicators of ReCiPe 2016 (V1.0) and their Unit of Measurement

Midpoint Indicators	**Unit**
Global warming	kg CO2 eq.
Stratospheric ozone depletion	kg CFC-11 eq.
Ionizing radiation	kB_q CO-60 eq.
Ozone formation: human health	kg NO_x-eq.
Fine particulate matter formation	kg PM2.5- eq. to air
Ozone formation: terrestrial ecosystem	kg NO_x-eq.
Terrestrial acidification	kg SO_2 eq.
Freshwater eutrophication	kg P-eq.
Marine eutrophication	Kg N eq.
Terrestrial ecotoxicity	kg 1,4-DCB eq.
Freshwater ecotoxicity	kg 1.4-DCB eq.
Marine ecotoxicity	kg 1.4-DCB eq.
Human carcinogenic toxicity	kg 1.4-DCB eq.
Human non-carcinogenic toxicity	kg 1.4-DCB eq.
Land use	m^2 area crop eq.

Mineral resource scarcity	kg Cu-eq.
Fossil resource scarcity	kg oil-eq.
Water consumption	m^3
Endpoint Indicators	
Damage to human health	Disability Adjusted Life Year (DALY)
Damage to ecosystem	Species * yr.
Damage to resource availability	USD

Note. For more information, see the 'definition of terms' section in Chapter 1.

Overall Data Analysis Plan

The main objectives guiding this research study were, 1) finding a substitution rate of clothing reuse for U.S. respondents and comparing that with average substitution rate value for other countries, 2) identifying consumer typologies based on different consumer characteristics (i.e., age, sex, race, and income), behavior (motivations and barriers) and substitution rate, 3) investigating how different factors, such as age, sex, race, income, and behavior predict substitution rate, and 4) assessing the potential environmental benefit of clothing reuse. To serve the first research objective, a mathematical calculation was used, which was discussed earlier. A table of how substitution rate was calculated is presented in Appendix A. The substitution rate thus found was then compared with substitution rate data of other countries. This comparison was helpful in understanding consumer differences in terms of their substitution rate. For this purpose, a one-sample t-test was used with looking into Cohen's *d* for effect size. One-sample t-test compares a sample mean with a known population mean to reveal if the difference is significant, whereas Cohen's d informs how large the effect is (Ross & Willson, 2017).

The second research objective was to identify and analyze consumer typologies based on different consumer characteristics, behavior, and substitution rate. To serve this purpose, cluster analysis was conducted with variables including age, gender, race, household income, motivations, barriers, and substitution rate. Cluster analysis is a method of classifying subjects into distinct groups (i.e., clusters) based on their similarities or differences. In cluster analysis, subjects are separated into groups, where subjects within a given cluster are more similar than the subjects outside the group (Sharpe, 2010). Subjects become homogenous inside the group, whereas heterogeneous outside groups. This clustering identifies how different consumer factors go together and thereby helped analyze consumers by clusters (Tashakkori et al., 1998). Overall, the analysis helps summarize the characteristics of subjects, and identify the underlying structure of data.

The third objective was to explore the impact of demography and consumer motivation/barriers on substitution rate and how they predict it. For that purpose, a Poisson regression analysis was conducted. Poisson regression is particularly suitable to analyze count and rate variable (Gardner et al., 1995, PennState, n.d.). It is a type of generalizing linear model (GLM), which is based on a log-linear model. Poisson regression revealed how age, sex, race, income, and motivation/barrier influenced the substitution rate of consumers while taking care of the relative impact of each other.

The fourth objective was to assess the potential environmental impact of clothing reuse. Secondhand clothing consumption is a major form of clothing reuse today (Guiot & Roux, 2010; Han, 2013), and the t-shirt is a popular secondhand purchase category (Nørup et al., 2019; Napompech & Kuawiriyapan, 2011). For that reason, a men's t-shirt was investigated to identify the environmental benefit of using it as secondhand. Life Cycle Assessment Method (LCA) was used to analyze the impact. LCA is the internationally recognized and most used method of conducting an environmental assessment of a product. An overview of the overall data analysis plan is given in Table 3.17.

Table 3.17.

Data Analysis Plan

Research Question	Analysis Plan
1. How does the substitution rate of U.S. consumers differ from the rates reported for selected European and African countries?	Mathematical calculation of substitution rate from survey data One sample t-test (the U.S. vs avg. substitution rate of other countries); Cohen's *d* for effect size.
2. What are the typologies of U.S. SHC consumers in terms of age, gender, race, household income, motivation, barrier, and substitution rate?	Cluster Analysis of mixed data using Partitioning Around Medoids (PAM) algorithm
3. Do age, gender, household income, motivation, and barrier predict the substitution rate of secondhand clothing reuse?	Poisson regression analysis
4. What potential environmental benefit can be realized from avoiding a new clothing item purchase (i.e., 100% cotton men's t-shirt, 120 gm), assuming an average substitution rate (i.e., 56.7%)?	LCA of secondhand use of a 100% cotton men's knit t-shirt

Chapter 4 - Findings

The study investigated the U.S. substitution rate of secondhand clothing consumption and compared the value with the average rest of the world (ROW) data. In addition, the study examined if the participants could be classified into different groups based on their demographic characteristics (i.e., age, gender, race, and household income), SHC purchasing behavior (i.e., motivation and barrier) and substitution rate. The study also investigated if those characteristics and behaviors predict the substitution rate. Furthermore, the study assessed the potential environmental benefit of secondhand use of a 100% cotton men's t-shirt. This chapter presents the analysis and findings of the study.

Demographics of research participants

The study included participants who were living in the United States and who purchased secondhand clothing within the past 12 months. The survey was created using the Qualtrics tool and distributed via Amazon Mechanical Turk (Mturk). Based on the qualifying criteria, 920 participants responded to the survey. The demographic information of the participants is shown in Table 4.1. Among the participants, the 18-34 age group consists of about half of the sample, with 25-34 being the largest age group (39.46%). Previous studies also reported that MTurk participants are relatively younger (Difallah et al., 2018; Paolacci & Chandler, 2014). However, it should be noted that the 18-34 age group consists of about 24.24% of the U.S. population and is over-represented in the sample. The male participants consist of 47.72%, and the female consists of 51.74% of the sample, which is very much similar to the gender distribution of the population. Most of the participants were white/Caucasian (71.20%). Since the sample included only U.S. individuals, the white/Caucasian race was expected. However, Hispanic/Latino (4.89%) and Black/African American (8.48%) were under-represented in the sample, and

Asian/Asian American (12.72%) were relatively over-represented in the sample. This is also typical for Mturk participants, as reported by previous research studies (Berinsky et al., 2012; Difallah et al., 2018). The annual household income of about half of the participants were less than $60,000, with $30,000-39,999 group being the largest (12.61%). It should be noted that the average and median household income of the U.S. population was about $89,930 and $63,030 respectively in 2019 (PK, 2019).

Table 4.1.

Demographic Information of Survey Participants

Variables	Survey data (n=920)		U.S. data 2019 (N= 324,356,000)	
	Number	**Percent**	**Number (in thousands)**	**Percent**
Age Group				
18-24	94	10.22	33,105	10.30
25-34	363	39.46	45,209	13.94
35-44	208	22.61	41,027	12.65
45-54	142	15.43	40,700	12.54
55-64	80	8.70	41,755	12.87
65 or more	30	3.26	52,787	16.27
Prefer not to disclose	3	0.33	-	-
Gender				
Male	439	47.72	159,028	49.03
Female	476	51.74	165,328	50.97
Other	4	0.43	-	-
Prefer not to disclose	1	0.11	-	-
Race/Ethnicity				
White/Caucasian	655	71.20	248,132	76.50
Black/African American	78	8.48	43,464	13.40
Hispanic/Latino	45	4.89	59,357	18.30
American Indian/Alaska Native	10	1.09	4,217	1.30
Asian/Asian American	117	12.72	19,137	5.90

Native Hawaiian/Pacific Islanders	1	0.11	649	0.20
Others	10	1.09	-	-
Prefer not to disclose	4	0.46	-	-
Household Income				**N=128,579,000**
Less than $20,000	83	9.02	18,902	14.70
$20,000-$29,999	104	11.30	11,141	8.66
$30,000-$39,999	116	12.61	11,226	8.73
$40,000-$49,999	90	9.78	10,034	7.80
$50,000-$59,999	105	11.41	9,717	7.55
$60,000-$69,999	80	8.70	8,603	6.69
$70,000-$79,999	84	9.13	7,745	6.02
$80,000-$89,999	44	4.78	6,413	4.99
$90,000-$99,999	47	5.11	5,683	4.42
$100,000-$109,999	44	4.78	5,315	4.13
$110,000-$119,999	8	0.87	4,289	3.34
$120,000-$129,999	18	1.96	3,784	2.94
$130,000-$139,999	8	0.87	3,104	2.41
$140,000-$149,999	32	3.48	2,730	2.12
$150,000-$159,999	12	1.30	2,470	1.92
$160,000-$169,999	3	0.33	2,131	1.66
$170,000-$179,999	2	0.22	1,740	1.35
$180,000-$189,999	5	0.54	1,458	1.13
$190,000-$199,999	1	0.11	1,149	0.89
$200,000 and above	16	1.74	10,946	8.51
Prefer not to disclose	18	1.96	-	-

Note. The U.S census data was compiled from the U.S. Census Bureau (2019), U.S. Census Bureau (2019a), and U.S. Census Bureau (2019b).

Data Analysis and Results

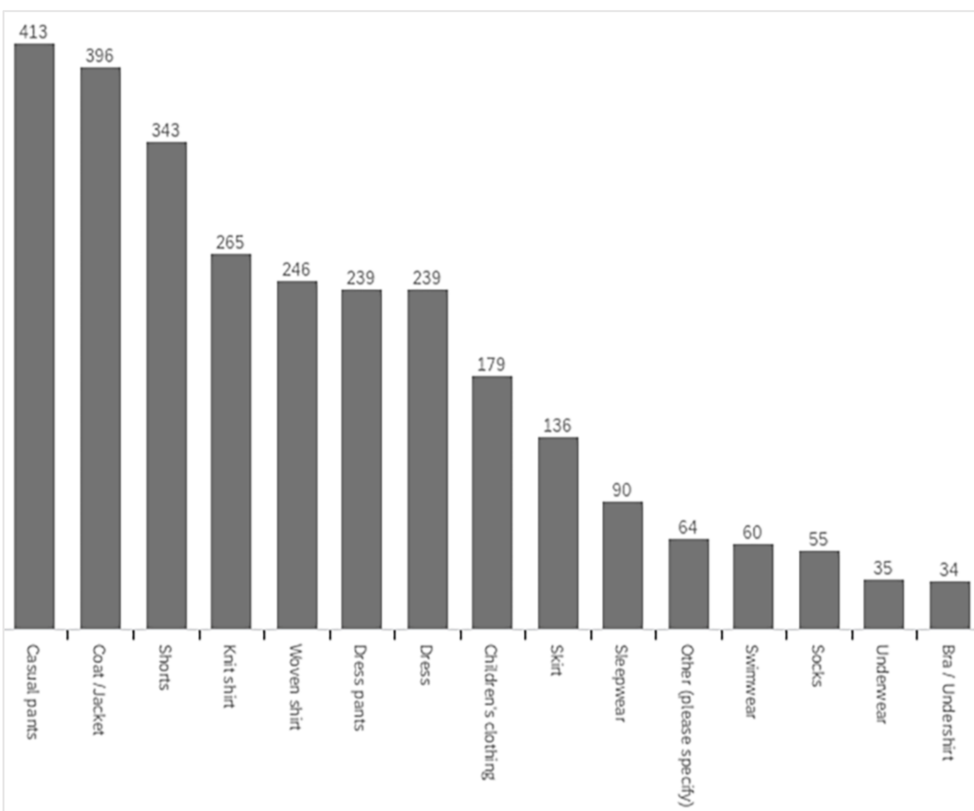
The following sections present the results from data analysis in relation to the research questions posed in the study.

RQ 1: How does the substitution rate of U.S. consumers differ from the rates reported for selected European and African countries?

In order to answer this question, participants were asked to identify the types of secondhand clothing they purchased (Figure 4.1), and if those purchases substituted for similar new purchases. For each SHC item purchased, they were asked to choose from three options: ‘yes’, ‘no’ and ‘uncertain’ (Figure 4.2), A ‘yes’ response indicated that a secondhand purchase served as a substitute for a new purchase; a ‘no’ response indicated that a secondhand purchase did not substitute for a new purchase, and an ‘uncertain’ response indicated that the participants could not decide whether the secondhand purchase served as a substitution or not. In this study, the ‘uncertain’ response was assumed to indicate a fifty-fifty chance of yes or no and was included as an error bar in the substitution rate calculation. This ‘uncertain’ option is equivalent to ‘maybe’ and ‘I don’t know’ options used in the previous studies (e.g., Nørup et al., 2019; Stevenson & Gmitrowicz, 2012).

Figure 4.1.

Secondhand Clothing Purchases by Category

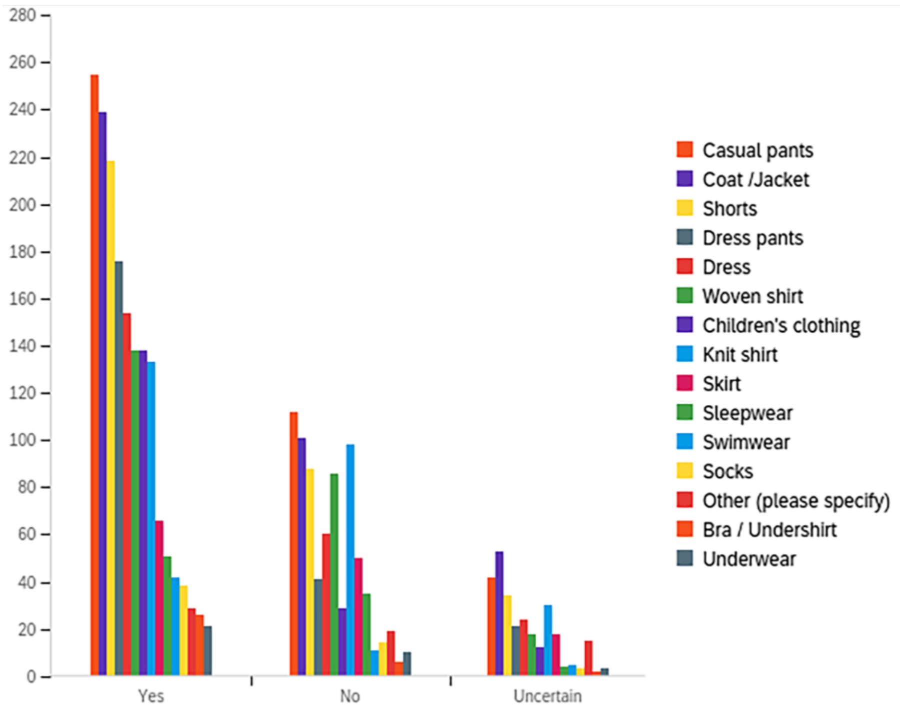


As seen in Figure 4.1, casual pants, coat/jacket, shorts, knit shirt, and woven shirt are the top five SHC items participants purchased in the past year. On the other hand, bra/undershirt, underwear, socks, swimwear, and other category are the bottom five categories. The 'other' category was open-ended for the participants. Participants mentioned the name of the SHC item if it was not listed in the options. This includes a range of products, such as casual shirt, sweatshirt, t-shirt, jeans, sweater, and tank-top, etc. However, some of these products represent the category listed in the survey options, for example, woven shirt (i.e., casual shirt), knit shirt (i.e., t-shirt, tank-top), and casual pant (i.e., jeans). In addition, some of the most mentioned items in the 'other' category do not fall into the clothing category, for example, accessory, handbag, purse, etc.

Figure 4.2, represents the participants' response with respect to the substitution of new products from secondhand consumption of various clothing types, such as casual pants, coat/jacket, shorts, dress pants, dress, etc. It is noticeable that the substitution of new purchases from secondhand purchases varies with participants and item categories. Some consumers substitute new purchases by their secondhand purchase (as indicated by 'yes' response), some do not (as indicated by 'no' response), and the others cannot decide (as indicated by 'undecided' response). To understand more about how secondhand purchases of various items saves a new purchase, the substitution rate of the SHC items was calculated.

Figure 4.2.

Substitution of New Purchase by Clothing Category



The substitution rate (SR) of the participants by clothing category is calculated using a formula, which is given below.

$$SR = \frac{\text{total number of items with 'Yes' response (a)} + \text{ ½ of the number of items with 'Uncertain' response (c)}}{\text{Total number of items purchased (d)}}$$

The findings of the U.S. substitution rate from this study are reported in Table 4.2, showing that children's clothing, bra/undershirt, dress pants, swimwear, and socks are the top five categories in terms of substitution rate value. This finding indicates that these are the items that saved new purchases the most within the items investigated. It can be noticed that the items consumer purchase most frequently do not have a higher substitution rate value. Rather, the items consumers purchase less frequently have a higher substitution rate value.

Table 4.2.

The U.S. Substitution Rate of SHC Purchase

Item	Yes (a)	No (b)	Uncertain (c)	Total (d)	Substitution Rate (%)	Uncertain (%)	Error bar (±)
Casual pants	255	112	42	409	67.48	10.27	5.14
Coat /Jacket	239	101	53	393	67.56	13.49	6.75
Shorts	218	88	34	340	69.12	10.00	5.00
Knit shirt	133	98	30	261	56.70	11.49	5.75
Woven shirt	138	86	18	242	60.74	7.44	3.72
Dress pants	176	41	21	238	**78.36**	8.82	4.41
Dress	154	60	24	238	69.75	10.08	5.04
Children's clothing	138	29	12	179	**80.45**	6.70	3.35
Skirt	66	50	18	134	55.97	13.43	6.72
Sleepwear	51	35	4	90	58.89	4.44	2.22
Other	29	19	15	63	57.94	23.81	11.91
Swimwear	42	11	5	58	**76.72**	8.62	4.31
Socks	38	14	3	55	**71.82**	5.45	2.73
Bra / Undershirt	26	6	2	34	**79.41**	5.88	2.94
Underwear	21	10	3	34	66.18	8.82	4.41
Average					**67.81**	**9.92**	**4.96**

The participants who purchased children's clothing, bra/undershirt, dress pants, swimwear, and socks might have made conscious and/or necessary purchases, as discussed in Chapter 2. In the event of a conscious/necessary purchase (such as environmental concern, financial reason, etc.), substitution rates go higher. The average substitution rate data is found to be 67.81% ± 4.96 (i.e., lower bound is 62.85%, and the upper bound is 72.77%). This finding suggests that, on average, every 100 SHC purchase substitutes between about 63 and 73 new purchases. To identify if there was any significant difference in substitution rate between the U.S. and the rest of the world (RoW) data, a one-sample t-test was conducted between the average U.S. substitution rate and the RoW data. It was found that the U.S. substitution rate was significantly higher (M = 67.81, SD = 8.45) than the average 45.13 substitution rate for RoW ($t[919] = 81.41$, $p < 0.001$). Cohen's d was estimated as 1.95, which is a large effect based on Cohen's (1992) guideline (Table 4.3). An effect size explains the magnitude of the difference. In this case, the large effect size indicates that the difference is large.

Table 4.3.

One Sample t-test Between the U.S and ROW SHC Substitution Rate

	United States		Rest of the World					
	M	*SD*	*M*	*SD*	One sample t-test			Cohen's *d*
					df	*t*	*p*	
Substitution Rate	67.81	8.45	45.13	14.07	919	81.41	0.001***	1.95

Note. M = mean, *SD* = standard deviation

*p < .05. **p < 0.01. ***p < .001.

However, there might be some rebound effect, which means that money saved from SHC purchasing might lead participants to buy additional clothing (new or secondhand) or spend it elsewhere in the economy. To investigate the rebound effect, the participants were asked whether they saved money from SHC purchasing and spent saved money immediately on additional purchasing (clothing or non-clothing). They were also asked whether they bought a new or secondhand item with the saved money. The findings associated with the rebound effect are shown in Table 4.4.

Table 4.4.

Rebound Effect

Survey question	Response		
	Yes	**No**	**I don't know**
1. Do you save money from purchasing secondhand clothing?	864 (93.51%)	41 (4.44%)	19 (2.06%)
2. If you save money from secondhand purchasing, do you immediately spend savings on additional purchases (clothing or non-clothing)?	240 (27.18%)	621 (70.33%)	22 (2.49%)
	New	**Secondhand**	**I don't know**
3. What types of additional items are you likely to buy with this saved money?	137 (57.08%)	91 (37.92%)	12 (5%)

It can be seen from Table 4.4 that 93.51% of participants saved money from SHC purchasing. Among them, only 27.18% spent the saved money on additional purchases. From them, 57.08% plan to buy new products whereas 37.92% plan to purchase secondhand products. This finding suggests that financial motivation is strong among SHC purchasers. It can also be reasonably said that the rebound effect is low because only 27.18% of those who save money from SHC plan to spend the money on the additional purchases. Also, not everybody buys new products as an additional purchase.

Overall, the finding related to the first research question is that the average U.S. substitution rate is 67.81% ± 4.96; it is significantly higher than the average RoW substitution rate, and the rebound effect is low. Other relevant findings are that casual pants, coat/jacket, shorts, knit shirt, and woven shirt are the top five while bra/undershirt, underwear, socks, swimwear, and other category are the bottom five purchased SHC categories. The substitution of new purchases by secondhand purchases varies with participants and item categories.

RQ 2: What are the typologies of U.S. SHC consumers in terms of age, gender, race, household income, motivation/barrier, and substitution rate?

To answer this research question, a cluster analysis technique for mixed data (i.e., continuous, ordinal, and nominal) was conducted based on 'partitioning around medoids (PAM)' algorithm. Clustering can be done around the mean or medoid. Medoid is the most centrally located entity of a cluster having the least sum of distances to other entities (Jin & Han, 2011). Clustering around the mean is more sensitive to outliers, whereas clustering around the medoid is more robust to outliers and extreme values (Jin & Han, 2011). The PAM method is an iterative process and it includes the following steps:

1. Choosing k random entities for medoids
2. Assigning each subject to its closest medoid (using a distance matrix)
3. For each cluster, identifying the subjects yielding the lowest average distance with respect to medoids

It was observed that five clusters would be optimal for the dataset, as shown in Figure 4.3. An optimal number of clusters is usually the location of the bend of the graph (Kassambara, 2017). From this bend, there is a very small change in the within-group sum of squares. It is worth mentioning that the motivation and barrier scales were broken down into its various dimensions. For instance, the motivation to SHC purchase scale was broken down into critical (items 1,2,4), economic (items 5,6), recreational (item 3,9,10), and fashionability (items 7,8,11) motivations. And the barriers towards the SHC purchase scale were broken down into knowledge (items 1,10), attitude (items 2,3,5,12), product's attribute (items 4,7,8,9), economic (item 6), preference (item 13), store attributes (item 11), and society's expectation-related barriers (item 14). The finding from cluster analysis is presented in Table 4.5.

Figure 4.3.

Determining the Optimal Number of Clusters

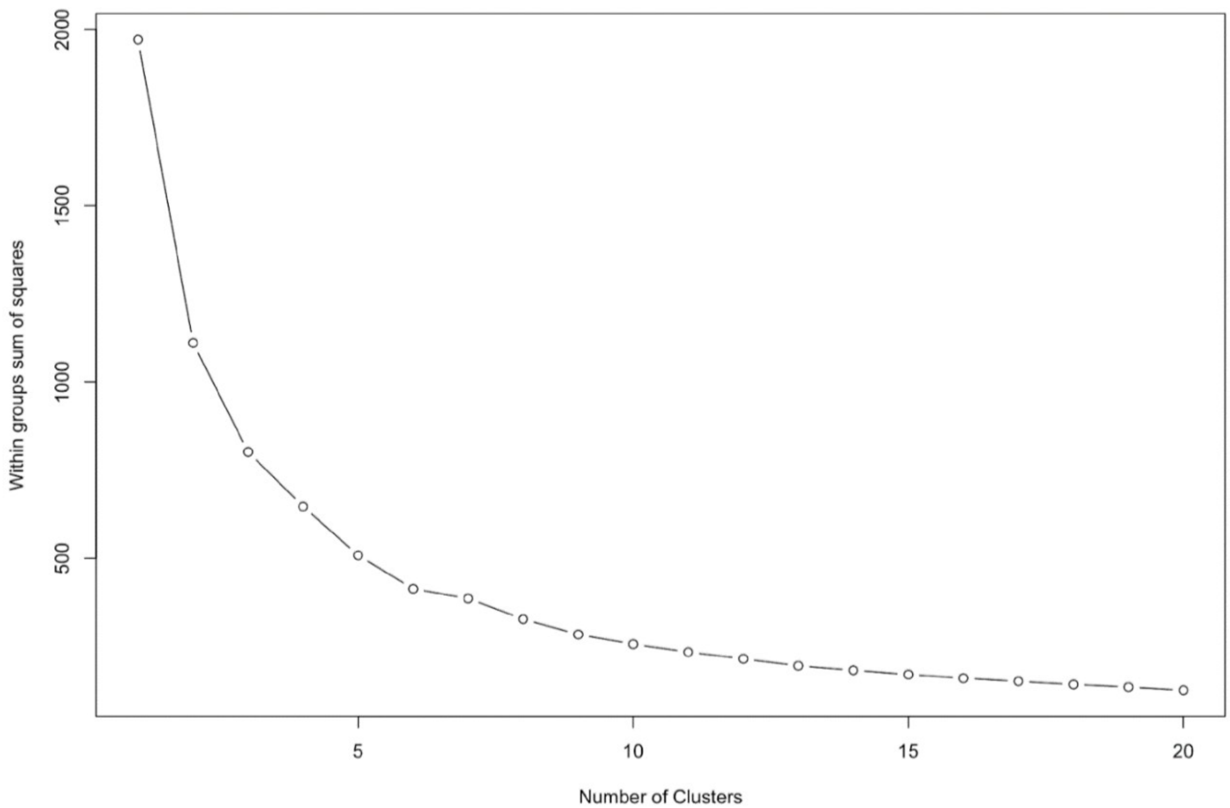


Table 4.5.

Characteristics of Five Clusters Based on Age, Gender, Race, Household Income, Motivation, Barrier, and Substitution Rate

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Age (frequency, percent)					
18-24	12 (7.27)	18 (12.24)	11 (5.45)	21 (11.35)	32 (14.41)
25-34	58 (35.15)	66 (44.90)	64 (31.68)	83 (44.86)	84 (37.84)
35-44	37 (22.42)	27 (18.37)	58 (28.71)	39 (21.08)	45 (20.27)
45-54	24 (14.55)	21 (14.29)	38 (18.81)	25 (13.51)	32 (14.41)
55-64	17 (10.30)	12 (8.16)	22 (10.89)	11 (5.95)	18 (8.11)
65 or more	17 (10.30)	3 (2.04)	9 (4.46)	6 (3.24)	11 (4.95)
Gender (frequency, percent)					
Male	71 (47.65)	90 (61.22)	73 (35.96)	101 (54.59)	98 (44.14)
Female	78 (52.35)	56 (38.10)	129 (63.55)	84 (45.41)	122 (54.95)
Others	0 (0.00)	1 (0.68)	1 (0.49)	0 (0.00)	2 (0.90)
Race/Ethnicity (frequency, percent)					
White/Caucasian	114 (76.51)	102 (69.39)	153 (77.27)	129 (70.11)	148 (66.67)
Black/African American	13 (8.72)	9 (6.12)	17 (8.59)	15 (8.15)	24 (10.81)
Hispanic/Latino	1 (0.67)	2 (1.36)	6 (3.03)	12 (6.52)	14 (6.31)
American Indian/Alaska Native	9 (6.04)	4 (2.72)	4 (2.02)	3 (1.63)	3 (1.35)
Asian/Asian American	12 (8.05)	30 (20.40)	18 (9.09)	23 (12.50)	31 (13.96)
Native Hawaiian/Pacific Islanders	0 (0.00)	0 (0.00)	0 (0.00)	1 (0.54)	0 (0.00)
Others	0 (0.00)	0 (0.00)	0 (0.00)	1 (0.54)	2 (0.90)
Household Income (frequency, percent)					
30k or less	34 (22.97)	29 (19.86)	37 (18.50)	43 (24.29)	43 (19.72)
30k-60k	52 (35.14)	50 (34.25)	68 (34.00)	58 (32.77)	78 (35.78)
60k-90k	33 (22.30)	31 (21.23)	54 (27.00)	36 (20.34)	51 (23.39)
90k-120k	12 (8.11)	21 (14.38)	19 (9.50)	23 (12.99)	24 (11.01)
120k and more	17 (11.49)	15 (10.27)	22 (11.00)	17 (9.60)	22 (10.09)
Motivations (mean)					
Critical	2.48	5.11	4.44	3.42	4.70
Recreational	2.78	5.25	5.03	3.49	5.16
Economic	4.44	5.59	5.96	4.39	5.70
Fashion-ability	3.22	5.16	4.84	3.61	5.05
Barriers (mean)					
Knowledge	1.92	5.17	1.56	3.50	2.68

Attitude	2.61	5.32	1.93	4.21	3.55
Product's attribute	2.64	5.35	2.16	4.37	3.86
Economic	2.30	5.35	1.92	4.26	3.73
Preference	3.31	5.67	2.12	4.55	4.33
Store attributes	2.43	5.60	1.94	4.29	3.70
Society's expectation	1.77	5.41	1.36	3.71	2.58
Substitution rate (mean)	0.68	0.80	0.62	0.73	0.68

Note. Both motivation and barrier scale was 7-point Likert Scale, 1 = strongly disagree, 7 = strongly agree. A higher score denotes higher motivation or barrier.

During characterizing the clusters, this study added age groups until they make 70% of the sample. Also, to understand which motivation and barrier characterized a cluster, the study used the highest motivation and barrier score for a particular cluster. Therefore, it can be noticed from Table 4.5 that Cluster 1 is characterized by 18-54 age group (79.39%), nearly equally distributed male (47.65%) and female (52.35%) individuals, predominantly white/Caucasian (76.51%), household income of $30,000-$90,000 (80.41%), higher economic motivation (*M*=4.44), higher preference-related barrier (M=3.31), and 68% substitution rate. Cluster 2 is characterized by 18-44 age group (75.51%), mostly male (61.22%), predominantly white/Caucasian (69.39%), household income of $30,000-$90,000 (75.34%), higher economic motivation (M=5.59), higher preference-related barrier (M=5.67), and 80% substitution rate. Cluster 3 is characterized by 18-54 age group (84.65%), mostly female (63.55%), predominantly white/Caucasian (77.27%), household income of $30,000-$90,000 (79.50%), higher economic motivation (M=5.96), higher lack of desirable product's attribute-related barrier (M=2.16), and 62% substitution rate. Cluster 4 is characterized by 18-44 age group (77.79%), fairly similarly distributed male (54.59%) and female (45.41%) individuals, predominantly white/Caucasian (70.11%), household income of $30,000-$90,000 (77.40%), higher economic motivation (M=4.39), higher preference-related barrier (M=4.55), and 73% substitution rate. Cluster 5 is characterized by 18-44 age group (72.52%), fairly similarly distributed male (44.14%) and female (54.95%) individuals, predominantly white/Caucasian (66.67%), household income of $30,000-$90,000 (78.89%), higher economic motivation (M=5.70), higher lack of desirable product's attribute-related barrier (M=3.86) and 68% substitution rate.

If we compare among clusters, the findings indicate that the substitution rate goes higher with predominantly male participants. It is also noticeable that the substitution rate goes lower with relatively older participants in a cluster. Also, it can be seen that clusters with a fairly similar gender distribution produced a 68% substitution rate, which is on par with the 67.81% substitution rate found for the total sample (Table 4.2). Furthermore, the findings reconfirm that SHC consumers are economically motivated because the economic motivation was higher across the clusters. It is worth noting that cluster analysis is exploratory, and interpreting clusters is highly subjective (Jin & Han, 2011). Therefore, further predictive analysis is needed to fully understand the association of different variables.

RQ 3: Do age, gender, household income, race, and motivation/barrier predict the substitution rate of secondhand clothing consumption?

To answer this question, a Poisson regression analysis was conducted. Poisson regression analysis is used to predict the dependent variables that are count or rate data (Gardner et al., 1995), such as the number of people, substitution rate, etc. It is a type of generalizing linear model (GLM), which is based on a log-linear model. Figure 4.4 shows the distribution of substitution rate data. The distribution does not follow a normal distribution. Therefore, the data is transformed into a log scale for regression analysis (Figure 4.5).

Figure 4.4.

Distribution of Substitution Rate

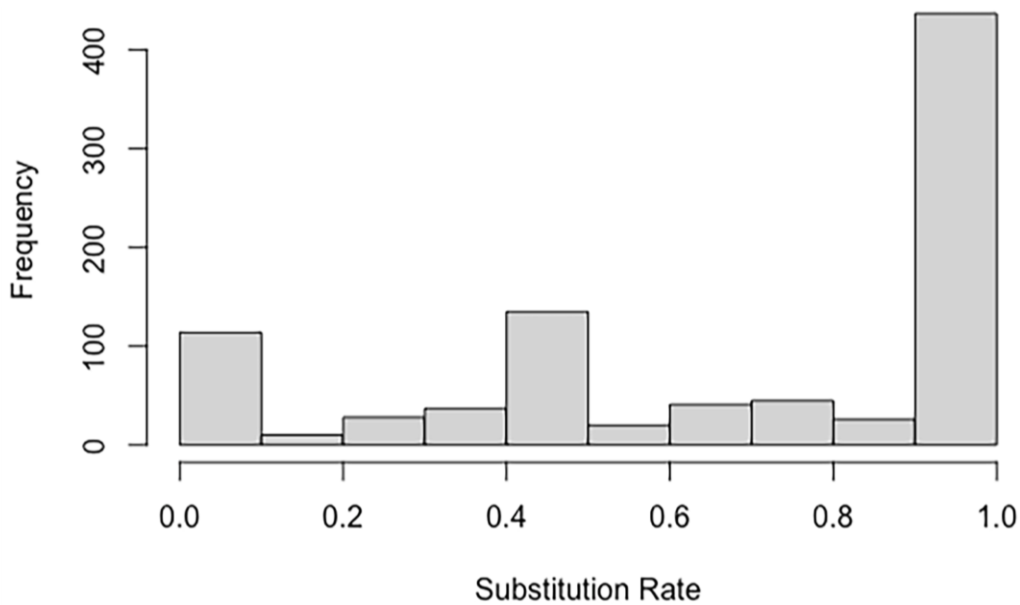
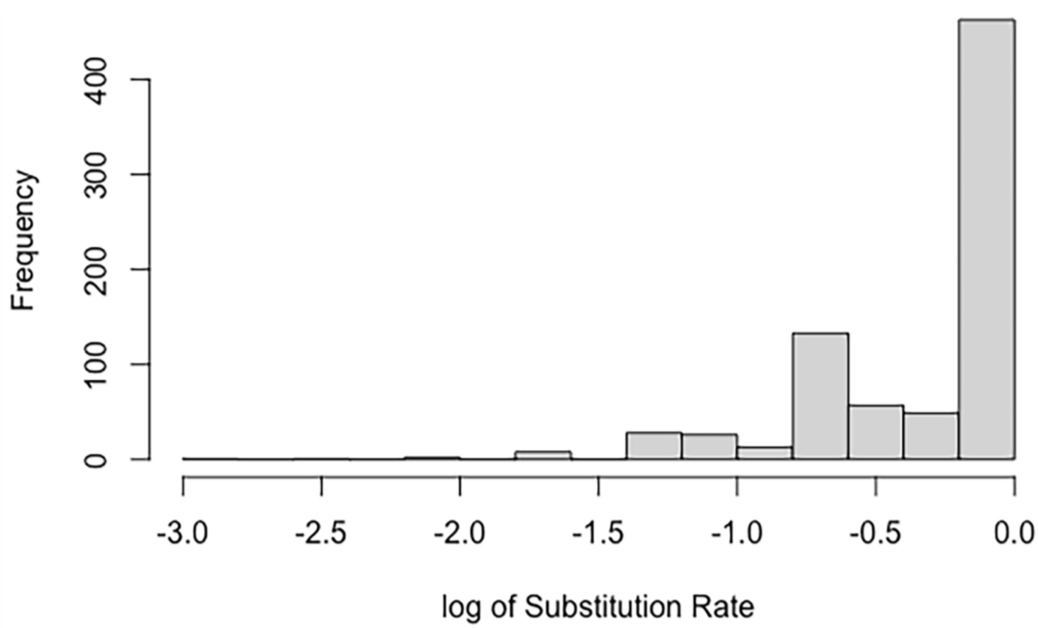


Figure 4.5.

Distribution of Log Value of Substitution Rate



In order to analyze the data better, the household income of the participants was divided into two groups around the median U.S. household income of $63,030 (PK, 2019). The household income groups that were less than $60,000 were coded as 'below the median', and the income groups that were $60,000 or more were coded as 'above the median' in the regression analysis. The finding of Poisson regression analysis is shown in Table 4.6.

Table 4.6.

Result of Poisson Regression

Variables	Estimate	Std. Error	*p*-Value
Age			
25-34	0.077	0.145	0.596
35-44	0.053	0.155	0.729
45-54	0.038	0.167	0.817
55-64	-0.068	0.197	0.729
65 or more	-0.080	0.273	0.767
Gender			
Male	0.063	0.082	0.445
Other	-0.271	0.719	0.706
Race			
White/Caucasian	-0.001	0.402	0.997
Black/African American	0.128	0.419	0.759
Hispanic/Latino	-0.018	0.439	0.967
Asian/Asian American	0.011	0.416	0.978
Native Hawaiian/Pacific Islanders	-13.994	773.784	0.986
Other	0.106	0.544	0.845
Household Income			
Below the median	-0.052	0.082	0.524

Motivation	-0.006	0.049	0.887
Barrier	-0.027	0.040	0.486

Note. Reference group: gender (female), age group (18-24), Race (Native American/Pacific Islanders), Income (above the median). Null deviance: 242.92, *df*=892; residual deviance: 236.79, *df*=876.

*p<.05, **p<.01, ***p<.001

The result shows poor goodness of fit of the model (null deviance: 242.92, *df*=892; residual deviance: 236.79, *df*=876). The association of predictor variables with response variables is not statistically significant. Therefore, it can be said that age, gender, race, household income, motivation, and barrier were not good predictors of substitution rate. There might be other variables that would be able to better predict substitution rate other than the variables accounted for in this study (for instance, the price of the product, attitude towards purchasing secondhand, etc.).

To further analyze the data, the distribution of age vs. substitution rate, gender vs. substitution rate, race vs. substitution rate, and household income vs. substitution rate was analyzed. Figure 4.6 shows the frequency distribution of participants' age groups, and Figure 4.7 shows a boxplot comparison of the substitution rate of different age groups. It can be seen from Figure 4.7 that there is a variation of substitution rate within different age groups. For instance, the median substitution rate values for 25-34 and 45-54 age groups are nearly 100%, whereas other age groups have mixed values for the substitution rate.

Figure 4.6.

Frequency Distribution of Age Groups

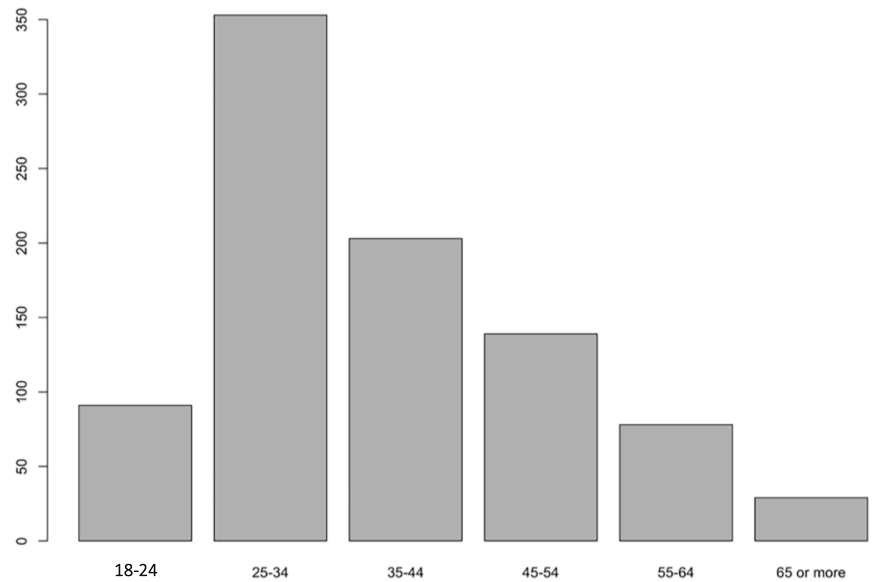
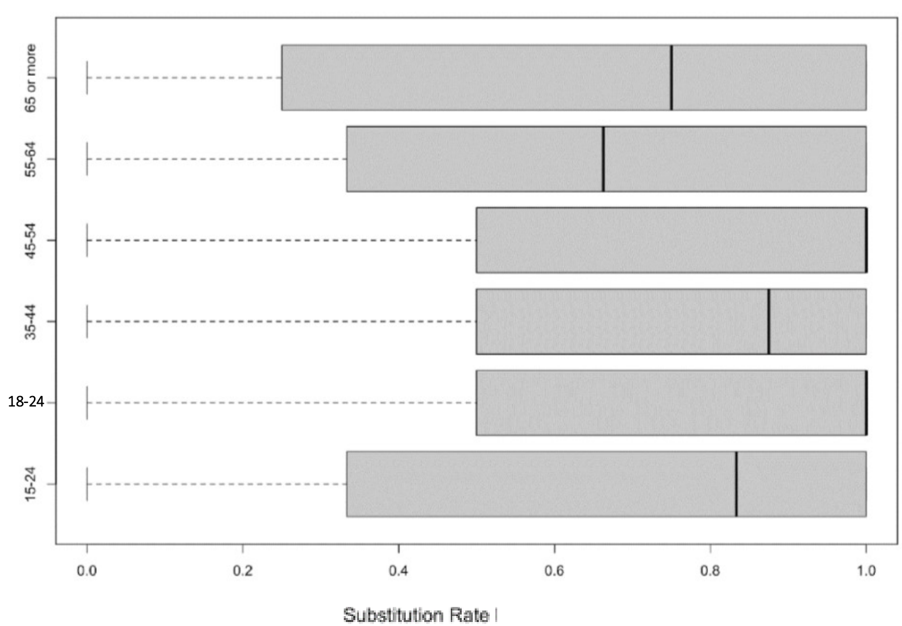


Figure 4.7.

Age vs. Substitution Rate of the Participants



To identify whether the difference in the substitution rate of different age groups is significant, a one-way analysis of variance (ANOVA) was conducted. The output of ANOVA is shown in Table 4.7, demonstrating that the difference of substitution rate across different age groups is not statistically significant (F [5, 887] = 1.65, p = .14).

Table 4.7.

Means, Standard Deviations, and One-Way Analyses of Variance of Substitution Rate Across Different Age Groups

Measure	18-24		25-34		35-44		45-54		55-64		65 or >		*F* (5, 887)	*p*
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*		
SR	0.66	0.37	0.72	.35	0.70	0.34	0.70	0.38	0.62	0.38	0.61	0.38	1.65	.14

Note. SR= substitution rate

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Similarly, the frequency distribution of participants' gender is shown in Figure 4.8, and a comparison of substitution rate by gender is shown in Figure 4.9, indicating that there is a difference in the substitution rate across different gender groups. The median substitution rate value for female participants is about 75%, for male participants is about 100%, and for other participants (i.e., bisexual, transgender, etc.) is about 50%. Therefore, a one-way analysis of variance (ANOVA) was conducted to see if there is any significant difference among these age groups. The ANOVA output is presented in Table 4.8, demonstrating that the difference of substitution rate across different gender groups is statistically significant (F [2, 890] = 3.23, p < .05).

Figure 4.8.

Frequency Distribution of Gender

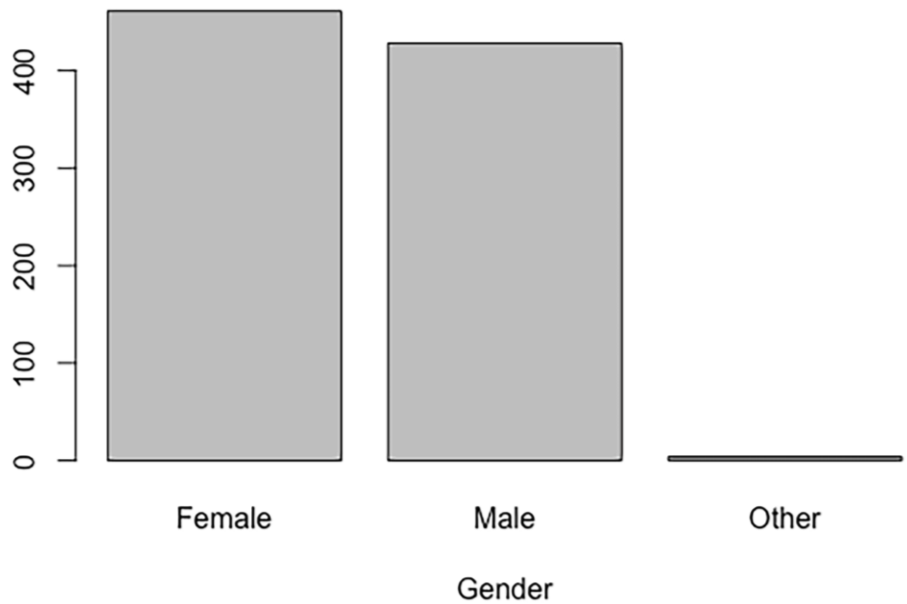


Figure 4.9.

Gender vs Substitution Rate of the Participants

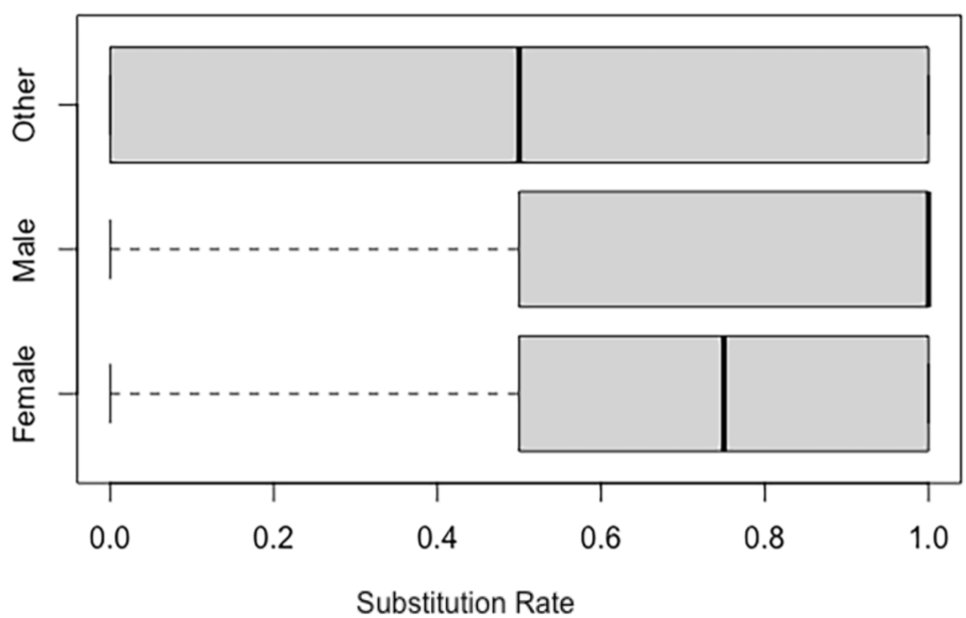


Table 4.8.

Means, Standard Deviations, and One-Way ANOVA Analyses of Variance of Substitution Rate Across Different Gender Groups

Measure	Male		Female		Other		$F(2, 890)$	p
	M	SD	M	SD	M	SD		
SR	0.73	0.35	0.67	0.36	0.50	0.51	3.23	0.04*

Note. SR= substitution rate

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Likewise, the frequency distribution of different race/ethnicity groups is shown in Figure 4.10, and a comparison between race/ethnicity and substitution rate is shown in Figure 4.11. It should be noted that there was only one Native Hawaiian/Pacific Islander participant, hence omitted from the analysis.

Figure 4.10.

Frequency Distribution of Race

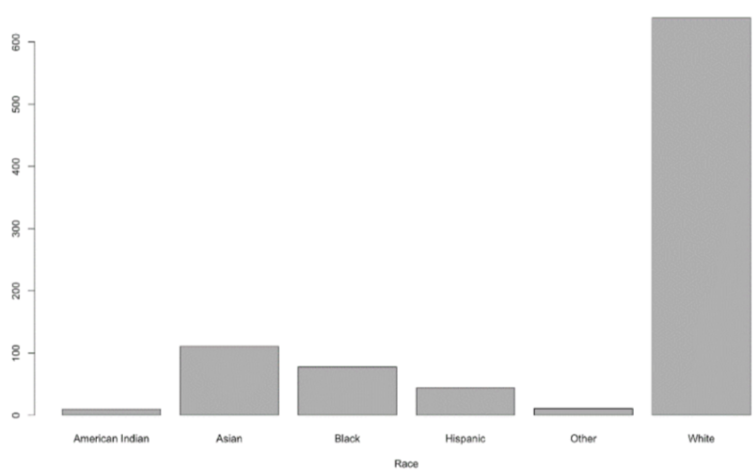


Figure 4.11.

Race vs. Substitution Rate

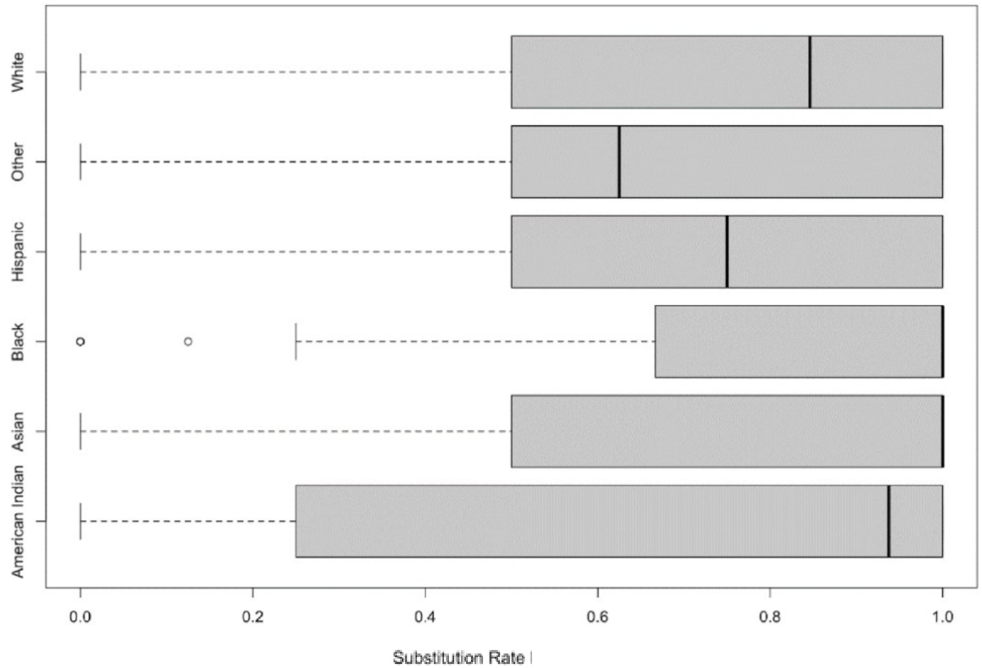


Figure 4.11 shows that there is a difference in the substitution rate across different race groups. The median substitution rate value for white participants is about 85%, for Black/African American participants is about 100%, for Hispanic/Latino participants is about 75%, for American Indian/Alaska Native participants is about 95%, for Asian/Asian American participants is about 100% and for other participants (i.e., middle-eastern, multi-racial, mixed, etc.) is about 65%. Therefore, a one-way analysis of variance (ANOVA) was conducted to see if there is any significant difference among these racial groups. The ANOVA output is presented in Table 4.9, demonstrating that the difference of substitution rate across different race/ethnicity groups is not statistically significant (F [5, 887] = 1.25, p = .28).

Table 4.9.

Means, Standard Deviations, and One-Way ANOVA Analyses of Variance of Substitution Rate Across Different Race/Ethnicity Groups

Measure	White		Black/ African American		Hispanic/ Latino		American Indian/Alaska Native		Asian/Asian American		Other		F(5, 887)	p
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*		
SR	0.69	0.36	0.79	0.31	0.69	0.33	0.65	0.44	0.71	0.36	0.68	0.32	1.25	0.28

Note. SR= substitution rate

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

The frequency distribution of household income of participants is shown in Figure 4.12, and a comparison between household income and substitution rate is shown in Figure 4.13. It can be seen from Figure 4.13 that the median substitution rate is higher for households with higher incomes. This suggests that the motivation for purchasing SHC for higher-income participants may not be financial, but rather critical. Higher-income participants might have substituted new purchases with SHC purchases due to critical motivation (for example, environmental concern). To identify if this difference of substitution rate among different household income groups is significant, a one-way ANOVA was conducted. The ANOVA output is presented in Table 4.10, demonstrating that the difference of substitution rate across different household income groups is not statistically significant (F [4, 888] = 0.95, p = .44).

Figure 4.12.

Frequency Distribution of Household Income of the Participants

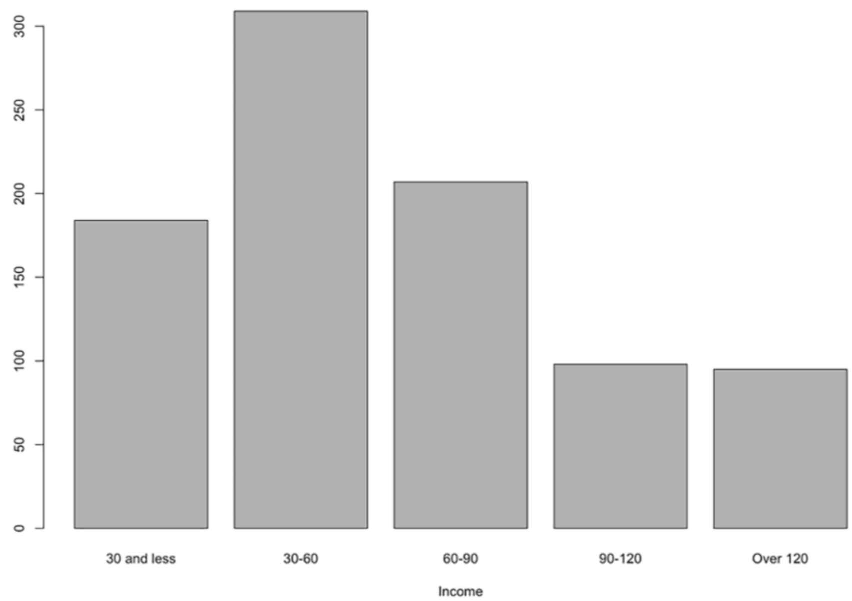


Figure 4.13.

Household Income vs. Substitution Rate

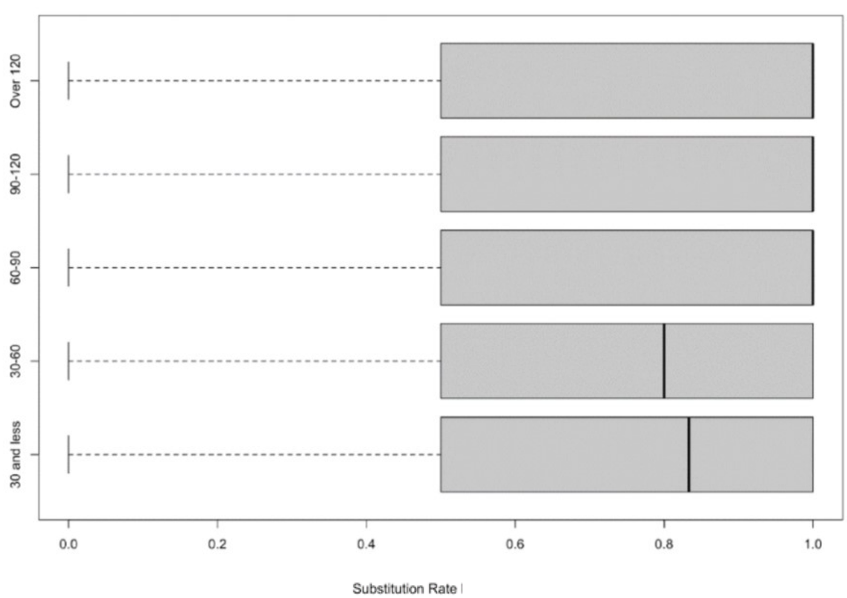


Table 4.10.

Means, Standard Deviations, and One-Way Analyses of Variance of substitution rate across different income groups

Measure	30k and less		30-60k		60-90k		90-100k		Over $120k		F (4, 888)	p
	M	SD	M	SD	M	SD	M	SD	M	SD		
SR	0.69	0.36	0.67	0.37	0.70	0.37	0.73	0.32	0.74	0.33	0.95	0.44

Note. SR= substitution rate

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Finally, the motivation and barriers associated with SHC purchasing of the participants were explored from descriptive statistics. Regarding motivation, the participants were asked to indicate their agreement with 11 items representing different dimensions of the motivation of purchasing SHC items, for example, financial, recreation, critical, and fashion. The findings of the 11-item 7-point Likert scale (1=strongly disagree, 7=strongly agree) is presented in Figure 4.14, showing that the participants were mostly driven by economic and product's attribute motivation.

The average item-wise score and the standard deviation are shown in Table 4.11. The findings showed that the economic motivation played a greater role for the participants' SHC purchase, as indicated by the relatively higher average score for 'because the item was cheaper' (M=5.68, SD=1.39). The participants were also motivated by the product's quality, as indicated by the relatively higher score of 'because the items are attractive' (M=5.03, SD=1.42). On the other hand, the participants had low fashionability motivation, as indicated by the relatively lower average score of 'because it is trendy to buy secondhand' (M=3.44, SD=1.80).

Figure 4.14.

Reasons for Purchasing Secondhand Clothing

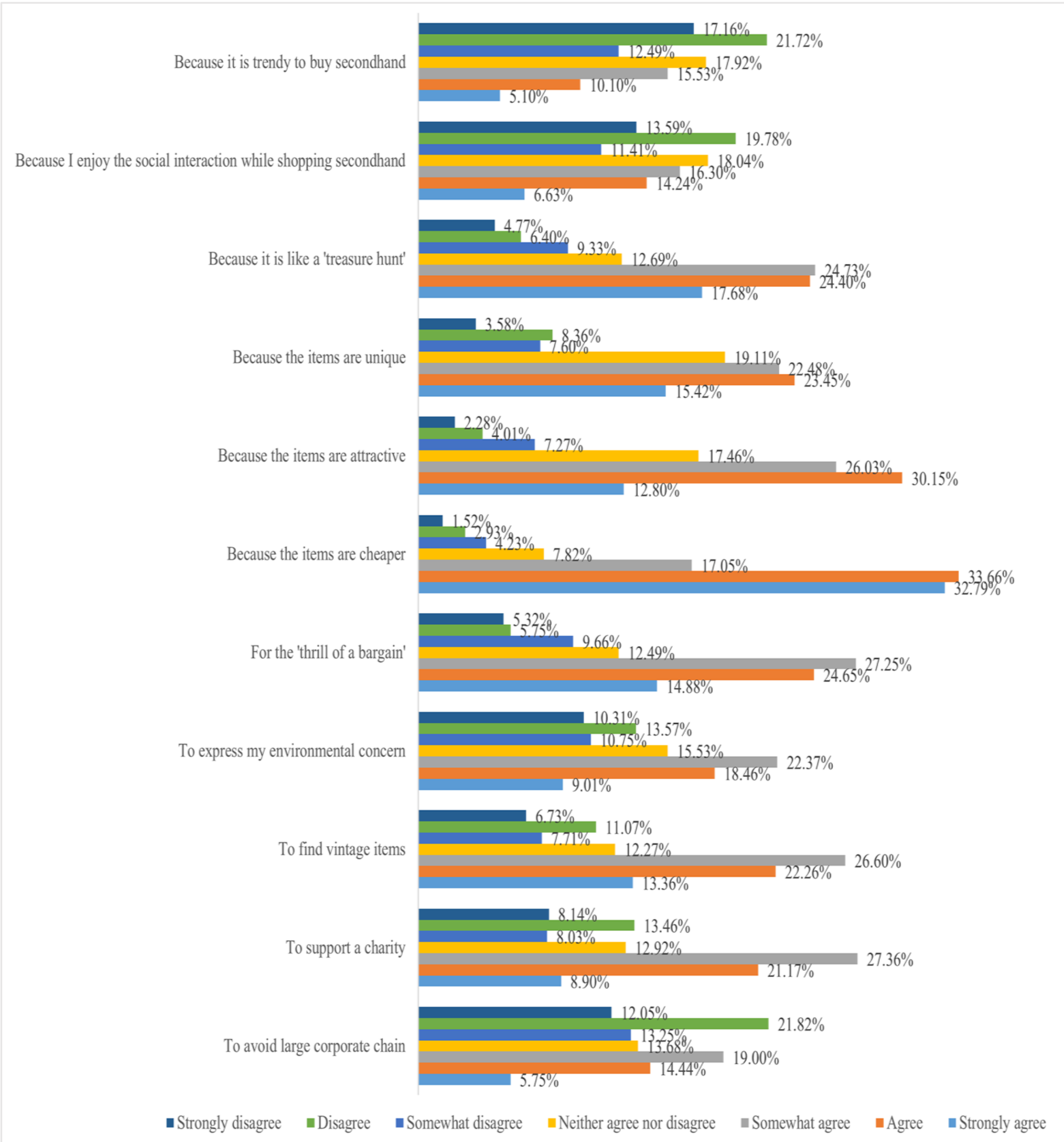


Table 4.11.

Reasons for Purchasing Secondhand Clothing Score; Mean (M) and Standard Deviation (SD)

	M	*SD*
Because the items are cheaper	5.68	1.39
Because the items are attractive	5.03	1.42
Because it is like a 'treasure hunt'	4.90	1.67
For the 'thrill of a bargain'	4.84	1.64
Because the items are unique	4.81	1.62
To find vintage items	4.61	1.76
To support a charity	4.37	1.77
To express my environmental concern	4.17	1.82
Because I enjoy the social interaction while shopping secondhand	3.73	1.84
To avoid large corporate chain	3.72	1.82
Because it is trendy to buy secondhand	3.44	1.80
Average	**4.48**	**1.69**

Note. 1=strongly disagree, 7=strongly agree; a higher mean value represents higher motivation to purchase SHC items.

Regarding barriers, the participants were asked to indicate their agreement with 14 items representing different dimensions of the barrier of purchasing SHC items, for example, lack of knowledge, attitude, personal preference, hygiene, etc. The findings of the 14-item 7-point Likert scale (1=strongly disagree, 7=strongly agree) are presented in Figure 4.15, showing that the knowledge and society's expectation were not major barriers for the participants. Personal preference and product availability were two major barriers to purchasing SHC.

To understand the score better, the average item-wise score and the standard deviation are presented in Table 4.12. The findings showed that one of the main barriers to purchasing SHC was product availability, as indicated by the relatively higher score of the item 'It is hard to find items with good fit' (*M*=3.92, *SD*=1.81). Another major barrier was personal preference, as indicated by the relatively higher score of the item 'I prefer to buy new clothes' (*M*=3.92, *SD*=1.76). On the other hand, the participants were knowledgeable about the secondhand venues, as indicated by the relatively lower score of the item 'I don't know where to purchase secondhand clothing' (*M*=2.74, *SD*=1.83). Society's expectation was also not a major barrier for the participants, as indicated by the relatively lower score of the item 'it is embarrassing to buy or wear secondhand clothes' (*M*=2.87, *SD*=1.76)

The overall finding of the third research question is that age, gender, household income, race, motivation, and barrier were not good predictors of the substitution rate of SHC consumption. However, a statistically significant difference in substitution rate was found between male and female participants. This is reasonable because there is substantial variation in male and female clothing buying behavior. It should also be noted that the cheap price of SHC was the major reason for participants' SHC purchase.

Figure 4.15.

Reasons for Not Purchasing Secondhand Clothing

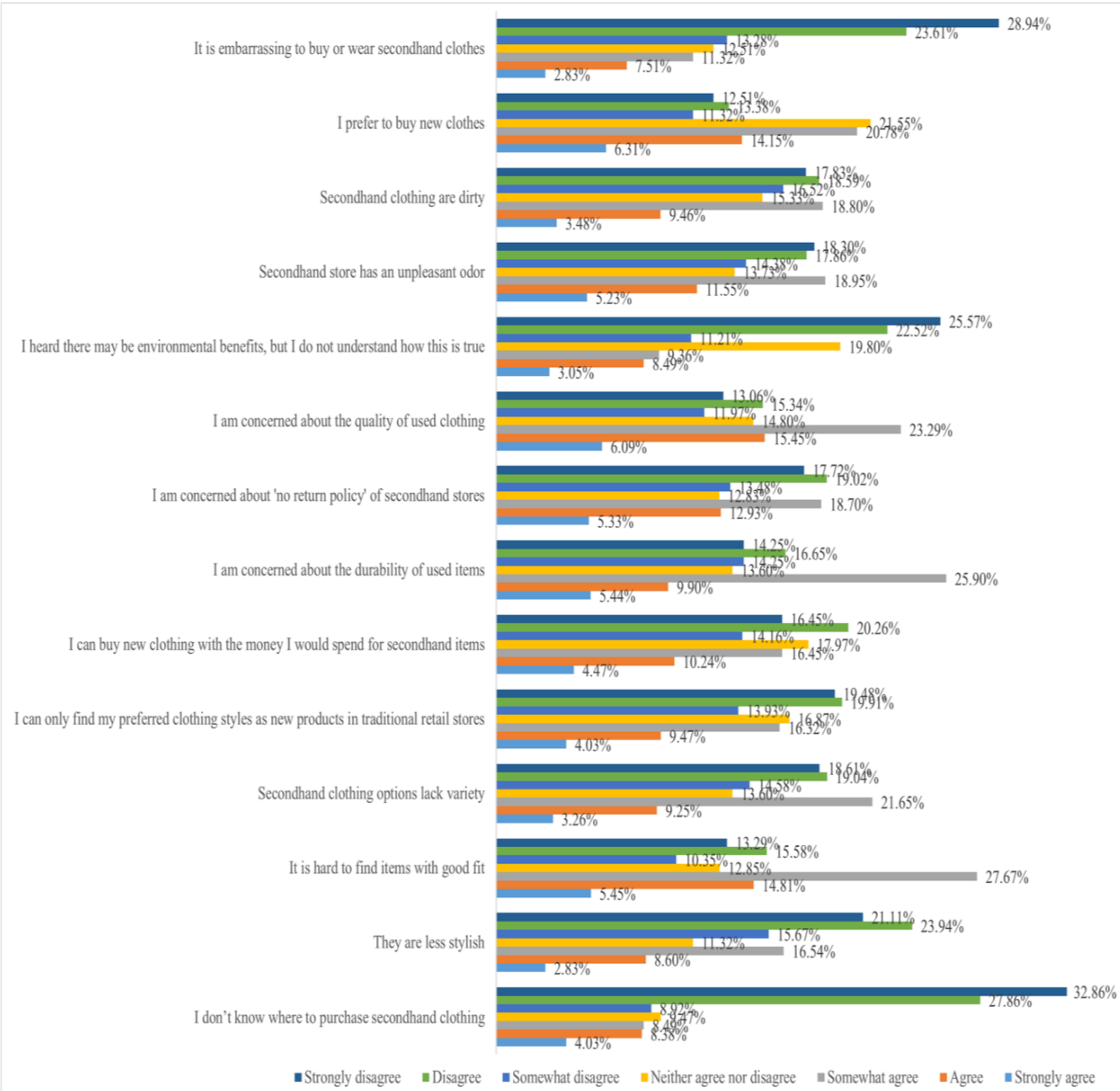


Table 4.12.

Reasons for Not Purchasing Secondhand Clothing Score; Mean (M) and Standard Deviation (SD)

	Mean	**Std. Deviation**
It is hard to find items with good fit	3.92	1.81
I prefer to buy new clothes	3.92	1.76
I am concerned about the quality of used clothing	3.91	1.82
I am concerned about the durability of used items	3.72	1.78
I am concerned about 'no return policy' of secondhand stores	3.56	1.87
Secondhand store has an unpleasant odor	3.53	1.85
I can buy new clothing with the money I would spend for secondhand items	3.46	1.77
Secondhand clothing options lack variety	3.41	1.77
Secondhand clothing are dirty	3.41	1.75
I can only find my preferred clothing styles as new products in traditional retail stores	3.35	1.78
They are less stylish	3.15	1.75
I heard there may be environmental benefits, but I do not understand how this is true	3.03	1.75
It is embarrassing to buy or wear secondhand clothes	2.87	1.76
I don't know where to purchase secondhand clothing	2.74	1.83
Average	**3.43**	**1.79**

Note. 1=strongly disagree, 7=strongly agree; a higher mean value represents a higher barrier to purchase SHC items.

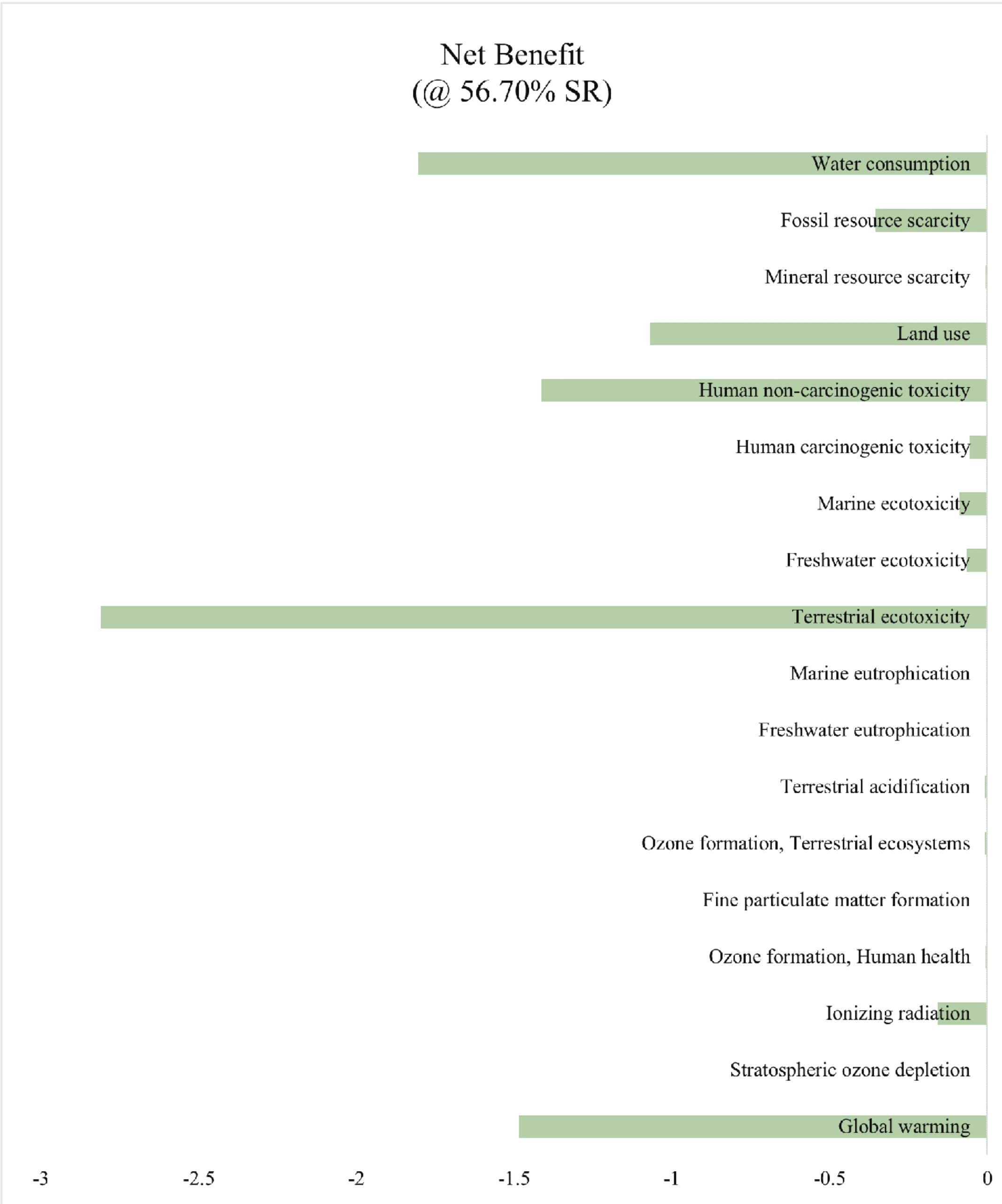
RQ 4: What potential environmental benefit can be realized from avoiding a new clothing item purchase (i.e., 100% cotton men's t-shirt, 120 gm), assuming an average substitution rate (i.e., 56.7%)?

To answer this question, a life cycle assessment of a men's t-shirt (see Table 3.5 for product detail) was conducted. The Ecoinvent v3.4 was used to model background data (i.e., energy, chemical, and auxiliaries production). The foreground data (i.e., cotton cultivation, spinning, knitting, etc.) was collected from published studies. The main piece of information to investigate the benefit of secondhand use, the substitution rate data of men's t-shirt, came from a questionnaire survey (Table 4.2). SimaPro v8.5.2.0 (Pre Consultants, 2020) was used for data analysis.

Figure 4.16 shows the potential environmental benefit of secondhand use of the men's t-shirt across the 18 mid-point categories [see the list of categories in Table 3.16. It can be seen from the figure that the top five environmental savings (i.e., net benefit) come from terrestrial eco-toxicity (2.81 kg 1, 4-DCB), water consumption (1.80 m^3), global warming (1.49 kg CO2 eq.), human non-carcinogenic toxicity (1.41 kg 1, 4-DCB) and land use (1.07 m^2a crop eq.) impact categories. It is noteworthy to mention that the impact from second life is negligible comparing to the first-life impact of the t-shirt. The reason is that the majority of embedded resources come from the life cycle phases of the first life of the t-shirt (i.e., cotton cultivation, yarn, fabric, dyeing, cut-and-sew, transportation, and end-of-life waste management). The only impact that comes from the second life of the t-shirt is from one iteration of use-phase laundering. However, with a different approach in the allocation of the impact across the first and second life of the product, the output would have been different. This issue is explained in the discussion chapter. Figure 4.17 shows a breakdown of the first-life impact of the t-shirt by life cycle stages.

Figure 4.16.

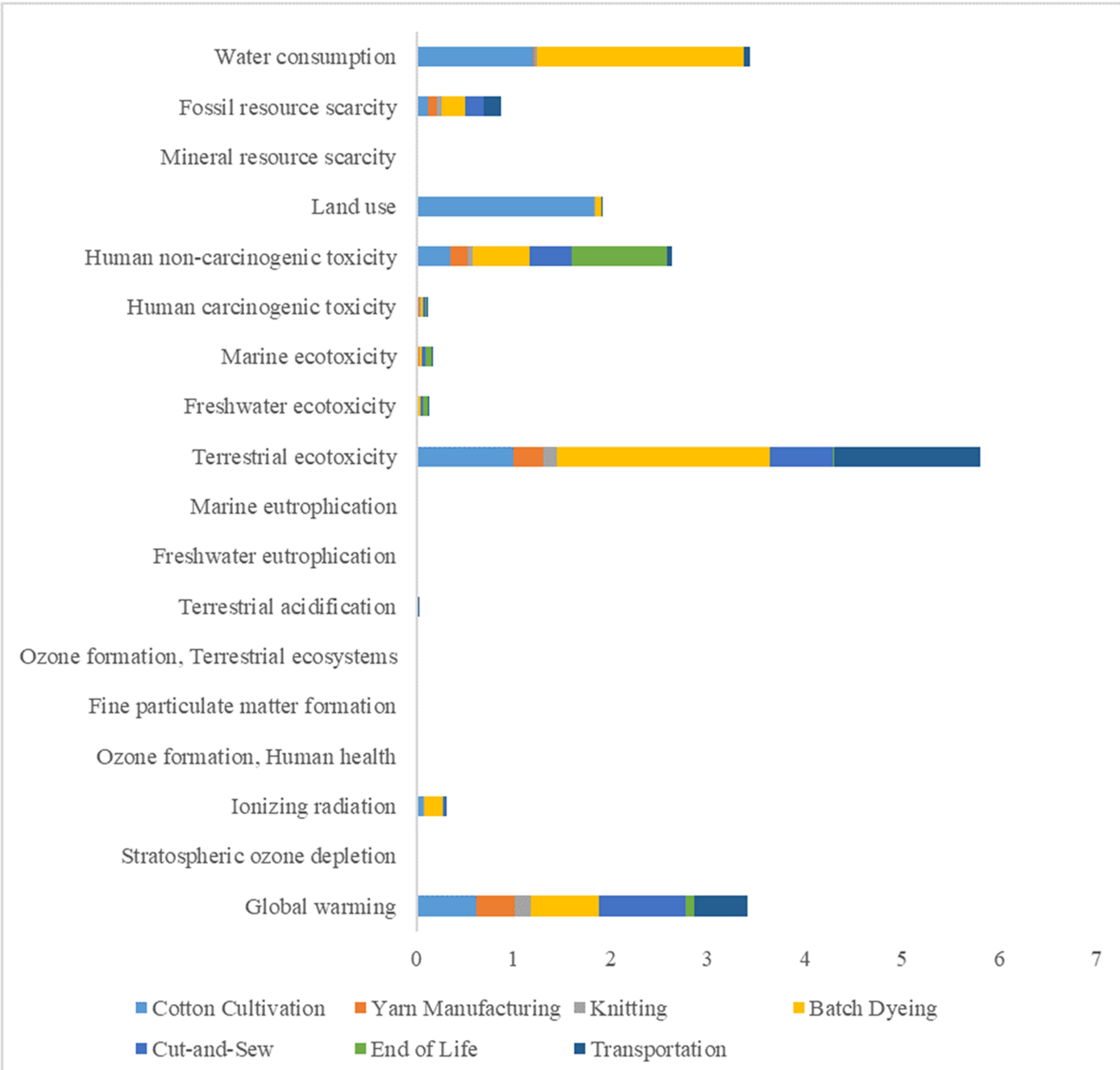
The Potential Environmental Benefit of Secondhand Use of the Men's T-shirt



Note. The t-shirt is single jersey, Size M, 120 gm, batch-dyed; cotton is from India, textile production is in Bangladesh, and use phase is in the USA; the U.S. substitution rate (SR) for the t-shirt is 56.70%; Negative signs represents savings in the respective unit.

Figure 4.17.

Environmental Impact of the First Life of the T-shirt

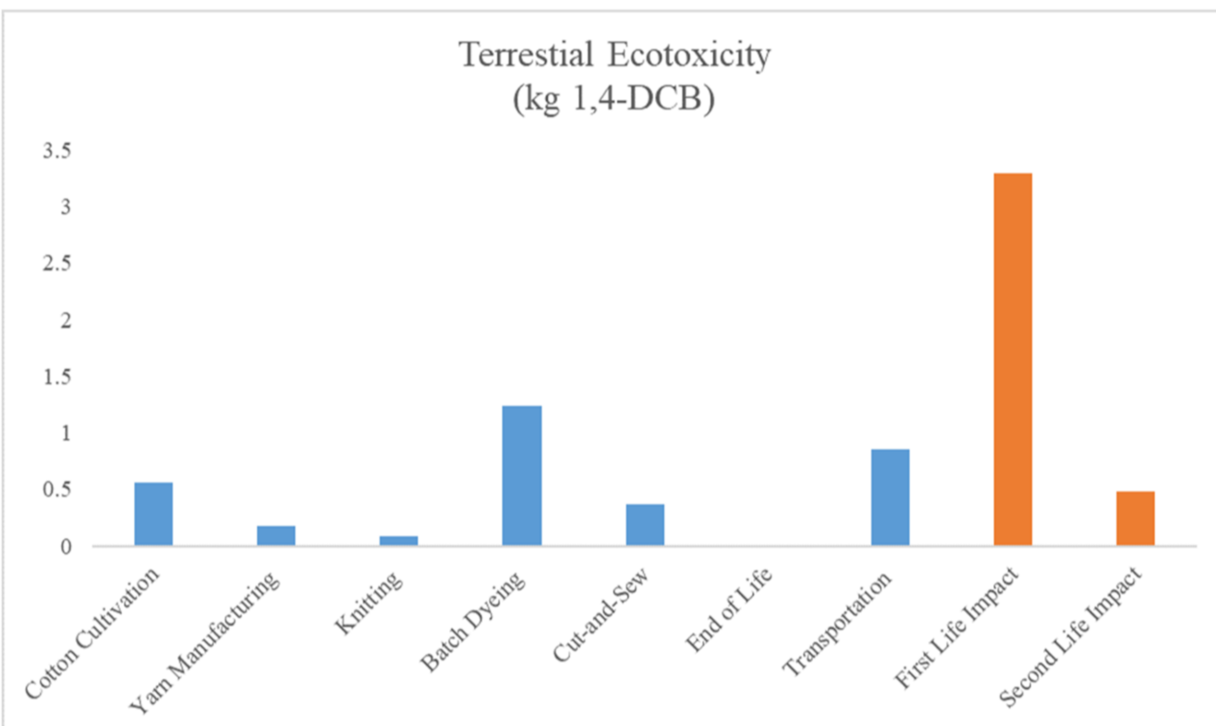


Note. The t-shirt is single jersey, Size M, 120 gm, batch-dyed; cotton cultivation is in India, textile production is in Bangladesh, and end-of-life waste treatment is in the USA; 100% maritime shipping was considered; savings are in respective units.

As stated above, the largest environmental savings came from the terrestrial eco-toxicity impact category. Figure 4.18 shows the impact of various life cycle stages of the t-shirt on the terrestrial eco-toxicity impact category along with total first-life and second-life impact on this impact category. It can be observed from the figure that batch dyeing (1.24 kg 1, 4-DCB), transportation (0.86 kg 1, 4-DCB), cotton cultivation (0.56 kg 1, 4-DCB), cut-and-sew (0.37 kg 1, 4-DCB) and yarn manufacturing (0.18 kg 1, 4-DCB) made the most impact. Overall, the total first-life impact (3.29 kg 1, 4-DCB) is more than six times greater than the second-life impact (0.48 kg 1, 4-DCB) of the t-shirt.

Figure 4.18.

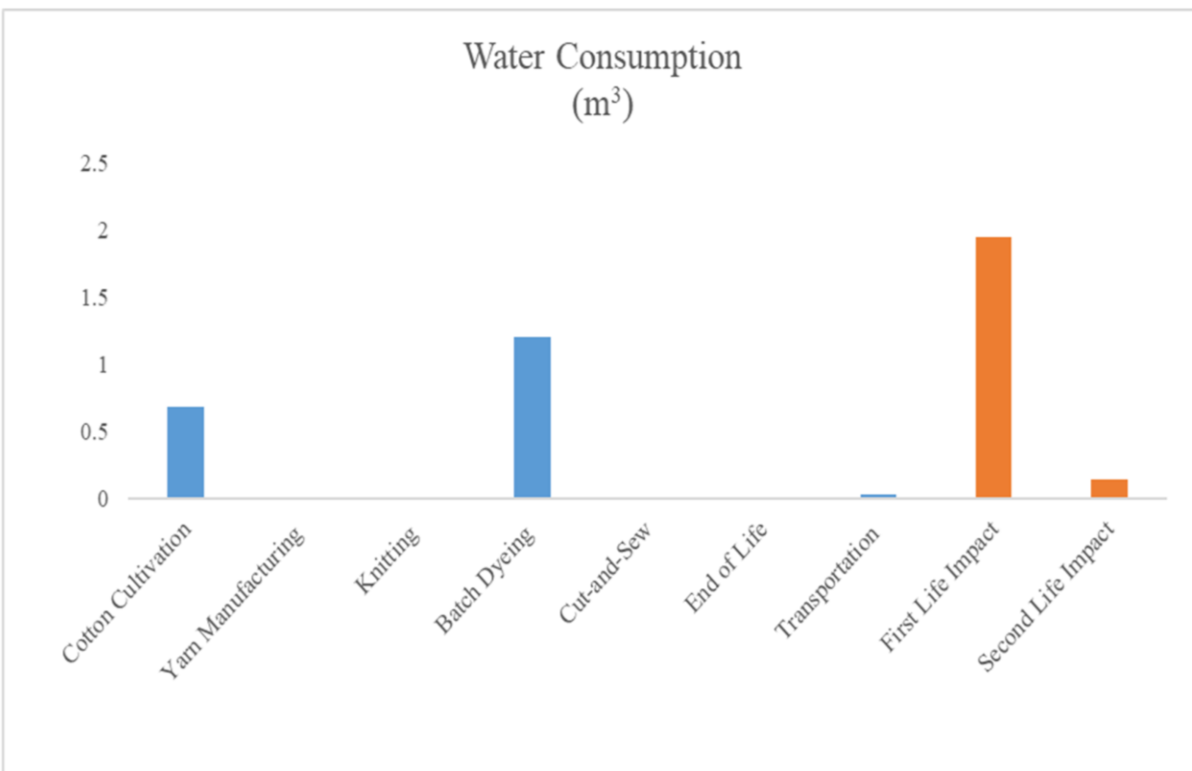
Environmental Savings on Terrestrial Eco-toxicity Impact Category Across Various Life Cycle Stages of the T-shirt; the Substitution Rate is 56.70%.



The second-largest environmental savings comes from water consumption. Figure 4.19 shows the impact of various life cycle stages of the t-shirt on the water consumption impact category along with total first-life and second-life impact. It can be observed from the figure that batch dyeing (1.2 m^3) and cotton cultivation (0.68 m^3) made the most impact. Overall, the total first-life impact (1.94 m^3) is more than thirteen times greater than the second-life impact (0.14 m^3). The majority of this first-life water consumption is connected to a massive amount of water usage in cotton cultivation and textile dyeing activities.

Figure 4.19.

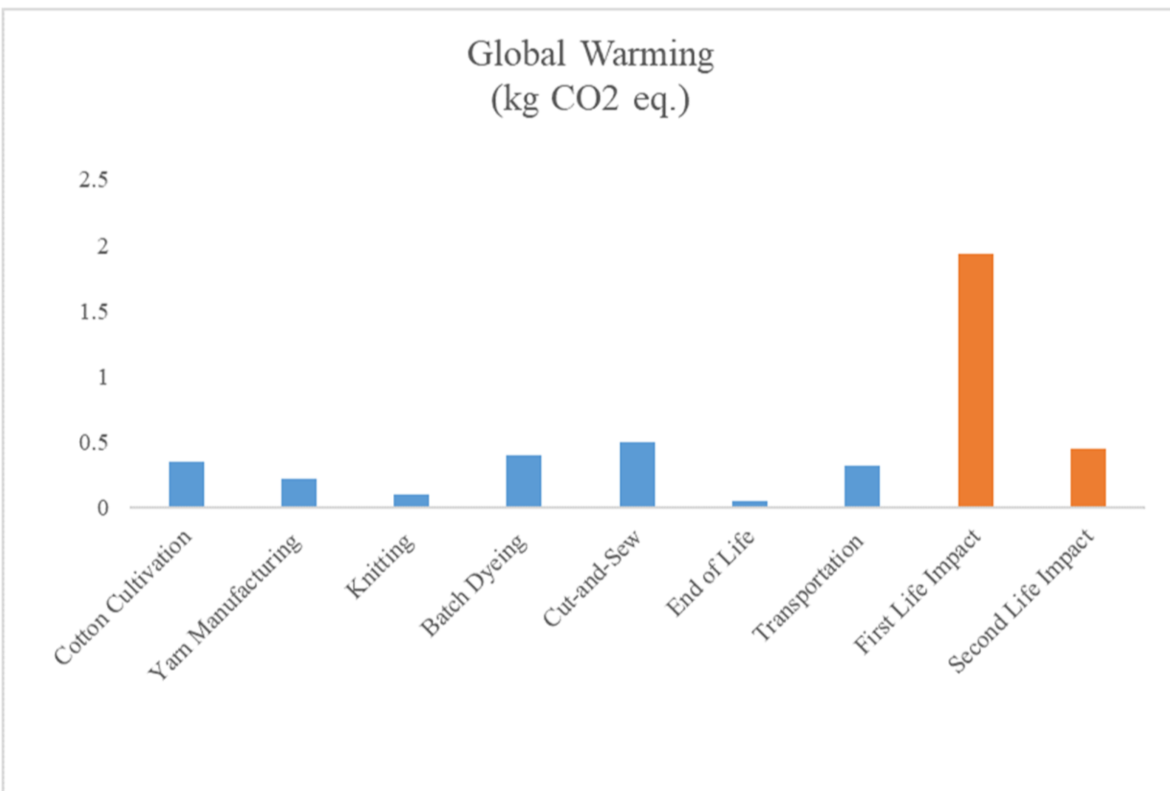
Environmental Savings on Water Consumption Impact Category Across Various Life Cycle Stages of the T-shirt; the Substitution Rate is 56.70%.



The third-largest environmental savings came from global warming. Figure 4.20 shows the impact of various life cycle stages of the t-shirt on the global warming impact category along with total first-life and second-life impact. It can be observed from the figure that cut-and-sew (0.50 kg CO2 eq.), batch dyeing (0.40 kg CO2 eq.), cotton cultivation (0.35 kg CO2 eq.), transportation (0.32 kg CO2 eq.) and yarn manufacturing (0.22 kg CO2 eq.) made the most impact. Overall, total first-life impact (1.94 kg CO2 eq.) is more than four times greater than the second-life impact (0.45 kg CO2 eq.).

Figure 4.20.

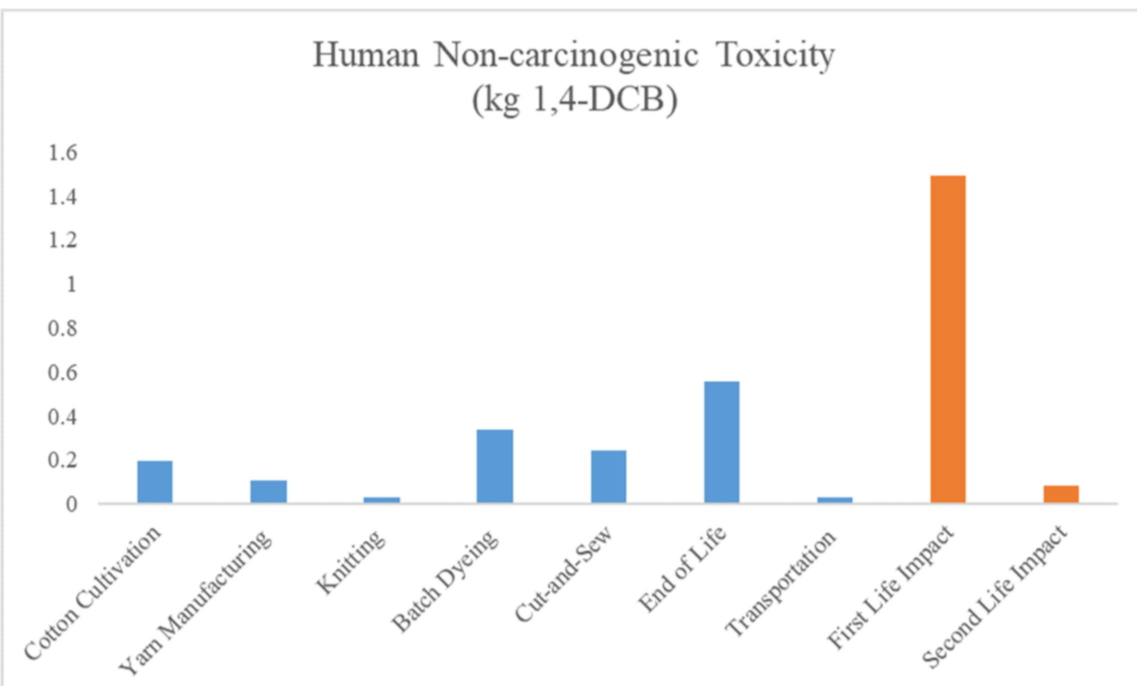
Environmental Savings on the Global Warming Impact Category Across Various Life Cycle Stages of the T-shirt; the Substitution Rate is 56.70%.



The fourth-largest environmental savings came from human non-carcinogenic toxicity. Figure 4.21 shows the impact of various life cycle stages of the t-shirt on the human non-carcinogenic toxicity impact category along with total first-life and second-life impact. It can be observed from the figure that end-of-life textile waste treatment (0.56 kg 1, 4-DCB), batch dyeing (0.33 kg 1, 4-DCB), cut-and-sew (0.25 kg 1, 4-DCB), cotton cultivation (0.19 kg CO2 eq.), and yarn manufacturing (0.11 kg 1, 4-DCB) made the most impact. Overall, the total first-life impact (1.49 kg 1, 4-DCB) is more than eighteen times greater than the second-life impact (0.08 kg 1, 4-DCB).

Figure 4.21.

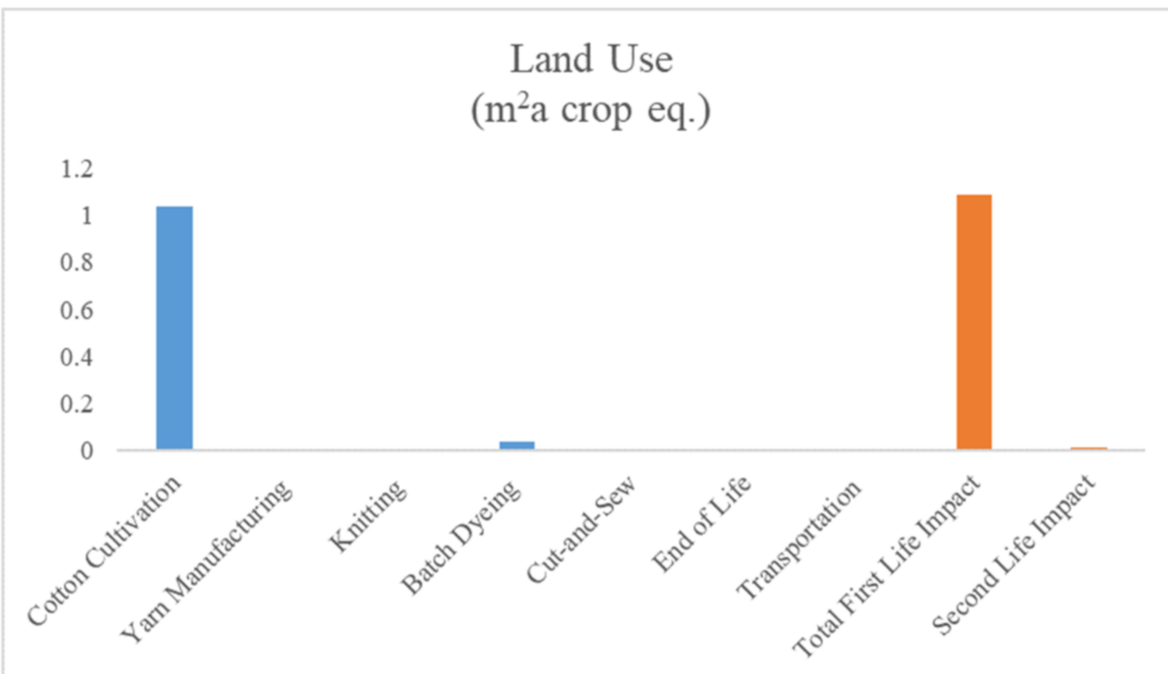
Environmental Savings on Human Non-carcinogenic Toxicity Impact Category Across Various Life Cycle Stages of the T-shirt; the Substitution Rate is 56.70%.



The fifth-largest environmental savings came from the land-use impact category. Figure 4.22 shows the impact of various life cycle stages of the t-shirt on land use along with total first-life and second-life impact. It can be observed from the figure that the most of the land use comes from cotton cultivation (1.04 m^2a crop eq.) and the second-life impact on land use is very negligible (0.015 m^2a crop eq.).

Figure 4.22.

Environmental Savings on Land Use Impact Category Across Various Life Cycle Stages of the T-Shirt; the Substitution Rate is 56.70%.



Scenario Analysis

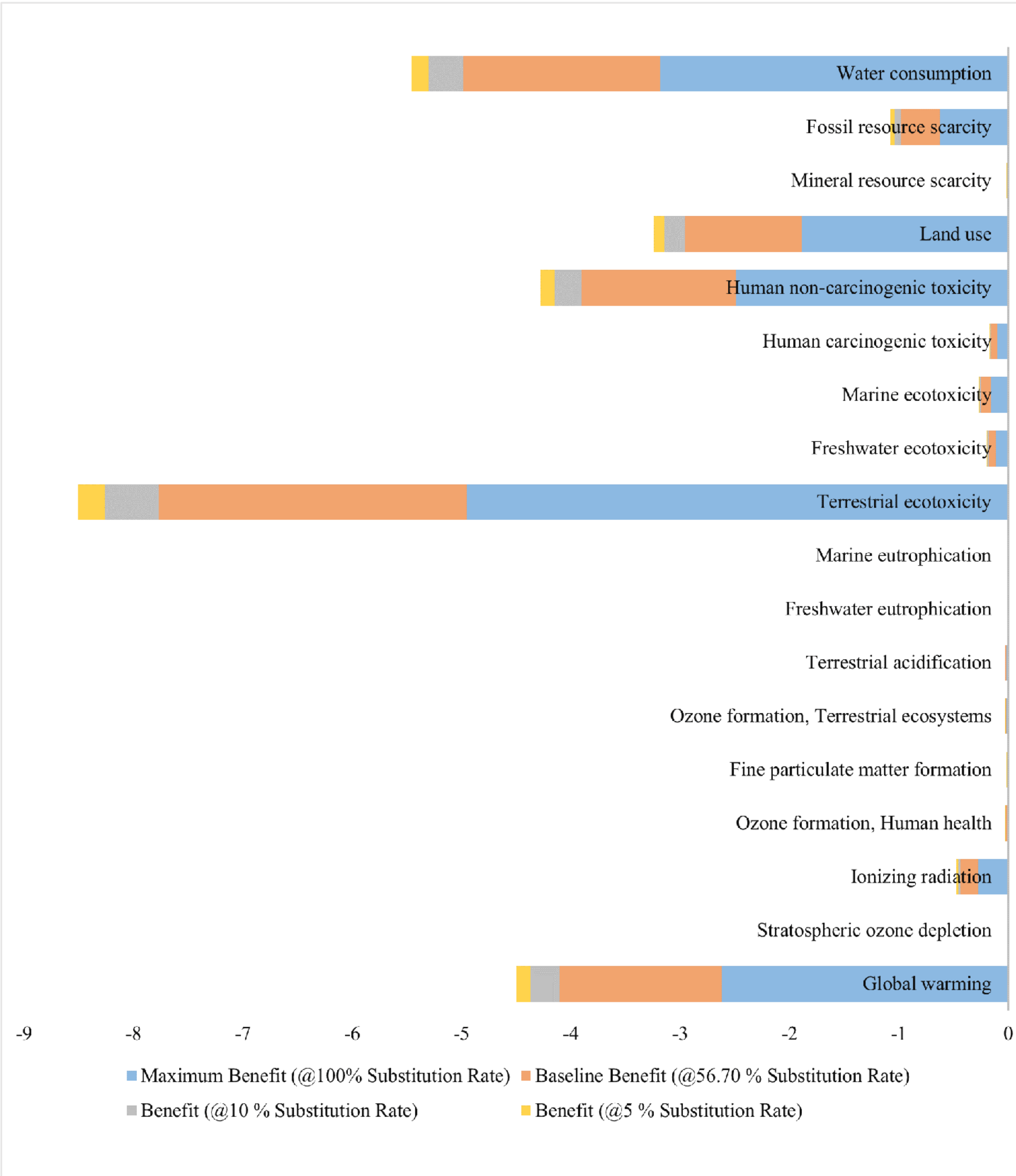
Change in Substitution Rate

Substitution rate refers to the extent to which secondhand purchase replaces similar new purchases. For every secondhand purchase, the substitution rate lies between zero to one, with zero meaning secondhand purchase does not replace a new purchase and one meaning secondhand purchase replaces a similar new purchase. Hence, zero (or 0%) substitution rate has no environmental saving, whereas one (or 100%) substitution rate has maximum environmental saving. In this study, the substitution rate value of men's cotton knit shirt for U.S. participants was found as 56.7%, and the environmental savings were calculated based on the value.

However, it is important to investigate how environmental savings changes with changes in the substitution rate. Therefore, a scenario analysis was conducted by taking a 56.70% substitution rate as a baseline and comparing it with 5%, 10%, and 100% substation rate. The 100% substitution rate was the upper limit whereas 5% substitution was the lower limit (a 0% substitution rate would have been meaningless). The 10% substitution rate value was used to have an additional point of comparison. Figure 4.23 shows the environmental benefit for different substitution rate values. It is worth noting that the environmental benefit can be achieved with as low as a 5% substitution rate for several impact categories, such as global warming, terrestrial eco-toxicity, human non-carcinogenic toxicity, water consumption, and land use.

Figure 4.23.

Scenario Analysis of Substitution Rate; Negative Value Represents Savings.



Change in Transportation Mode

In this study, 100% of maritime shipping was assumed. However, about 92% of the textile products are imported globally via maritime shipping and the rest 8% are transported via air freight (Beton et al., 2014; Rodrigue et al., 2006). Typically, the environmental impact of maritime shipping is less than air freight. Therefore, a scenario analysis was conducted with 92% maritime shipping and 8% air freight. The result was compared with a baseline value of 100% maritime shipping. An estimated 12,919 km was considered for air distance from Dhaka, Bangladesh, to Los Angeles, USA (Table 4.13). The scenario analysis is presented in Figure 4.24.

Table 4.13.

Transportation Mode Scenario

Transportation mode	Distance (Dhaka, BD to Los Angeles, USA)
Sea	17,201 km[1]
Air	12,919 km[2]

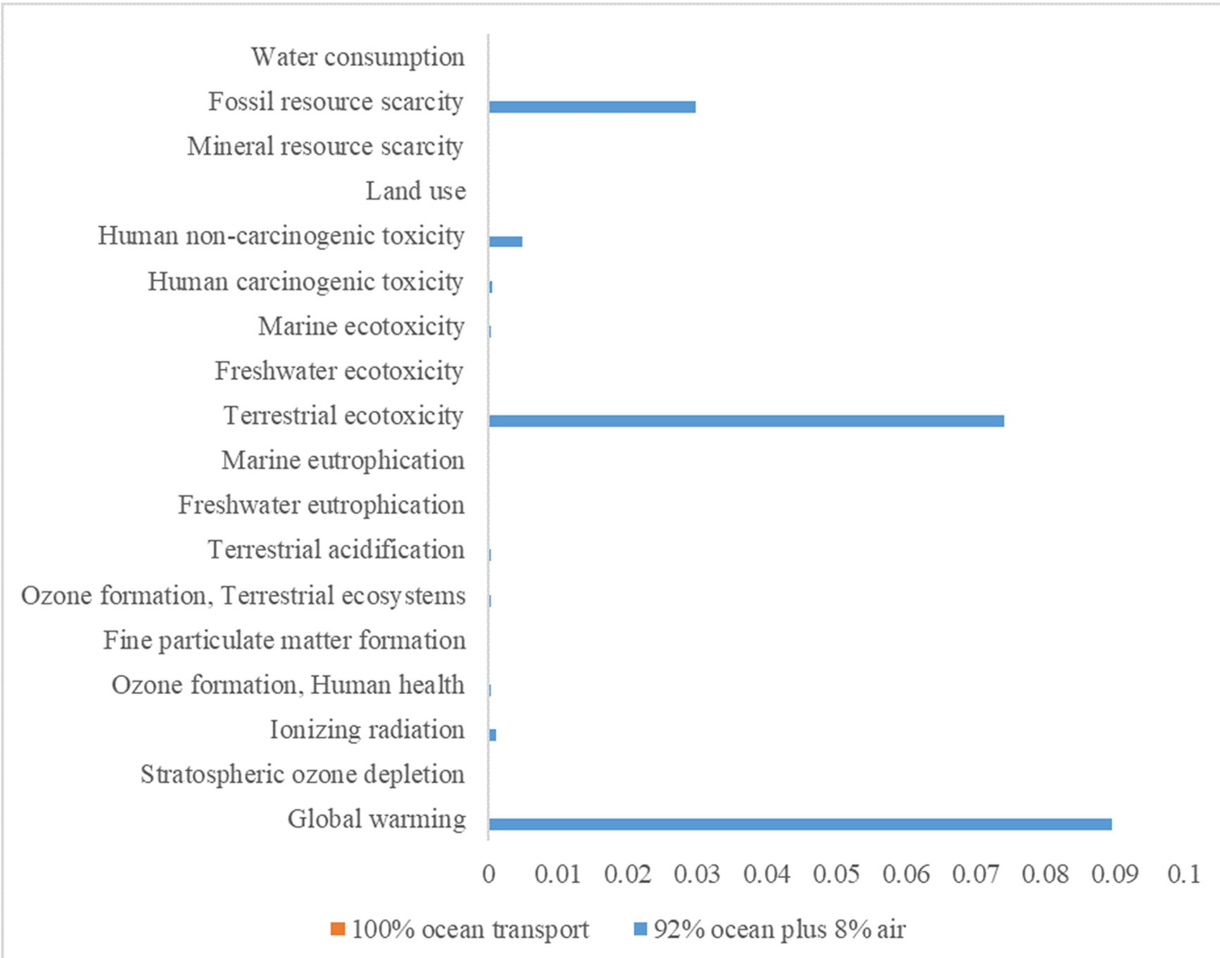
Note. The airport in BD is Hazrat Shahzalal International Airport, the airport in the USA at Los Angeles International airport.

1. Sea distance is estimated using https://sea-distances.org/ (BD-MY=1,390, MY- CN=1,782, CN-LAS=6,116; total= 9,288 nautical miles; 1 nautical mile=1.85 km)

2. Air distance is calculated using http://www.pier2pier.com/

Figure 4.24.

Scenario Analysis of Transportation Modes



It can be observed from Figure 4.24 that with adding only 8% air transport, the impact increases significantly, especially in global warming, terrestrial eco-toxicity, human non-carcinogenic toxicity, and fossil resource scarcity. Comparing with 100% maritime shipping, 92/8 maritime/air transport results in about 2,256 times more global warming, 18,444 times more terrestrial eco-toxicity, 1,517 times more human non-carcinogenic toxicity and 2,471 times more fossil resource scarcity. Therefore, maritime shipping is encouraged for global textile products shipping.

Uncertainty Analysis

Data uncertainty is an integral part of all LCA (Huijbregts, 2001). There is always some degree of uncertainty associated with LCA because of various assumptions used in analysis. Lack of data or data insufficiency should not hinder LCA experiments. Regardless of assumptions and data insufficiency, LCA still provides important environmental insights for decision making. A common statistical method of dealing with uncertainty is Monte Carlo uncertainty analysis (Cotton Incorporated, 2017; Heijungs & Huijbregts, 2004). A Monte Carlo simulation takes a random sample of a wide range of possibilities and calculates the spread of the result to help reduce uncertainty (Golsteijn, 2015). It delivers the "…most practical and accurate method of calculating overall uncertainty in an LCA" (Raynolds et al., 1999, p.5). In this study, the Monte Carlo simulation was run with 1,000 iterations at the 95% confidence level to estimate uncertainties for the five impact categories having the most environmental savings. Overall, the distribution follows a normal distribution, and the uncertainty characterization falls within the range, except human non-carcinogenic toxicity (Appendix D). The uncertainty distribution of human non-carcinogenic toxicity is skewed, suggesting a large degree of uncertainty introduced to it.

Overall, in response to the research question 4, the LCA findings showed that the highest impacts (that can be avoided) occurred in the terrestrial eco-toxicity (2.81 kg 1, 4-DCB), water consumption (1.80 m3), global warming (1.49 kg CO2 eq.), human non-carcinogenic toxicity (1.41 kg 1, 4-DCB) and land use (1.07 m2a crop eq.) impact categories. The secondhand use of the t-shirt resulted in a 43.5% reduction in global warming. Textile manufacturing (i.e., yarn manufacturing, knitting, batch dyeing, and cut-and-sew) was the largest contributor to the major impact categories. With as low as a 5% substitution rate, the environmental benefit could still be achieved in these impact categories. Considering the U.S. import scenario of category 338 and 339 products from Bangladesh, there was a potential savings of 1,268,848,405 kg CO_2 eq. in global warming, 1,539,905,776 m^3 in water consumption, and 912,982,077.3 m2a crop eq. in land use impact category.

Chapter 5 - Discussion and Conclusion

The study examined the substitution rate of SHC consumption for U.S. consumers. Along with substitution rate, the study also investigated how different factors, such as consumer demographics (i.e., age, gender, race, and household income) and purchasing behavior (i.e., motivation and barrier) impacted the substitution rate. Based on the substitution rate, the study further assessed the potential environmental benefit of secondhand consumption of a men's cotton t-shirt. The following research questions guided the study:

RQ 1. How does the substitution rate of U.S. consumers differ from the rates reported for selected European and African countries?

RQ 2. What are the typologies of U.S. SHC consumers in terms of age, gender, race, household income, motivations, barriers, and substitution rate?

RQ 3. Do age, gender, race, household income, motivations, and barriers predict the substitution rate of SHC consumption?

RQ 4. What potential environmental benefit can be realized from avoiding a new clothing item purchase (i.e., 100% cotton men's t-shirt, 120 gm), assuming an average substitution rate (i.e., 56.7%)?

The research employed quantitative approaches, including two components: 1) online questionnaire survey, and 2) Life Cycle Assessment (LCA). The questionnaire survey included 17 items and was developed from published studies. Among the items, the survey included two instruments: 1) 11-item 7-point motivation to SHC Likert scale and 2) 14-item 7-point barrier to SHC Likert scale. The scales were developed from published studies with modifications. The

LCA estimated the environmental benefit of SHC consumption, and it followed ISO guidelines (ISO 14040:2006; ISO 14044:2006).

The online questionnaire survey was created using the Qualtrics tool and distributed via Amazon Turk (Mturk). The survey gathered data regarding substitution rate, motivations, and barriers towards SHC, demographics, and other relevant data (such as rebound effect, the secondhand lifetime of clothing). For LCA analysis, the Ecoinvent v3.4 database was used for the background data (i.e., energy, chemical, and auxiliaries production). The foreground data (i.e., cotton cultivation, spinning, knitting, etc.) was collected from published studies. SimaPro v8.5.2.0 was used to model the LCA.

The population of interest in this study was secondhand clothing shoppers of the United States. Through survey distribution via Mtruk, the study gathered a sample of 920 participants. The participants were U.S. residents and purchased SHC within the past 12 months. Among the participants, the male participants consisted of 47.72%, and the females consisted of 51.74% of the sample, which was very much similar to the gender distribution of the population. The age of the participants was between 18 and 65 or over, with the 18-34 age group included half of the sample. Although the sample represented most of the race/ethnicity groups, the majority of participants were white/Caucasian (71.20%). The annual household income of the participants ranged from $20,000 or less to $200,000 or more. The household income of 498 of the participants was less than $60,000, and that of 404 was more than $60,000.

Various data analysis techniques were used to bring out the most insight from the collected data. The substitution rate was calculated from the collected data using a formula (1). Afterward, a one-sample t-test was used to understand if the substitution rate of U.S. participants was significantly different from the ROW substitution rate value. To explore the typologies of the participants in terms of their age, gender, race, household income, motivation/barrier towards SHC, and substitution rate, a cluster analysis was conducted. To examine whether the age, gender, race, household income, motivation, and barrier towards SHC of the participants predict the substitution rate, Poisson regression analysis was employed. To further analyze the data, one-way ANOVA was used among the substitution rate of various age groups, genders, races/ethnicities, and household income groups. Finally, LCA was used to estimate the potential environmental benefit of secondhand consumption of a men's cotton knit t-shirt considering the substitution rate of U.S. consumers reported in the result section. Various scenario analyses were conducted to estimate the benefit under different assumptions. The data quality and data uncertainty analyses were also conducted for making a better sense of the LCA result.

The first three research questions posed in the study were associated with the substitution rate and the last one was about the environmental impact of SHC consumption. In relation to the first research question, the study found that the average U.S. substitution is 67.81% ± 4.96; it is significantly higher than the average substitution rate of the selected European and African countries, and the rebound effect is low. Other relevant findings were that casual pants, coat/jacket, shorts, knit shirt, and woven shirt are the top five while bra/undershirt, underwear, socks, swimwear, and other category are the bottom five purchased SHC categories. The substitution of new purchases by secondhand purchases varies with participants and item categories. With regard to the second research question, the findings from cluster analysis suggest that male participants have a higher substitution rate. It was also found that older participants were associated with a lower substitution rate. In response to the third research question, the regression model found that age, gender, race, household income, motivation, and barrier were not good predictors of the substitution rate of SHC consumption. Further analysis showed that the substitution rate differed significantly across different gender groups. Also, the finding showed that the cheap price of SHC item was the major motivation participants' purchase SHC items.

Regarding the last question, the LCA findings showed that the highest impacts (that might be avoided) occurred in the terrestrial eco-toxicity (2.81 kg 1, 4-DCB), water consumption (1.80 m^3), global warming (1.49 kg CO2 eq.), human non-carcinogenic toxicity (1.41 kg 1, 4-DCB) and land use (1.07 m^2a crop eq.) impact categories. The secondhand use of the t-shirt revealed a potential reduction of 43.5% in global warming compared to throwing away after the first life. Textile manufacturing (i.e., yarn manufacturing, knitting, batch dyeing, and cut-and-sew) was the largest contributor to the major impact categories. With as low as a 5% substitution rate, the environmental benefit could still be achieved in these impact categories.

The following sections discuss the findings of the study in relation to the current body of knowledge. To keep the discussion focused, the finding of the study is discussed into two sections: the substitution rate of U.S. SHC consumers and the environmental benefit of SHC consumption. As the first three research questions of the study were related to the substitution rate, therefore those are discussed under the substitution rate section. Afterward, the LCA findings are discussed highlighting key assumptions and limitations, uncertainty, and data quality. Following the discussion, the overall implication, limitations, and future recommendations, and conclusions of the study are presented.

Substitution Rate

This study found that the substitution rate varies with individual products and consumers. For instance, many participants indicated that secondhand purchases of casual pants, coat/jacket, and shorts were substituted for new purchases, while many other participants indicated otherwise. Likewise, these three clothing categories were also at the top of the list with participants' being uncertain about their substitution of new purchases. This finding is supported by previous studies. For instance, Stevenson and Gmitrowicz (2012) reported varied substitution rate values for different clothing categories. In their study, children's clothing, ladies' top and trouser/jeans were the three most purchased items in secondhand categories and represented about 32%, 31%, and 24.5% substitution rate respectively. Similarly, Nørup et al. (2019) also reported a variation in substitution rate values by clothing categories. This is reasonable because consumers vary in their motivations for SHC purchase and these motivations change with every purchase. Hence, it is logical to expect a variation of substitution rate by products and consumers. This finding justifies more studies in the future to create substitution rate-related data inventory for different clothing items in various geographical locations. A country-specific data inventory will be helpful for future LCA modeling of clothing reuse.

Another interesting finding of this study was that the secondhand clothing items that consumers purchase less frequently have relatively higher substitution rate. For instance, the participants of this study indicated that bra/undershirt, underwear, socks, swimwear, and other categories (i.e., sweater, sweatshirt, etc.) were the bottom five SHC categories purchased (Figure 4.1). Among these categories, bra/undershirt (SR=79.41%), swimwear (SR=76.72%), and socks (SR=71.82%) made to the list of top five in terms of the substitution rate value. The other two categories in the top five are children's clothing (SR=80.45%) and dress pants (SR=78.36%), with children's clothing got the highest SR value. This finding is partially supported by Nørup et al. (2019). In her study, children's clothing had the highest SR (57%), and socks were fourth (SR=48%) within thirteen categories she investigated. Underpants (SR=39%) and bras

(SR=38%) were tenth and eleventh with swimwear had the lowest substitution rate value. Across the studies, children's clothing is reported to have the highest substitution rate value (Nørup et al., 2019; Stevenson & Gmitrowicz, 2012), which is supported by the finding of this study as well. One of the reasons children's clothing has the highest substitution rate value might be that children grow fast, and their clothing remains in good quality for secondhand use. Therefore, as discussed in Chapter 2, parents might be intentionally purchasing secondhand items because they are relatively cheap and offer good quality, resulting in a higher substitution rate. On the other hand, as bra/undershirt, underwear, socks, and swimsuit are intimate products, consumers do not presumably purchase them in poor quality or highly-used state. Therefore, It is reasonable to assume that SHC stores accept good quality (perhaps unused or gently used) items from donor and seller. As pointed out by Ha-Brookshire and Hodges (2009), consumers feel guilty about the amount of clothing they own and limited use of them, hence they get rid of them by donating. They also hesitate to donate intimate items (Ha-Brookshire & Hodges, 2009), and therefore if they donate, it would supposedly be a good quality item. From this perspective, it is logical to have a higher substitution rate value for these items because consumers might be making an intentional purchase due to the good quality but cheap price of these items.

Looking into the most purchased SHC items, the top five in this study were casual pants, coat/jacket, shorts, knit shirt, and woven shirt (Figure 4.1). Casual pant was also reported to be the highest secondhand purchase category in Nørup et al. (2019) study. It should be noted that Nørup et al. (2019) grouped all casual pants (i.e., jeans, shorts, and trousers) into trouser category. As mentioned above, Stevenson and Gmitrowicz (2012) also reported trouser/jeans as one of the top secondhand purchase categories. Casual pants/Trousers are also the most purchased SHC category for Asian consumers. For instance, Napompech and Kuawiriyapan

(2011) reported trouser as the most purchased category for Thai women. Among 237 consumers they surveyed, 99 consumers (22.9%) reported having purchased trousers. One of the reasons for casual pants' being the top secondhand purchase category might be their durability. Casual pants (i.e., jeans, shorts) are relatively more durable than other clothing items. Another reason might be their quality that unlike knit items (i.e., t-shirts, collared knit shirt, etc.), casual pants (i.e., jeans, shorts) usually have twill fabric structure and do not typically degrade quality (i.e., dimensional stability). On the other hand, the reason for consumers' not purchasing some items, such as bra, underwear, socks, swimwear, and nightwear might be that these items are intimate, and consumers might have hygiene and preference issues with them.

There is also a wide range of variation in country-wise substitution rate data. For instance, the average substitution rate for U.S. consumers found in this study is 67.81 ± 4.96 (i.e., lower bound is 62.85%, and the upper bound is 72.77%). This finding suggests that, on average, every 100 SHC purchase substitutes between about 63 and 73 new purchases. This average value of 67.81 ± 4.96% for U.S. consumers is closer to 63 ± 6% SR value of Angola (Nørup et al., 2019) and 60% SR value of Sweden (Farrant et al., 2010). Among the studies, only Estonia has a higher substitution rate value (75%) than the United States (Farrant et al., 2010). Britain (28.5%), Italy (47.25%), Malawi (35 ± 1) and Mozambique (37 ± 5%) have lower SR value than the United States (Castellani et al., 2015; Nørup et al., 2019; Stevenson & Gmitrowiczs, 2012). This difference in substitution rate value among different countries is statistically significant (Table 4.3). Understanding the factors contributing to this variation is a challenging task because there might be a host of many factors influencing the substitution rate of the consumers. These factors have not been thoroughly explored yet. However, this study made an initial attempt to investigate the impact of different factors on the substitution rate of the consumers.

Based on the cluster analysis, this study found distinct SHC consumer groups with specific characteristics. The findings from cluster analysis also showed a pattern of how different factors influenced the substitution rate value. For instance, the findings indicated that the substitution rate went higher with predominantly male participants within a cluster (Table 4.5), which is supported by Stevenson and Gmitrowicz (2012). In their study, they found that females exhibited more 'spur of the moment' secondhand shopping than males. Therefore, as stated in Chapter 2 (Table 2.4), it might be the case that females shop more impulsively, which leads to additional purchase instead of an intentional purchase, resulting in a lower substitution rate. Also, the findings from cluster analysis indicated that the substitution rate went lower with relatively older participant groups (Table 4.5). This finding is also supported by Stevenson and Gmitrowicz (2012). One of the possible reasons for older consumers' lower substitution rates might be that they are hedonistically motivated (Guiot & Roux, 2010). When consumers are hedonistically motivated, they focus more on shopping enjoyment rather than buying products, leading to a lower substitution rate.

One of the implications of this finding is that it characterized the association of consumer's age and gender with substitution rate. This characterization provides strong incentives to investigate more of the impulsive buying behavior of SHC products. The reason is that SHC-based business models are touted as environmentally-beneficial on the ground of resource utilization and waste minimization. Impulsive SHC buying behavior will lead to a lower substitution of new clothing purchases and compromise the agenda of resource utilization and waste minimization. Also, SHC-based brands and retailers should offer additional incentives (such as economic) to older consumers so that their substitution rate goes higher. Thus, their SHC consumption will potentially lead to increased environmental benefits. However, cluster analysis is not a predictive analysis, rather it is an exploratory analysis based on the distance of objects under study (i.e., mean or medoid). Therefore, in order to fully predict the influence of different variables on the substitution rate, a predictive analysis (such as regression analysis) is necessary. This study conducted a Poisson regression analysis to understand the predictability of different variables on the substitution rate.

Based on Poisson regression analysis, it was found in this study that age, gender, race, household income, motivation, and barrier were not good predictors of the substitution rate of U.S. consumers. There might be other variables that would be able to better predict substitution rate other than the variables accounted for in this study (for instance, price of the product, attitude towards purchasing secondhand, environmental concern, etc.). However, in this study, a statistically significant difference in substitution rate value was found between genders, with the male showing higher average substitution rate value (73%) than that of females (67%) (see Table 4.8). Stevenson and Gmitrowicz (2012) also reported a slight variation of substitution rate by genders (i.e., male=28%, female=27%), but it was not statistically significant in their study. This variation can be linked to the shopping behavior of males and females. For instance, in their study, Stevenson and Gmitrowicz (2012) found that females exhibited more ‘spur of the moment’ secondhand shopping than males, which suggests more impulsive buying. When an impulsive secondhand purchase occurs, it does not necessarily lead to the substitution of a new purchase.

Although not statistically significant, a variation of substitution rate in terms of age, race, and household income was also found in this study. It was found that the 25-34 age group has the highest average SR value (72%), followed by the 35-44 age group (SR=70%). The lowest substitution rate was found for 65 or more age group (SR=61%). This finding is supported by

Stevenson and Gmitrowicz's (2012) study, where they reported that 25-34 and 35-44 age groups being the top two in terms of substitution rate value. They also found 65 or over having the lowest substitution rate value. The explanation of this phenomenon is evident in Guiot and Roux's (2010) study. They reported that older consumers were more hedonistically motivated and younger consumers more utilitarian and economically motivated when purchasing secondhand. In the case of utilitarian and economically motivated secondhand purchases, consumers seek to replace new purchases with a cheaper alternative, leading to higher substitution rate value. Whereas, in the case of hedonistic purchase, consumers enjoy the shopping experience more than purchasing products, leading to lower substitution rate value.

In terms of race/ethnicity, the Black/African American shows the highest substitution rate value (79%) followed by Asian/American (71%), with American Indian/Alaska Native showing the lowest SR value (65%). Both White/Caucasian and Hispanic/Latino represent 69% substitution rate value (Table 4.9). There is no previous study looking into racial association with substitution rate value. However, cluster analysis of this study provides good support for a group of Black/African consumers being critically motivated, as discussed earlier. However, the average substitution rate value for the Black/African participants suggests financial or utilitarian motivation. Therefore, further study is required to decide on the racial association on substitution rate value.

In terms of annual household income, participants with $120,000 and over got the highest substitution rate (74%), closely followed by the $90,000-$100,000 income group (SR=73%). The lowest substitution rate was demonstrated by the $30,000-$60,000 income group (SR=67%). In their study, Stevenson and Gmitrowicz (2012) also reported that the substitution rate value increases with income. The same trend of lower substitution rate for lower-income and higher substitution rate value for higher-income was also reported in Nørup et al. (2019) study. This suggests critical motivation of the higher income group, such as ‘distance from the system,’ and ‘ethics and ecology’ (Guiot and Roux, 2010). Higher-income consumers might be more concerned about environmental pollution and waste generation from fast fashion, and hence, prefer to shop secondhand to exercise their political consumerism. Higher-income might be influenced by other mediating variables, such as education and social status. Therefore, further studies should investigate the influence of income on the substitution rate.

Rebound Effect

Like previous studies (Cervellon et al., 2012; Laitala & Klepp, 2018; Roux & Guiot, 2008; Williams & Paddock, 2003), this study also found financial motivation being the main motivation of purchasing SHC products (Table 4.11). Money saved from SHC purchasing might lead consumers to buy additional clothing (new or secondhand) or spend it elsewhere in the economy, a phenomenon called rebound effect (Hertwich, 2005). Therefore, it is necessary to investigate if consumers buy additional clothing items with the saved money. In order to get the environmental benefit, SHC purchases must substitute for some new purchases. Schmidt et al. (2016) reported that with as low as 33% substitution rate, clothing reuse provides more environmental benefits than recycling and incineration. As presented in Figure 4.23, there would still be a potential environmental saving from secondhand consumption with as low as 5% substitution rate. Because, the world is producing between 80-100 billion pieces of clothing items each year (Batelier, 2018; Siegle, 2017). With a 5% substitution rate from secondhand consumption, there would be a reduction in demand of 4-5 billion new items. However, it is fairly challenging to investigate whether SHC purchase substitutes any real production or not. The SR value provides a theoretical foundation to estimate the potential benefit of reuse.

The rebound effect, in the context of SHC purchase and SR, is what consumers do with their saved money from the secondhand purchase. If they do not use the saved money in additional purchases, then SR would be stable. If they use the saved money to buy new clothing products, then SR would be highly compromised. If they use the saved money to buy used clothing, the SR would still be stable. Because consumers will substitute more new clothing purchases in doing so. One challenging issue is to investigate whether they spend their saved money somewhere else in the economy (such as buying jewelry instead of clothing). Then, it would be highly complicated to account for the estimation of the substitution rate. Due to the complexity of calculating the rebound effect, an in-depth investigation of the rebound effect was out of the scope of the study. However, this study estimated the potential size of the rebound effect as 4.87% (Appendix C) which was pretty low. Also, while it is understandable that the issue of rebound effect impacts the SR, it was not adjusted in the LCA modeling because it was considered low. Further study should investigate the size and nature of the rebound effect interacting with the substitution rate of the secondhand consumption.

Environmental Benefit of SHC Consumption

In order to investigate the potential environmental benefit of SHC consumption, an LCA of a 100% cotton men's knit t-shirt (see Table 3.5 for product detail) was conducted. The Ecoinvent v3.4 was used to model background data (i.e., energy, chemical, and auxiliaries production). The foreground data (i.e., cotton cultivation, spinning, knitting, etc.) was collected from published studies. The substitution rate data of men's t-shirt was calculated from a questionnaire survey (Table 4.2). SimaPro v8.5.2.0 (Pre Consultants, 2020) was used for LCA modeling. The first three steps of LCA (i.e., goal and scope definition, life cycle inventory analysis, and impact assessment) are discussed in chapter 3 and chapter 4. This section provides the LCA interpretation of the product. According to ISO 14040:44, the LCA interpretation needs to provide a discussion of key findings, data quality, uncertainty, limitations, recommendations, and conclusion. The following sections provide a discussion of those aspects.

Summary of LCA Findings

The LCA of the men's cotton t-shirt provides several key findings. All the estimation was based on a 56.7% substitution rate for the t-shirt and based on the assumption that the secondhand consumption leads to a decreased production of new items proportionate to the substitution rate.

- Terrestrial eco-toxicity, water consumption, global warming, human non-carcinogenic toxicity, and land use were the top-five impact categories. Textile dyeing was one of the biggest contributors to these impact categories.
- The secondhand use of the t-shirt results in a reduction of 1.49 kg CO2 eq., a 43.5% reduction of global warming. The highest impacts (that can be avoided) occurs in the terrestrial eco-toxicity impact category.
- At 56.7% substitution rate, the secondhand use of the t-shirt results in a potential saving of an estimated 1.49 kg CO2 eq. GHG emission, 1.8 m^3 water consumption, and 1.06 m^2a eq. land use.
- Textile manufacturing (i.e., yarn manufacturing, knitting, batch dyeing, and cut-and-sew) was the largest contributor to the major impact categories. Cotton cultivation had the

biggest impact on water consumption and land use. The impacts from yarn manufacturing, knitting, and cut-and-sew were primarily from electricity consumption. The impact from batch dyeing comes from chemical use, water, and electricity use, leading to higher terrestrial ecotoxicity.

- The environmental impact from the second life of the t-shirt is negligible in comparison with the first life of the product. This is because of the specific allocation method employed in the analysis. Future studies should include different allocation methods.
- With as low as a 5% substitution rate, there is potential environmental benefit across the impact categories included. Further study should investigate the size of this potential benefit in the context of global secondhand consumption.

The clothing supply chain is globally scattered and complex (Bostrom & Micheletti 2016). Therefore, solving only local issues (such as a reduction in water and harmful chemicals use) does not necessarily tackle systemic issues. Rather, it increases the possibility of burden-shifting, which means reducing a burden in one location of a product system shifts the burden elsewhere in the system, thereby hindering the overall environmental goal. For instance, tackling clothing waste management issues in the United States might encourage consumers to consume more, and thereby potentially increasing manufacturing-related pollution elsewhere (such as Bangladesh). Therefore, it is important to look into the clothing supply chain from system perspectives. The LCA investigates the environmental burden of a product from a system perspective and identifies hotspots in the system. This study investigated a 100% men's cotton knit t-shirt. The cotton was cultivated in India, textile production (i.e., yarn, fabric, dyeing, and cut-and-sew) in Bangladesh and consumption in the United States. The finding shows that the secondhand use of the t-shirt potentially reduces 1.49 kg CO_2 eq. in the global warming category, considering 56.7% substitution rate for t-shirts in the United States. The result also reveals that the textile production process (yarn, fabric, dyeing, cut-and-sew) is the main hotspot of environmental impact. Textile dyeing contributes substantially to most of the impact indicators. According to Quantis (2018), the impact of the global clothing industry on climate change (i.e., global warming) increased 35% between 2005 and 2016 and projected to increase 49% between 2016 and 2030 if business-as-usual continues. They also reported that the global clothing industry needs to cut 80% of its emissions by 2050 to align with below 2 degree Celsius temperature target as set by the Intergovernmental Panel on Climate Change (2018). In that context, renewable energy-based textile production (i.e., yarn, fabric, cut-and-sew, etc.) and post-consumer waste minimization (through reusing and recycling) are the two fundamental ways to achieve the climate target. Therefore, reuse seems to be relatively easy-fix compared to the shifting to a renewable-based textile manufacturing. Hence, there should be proper infrastructure (such as door to door collection) of bringing maximum used clothing to the relevant consumer segments. Also, consumers should be educated and encouraged more to use SHC products.

The top impact categories found in this study were terrestrial eco-toxicity, water consumption, global warming, human non-carcinogenic toxicity, and land use. The main contributors to these impacts can be tracked down to heavy metals from cotton agricultural, textile dyeing, and EoL waste management, water, and energy (i.e., electricity, heat) use in textile processing, and agricultural land use. The toxicity impact can be reduced by switching to organic cotton and reducing landfill waste. Similarly, the textile suppliers should use non-toxic dyes and chemicals. However, organic cotton makes up only 0.5% of global cotton farming (Textile Exchange, 2018) and 73% of the world's clothing waste is either landfilled or incinerated (Ellen MacArthur Foundation, 2017). Likewise, the textile wet process consumes about 8,000 different types of dyes and auxiliary chemicals, most of which are potentially carcinogenic (Kant, 2011). Therefore, there are a lot of opportunities to better these aspects of the clothing supply chain and future studies should investigate ways to improve the processes. Regarding water issues, it is very well known that cotton is a thirsty crop and textile processing consumes a huge amount of water (World Wildlife Fund, n.d.). Therefore, there should be alternatives for less water-intensive cotton cultivation. Also, the water footprint of the current textile wet process should be improved. As per energy consumption, Quantis (2018) reported that circular textiles (such as recycling or modular design) alone would not be able to achieve the required climate target, as stated earlier. To achieve the climate goal, textile suppliers must need to adopt renewable energy-based production. Therefore, consumers should be aware of this and put higher pressure on the brands to set transparent environmental targets. Also, policymakers should incentivize brands and retailers to shift towards a renewable-energy based production along with promoting reuse and recycle.

Previously, Schmidt et al. (2016) reported that with as low as 33% substitution rate, clothing reuse provides more environmental benefits than recycling and incineration. The finding of this study lends strong support to the existing knowledge that reuses that with as low as 5% SR value, reuse still leads to potential environmental savings. However, it was out of the scope of this study to identify the size of the benefit of reuse over recycling, landfill, and incineration. Nevertheless, clothing reuse or extended use should be highly encouraged because there are two-pronged benefits of reusing: it reduces the waste-related environmental burden and cuts virgin material consumption. Reducing waste-related environmental burden entails landfill space, harmful gases, leachates, and other toxic substances. On the other hand, cutting on virgin material consumption reduces all the associated raw materials, chemicals, energy, and emission footprint.

Key Assumptions and Limitations

It is important to take caution during interpreting LCA findings. Many assumptions were made in the LCA study. These assumptions need to be carefully evaluated before interpreting the findings. The key assumptions are discussed below:

1. It is challenging to track the exact manufacturer and their raw material suppliers from the label of secondhand clothing. Therefore, it was assumed that the raw material (i.e., cotton) was imported from India. However, Bangladesh also imports a major share of cotton from Uzbekistan (16% of total imports), according to USDA Foreign Agricultural Service (2018). This study did not model the cotton cultivation and transportation scenario for Uzbekistan, nor for the other suppliers.
2. Specific inventory data for textile production in Bangladesh is limited. Therefore, Ecoinvent global average data for various production stages and their background data was used, assuming that the data represents the production scenario of Bangladesh.
3. The substitution rate of SHC was calculated from the responses collected from the online questionnaire survey of 920 participants distributed on Mturk. There might be a variation of substitution rate for a different sample size. Also, the rebound effect and product durability may highly influence the substitution rate, which needs further investigation.
4. The actual transportation scenario is also challenging to estimate without tracking the actual product. In this study, 100% maritime shipping with a specific shipping route was assumed. In the real scenario, that might not be the case. To reduce uncertainty, a global

shipping scenario was analyzed. However, caution should be taken while generalizing the shipping-related impact.

5. This study did not credit the environmental saving from firsthand consumer use phase as a result of secondhand clothing consumption. Also, the lifetime of firsthand and secondhand were considered the same and the use phase was also assumed to be the same. However, a difference in the first life and second life of the item will change the substitution rate. In addition, the study modeled the impact of a single laundering as the main impact of secondhand use. This was primarily on the assumption that consumers typically wash secondhand products before the first use.

Data Quality Assessment

Most of the primary data used in this study were collected from recent studies. The oldest two studies used to create the foreground inventory were Jungmichel (2010) and Yamaguchi (2011), which is still within ten years duration. All the background data were modeled using Ecoinvent v3.4, representing the most up-to-date data in the field. Therefore, the temporal representativeness of the data is considered high.

The cotton cultivation scenario was modeled from Cotton Incorporated (2017), and it represents the average agricultural conditions of various geographical parts of India. The yarn production and knitting scenario were modeled using proxy data created from several studies, hence not fully representative of Bangladesh, where the production took place. The batch dyeing and finishing data were modeled using proxy data from India. As Bangladesh is a neighboring country of India, there would be a very little variation of this data; hence, this might be considered representative. The cut-and-sew data is representative of Bangladesh. Therefore, the geographical representativeness of the data is considered high. All the primary and secondary data represents the typical technologies under study. Therefore, the technological representativeness of the data is considered to be very high.

In this study, a pedigree method proposed by Weidema (1998) was used to assess the inventory data of each life cycle stage of the t-shirt. For each life cycle stage, the data quality was scored on a scale from 1-5, as shown in Table 5.2. The final scoring of data quality is shown in Table 5.2.

Table 5.1.

Pedigree Matrix of LCA Data Quality Assessment

Indicator Score	**1**	**2**	**3**	**4**	**5**
Time	Less than 3 years of difference to year of study	Less than 6 years of difference	Less than 10 years of difference	Less than 15 years of difference	Age of data unknown or more 15 years of difference
Geography	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown area or area with very different production condition
Technology	Data from enterprises, processes, and materials under study	Data from processes, and materials under study but from different enterprises	Data from processes, and materials under study but from different technologies	Data on related processes or materials but from same technology	Unknown technology or data on related processes or materials but from different technology
Reliability	Verified data based on measurements	Verified data partly based on assumptions or non-verified data	Non-verified data partly based on assumptions	Qualified estimate (e.g. by industrial expert)	Non-qualified estimate or unknown origin

		based on measurements			
Completeness	Representative data from a sufficient sample of sites over an adequate period to even out normal fluctuations	Representative data from a smaller number of sites but for an adequate period	Representative data from an adequate number of sites but from shorter periods	Representative data but from a smaller number of sites and shorter periods or incomplete data form an adequate number of sites and periods	Representativeness unknown or incomplete data from a smaller number of sites and/or from shorter periods

Note. Derived from Weidema (1998).

Table 5.2.

Scoring of Data Quality

Process	Time	Geography	Technology	Reliability	Completeness
Cotton cultivation	2-3	2	2	2-3	3-4
Yarn manufacturing	2-3	4	2	3	3-4
Knitting	2-3	4	2	3	3-4
Dyeing	3	3	2	3	4-5
Transportation	3	2	2	2-3	2-3
End of life treatment	2	1	2	1	1-2
Clothing care	2-3	1	2	1-2	2-3

As seen from Table 5.2, most of the process data used were within six to ten years duration. In terms of geographic representativeness, most of the data were from average larger areas or similar production conditions. Cotton cultivation (i.e., India) and transportation (i.e., global scenario) represent average data from a larger area, while EOL and clothing care represents the area under study (i.e., USA). In terms of technological representativeness, the data were used from processes and materials under study but different enterprises. Overall, the data were reliable, and the inventory was reasonably complete.

The Implication of the Study

Understating the substitution rate is key to understanding the potential environmental benefit of SHC consumption. If secondhand use does not substitute a new purchase, there would not be any environmental benefit. Rather, the environmental impact might actually increase if consumers buy additional new products (Schmidt et al., 2016). Past studies clearly demonstrated the need to investigate the substitution rate in the places where there is a need to understand the impact of SHC consumption (Nørup et al., 2019; Stevenson & Gmitrowicz, 2012). This study made the first attempt to identify the substitution rate associated with SHC for U.S. consumers. In addition, the study made an initial attempt to examine the impacts of other factors on substitution rate value, such as age, gender, race, household income, motivation, and barrier. Based on the substitution rate value, this study also investigated the potential environmental benefit of a secondhand men's t-shirt.

This study filled an important data gap as related to the substitution rate value of SHC consumption. To understand the global scenario of the environmental impact of SHC, a global average of substitution rate value for various clothing products is needed. Before this study, there were only a few substitution rate-related studies representing only Europe and Africa. This study would strengthen the existing substitution rate-related inventory by adding U.S value. With more such studies in other geographic areas, it would be possible to create a global average substitution rate value for SHC that is crucial to model future LCA studies pertaining to SHC consumption. Moreover, as the United States is the largest exporter of SHC (The Observatory of Economic Complexity, n.d.), this study will particularly be helpful for future modeling of the impact of SHC consumption within the United States.

Studies concerning the environmental impact of SHC are under-represented in the USA (Schmidt, 2016). This study is also an early attempt to understand the potential environmental impact of SHC consumption in the context of the United States. There are predictions that the SHC market of the USA will increase substantially in the future (O'Connell, 2019; Imran et al., 2018). Therefore, this study provides an estimation of how SHC consumption would potentially benefit the environment. Building on this study, future studies would be able to assess the environmental impact of SHC imported in the United States from other geographic areas.

This study has implications for brands and retailers with rental, subscription, and swapping-based SHC business, such as ThredUp, Rent the Runway, the New York & Company Closet, Tulerie, etc. They would be able to have a solid idea of how consumers are making an impact with their SHC purchase. As such, they can provide consumers with more information about how purchasing secondhand contributes to the environment. Also, they would be able to better understand the SHC purchasing behavior for different consumer segments, such as male vs female, younger vs older, etc., as associated with the substitution rate. Thus, the finding would offer them with additional marketing perspectives and opportunities.

The study also has implications for consumers. The findings of this study would inform the consumers that reusing is better than purchasing new clothes. In addition, the study provides support that substituting as few as five percent of their clothing is still considerably environmentally-friendly. Overall, this study lends strong support to the existing body of knowledge that clothing reuse is better than disposing of clothes having useful life left.

Regarding policy implication, this study provides a strong incentive to implement an improved clothing collection scheme. At present, there is a clear lack of infrastructure to collect the maximum number of used yet wearable clothes. Consumers also have poor knowledge of how they can dispose of their clothes responsibly. Therefore, policy initiatives should be taken to ease the collection of unwanted clothes and minimize clothing waste. Along with that, initiatives should be taken to educate consumers about the harmful consequence of clothing waste and the benefit of reusing.

Limitation and Future Recommendation

The study has several limitations. First, the study used a Mturk sample of 920 participants of diverse demographics. The sample does not fully represent the U.S. population. There would certainly be a variation of substitution rate value in different parts of the United States. Therefore, future studies should use a larger and more representative sample. Future studies should also report the size of the variation and how that compares with the RoW data.

Second, the study used an online questionnaire survey to identify the substitution rate value of SHC consumption for U.S. consumers. The participants were individuals who bought SHC within the past 12 months. The question required participants to indicate if their secondhand purchases substituted similar new purchases. Therefore, one of the potential limitations might be that the response did not fully reflect the real scenario because it may be challenging for a respondent to remember if their secondhand purchase substituted a new purchase. As a result, the reporting became highly subjective and might have caused some bias in the result. However, any survey-based study is typically prone to subjective bias and hence unavoidable. With that being said, future studies might gather data from purchasers of SHC in the actual purchase locations. This would still be prone to subjective bias but would enable participants to report from fresh memory.

Third, the substitution rate should be interpreted cautiously. The rebound effect might interfere with substitution rate value. In this study, an attempt was made to estimate the rebound effect, however, it was not included in the LCA modeling (Appendix C). Further research is required to investigate the nature and relation of the rebound effect as related to the substitution rate. In addition, there might be a case where reuse does not offer much benefit, although the substitution rate is higher. For instance, if reusing activities consume a substantial amount of fossil energy and/or reusing occurs for an environmentally clean product (Sandin & Peters, 2018). Therefore, future studies should carefully consider these issues when investigating the substitution rate. Another aspect that might interfere with the substitution rate is the durability of the products. If there is a difference in the duration of first life and second life of clothing items, it will lead to a variance in substitution rate. For instance, if the average first life and second life of a t-shirt in the United States is 4.5 years (Daystar et al., 2019) and 2.5 years (assumption) respectively, the substitution rate may be calculated as 56% (i.e., 2.5/4.5). Thus, product type product durability, reusing activity, and rebound effect need to be investigated to achieve triangulation of understanding of the substitution rate value.

Fourth, the LCA modeling of the t-shirt was based on various assumptions and parameters. Therefore, like any LCA study, there is a certain degree of uncertainty associated with the analysis. Appropriate considerations should be given while interpreting the findings. One of the major limitations of the LCA was that it used very little country-specific parameters and emission scenarios. Due to the data gap, global average data was used for the background as well as emission data. Therefore, the finding does not fully represent the geography as stated in the system boundary (Figure 3.2) and later clarified in data quality assessment (Table 5.2). There is a clear lack of foreground data in the context of Bangladesh. Future research should focus on improving as well as using more representative geographic data in LCA modeling.

Conclusion

To the best of the researcher's knowledge, this study made the first effort to investigate the substitution rate of SHC consumption for U.S. consumers. Utilizing an online questionnaire survey, this study estimated an average 67.81± 4.96% SR for U.S. consumers. This finding suggests that every 100 secondhand clothing purchase substitutes between about 63 and 73 new purchases. Like past studies, children's clothing had the highest substitution rate. Besides, it was also found that less frequently purchased SHC items have higher substitution rates. Regarding the influence of other factors on the substitution rate, the study found that male consumers had a higher substitution rate than females. Also, the substitution rate for younger consumers was higher than older consumers. Furthermore, this study also found that higher income is associated with a higher substitution rate value. However, age, gender, race, household income, motivation, and barrier were not good predictors of the substitution rate in the regression model.

This study also made an initial attempt to investigate the environmental impact of SHC consumption in the context of the United States. The result showed that the secondhand use of the t-shirt results in a potential saving of an estimated 1.49 kg CO2 eq. GHG emission, 1.8 m^3 water consumption, and 1.06 m^2a eq. land use, considering a 56.7% substitution rate. Like past studies, the study found textile production (i.e., spinning, knitting, and dyeing) was the major environmental hotspot.

A clothing item typically makes a long global journey and embeds substantial resources during its lifetime. Once the product is thrown away early in its lifetime, it buries all these embedded resources. For instance, the global textile industry consumes 98 million tons of non-renewable resources and 93 billion cubic meters of water per year (Ellen MacArthur Foundation, 2017). Throwing away clothes would lose all these valuable resources. Reusing improves utilization, hence saves valuable resources. The finding of this study supports the fact that reuse is a better sustainable strategy. For a sustainable TA industry, better utilization of resources is essential. As Ellen MacArthur Foundation (2017) reported, "increasing the average number of times clothes are worn is the most direct lever to capture the value and design out waste and pollution in the textile system" (p.24). One key message from this study is that no matter how much a secondhand purchase substitutes, there is still environmental benefit.

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Appendix A - Calculating Substitution Rate

The table below shows the calculating method of the substitution rate of clothing reuse. The error bar was calculated from half of uncertain (%) responses. The formula that was used to calculate the substitution rate is given below. A fake data (hypothetical) is used in the table to show the calculation. From the hypothetical data, the substitution rate can be calculated as 75% and the error bar as 12.5. Therefore, the final figure would be 75 ± 12.5%, meaning that the range of the substitution rate data for the respondents is 62.5 to 87.5.

Substitution Rate,

S =

$$\frac{\text{total number of items with 'Yes' response (c)} + \frac{1}{2}\text{ of the number of items with 'uncertain' responses(a)}}{\text{Total number of items purchased (d)}}$$

Table A.3.

Calculation Method of Substitution Rate of SHC Consumption

Item	a)'uncertain' responses	b) 'no' responses	c) 'yes' responses	d) total number of items purchased/ total number of responses	Substitution rate (%)	uncertain (%)	Error bar
Secondhand clothing	100	50	250	400	75	25	12.5

Appendix B - Summary of Pretesting and Pilot Testing

The summary of pretesting is summarized below:

Table B.4.

Summary of Pretesting

Participants	Duration (min)	Overall comments
1.	12	a) Include ‘casual wear’ and ‘jacket’ as SHC category, b) include ‘maybe’ instead of ‘may be’, c) Include ‘I don’t know’ option in the survey question related to clothing lifetime, d) change the wording of rebound effect question to ‘if you saved money through secondhand purchasing, do you save it or does it become additional spending money (could include non-clothing items)?’
2.	9	No concerns
3.	10	Use ‘SHC is unhygenic’ option as a barrier to SHC pucchase.
4.	11	Overll survey made sense. Before you introduce the survey, clearly define what you mean by secondhand clothing and provide some examples of stores. I think that would help your audience better understand what shopping habits you're targeting with your research.
5.	10	You may want to consider making the word "refuse" bold so participants know that question was different from a prior similar one.
6.	9	No concerns
7	11	No concerns
8	-	a) Check the fonts - make sure the use of fonts is consistent. b) The name of a online retailer is ThredUP, not ThreadUp. c) Add more Household Income categories instead of grouping all the participants with higher than 100,000 annual income into one single group, may be add groups 100,001-150,000, 150,001-200,000, and then 200,001 and above (or even more categories as needed)?
9	-	a) Why is "today" in the question? Please just write, "Have you purchased any secondhand clothing within the last 12 months? Definition of second hand clothing that is found after the above question should come before the above question. b) I would recommend adding "for each secondhand clothing item purchased" as a point of clarification. c) Rewrite as "Do you save money from purchasing secondhand clothing?

		d) Rewrite as, "If you save money from purchasing secondhand clothing..." e) Rewrite as "Please tell us about your motivation for purchasing..." f) For demographics you might consider a "prefer not to disclose" option for all of the questions.
10	-	a) change the format of informed consent form b) rework on SHC categories c) rewrite as 'when you last purchased these secondhand clothing items, would you have purchased a new item if you had not found a secondhand version available? d) change the options of clothing lifetime question e) rewrite as 'save money when purchasing secondhand clothing? f) rewrite as 'do you immediately spend your savings on additional purchases (clothing or non-clothing)?' g) capitalize as NOT.

The summary of pilot testing is summarized below:

Table B.5.

Summary of Pilot Test

No. of participants	20
Platform	Mturk
Summary	a). qualtrics worked well; suvey distribution on Mturk worked well. b) average duration of participation was within 10 mins. c) casual pants, coat/jacket, and shorts were top SHC category; bra, shocks, underwear skirt were less-purchased SHC category d) overall demographic representation was good. e) the insruments worked well.

Appendix C - Rebound Effect

Table C.6.

Estimation of the Rebound Effect

Survey question	Response		
	Yes	**No**	**I don't know**
1. Do you save money from purchasing secondhand clothing?	864 (93.51%)	41 (4.44%)	19 (2.06%)
2. If you save money from secondhand purchasing, do you immediately spend savings on additional purchases (clothing or non-clothing)?	240 (27.18%)	621 (70.33%)	22 (2.49%)
	New	**Secondhand**	**I don't Know**
3. What types of additional items are you likely to buy with this saved money?	137 (57.08%)	91 (37.92%)	12 (5%)

Step 1: The number of participants who might be involved with <u>new</u> purchases is,

Total number of participants*Q1 (Yes response)*Q2 (Yes response)* Q3 (New responses)

=924*93.51%*27.18%*57.08%

= 134.05

Step 2: The number of participants who might be involved with <u>secondhand</u> purchases is,

Total number of participants*Q1 (Yes response)*Q2 (Yes response)* Q3 (Secondhand responses)

=924*93.51%*27.18%*37.92%

=89.05

Step 3: Rebound effect = (Step 1- Step 2)*100/Total no. of participants

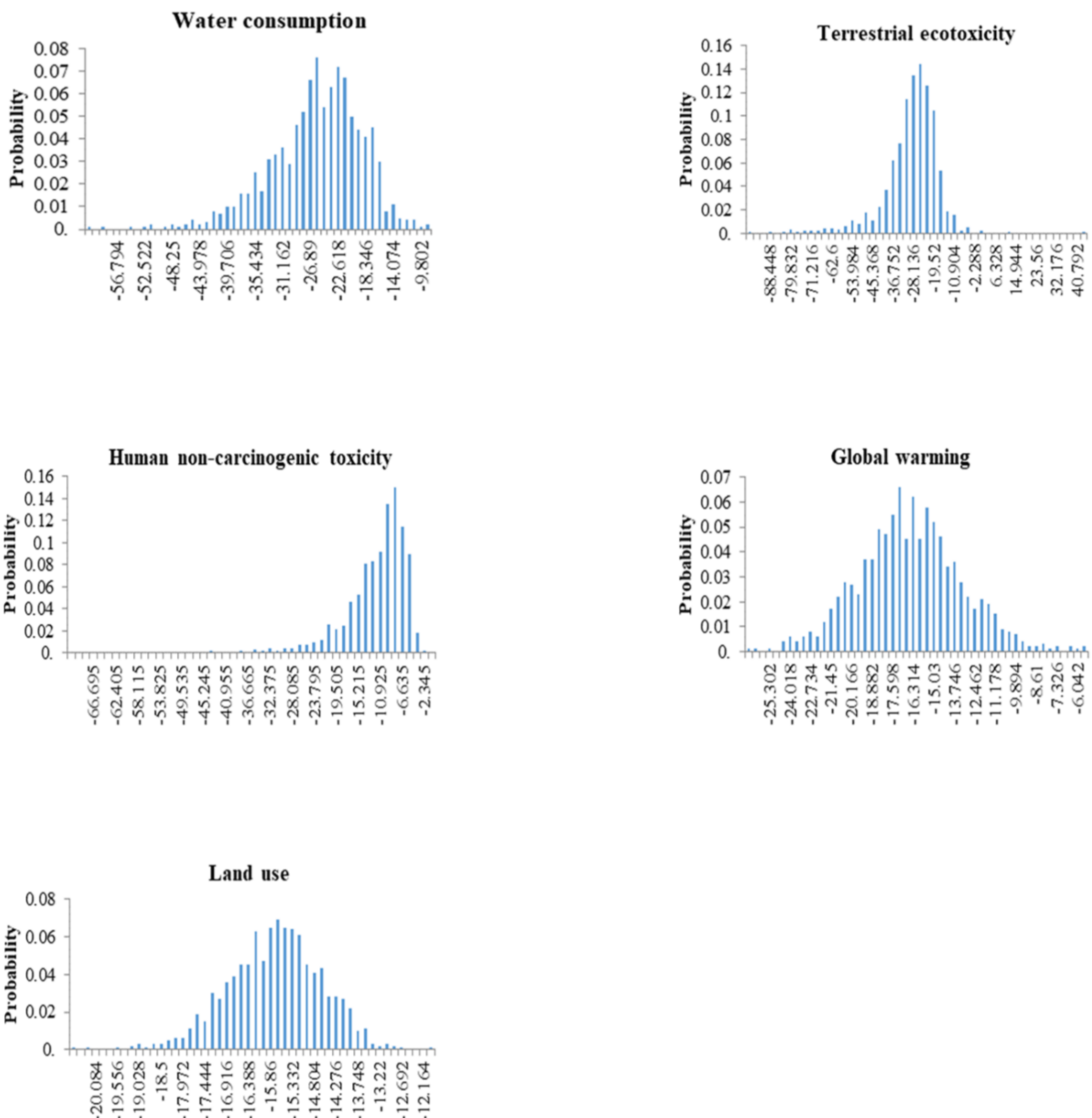
= (134.05-89.05)*100/924 = 4.87%

Step 4: Adjusted substitution rate (SR) = actual SR- Rebound effect = 67.81– 4.87 = 62.94%

Appendix D - Uncertainty Analysis

Figure D.25.

Uncertainty Analysis



Appendix E - Data Source

Table E.7.

LCI Data Source

Life Cycle Phase	Process	Material	Amount/ kg t-shirt	Reference	Modeled with/dataset used
Cotton cultivation	Field preparation	Arable land occupation	0.0015 ha	Bevilacqua et al. (2014)	Transformation, from annual crop Transformation, to annual crop Carbon dioxide, in air Energy, gross calorific value, in biomass
		Plough	0.00077273 ha	Generic	Tillage, ploughing/US*US-EI U
		Harrowing	0.00077273 ha	Generic	Tillage, harrowing, by spring time harrow/ US*US-EI U
		Hoeing	0.00077273 ha	Generic	Hoeing/ US*US-EI U
		Currying	0.0015455 ha	Generic	Tillage, currying by weeder/US*US-EI U
		Sowing	0.00077273 ha	Generic	Sowing/ US*US-EI U
		Fertilizing	0.0023182 ha	Generic	Fertilizing, by broadcaster/ US*US-EI U
		Plant protection	0.015455 ha	Generic	Application of plant protection products, by field sprayer/ US*US-EI U
	Cultivation	Irrigating	2.9759 m^3	Cotton Incorporated, 2017	Irrigating/ US US-EI U

	Parathion	0.00047394 kg	Generic	Parathion, at regional storehouse/ US US-EI U
	Pyretroid	0.00047394 kg	Generic	Pyretroid-compounds, at regional storehouse/ US US-EI U
	Organophosphorus	0.00047394 kg	Generic	Organophosphorus -compounds, at regional storehouse/ US US-EI U
	Pesticides	0.0012 kg	Shah et al., 2018	Pesticides unspecified, at regional storehouse/ US US-EI U
	Glyphosate	0.0023182 kg	Generic	Glyphosate unspecified, at regional storehouse/ US US-EI U
	Organic chemicals	0.000019318 kg		Chemical organic, at plant/GLO US-EI U
	Urea	0.062 kg	Shah et al., 2018	Urea, as N, at regional storehouse/ US US-EI U
	Ammonia	0.10045 kg	Generic	Ammonia, liquid, at regional storehouse/ US US-EI U
	N	0.1489 kg	Cotton Incorporated, 2017	Ammonium nitrate, as N, at regional storehouse/ US US-EI U
	P205	0.0489 kg	Cotton Incorporated, 2017	Triple superphosphate, as P2O5, at regional storehouse/ US US-EI U
	K2O	0.0071 kg	Cotton Incorporated, 2017	Potassium chloride, as K2O, at regional storehouse/ US US-EI U
Harvesting	Baling	0.005 p	Generic	Baling/US*US-EI U
	Van	0.015068 km	Generic	Operation, van <3.5 t/ US US-EI U
	Lorry	0.326 tkm	Bevilacqua et al. (2014)	Transport, lorry 3.5-16 t, fleet average/ US US-EI U
	Packaging	0.0000000003 p	Generic	Packaging box production unit/US-/I US-EI U

	Ginning	Electricity	0.5971 kWh	Cotton Incorporated, 2017	Electricity low voltage, production UCTE*, at grid/UCTE US-EI U
Fabric	Yarn manufacturing	Cotton fiber	1.36 kg	Cotton Incorporated, 2017	Cotton fiber from above made process
		Electricity	2.3936 kWh	Moazzem et al., 2018	Electricity, low voltage{IN}| market group for electricity, low voltage | APOS, U
		Water	1.7952 kg	Hossain, 2017	Tap water {GLO}| market group for | APOS, U
		Lubricating oil	0.00068 kg	Roos et al., 2015	Lubricating oil, at plant/ US US-EI U
		Transport	0.612 tkm	Generic	Transport, lorry 16-32 t, EURO3/ US US-EI U
		Packaging box	0.0000000013 p	Generic	Packaging box production unit/ US-/I US-EI U
	Knitting	Cotton fiber	1.02 kg	Cotton Incorporated, 2017; Roos et al., 2015	Cotton fiber from above made process
		Electricity	1.04 kWh	Roos et al., 2015	Electricity, low voltage{IN}| market group for electricity, low voltage | APOS, U
		Water	1.04	Hossain, 2017	Tap water {GLO}| market group for | APOS, U
		Lubricating oil	0.1 kg	Roos et al., 2015	Lubricating oil, at plant/ US US-EI U
	Dyeing	Cotton fiber	1.13 kg	Cotton Incorporated, 2017	Cotton fiber from above made process
		Tap water	55.699621 kg	Murugesh & Selvadass (2013)	Tap water, at user/ US US-EI U
		Softened water	3.14 kg	Generic	Water, completely softened, at plant/ US US-EI U

		Hydrogen peroxide	.04068 kg	Generic	Hydrogen peroxide, 50% in H2O, at plant/ US US-EI U
		Sodium hydroxide	3.164 kg	Murugesh & Selvadass (2013)	Hydrogen peroxide, 50% in H2O, production mix, at plant/ US US-EI U
		Dyes	0.012656 kg	Murugesh & Selvadass (2013)	Synthetic dye and pigment manufacturing/US U
		Sodium dithionite	0.09492 kg	Generic	Sodium dithionite, anhydrous, at plant/ US US-EI U
		Organic chemicals	0.0048		Chemicals organic, at plant/GLO US-EI U
		Ethoxylated alcohols	0.185	Generic	Ethoxylated alcohols, unspecified, at plant/ US-EI U
		Fuel oil	0.37 kg	Generic	Light fuel oil, at regional storage/ US-US-EI U
		EDTA	0.003955 kg	Murugesh & Selvadass (2013)	EDTA, ethylenediaminetetracetic acid, at plant/ US-US-EI U
		Acetic acid	0.003955 kg	Murugesh & Selvadass (2013)	Acetic acid, without water, in 98% solution state {GLO}| market group for |APOS, U
		Soap	0.02373 kg	Murugesh & Selvadass (2013)	Soap, at plant,/ US-US-EI U
		Electricity	0.413241 kWh	Murugesh & Selvadass (2013)	Electricity, low voltage{IN}| market group for electricity, low voltage | APOS, U
		Wood fuel	1.570520563 kg	Murugesh & Selvadass (2013)	Wood fuel, unspecified NREL/RNA U
T-shirt production	Cut-and-sew	Fabric	1.18 kg	Cotton Incorporated, 2017	Knit garment from above made process
		Electricity	4.9324 kWh	Jungmichel (2010)	Electricity, low voltage{IN}| market group for electricity, low voltage | APOS, U

Consumer Care	Washing/drying	Garment Detergents Water	1 kg 0.0204825 kg 16.488993 kg	 Schenck, 2013 EPA, 2015; Yamaguchi et al., 2011	Knit garment from above made process Liquid laundry detergents/US U Tap water, at user/ US US-EI U
		Electricity	0.3842175 kWh	Cotton Incorporated 2017; Yamaguchi, et al., 2011; CFR, 2015	Electricity, low voltage, at grid, 2011/US US-EI U
Transportation	Transportation	Garment	1 kg		Knit garment from above made process
		Road transport	2259 kg-km	Own calculation	Transport, lorry >16t, fleet average/ US-US-EI-U
		Road transport	2442 kg-km	Own calculation	Transport, lorry >16t, fleet average/US-US-EI-U
		Maritime shipping	17201 kg-km	Own calculation	Transport, barge ship, container, 4700t, 50%LF, default/GLO Mass
		Air freight	12,919 kg-km	Own calculation	Transport, freight, aircraft {GLO}| market for | APOS, U
End of life	Waste management	Garment	1 kg		Knit garment from above made process
		Treatment	1 kg	U.S. EPA (2019)	Textiles waste scenario {US}| treatment of waste | APOS, U

Appendix F - IRB Approval

Figure F.26.

IRB Approval Letter

KANSAS STATE UNIVERSITY | University Research Compliance Office

TO: Dr. Melody LeHew
Interior Design and Fashion Studies
Justin Hall

Proposal Number: 10147

FROM: Rick Scheidt, Chair
Committee on Research Involving Human Subjects

DATE: 05/12/2020

RE: Proposal Entitled, "An investigation of the US substitution rate and environmental impact associated with secondhand clothing consumption"

The Committee on Research Involving Human Subjects / Institutional Review Board (IRB) for Kansas State University has reviewed the proposal identified above and has determined that it is EXEMPT from further IRB review. This exemption applies only to the proposal - as written – and currently on file with the IRB. Any change potentially affecting human subjects must be approved by the IRB prior to implementation and may disqualify the proposal from exemption.

Based upon information provided to the IRB, this activity is exempt under the criteria set forth in the Federal Policy for the Protection of Human Subjects, **45 CFR §46.101, paragraph b, category: 2, subsection: ii.**

Certain research is exempt from the requirements of HHS/OHRP regulations. A determination that research is exempt does not imply that investigators have no ethical responsibilities to subjects in such research; it means only that the regulatory requirements related to IRB review, informed consent, and assurance of compliance do not apply to the research.

Any unanticipated problems involving risk to subjects or to others must be reported immediately to the Chair of the Committee on Research Involving Human Subjects, the University Research Compliance Office, and if the subjects are KSU students, to the Director of the Student Health Center.