AN ABSTRACT OF THE DISSERTATION OF

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Title: Design for Clean Technology Adoption: Application of Discrete Choice Analysis and the Theory of Planned Behavior for Development Engineering.

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Clean technologies can address multiple challenges associated with climate change, environmental protection, and human health. However, the impact desired by introduction of such technologies is achievable only if new options effectively replace inefficient, conventional practices. This ‘design for adoption’ requires understanding of user motivations, associated beliefs, context of use, and technology’s performance. To address this need, this work develops an integrated methodology that links the Theory of Planned Behavior to predict behavior intentions with Discrete Choice Analysis to systematically incorporate users’ behavioral intentions into the engineering design process. Drawing on a case study of improved biomass cookstove projects in Honduras and Uganda, the developed framework provides insight into consumer attitudes both before and after trial phases of a given technology, and then simulates the long-term community-scale adoption behavior based on the influences of social networks using Agent Based Modeling. Results can inform technology designers and international development programs on key attributes to consider to

optimize technology design and intervention strategies and ultimately improve the long-term adoption rate of clean cookstoves in a given target market. These methods are expected to be extensible to other sectors as well, where the uptake of clean technologies can benefit from a systematic understanding of the multitude of behavioral, social, and technology design attributes that are relevant in different settings.

Design for Clean Technology Adoption: Application of Discrete Choice Analysis and the Theory of Planned Behavior for Development Engineering

by
Mohammad Hossein Pakravan

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Mohammad Hossein Pakravan, Author

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# DEDICATION

Dedicated to the people that have low resources but high aspirations, have low incomes but high happiness, and whom do not need awareness to respect.

# Chapter 1 – General Introduction

What motivates technology adoption in low income-regions? For years, international development has sought to provide technologies to address the many challenges for people living at the 'bottom of the pyramid'. Despite these efforts, evidence suggests that technology accessibility and ownership do not necessarily translate to technology adoption and use. During the past three years, I have studied technology adoption in low resource settings to find out what drives technology adoption and what are the impacts of humanitarian-based technologies in practice. To find systematic answers to these questions, this research integrated methodologies from engineering design, economics, and psychology. Sponsored by the National Science Foundation – Civil, Mechanical, and Manufacturing Innovation division, this dissertation highlights how user behavior and use-context should systematically inform engineering design in a quantitative approach. The holistic framework developed in this work provides insights for technology designers, policy makers, and international development project managers to follow a more user-oriented, context-appropriate and systematic approach to design more marketable clean technology alternatives. As a result, products and intervention strategies are more likely to align with user intentions and beliefs, which improves the likelihood of technology adoption.

Although this work is extensible to a variety of technologies and sectors, we evaluated the model in the context of biomass cookstove projects in low-resource regions. Nearly 2.7 billion people (approximately one out of three people globally) use conventional and inefficient open fire cooking practices to cook meals and heat water (OECD/IEA 2017). There are a variety of significant problems associated with such practices. First, increasing population has pushed the harvest of firewood to unsustainable rates. Estimates suggest that globally 27–34% of firewood harvest is unsustainable, threatening 275 million people in south Asia and East Africa that reside in fuelwood depletion hotspots (Bailis et al. 2015). Inefficient firewood combustion results in increased emissions, such that use of solid fuels for cooking is estimated to contribute to 18–30% of global anthropogenic black carbon emission (Masera et al. 2015). Black carbon is identified as the second strongest contributor to climate change after carbon dioxide due to its high solar radiation absorption and increasing melting point of ice surfaces (Ramanathan and Carmichael 2008). In addition, because people are present during the time of cooking, which often occurs indoors in poorly ventilated spaces, people (particularly women and children) are exposed to byproducts of inefficient combustion such as carbon monoxide, volatile organic compounds and particulate matter (Winijkul, Fierce, and Bond 2016). Prolonged exposure to such chemicals contributes to nearly four million premature deaths every year, making household air pollution the single most important environmental health risk factor globally (World Health Organization 2016). Finally, such rudimentary practices are not typically safe, exposing children to open fire and hot surfaces. As a result, many injuries in childhood are related to burns caused by cooking fires (Albertyn et al. 2012).

For more than three decades, international organizations, governments and NGOs have been working to design and implement improved cookstoves (ICS) and fuels to address this issue. Part of these efforts have focused on designing effective cookstoves to reduce pollution emissions, fuel wood consumption, tending time and increase thermal efficiency. In order for a cookstove to be an “improved” design, principles for wood burning cookstoves have been developed (Bryden et al. 2006). These ten principles provide instructions related to insulation, dimensional ratios, fuelwood burning location, fire power adjustments, air flow and draft considerations, grate usage under the fire, and properly sized gaps. However, given that improvements in cookstove design is a multi-objective process, increasing the thermal efficiency alone is only part of the solution.

Well-designed and highly efficient ICS should nearly or completely displace traditional devices to achieve the target goals addressing air pollution, deforestation and safety. However a number of studies have explored the lack of interest in adopting improved cookstoves in low resources communities in developing world. A survey from nearly two thousand households in rural communities in north India found that although 68% of respondents were aware of negative health impacts of traditional practices, less than 10% of households that owned a better technology used it as their main energy supply method (Jeuland et al. 2015). Results of their study suggest that user preferences, social marketing and behavioral analysis should be studied for better adoption rates. A similar survey in Bangladesh revealed that  at market prices, the adoption rate for two different types of improved cookstoves were 2% and 5% (Mobarak et al. 2012). Reducing the cost of cookstoves by 50% in their study adoption rate only improved by 12%. Thus, they suggest that designing nontraditional cookstoves should consider those attributes that households and individuals value. Another study developed a four-year long analysis on the implementation in one of the poorest places in India (Orissa) (Hanna, Duflo, and Greenstone 2016). Their experiment revealed that although initial household adoption was far from universal, up-take declined as households failed to bear the maintenance costs. Even in early adoption period when stoves were fully functional, the majority of technology adopters still continued to use their traditional stove.

The problem of technology adoption is not limited to ICS. 7 out of 17 sustainable development goals presented by United Nations to shed highlight the aspects of international development are associated with technology based interventions (United Nations 2015). However, not every technology can be treated the same in terms of adoption and what leads people to make the choice to change behavior. Adopting such technologies requires extensive understanding of the behaviors that do not have a direct, tangible and rapid perceived benefit, rather an abstract concept in mind that promises collective benefits and/or indirect long-term benefits. For this purpose, a review of literature shed light into the well-established theories and models that have been successful in the past for such behaviors.

Widespread beliefs and personal visions significantly contribute to volitional behaviors that do not necessarily produce tangible benefits perceived in real time. One good example of such behaviors is using an environmentally conscious choice such as recycling, purchasing green products, and paying attention to carbon footprint of choices in general. Similar to environmentally responsible behaviors, healthy behaviors do not necessarily pay off their tangible benefits immediately. For instance, quitting smoking cigarettes does not improve health conditions the next day, and exercise does not result in weight loss overnight. Therefore, it is important to find out what is the driving force for such behaviors that are not based on instantaneous perceived utility. Answering this question can lead us to better understand what could motivate households in less developed settings to adopt a cleaner cooking practice, or other beneficial technologies.

The Theory of Planned Behavior (TPB) was selected as the most promising, validated theory from the litearture to form the basis of this research. It was further developed to suit the topic at hand and integrated into models to provide better understanding of clean technology adoption in low-resource regions. This included first evaluation of the usability of this theory in data scarce contexts. Lessons learned from the first data collection in Copan Ruinas, Honduras, were applied to a second study in Apac, Uganda. Extensive data collection in 175 households provided satisfactory input for further analysis. These real-world data were investigated from several angles. First, the correlation of household beliefs with their intention to cook more meals with ICS was analyzed. Based on this, a framework was developed to integrate TPB with Usage Context-Based Design (UCBD), an engineering design method in decision-based design and inspired by discrete choice analysis. This understanding of how local demand for different types of stoves is linked with households' decision-making behavior, an Agent Based Model (ABM) of a theoretical community consisting 1000 households with heterogeneity similar to surveyed households in Apac, Uganda was then created. The ABM approach provided insights to predict long-term behavior of households as members of a community interact with each other and influence each other's stove choices. This enables the research to simulate community-scale and long-term adoption behavior of the community as a function of key programmatic and contextual factors such as price elasticity of demand, strength of intra-communal links, rate of stove malfunctions, and household behavioral updates influences long-term adoption pattern throughout community.

Results of this research reveal that the decision to use an ICS is two-fold. On the user's side, the choice of stove is influenced by country, widespread beliefs and power dynamics in the household. On the technology side, fuel type, price, and durability are the main factors that can shape the market share of each alternative. In addition, it was found that households' influential beliefs that formulates their intentions to cook with an ICS shifts after a trial phase based on their experiences. Although the data collected for this initial research was not sufficient to draw many practical conclusions, it did successfully create a method to quantify influence of a variety of factors. Further studies are recommended to investigate the specific role of additional usage-context attributes.

Application of this framework in a variety of global development sectors could inform technology designers to develop products that are more in line with the beliefs that users hold and their priorities. Project managers and implementers benefit from this study by understanding the target population in a systematic way so that information campaigns, marketing strategies and intervention plans will be reflective of the target population's social network, widespread beliefs, and local characteristics that influence the adoption patterns. This will lead products and projects to be more context specific, and as a result, have improved likelihood of adoption and impact. This model could be further coupled with a village-level models that integrate different aspects of life from energy to clean water, to empowerment provides a unique opportunity to holistically approaches that lead to successful, efficient, systematic, and appropriate international development interventions.

The following three chapters present the three stages of this research in the format of academic peer-reviewed publications. In Chapter 2, the application of TPB in data scarce settings is discussed. Results of data collection in Copan Ruinas, Honduras and Apac, Uganda shed light into further integration of TPB with engineering design. Following successful data collection based on TPB, in Chapter 3 the integrated engineering design framework based on TPB and UCBD is presented. This chapter presents how user behavior quantification along with technology attributes and usage context could form a robust utility function to model decision-making behavior of households. Finally, the developed decision-making model was then incorporated into an ABM environment described in Chapter 4 to investigate community scale adoption behavior through time.

# Chapter 2

## Analysis of user intentions to adopt clean energy technologies in low resource settings using the Theory of Planned Behavior

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## Abstract

Understanding and integrating the user's decision-making process into product design and distribution strategies for clean energy technologies may lead to higher adoption rates and ultimately increased impacts, particularly for those products that require a change in habit or behavior. One validated method from the literature that effectively quantifies a user's decision-making behavior in health and environmental applications is the Theory of Planned Behavior (TPB). This model characterizes the main psychological attributes that make up a user's intention for volitional behaviors based on attitudes toward the behavior, social norms, and users' perception of their power to control their behavior. However, this method has not yet been applied in design for global development, where understanding the tendency to adopt beneficial technologies is critical to programmatic impact but user data are limited. Therefore, this study applies TPB to the adoption of biomass cookstoves in two rural communities in Honduras and Uganda before and after a trial period with a subject technology. Using multiple ordinal logistic regressions, the intention to adopt cookstoves is modeled through data collected by extensive social surveys. Results quantify the influence of these factors on households' intentions to cook their main meals with improved cookstoves, discuss potential sources of bias and statistical challenges that may invalidate models, particularly in data-scarce low-resource regions, and outline methods to address them. Analyses indicate how priorities of households and their expectations of a clean technology change after a trial phase. For example, participants with slightly stronger beliefs regarding the importance of reducing smoke emissions were 3.3 times as likely to cook main meals with clean cookstoves. In addition, participants that perceive changing their habits of cooking with traditional devices as slightly easier than average are 2.7 times more likely to cook principal meals with clean cookstoves. Insight provided using such application of TPB could be utilized for design of the technologies, policies, and marketing that require user behavior changes to be effective.

## 2.1 Introduction

Examining drivers of users' intentions for using clean technologies can provide insight for design and marketing strategies to maximize effectiveness and uptake. For energy-efficiency and other goal-oriented products, this can result in increased and sustained adoption, ultimately leading to greater environmental and health impacts (E. M. Rogers 1995). Understanding user intentions is especially important in design for development, where cultural barriers and unfamiliarity with usage contexts in diverse communities renders design of appropriate technologies a challenging task. Many technologies have been developed and disseminated to address basic human needs and fight extreme poverty, however, despite such efforts, there is significant room to improve rates of adoption and sustained use. For this purpose, comprehensive approaches are required to include energy services that bind user needs, culture, and social norms along with supply side challenges such as efficiency (Bouzarovski and Petrova 2015).

Improved cookstoves (ICS) are one example of an energy-efficient technology where user adoption is critical. Currently, traditional cooking practices have a multitude of negative consequences on livelihoods for people in developing communities. For 2.7 billion of the world's population, firewood is the primary source of energy and can meet more than 90% of a households' energy needs for cooking and heating (N. G. Johnson and Bryden 2012b; Legros et al. 2009). Household air pollution from incomplete combustion contributes to 3.5-4 million premature deaths every year representing the second leading cause of death for women globally (Lim et al. 2013; Smith et al. 2014). Contributions to global climate change are also significant, as recent estimates show 34 – 45% of the warming due to black carbon is generated by traditional biomass combustion and up to 8% of warming overall (Robert Bailis et al. 2015; Masera et al. 2015). To address these challenges, many types of ICS with increased heat transfer and combustion efficiency have been developed and widely disseminated with the goal of reducing the emission of toxic chemicals and biofuel consumption. However, despite the potentially significant benefits to livelihoods and climate, low adoption rates are observed in many projects (M. Johnson, Edwards, and Masera 2010; Lewis and Pattanayak 2012; Ruiz-Mercado, Canuz, and Smith 2012). Some studies suggest that systematic integration of users in design and implementation can lead to increased uptake (Jeuland et al. 2015; Lim et al. 2013; Mobarak et al. 2012), but to do so an effective method is needed.

There are a range of methods taken from the social sciences to predict human behavior in various sectors through quantitative modeling approaches. One way to describe user behavior in terms of using a new clean alternative is through modeling the attributes that influence a person's intentions. Intention is the central factor that determines whether an action is performed and indicates an individual's openness and the level of effort they are willing to exert to conduct an action (Ajzen 1985). One of the more prominent methods that explores behavioral attributes that formulates intentions is the Theory of Planned Behavior (TPB). In this method, intentions are considered the main determinant of behavior, and are based on three categories of beliefs: behavioral, normative, and control. Behavioral beliefs describe the attitude toward behavior that captures an individual's personal beliefs and evaluations regarding an action. Normative beliefs are the outcomes of society's norms and an individual's evaluation regarding social norms related to their behavior. Control beliefs determine the level of control an individual perceives they have for conducting or avoiding a particular behavior. TPB is one of the well-established user behavioral intention analysis methodologies that proposes a systematic and efficient evaluation of the attributes that lead to reasoned behavior (Armitage and Conner 2001).

The goal of this study is to analyze the motivation for consumers in low-resource communities to adopt clean technologies such as ICS by applying TPB. Household surveys were developed to describe the three categories of TPB through Likert-scale survey questions to evaluate the influential attributes that formulate intention for stove adoption. The surveys were implemented in 380 rural households in Copan Ruinas, Honduras and 170 rural households in Apac, Uganda both before and after provisioning ICS. This paper details the development and use of the survey questions and analyzes collected data to determine the most significant factors contributing to the user's intention formation.  Results introduce a new approach to design and implementation of clean technologies that demand user behavior modifications to successfully replace traditional practices.

## 2.2 Background

By nature, individuals are faced with a number of competing preferences and objectives for meeting their needs. It is, therefore, necessary to formulate product design and implementation strategies based on an understanding of users' priorities. Despite the potential positive impacts of using clean energy technologies such as solar panels, electric vehicles, or clean biomass cookstoves, successful user adoption of such products can be a challenge because the technology must be aligned with the user's needs and motivations requiring change to their traditional behavior. According to the diffusion of innovations theory, diffusion occurs through a process of communication of a specific innovation through social channels over time between members of a community (Rogers, 1995). Based on perceptions of relative advantage, compatibility, complexity, trialability, and observability, the user decides whether or not to adopt a technology (Rogers, 2002). Therefore, technology adoption is highly dependent on user's perceptions.

Several studies have identified the importance of the community and user perspective on cookstove adoption. Despite the importance of demand-side attributes that influence clean energy technologies' adoption, many energy access models emphasize increasing technology accessibility for higher adoption rates, however, accessibility is likely not the bottleneck whereas adoptability and usability may be (Moses, Pakravan, and MacCarty 2019). A study in Malaysia ranked multiple attributes that associated user experience with small scale household renewable energy technologies' adoption such as awareness, ease of use, cost, perceived behavioral control, and relative advantage (Alam et al. 2014). Results of their study suggest that manufacturers should design technologies that are easy to use in order to increase the likelihood of users' uptake. Malakar, Greig and van de Fliert (2018) discuss how incorporating attributes of cooking as a social practice could inform policies for more effective technology adoption strategies. Another study reviewed a survey of 137 stove dissemination programs to evaluate main reasons for success and failure of such projects and found that widespread adoption requires both engineering advancements and effective involvement of both users and local manufacturers (Barnes et al. 1994). They argue that considering the needs of main users, in this case the female cooks, at the time of designing the stoves is crucial for increasing the likelihood of bringing benefits of ICS to more people. Incorporating the users into the design process by understanding their motivations and decision-making process is known to be essential to successful dissemination but still remains a challenge over twenty years from the time of that study.

### 2.2.1 Considerations for residential energy technology adoption

A residential clean energy technology should align with users' attitudes and beliefs to benefit both the user and environment. Addressing consumer preferences is not limited to only the design of a user-centered technology, but also the development of strategies that convert the *need* into *demand* for the technology (Brown and Katz, 2011). Understanding how women, as the main cooks, prioritize cleaner cooking practices over other household goals highlights the importance of systematic analysis of user's beliefs and attitudes that formulate behaviors. If households do not perceive the importance of changing their traditional cooking behavior, they are less likely to adopt a new cooking technology. A study in urban settings in India monitored user behavior in early stages of improved cookstove adoption for six weeks (Thandapani and Woodbridge 2011). Results revealed that although the single user studied expressed interest in cooking with the ICS, her experience with the stove led her not to. Based on her habits she did not regularly remove the ashes from the stove, and she only used one of the two burners provided, reducing the ICS efficiency significantly. Finally, she perceived the reduced smoke emission from the ICS as a drawback since smoke keeps mosquitos away during cooking. In this case, lack of attention to the user's attitude toward cooking and habits resulted in a less efficient and more burdensome experience for the user that led her to stop using the ICS, suggesting that addressing these attributes during design and distribution of clean technologies could increase adoption rates.

Cooking occurs multiple times each day, and traditional cooking practices are deeply entrenched in a culture. As a result, rapid technology dissemination along with a brief informational campaign without any support or follow-up in later stages is not likely to impact household's behavior over time. A long-term study in rural India followed stove adoption behavior in a community for four years (Hanna, Duflo, and Greenstone 2016). The study's results indicated that even though performance of the introduced technology was effective in laboratory tests, low stove valuation by users prevented improvements in health or firewood consumption because stoves were not used frequently enough to displace traditional cooking methods. Their study concluded that if users decide not to use the stove regularly and properly, avoid regular maintenance, or do not update their beliefs about how to use it, desired health and fuel savings may not be achieved. Therefore, it is important to update users' attitude and knowledge about the importance of changing traditional cooking methods through a medium to long term information campaign. A similar study in rural Bangladesh traced low ICS adoption rates to lack of user valuation regarding importance of the cleaner cooking practices, despite that 94% of respondents believed that smoke emissions of traditional cooking practices are unhealthy (Mobarak et al. 2012). That study determined that cleaner cooking practices had a lower priority in the household than several other demands such as sanitary latrines, electricity access, school attendance, and doctor consultations. As a result, information campaigns to inform households regarding negative consequences of traditional practices combined with more user-oriented technologies were recommended to achieve higher adoption rates.

Information campaigns can effectively increase public awareness regarding the issues associated with inefficient practices and present technological alternatives as a solution, helping to not only inform users about issues and also to increase social influence to adopt clean energy technologies in a community. Recent work in decision-making analysis suggest that choices are social, meaning that society plays an important role in influencing users for making decisions (He et al. 2014; McFadden 2010). This social pressure is a function of community scale social relationships, where bonding social capital, or the intra-communal links, can significantly contribute to the likelihood of individual technology usage (Adrianzén 2014). Reviewing three case studies of technology adoption in rural communities, Kumar and Igdalsky (2019) argue that three social networks attributes influence the overall ICS dissemination including: the social structure of the community, network of women, and influential community members (P. Kumar and Igdalsky 2019). This means that households are more likely to adopt a technology if their social ties are satisfied with it and less likely to keep using a technology if their trusted peers discourage them based on failed performance or other negative experiences.

One of the most practiced methods to update users' preferences for changing their behavior toward positive actions such as handwashing or recycling is behavior change communication (BCC) (Briscoe and Aboud 2012). There are multiple methods used to inform individuals regarding the negative health or environmental impacts of current behaviors such as nutrition sensitive agriculture (Ruel, Quisumbing, and Balagamwala 2018), water treatment interventions (Parker Fiebelkorn et al. 2012), and sanitation and hygiene improvement (Huda et al. 2012). Regarding traditional cooking practices, a study in four lower-middle income countries indicated affordability as the main barrier to adoption of ICS. However, many of the respondents who expressed this also had discretionary consumer items such as TVs and mobile phones at the time of the survey (Evans et al. 2017). The authors suggest that effective BCC techniques should be applied for increasing awareness to encourage users to prioritize the ICS usage over other goals.

Although BCC is important in increasing the awareness regarding improvements in health associated with adopting a clean technology, increasing awareness may lead to technology acquisition but not necessarily technology usage. In the case of ICS adoption, there are different attributes that must be addressed along with effective supply side policies to lead to gradual transition of households from traditional practices to ICS (Shankar et al. 2014). These include financing options for buying ICS, cultural considerations, and effective user engagement. Such a transition driven by consistent and correct use of ICS will eventually maximize the benefits of ICS adoption.

The Global Alliance for Clean Cookstoves, now the Clean Cooking Alliance, has defined a value chain from distribution and initial uptake to sustained adoption of clean cookstoves. Based on indicators across this value chain,  five important measurement areas of clean cookstove adoption are defined as distribution and uptake, promotion, policy and coverage, adoption, and sustained adoption (P. Kumar and Mehta 2016). Sustained adoption is the ultimate goal of clean technology diffusion projects and can occur when three conditions are met: (1) the individual has the opportunity to adopt the technology, (2) the individual is able to work with it, and (3) the individual is motivated to change their behavior (Jürisoo, Lambe, and Osborne 2018). These conditions can be achieved via user-oriented recommendations to improve impacts of technology projects including developing user manuals and trainings that are accessible to the audience, design for usability, and customer service after a sale (Moses, Pakravan, and MacCarty 2019). These user-oriented recommendations must be developed through a better understanding of user motivation and behavior.

### 2.2.2 Models of behavior

Although various studies have identified attributes that influence individuals' decision-making regarding technology adoption, there is a need for improved systematic and comprehensive analysis of these significant attributes. Because user preferences and values are reflected through their intentions, a better understanding of users' behavioral intention could inform the designers and project implementers about best approaches for technology design and dissemination to improve adoption. Borrowing methods from other sectors may enable researchers to better characterize these intentions in terms of energy efficient technology adoption. To develop a method that incorporates these aspects of the decision-making process, theories from disciplines beyond typical engineering design are needed.

There are several validated approaches that investigate technology adoption, including the diffusion of innovations theory (E. M. Rogers 1995), technology acceptance model (Davis 1989), social cognitive theory (Bandura and Cervone 1986), Unified Theory of Acceptance and Use of Technology (Viswanath Venkatesh et al. 2003), and TPB (Ajzen 1985). Reviewing these models suggest that certain attributes have been incorporated in more than one approach which increases the likelihood that these attributes do play an important role in explaining technology adoption behavior. Such attributes include user attitudes, perceptions, evaluations, social influences, and hindrances (Sharma and Mishra 2014). Methods to predict health and environmental behaviors are of interest because the goal of clean technologies is essentially to perform the same tasks as conventional technologies but with less negative consequences to environment and/or health. Since such environmental or health impacts may be intangible or long-term, the benefit of using clean technologies may not be instant and perceivable by users. Therefore, it is important to apply a model that is proven to successfully predict pro-environmental and health behaviors.

Figure 2.1 shows the methods developed in the behavioral health and environmental psychology fields for predicting behavior. The left circle describes existing methodologies that are prominent in predicting health related behaviors based on models reviewed by Conner and Norman (2005). In environmental psychology, multiple theories are proposed to study the interaction of individuals with their surroundings, with the most frequently applied models shown in the circle on the right (Gifford, Steg and Reser, 2011; Klöckner, 2015).

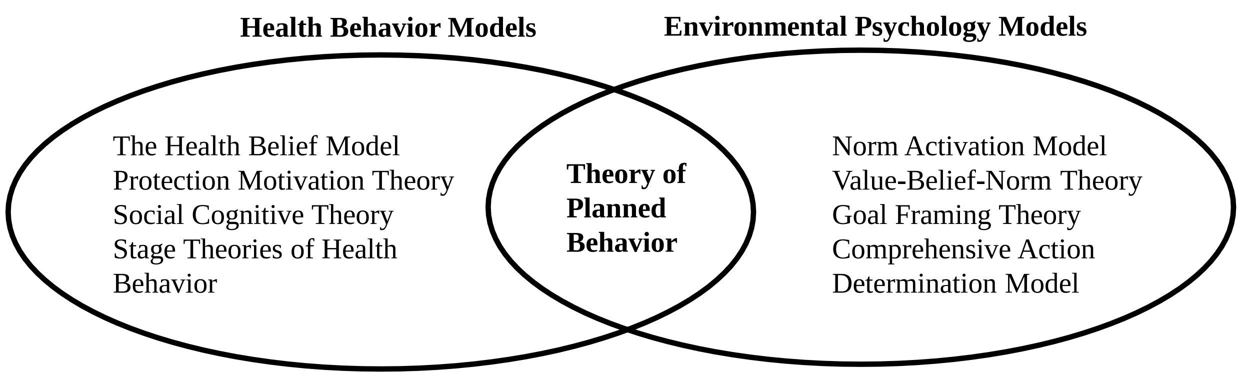


Figure 2.1 Decision making theories in both health-related behaviors and environmental behaviors (Mohammad H. Pakravan 2018)

As illustrated by the overlap in the Figure 2.1, the Theory of Planned Behavior (TPB) is a method that predicts individuals' behaviors from both health and environmental contexts. This model was selected as the focus of this study because it has been proven to be robust in both health and environmental contexts, and both are applicable to the design of clean technologies. Additionally, TPB is among the parsimonious models of behavior analysis, which is particularly important in the domain of social studies in low resource settings. Since data collection in such settings demands extra logistical requirements and expenses, lean approaches with the strongest prediction power based on minimum data points and model attributes are best suited for such studies.

Developed by Icek Ajzen (Ajzen 1985, 1991), TPB assumes that the best predictor of behavior is intention. Here, intention is a variable representing readiness of an individual to perform or avoid a certain behavior. This assumption is validated through multiple studies related to attitude-behavior relation models in the literature (Abraham, Sheeran, and Johnston, 1998; Conner and Norman, 1996; Maddux, 1999). A meta-analysis of experimental evidence suggests that a medium-to-large intention change is likely to lead to a small-to-medium behavior change (Webb and Sheeran, 2006). Health and environmental behaviors including food consumption decisions (Ajzen, 2015), contribution of specific job factors and work-family conflicts on healthy work intention (Shukri, Jones, and Conner, 2016), recycling (Botetzagias, Dima, and Malesios, 2015), and consuming green products by youth (Yadav and Pathak, 2016) have all been analyzed using TPB. There are multiple reviews and meta-analyses of studies that have applied TPB for the psychological decision-making process related to health and environment (Albarracín et al., 2001; Armitage and Conner, 2001; Conner and Armitage, 1998). The popularity of TPB is due to the structural simplicity and universal applicability of the theory across behavioral domains (Klöckner, 2015). According to this theory, intention is composed of three categories of attributes that form the decision (Table 2.1).

Table 2.1. TPB Constructs

| | | |
|---|---|---|
| ATB | Attitude Toward Behavior | Outcome of an individual's personal beliefs and her evaluations regarding validity of such beliefs. |
| SN | Social and Subjective Norms | Outcome of an individual's normative beliefs about a specific behaivor, beliefs about whether people important to the person approve or disapprove the behavior, and his or her evaluation of the social pressure for conforming to such normative beliefs. |
| PBC | Perceived Behavioral Control | An individual's perception for the control she has over the behavior is a function of her control beliefs and the power she feels in such control beliefs. |

The present study applies TPB to quantify users' intentions for adopting clean energy technologies that are beneficial to both environment and health in the context of ICS adoption in low resource settings.

## 2.3 Methodology

This study hypothesizes that when a clean cookstove is affordably accessible, a household's intention to use available alternatives is the main determinant of the choice whether or not to adopt, and that the intention can be quantified using the three categories of attributes of TPB referred to as TPB constructs (Table 2.1). Therefore, intention is explained based on attitude toward behavior, social norms, and perceived behavior controls. These attributes are quantified through conducting TPB based surveys in target communities (Figure 2.2).

### 2.3.1 Survey design

Survey questions to capture TPB constructs were designed based on standard methods presented in the literature (Francis *et al.*, 2004; Ajzen, 2013; Oluka, Nie, and Sun (2014)). After careful definition of research question and purpose of the study, a pilot study to capture widespread beliefs in the target community was conducted. Results of the pilot study informed new questions based on prominent beliefs in the community that respondents heterogeneously prioritize and have different evaluations of them. Attributes that are designed to directly measure TPB constructs should be internally consistent ensuring such questions reliably measure the same construct, and questions should be carefully designed to avoid any implicit bias. Figure 2.2 presents an example of how different questions capture beliefs and evaluations under the umbrella of TPB constructs in this study. Responses are based on a Likert scale to provide a quantitative basis for further analysis.

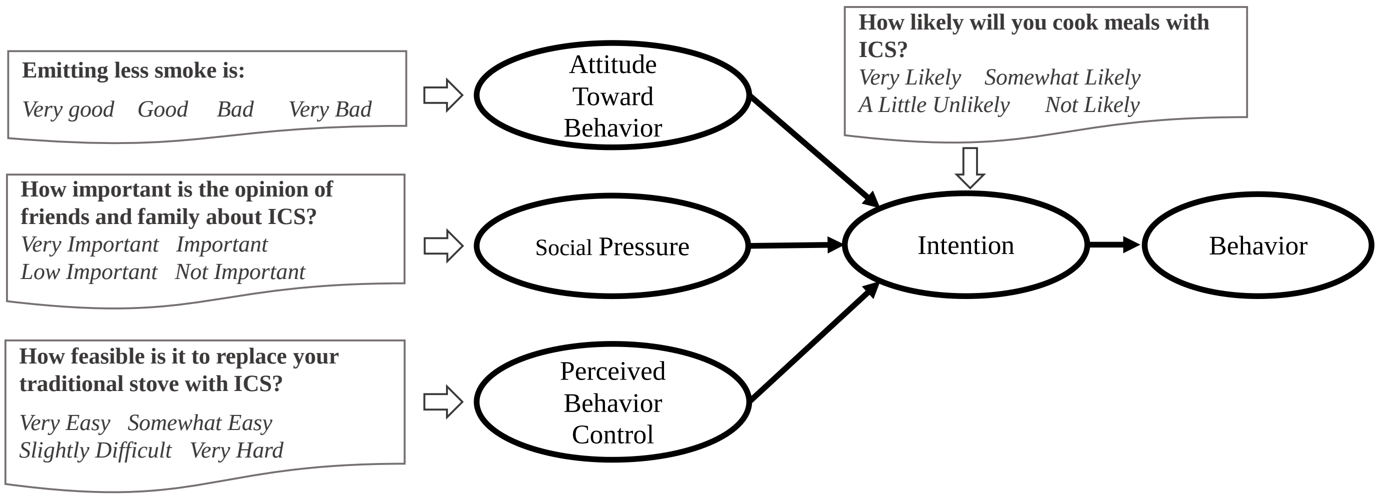


Figure 2.2. TPB framework and example survey questions (Pakravan, 2018)

Using the survey results, attitude toward adoption (ATB), social norms (SN), and perceived behavior control (PBC) serve as explanatory variables and weight of their correlation with intention as the dependent variable was estimated (Equation 1). These variables are based on coded responses of relevant survey questions presented in Appendix. The error term captures every other explanatory variable of intention that are not included in the model. Following statistical guidelines, multiple regression analyses were used to find the most relevant attributes with the highest model significance (Hankins, French, and Horne, 2000). The level of each category's influence on the intention is determined by conducting ordinal logistic regression to calculate the weight of influence of each category. Since ordinal logistic regression applies a mathematical transformation of Equation (1), coefficients are reported either as log odds or odds ratios. If the model does not violate parallel regressions assumption, estimated coefficients can be interpreted quantitatively as odds ratios, indicating that one unit increase on the Likert scale in the explanatory variable is associated with the respective coefficient's change in the levels of dependent variable, with all other variables held constant. For example, one unit increase in the individual's attitude toward smoke reduction improves odds of higher levels of their intention to cook more meals with ICS β1 times.

$$Intention\ (Ordinal\ Logit) = \beta_0 + \beta_1\,(ATB) + \beta_2\,(SN) + \beta_3\,(PBC) + \varepsilon \qquad (1)$$

The intention as dependent variable in the regression model was captured by asking multiple questions regarding households' willingness to cook more meals with ICS, their main meals of the day with ICS, or asking them to approximate the number of meals they plan to cook with it each week (Appendix I). For each of the three attributes of TPB, three to five questions were asked to capture a multitude of beliefs related to that category. Responses of each question were designed to be simple and understandable for the respondents and used to capture a range of options based on a Likert scale. The responses were coded from ‘1’ representing ‘strongly disagree’ or equivalent to ‘5’ representing ‘strongly agree’ or equivalent. Some of the questions had the option ‘I don’t know’ for those respondents who could not hold any opinion toward one side or another. For the purpose of analysis, ‘I don’t know’ responses were coded as missing observations to avoid any bias in the analysis caused by putting statistical weight on a respondent’s inability to pick a side.

### 2.3.2 Data collection

Survey data were collected from a total of 549 households, including 379 households in the Copan Ruinas region of Honduras, and 170 households in the Apac district of Uganda (Table 2.2). All research with human subjects was overseen by the Oregon State University Institutional Review Board under study number 7257. Field partners carried out a general impact assessment survey before and after distribution of ICS to the participating households. In the baseline surveys taken prior to ICS distribution, the households’ experiences with traditional stoves and their impacts on livelihood, as well as expectations regarding an improved cookstove were measured. After a trial phase for the cookstove (sixty days in Honduras and thirty days in Uganda), the follow-up survey was conducted to re measure the TPB attributes, and to evaluate user experiences and behavior impacts of ICS adoption. The households in Honduras sample received their ICS fully subsidized, while in Uganda’s sample the stove price of 8,000 to 10,000 Ugandan Shillings (~ \$2.20-\$2.70 USD), equivalent to 40% of the average weekly income of the head of household was partially subsidized.

Table 2.2 Demographic information of study's samples

| | Honduras | Uganda |
|---|---|---|
| Sample size | 379 | 110 |
| Number of villages | 8 | 2 |
| Affected population | 1765 | 581 |
| Number of children (under 17) | 684 (39% of affected population) | 204 (35% of affected population) |
| Main cook’s age distribution | Minimum: 15<br>Maximum: 94<br>Average: 37.4<br>Std. dev.: 14.5 | Minimum: 15<br>Maximum:75<br>Average:36.16<br>Std. dev.:15.32 |
| Income average (per week) | 770 HNL<br>(~ 32 USD) | 24000 UGX<br>(~ 6.70 USD) |
| Education<br>(primary income earner) | No education 70%<br>Incomplete primary 30% | No education 10%<br>Incomplete primary 17%<br>complete primary 28%<br>Incomplete secondary 12%<br>Complete secondary 20%<br>College/university 11% |

## 2.4 Results and discussion

The TPB questionnaire served as a sub-section of the general impact assessment survey being implemented by the NGO partners. The TPB portion contained twenty-eight questions in the Honduras project and eighteen questions in the Uganda project to cover different aspects of beliefs and behavior components. Tables 3 through 6 present the mean, standard deviation and pair wise correlation of variables in each study.

Table 2.3 Means, standard deviations and correlations between variables – Baseline, Honduras

| | ATB1 | ATB2 | SN1 | SN2 | PBC1 | PBC2 | Intention |
|---|---|---|---|---|---|---|---|
| ATB 1 | 1.0 | | | | | | |
| ATB 2 | 0.46*** | 1.0 | | | | | |
| SN 1 | 0.11** | 0.16*** | 1.0 | | | | |
| SN 2 | 0.11** | 0.11** | 0.12** | 1.0 | | | |
| PBC 1 | 0.10* | 0.12** | 0.06 | -0.02 | 1.0 | | |
| PBC 2 | 0.08 | 0.17*** | -0.01 | -0.10* | 0.17*** | 1.0 | |
| Intention | 0.16*** | 0.12** | 0.00 | 0.04 | 0.14** | 0.15*** | 1.0 |
| Mean | 3.54 | 3.48 | 3.33 | 3.52 | 2.72 | 3.05 | 3.81 |
| Standard Deviation | 0.498 | 0.50 | 1.068 | 0.50 | 1.096 | 1.488 | 0.415 |

Table 2.41 Means, standard deviations and correlations between variables –Follow-up, Honduras

| | ATB1 | ATB2 | SN1 | SN2 | PBC1 | Intention |
|---|---|---|---|---|---|---|
| ATB 1 | 1.0 | | | | | |
| ATB 2 | 0.35*** | 1.0 | | | | |
| SN 1 | 0.14*** | -0.05 | 1.0 | | | |
| SN 2 | 0.14** | -0.13** | 0.14** | 1.0 | | |
| PBC 1 | 0.03 | 0.11** | 0.02 | -0.09* | 1.0 | |
| Intention | -0.13** | -0.07 | 0.06 | -0.02 | 0.04 | 1.0 |
| Mean | 4.74 | 4.77 | 4.47 | 4.26 | 4.89 | 2.66 |
| Standard Deviation | 0.457 | 0.440 | 0.828 | 1.138 | 0.551 | 0.600 |

Table 2.5 Means, standard deviations and correlations between variables – Baseline, Uganda

| | ATB1 | ATB2 | SN1 | SN2 | PBC1 | PBC2 | Intention |
|---|---|---|---|---|---|---|---|
| ATB 1 | 1.0 | | | | | | |
| ATB 2 | 0.29*** | 1.0 | | | | | |
| SN 1 | 0.14* | 0.15** | 1.0 | | | | |
| SN 2 | -0.06 | 0.12* | 0.18** | 1.0 | | | |
| PBC 1 | -0.09 | 0.12* | 0.19*** | 0.21*** | 1.0 | | |
| PBC 2 | 0.02 | 0.12* | 0.26*** | 0.13* | 0.41*** | 1.0 | |
| Intention 1 | 0.19** | 0.38*** | 0.25*** | 0.28*** | 0.45*** | 0.07 | 1.0 |
| Intention 2 | -0.03 | 0.16** | 0.20*** | 0.15** | 0.18** | 0.23*** | 0.32*** |
| Mean | 3.53 | 3.56 | 3.60 | 2.82 | 3.12 | 3.07 | 3.37 |
| Standard Deviation | 0.677 | 0.602 | 0.913 | 0.987 | 1.443 | 1.168 | 0.988 |

Table 2.6 Means, standard deviations and correlations between variables – Follow-up, Uganda

| | ATB1 | ATB2 | SN1 | SN2 | SN3 | PBC1 | PBC2 | PBC3 | Int.1 | Int.2 |
|---|---|---|---|---|---|---|---|---|---|---|
| ATB1 | 1.0 | | | | | | | | | |
| ATB2 | 0.36*** | 1.0 | | | | | | | | |
| SN1 | 0.24** | 0.18* | 1.0 | | | | | | | |
| SN2 | -0.02 | -0.06 | 0.27** | 1.0 | | | | | | |
| SN3 | 0.20* | 0.07 | 0.19* | 0.32*** | 1.0 | | | | | |
| PBC1 | -0.03 | -0.03 | -0.07 | -0.07 | 0.02 | 1.0 | | | | |
| PBC2 | 0.32*** | 0.19* | 0.13 | -0.02 | 0.08 | 0.41*** | 1.0 | | | |
| PBC3 | 0.22** | 0.22** | 0.19* | 0.00 | 0.17 | -0.08 | 0.12 | 1.0 | | |
| Int.1 | 0.33*** | 0.28*** | -0.06 | -0.16 | 0.21** | 0.06 | 0.35*** | 0.24** | 1.0 | |
| Int.2 | 0.20* | 0.04 | 0.00 | -0.14 | 0.27*** | 0.00 | 0.08 | 0.32*** | 0.44*** | 1.0 |
| Mean | 3.63 | 3.44 | 3.76 | 2.51 | 3.23 | 3.62 | 3.38 | 3.19 | 3.41 | 3.53 |
| Standard Deviation | 0.593 | 0.567 | 0.501 | 1.554 | 0.835 | 0.830 | 0.674 | 0.999 | 0.860 | 0.501 |

Although applying TPB to quantify users' experiences and expectations is a straightforward process, researchers must pay attention to the validity of models and data in addition to interpreting the results. In this section, the two datasets are analyzed separately to present verification procedure of TPB results.

2.4.1 Results from Honduras

Table 2.7 Results of TPB analysis in Honduras

| | **Baseline Model I** | **Baseline Model II** | **Baseline Model III** | **Follow-up Model I** | **Follow-up Model II** |
|---|---|---|---|---|---|
| **Dependent Variable** | *Will you cook your principal meals mainly with [ICS brand]?* | | | *How many meals do you cook each day with [ICS brand]?* | |
| **Independent Variable** | | | | | |
| **ATB 1**: *Fuelwood consumption* | | | -0.3587 (0.2997) | -0.2982 (0.3351) | |
| **ATB 2**: *Smoke emission* | 0.6143* (0.6633) | 0.6305 (0.7230) | 0.7361* (0.8713) | -0.7594** (0.3658) | -0.8395** (0.3285) |
| **SN 1**: *Support of friends and family* | -0.1009 (0.3222) | | | -0.0209 (0.1786) | |
| **SN 2**: *Importance of opinion of friends and family* | | -0.0279 (0.1998) | 0.0154 (0.1980) | -0.1325 (0.1267) | -0.1599 (0.1252) |
| **PBC 1**: *Obtaining permission or not* | | 0.3449*** (0.1621) | 0.3811*** (0.1758) | 0.0178 (0.2112) | 0.0855 (0.2112) |
| **PBC 2**: *Feasibility of changing habits* | 0.2565* (0.1781) | 0.2751* (0.2081) | 0.2836* (0.2093) | | |
| *N* | 255 | 239 | 237 | 297 | 309 |
| *Wald Chi-squared* | 6.47* | 18.28*** | 19.50*** | 7. 34 | 7.66* |
| *AIC* | 223.5094 | 205.6636 | 202.2235 | 434.4808 | 456.5564 |
| *BIC* | 237.6744 | 223.0459 | 223.0319 | 464.0306 | 478.9564 |
| *Log pseudo likelihood* | -107.7546 | -97.8318 | -95.1117 | -209.2404 | -222.2782 |

Results are in log odds.
* p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01
Robust standard errors are in parenthesis

Results of models of the first study are presented in the Table 2.7, showing the variables for each TPB construct that were most significant to predicting intention as measured by the dependent variable. Three models for the baseline study have higher probabilities to reject the null hypothesis of Wald Chi square test that all estimated coefficients are equal to zero. Therefore, independent variables in the baseline models are likely to influence the intention. Baseline Model II and III show more promising results than Model I. These two models both have more significant Wald Chi-square measures to reject the hypothesis of Wald Chi square test, as well as relatively lower AIC and BIC values. However, due to lack of representation of some categories of dependent variable in the dataset, parallel regression assumption could not be tested. As a result, reported coefficients are in log odds, hence should not be interpreted quantitatively. Results of three models of baseline suggest that reducing smoke emission is likely to have significant influence in households' intention to use an ICS. Less obligation to ask permission or consult with another family member to cook with ICS is likely to have positive influence on intention. Having a higher perception regarding feasibility to change long term habits in all three models suggests that it is likely to increase intention for cooking principal meals with ICS.

Models of follow-up study in Honduras are reported in log odds due to failure to evaluate parallel regressions assumption. Additionally, Model I fails to reject the null hypothesis of Wald Chi-square test suggesting that all independent variables are likely to have no significant influence in describing intention. However, the significant and negative coefficient of smoke emission attribute in both models suggest that individuals with stronger attitude toward reducing smoke emissions are less likely to cook main meals with ICS in a daily basis. This is an important finding indicating that households' expectations regarding smoke emission reduction is likely to be not fulfilled during trial. Further interpretation and quantification of users attitude change based on the baseline and follow-up study in Honduras is incorrect due to biases further discussed below. of the data is not Similar to the baseline study the data in follow-up suffers from lack of representation of some categories of dependent and independent variables and biases discussed in detail below. Addressing such biases has led this study to conduct a successful user behavior evaluation in Uganda.

2.4.1.1 Survey and Study Bias

Design of the study, implementation, and survey questions are among the key factors that determine quality and reliability of results. In the first study, some of the questions were biased in design and not interpretable. For example, one question asked, “How important is reducing fire smoke?” The word “important” in this question causes an inherent bias toward importance of less fire smoke. Therefore, the respondent is unintentionally directed to report higher levels of importance than what she may believe. The correct wording of survey questions should have no direction or inherent biases (Iarossi, 2006). For example, the correct way to ask the question mentioned above could be: “On a scale of one to five (one not important at all, five very important) what do you think about reducing the smoke a cookstove emits?”

In addition to potential biases in some of the survey questions, the overall design of the study was also associated with biases. Due to the objectives of the project partner, the stoves that were used by households during the trial phase were distributed without any cost to the participants. Since respondents were offered a free ICS, they reflected their gratitude through their answers to survey questions. This induces both the Hawthorne effect and socially desirable bias, in which respondents answer the survey questions in a way that they perceive the researcher wants to hear rather than expressing real opinions (Dodou and de Winter, 2014; McCambridge, Witton, and Elbourne, 2014). As a result, recorded data heavily leans toward the positive end of Likert scale questions. To avoid such biases researchers should design the study in a way that leads to recording respondents’ actual opinions. Based on this observation, it is important to avoid promises or practices of free gifts in exchange for collecting respondents’ opinions in future studies. Detailed discussion on how to remedy for these two biases are presented by Levitt & List (2011) and Nederhof (1985).

2.4.1.2 Data Separation and Internal Consistency

Data screening is important to correct for potential violations of the assumptions of TPB and/or regression analysis. The observations in the first dataset of this study were suffering from quasicomplete separation, and low internal consistency. When one or more levels of independent variables are not describing the outcome, such lack of representation is referred to as separation (Albert and Anderson, 1984). Complete separation causes estimated coefficients to approach infinity, while quasicomplete separation causes inflated coefficients. In the Honduras study’s follow-up dataset, the dependent variable (observed questions for intention) had no recorded observation for some levels of responses which led to invalid regression results and inflated coefficients. Several approaches that could be applied to address separation are discussed by Heinze and Schemper (2002), including omission of variables that have low or no variation and exact logistic regression. However, any approach has consequences that may influence the research hypotheses and invalidate conclusions from the analysis. The experience of researchers in this study suggests that the best way to address separation for conducting TPB analysis in low-resource regions is through increasing sample size, careful design of the questions that yields heterogeneous recorded responses from participants and parsimony in observed variables.

Internal consistency is a measure of reliability that informs how observed variables describe the attributes of interest (Trochim and Donnelly, 2008). In the application of TPB, if questions intend to directly ask about particular constructs of the model such as ATB, SN, and PBC, the questions should have a high degree of internal consistency (Ajzen, 2013). Therefore, it is important to select direct measures that show high reliability scores such as Cronbach alpha in the pilot study. For example, in the first study researchers included change in taste of food along with smoke emission and firewood consumption as observed variables while change in taste of food did not show consistency with smoke emission reduction and firewood consumption saving.

Learning from such errors, the second project in this study was able to successfully conduct TPB analysis and interpret results for future policy applications and design practices. In addition to controlling for discussed biases, robust standard errors were used to address potential existence of heteroscedasticity and models are corrected for parallel regression assumption to justify interpreting their coefficients in terms of odds ratios.

### 2.4.2 Results from Uganda

Lessons learned from the sources of error and issues discussed above informed design of a second study in the Apac district of Uganda. In the second study, the distributed ICS was partially subsidized to motivate respondents to participate in the study. Therefore, participants are more likely to report their opinions with less probability of occurrence of socially desirable bias. Results of the Uganda pilot test presented significant internal consistency between smoke emission, firewood consumption and stove durability for the attitude toward ATB. While changing habits, the husband's satisfaction of food, and self-confidence regarding change in kitchen equipment elicited to represent consistent measures of PBC. Questions designed based on these results were shared with community members before data collection to avoid potential biases and back translate procedure. Researchers also explained the purpose of the study and the method to collect data for behavior related Likert scale questions to the data collectors using a few videos to help avoid surveyor biases and elicit more granular responses from participants.

Table 2.8 Results of TPB analysis in Uganda

| | Baseline Model I [i] | Baseline Model II [ii] | Follow-up Model I [ii] | Follow-up Model II [ii] |
|---|---|---|---|---|
| **Dependent Variable** | *How many meals do you think you will cook with the improved cookstove during each week?* | | *Now that you have experienced [ICS brand] how likely is it that you cook all your main meals with that?* | *How often do you think you will use [ICS brand] in next few months to cook your main meals?* |
| **Independent Variable** | | | | |
| **ATB 1***: Fuelwood consumption* | 0.5541** | 1.1833 | 1.3361 | 2.6782** |
| | (0.4580) | (0.2765) | (0.6185) | (1.2842) |
| **ATB 2***: Smoke emission* | 1.1043*** | 3.2772*** | 1.1565 | 2.1335* |
| | (1.0895) | (1.2047) | (0.5150) | (0.9730) |
| **SN 1***: Support of friends and family* | 0.2708 | 1.4703** | | 0.4525 |
| | (0.2512) | (0.2803) | | (0.2513) |
| **SN 2***: Importance of opinion of friends and family* | 0.4237** | | 0.5373* | 0.6441 |
| | (0.2734) | | (0.1786) | (0.2007) |
| **SN 3***: Importance of neighbors' stove types* | | | 1.3852** | |
| | | | (0.2236) | |
| **PBC 1***: Obtaining permission or not* | 0.6833*** | | | 0.7950 |
| | (0.2579) | | | (0.2578) |
| **PBC 2***: Power to make decision independently* | 0.4619** | 0.8986 | | 2.5113*** |
| | (0.1140) | (0.1341) | | (0.8898) |
| **PBC 3***: Change of habit* | | | 2.7253*** | |
| | | | (0.7831) | |
| *N* | 172 | 172 | 87 | 83 |
| *Wald chi-squared* | 61.01*** | 24.94*** | 25.19*** | 17.98*** |
| *AIC* | 309.5092 | 343.6030 | 190.3458 | 103.9193 |
| *BIC* | 340.9841 | 368.7829 | 212.5389 | 120.8512 |
| *Log pseudo likelihood* | -144.7546 | -163.8015 | -86.1729 | -44.9596 |

[i] Results are in log odds.
[ii] Results are reported in odds-ratios.
* p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01
Robust standard errors are in parenthesis

Results include two models for the baseline data and two models for the follow-up. Model I in the baseline study violates parallel regressions assumption. Therefore, its results are reported in log odds instead of their interpretable mathematical transformations, which are odds ratios. Nevertheless, because the independent variables are statistically significant, they indicate a higher likelihood of influencing intention as the dependent variable. Therefore, Model I suggests that at the baseline and before users experience the clean cookstove, their intentions to cook with clean cookstove is likely to be formed because of their positive attitudes (ATB) toward less smoke emissions and less firewood consumption rather than other issues investigated. In terms of SN, the more individuals value opinion of their friends and family, they are more likely to cook with the improved cookstove. Both attributes that represent PBC are indicators of an individual’s power and perception of authority she exercises to change her cooking device. Both attributes show a statistically significant correlation with intention, but in contradictory ways. Estimated odds ratio related to variable PBC1 is more than one, suggesting that the more individuals have authority to change their cooking device, the more likely they are to cook with improved cookstove. However, odds ratio of the variable PBC2 is less than one, suggesting the more respondents perceive themselves as independent decision makers, the less likely they are to change their cooking device. One potential explanation for this contradictory finding could be that the more independency households feel in making decisions for appliances, they tend to allocate available resources to the most pressing needs such as medicines and food instead of ICS.

In Model II the results are corrected for parallel regression assumption by removing the variables that were violating parallel regression assumption. Therefore, results of Model II are presented in odds ratios. This model indicates households’ attitudes toward importance of reducing smoke emissions is the most important factor that influences their intention to adopt improved cookstoves. On average, households with slightly stronger belief about importance of reducing smoke emission (one level on a scale of one to five) are 3.27 times more likely to cook two more meals with improved cookstoves. In addition, if households find their friends and family supportive and encouraging for cooking meals with an improved cookstove, the number of meals they cook with improved cookstove is likely to increase: the odds of cooking two more meals with ICS during each week for a household that feels slightly higher encouragement from friends and family regarding cooking with ICS (one level on a scale of one to five) is 1.47 times as likely as others.

The study in Uganda was based on partially subsidized stoves. As a result, participants in the follow-up study represent only a subsample of baseline participants who were willing to pay for a subsidized improved cookstove. Therefore, the models in the follow-up study are based on a smaller sample size. The dependent variable in follow-up Model I contains data related to households' intentions to cook all their meals with ICS. Results of this model suggest that after a trial period, households' intentions to cook with ICS is not likely to be significantly influenced by their attitudes toward smoke emission and firewood consumption. This finding suggests that their expectations in terms of reducing smoke emissions and less firewood consumption are likely to have been fulfilled by the stove. However, their intentions to cook all their meals with improved cookstove or fully replacing their traditional stoves with improved ones is likely to be influenced by their social norms and perception of the control they have over changing their behavior. In terms of SN, a household with slightly stronger (one level on a scale of one to five) feeling about the importance of friends and family's opinion is 0.53 times as likely as average to fully adopt ICS. In contrary, a household with slightly more sensitivity (one level on a scale of one to five) about the type of stove that neighbors are using is 1.38 times as likely as average to fully adopt ICS. One potential explanation for this inconsistency could be the difference in experiences of friends and family from neighbors. The study is conducted in a community where not necessarily every friend and family are participating in the trial phase yet many neighbors have received offers to participate in the study. As a result, opinions of friends and family might be inconsistent with the experiences of participating neighbors. The most significant attribute that influences intention in Model I of the follow-up study is perception of difficulty of changing habits to replace ICS with traditional stove. Results suggest that a cook that perceives this transition slightly easier (one level on a scale of one to five) than average is 2.72 times as likely to fully replace traditional stove in favor of the ICS that she has experienced in the trial phase. This finding presents the importance of habits and demonstrating the ease of using the ICS in determining successful transition of communities toward clean energy technology adoption.

In Model II of the follow up study in Uganda, the dependent variable captures the intention for cooking main meals in the future with ICS. The difference of this dependent variable with the one in Model I is that in Model I the emphasis is about fully replacing traditional stoves with ICS, while Model II is focused on the intention for early future's intention to keep using the stove particularly after the experiment when they will not expect any other surveyor.  Results of this model suggest their intentions are likely to be influenced by their ATB variables related to smoke emissions and firewood consumption. Respectively, individuals with slightly stronger belief regarding importance of less firewood consumption and reducing smoke emissions are 2.67 and 2.13 times as likely as average to cook main meals in early future with ICS.  In addition, the ability to make the decision for choice of cooking device independently is a significant determinant of intention for using ICS post-study. Based on the results of Model II, odds for individuals who perceive slightly higher independency in making this decision are 2.51 times higher than average to cook main meals with ICS in early future.

## 2.5 Conclusions and future work

This study presents a quantitative methodology for comprehensive evaluation of user intentions to adopt clean energy technologies that are designed and promoted with the intention to reduce the health burden, fuelwood consumption, and detrimental environmental impacts of traditional cooking practices. Through application of TPB in measuring behavioral attributes that influence intention of households to adopt clean cookstoves, insights are provided for technology designers and international development programs to develop products and implementation strategies that are more user oriented and, therefore, more likely to effectively replace their traditional counterparts. Since TPB can be applied in a wide range of sectors, lessons learned here can be applied to a variety of development projects.

Results of this study suggest that households' intentions to use a clean cookstove for main meals change due to the influence of different categories of behavioral attributes prior and after a trial phase. In the Uganda's study participants' intentions to use improved cookstove in the baseline was highly influenced by their attitudes toward reducing smoke emissions and encouragement of their friends and families, while in Honduras prior to trying ICS, households' attitudes toward the importance of reducing smoke emissions are likely to be influential in formulating their intentions for cooking principal meals with ICS or not. In terms of perceived hindrances, seeking the permission of the head of the family is likely to be the most important attribute that constrains such intentions for the main cooks. In the follow-up studies, intentions to use the ICS are influenced by different attributes. In Uganda, participants' with stronger attitude toward reducing their firewood consumption were more likely to express higher intentions for cooking principal meals with ICS, and households that place more value on the experience of their neighbors had a higher intention to cook their main meals with the ICS. In addition, households that perceived less hindrances to cook with ICS had higher intentions to cook more main meals with this stove.

This study also identified potential challenges to using TPB to predict behavior in low resource communities where language, culture, and level of education can introduce biases and create uncertainty in the recorded data. Sources of bias that could negatively influence the validity of models were identified. In addition, design of questions to minimize separation and increase internal consistency are needed. Therefore, careful attention to design and execution of survey questions is desired. During the multiple data collections required for this study, the research team was able to apply lessons learned to reduce many biases by training surveyors and updating survey designs to be more accurate.

Applying TPB as a systematic approach to analyze users' decision-making process for adopting clean technologies presents a comprehensive approach that highlights the technology up take phase for designers and implementers. The method provides insight for technology designers to focus on the design attributes that could reasonably fulfill users' expectations and priorities. Technology distribution policies could also benefit from this method by holding targeted information campaigns that lead users to realistic expectation of the technology performance, as well as customer support and follow up that reflect the dominant concerns of users. An intention to adopt a technology alone does not always translate directly to the behavior due to barriers beyond control of households, such as lack of access to affordable clean alternatives. Future work is recommended to link actual behavior in a long-term basis to TPB constructs for high fidelity results. In addition, the use of TPB to inform utility functions and agent based models in decision support tools should also be explored.

# References


Abraham, C., Sheeran, P., & Johnston, M. (1998). From health beliefs to self-regulation: Theoretical advances in the psychology of action control. *Psychology & Health*, *13*(4), 569–591. https://doi.org/10.1080/08870449808407420

Adrianzén, M. A. (2014). Social Capital and Improved Stoves Usage Decisions in the Northern Peruvian Andes. *World Development*, *54*, 1–17. https://doi.org/10.1016/j.worlddev.2013.07.004

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In *Action Control* (pp. 11–39). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Orgnizational Behavior and Human Decision Processes*, *50*, 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2013). Theory of Planned Behaviour Questionnaire . Measurement Instrument Database for the Social Science. Retrieved from http://www.midss.org/sites/default/files/tpb.construction.pdf

Ajzen, I. (2015). Consumer attitudes and behavior: the theory of planned behavior applied to food consumption decisions. *Italian Review of Agricultural Economics*, *70*(2), 121–138. https://doi.org/10.13128/rea-18003

Alam, S. S., Nik Hashim, N. H., Rashid, M., Omar, N. A., Ahsan, N., & Ismail, M. D. (2014). Small-scale households renewable energy usage intention: Theoretical development and empirical settings. *Renewable Energy*, *68*, 255–263. https://doi.org/10.1016/J.RENENE.2014.02.010

Albarracín, D., Johnson, B. T., Fishbein, M., & Muellerleile, P. A. (2001). Theories of reasoned action and planned behavior as models of condom use: A meta-analysis. *Psychological Bulletin*, *127*(1), 142–161. https://doi.org/10.1037/0033-2909.127.1.142

Albert, A., & Anderson, J. A. (1984). On the existence of maximum likelihood estimates in logistic regression models. *Biometrika*, *71*(1), 1–10. https://doi.org/10.1093/biomet/71.1.1

Armitage, C. J., & Conner, M. (2001). Efficacy of the Theory of Planned Behaviour: A meta-analytic review. *British Journal of Social Psychology*, *40*(4), 471–499. https://doi.org/10.1348/014466601164939

Bailis, R., Drigo, R., Ghilardi, A., & Masera, O. (2015). The carbon footprint of traditional woodfuels. *Nature Climate Change*, *5*(3), 266–272. https://doi.org/10.1038/nclimate2491

Bandura, A., & Cervone, D. (1986). Differential engagement of self-reactive influences in cognitive motivation. *Organizational Behavior and Human Decision Processes*, *38*(1), 92–113. https://doi.org/10.1016/0749-5978(86)90028-2

Barnes, D. F., Openshaw, K., Smith, K. R., & Van Der Plas, R. (1994). *What Makes People Cook with Improved Biomass Stoves? A Comparative International Review of Stove Programs*. Retrieved from http://documents.worldbank.org/curated/en/738011468766789505/pdf/multi-page.pdf

Botetzagias, I., Dima, A.-F., & Malesios, C. (2015). Extending the Theory of Planned Behavior in the context of recycling: The role of moral norms and of demographic predictors. *Resources, Conservation and Recycling*, *95*, 58–67. https://doi.org/10.1016/J.RESCONREC.2014.12.004

Bouzarovski, S., & Petrova, S. (2015). A global perspective on domestic energy deprivation: Overcoming the energy poverty-fuel poverty binary. *Energy Research and Social Science*, *10*, 31–40. https://doi.org/10.1016/j.erss.2015.06.007

Briscoe, C., & Aboud, F. (2012). Behaviour change communication targeting four health behaviours in developing countries: A review of change techniques. *SSM*, *75*, 612–621. https://doi.org/10.1016/j.socscimed.2012.03.016

Brown, T., & Katz, B. (2011). Change by Design. *Journal of Product Innovation Management*, *28*(3), 381–383. https://doi.org/10.1111/j.1540-5885.2011.00806.x

Conner, M., & Armitage, C. J. (1998). Extending the Theory of Planned Behavior: A Review and Avenues for Further Research. *Journal of Applied Social Psychology*, *28*, 1429–1464. https://doi.org/10.1111/j.1559-1816.1998.tb01685.x

Conner, M., & Norman, P. (1996). *Predicting health behaviour : research and practice with social cognition models*. Open University Press. Retrieved from http://psycnet.apa.org/record/1996-97268-001

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Dodou, D., & de Winter, J. C. F. (2014). Social desirability is the same in offline, online, and paper surveys: A meta-analysis. *Computers in Human Behavior*, *36*, 487–495. https://doi.org/10.1016/J.CHB.2014.04.005

Evans, W., Johnson, M., Jagoe, K., Charron, D., Young, B., Rahman, A., … Ipe, J. (2017). Evaluation of Behavior Change Communication Campaigns to Promote Modern Cookstove Purchase and Use in Lower Middle Income Countries. *International Journal of Environmental Research and Public Health*, *15*(1), 11. https://doi.org/10.3390/ijerph15010011

Francis, J., Eccles, M. P., Johnston, M., Walker, A., Grimshaw, J., Foy, R., … Bonetti, D. (2004). Constructing Questionnaire Based on The Theory of Planned Behaviour, A Manual for Health Services Researchers. *ReBEQI WP2 Theory of Planned Behaviour Questionnaires: Manual for Researchers FOREWORD*, 42. https://doi.org/0-9540161-5-7

Gifford, R., Steg, L., & Reser, J. P. (2011). Environmental Psychology. In *The IAAP Handbook of Applied Psychology* (pp. 440–470). Blackwell Publishing Ltd. Retrieved from https://www.rug.nl/staff/e.m.steg/giffordstegreser2011.pdf

Hankins, M., French, D., & Horne, R. (2000). Statistical guidelines for studies of the theory of reasoned action and the theory of planned behaviour. *Psychology & Health*, *15*(2), 151–161. https://doi.org/10.1080/08870440008400297

Hanna, R., Duflo, E., & Greenstone, M. (2016). Up in smoke: The influence of household behavior on the long-run impact of improved cooking stoves. *American Economic Journal: Economic Policy*, *8*(1), 80–114. https://doi.org/10.1257/pol.20140008

He, L., Wang, M., Chen, W., & Conzelmann, G. (2014). Incorporating social impact on new product adoption in choice modeling: A case study in green vehicles. *Transportation Research Part D: Transport and Environment*, *32*, 421–434. https://doi.org/10.1016/J.TRD.2014.08.007

Heinze, G., & Schemper, M. (2002). A solution to the problem of separation in logistic regression. *Statistics in Medicine*, *21*(16), 2409–2419. https://doi.org/10.1002/sim.1047

Huda, T. M. N., Unicomb, L., Johnston, R. B., Halder, A. K., Yushuf Sharker, M. A., & Luby, S. P. (2012). Interim evaluation of a large scale sanitation, hygiene and water improvement programme on childhood diarrhea and respiratory disease in rural Bangladesh. *Social Science & Medicine*, *75*(4), 604–611. https://doi.org/10.1016/J.SOCSCIMED.2011.10.042

Iarossi, G. (2006). *The Power of Survey Design A User's Guide for Managing Surveys, Interpreting Results, and Influencing Respondents*. The World Bank. https://doi.org/10.1596/978-0-8213-6392-8

Jeuland, M. A., Bhojvaid, V., Kar, A., Lewis, J. J., Patange, O., Pattanayak, S. K., … Ramanathan, V. (2015). Preferences for improved cook stoves: Evidence from rural villages in north India. *Energy Economics*, *52*, 287–298. https://doi.org/10.1016/j.eneco.2015.11.010

Johnson, M., Edwards, R., & Masera, O. (2010). Improved stove programs need robust methods to estimate carbon offsets. *Climatic Change*, *102*(3–4), 641–649. https://doi.org/10.1007/s10584-

010-9802-0

Johnson, N. G., & Bryden, K. M. (2012). Factors affecting fuelwood consumption in household cookstoves in an isolated rural West African village. *Energy*, *46*(1), 310–321. https://doi.org/10.1016/j.energy.2012.08.019

Jürisoo, M., Lambe, F., & Osborne, M. (2018). Beyond buying: The application of service design methodology to understand adoption of clean cookstoves in Kenya and Zambia. *Energy Research & Social Science*, *39*, 164–176. https://doi.org/10.1016/j.erss.2017.11.023

Klöckner, C. A. (2015). Decision Models — What Psychological Theories Teach Us about People's Behaviour. In *The Psychology of Pro-Environmental Communication* (pp. 69–102). London: Palgrave Macmillan UK. https://doi.org/10.1057/9781137348326_4

Kumar, P., & Igdalsky, L. (2019). Sustained uptake of clean cooking practices in poor communities: Role of social networks. *Energy Research and Social Science*, *48*(February 2018), 189–193. https://doi.org/10.1016/j.erss.2018.10.008

Kumar, P., & Mehta, S. (2016). Poverty, gender, and empowerment in sustained adoption of cleaner cooking systems: Making the case for refined measurement. *Energy Research and Social Science*, *19*, 48–52. https://doi.org/10.1016/j.erss.2016.05.018

Legros, G., Havet, I., Bruce, N., & Bonjour, S. (2009). *the Energy Access Situation in Developing Countries, A Review Focusing on the Least Developed Countries and Sub-Saharan Africa*. *UNDP WHO New York*. Retrieved from http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:THE+ENERGY+ACCESS+SITUATION+IN+DEVELOPING+COUNTRIES+A+Review+Focusing+on+the#0

Levitt, S. D., & List, J. A. (2011). Was There Really a Hawthorne Effect at the Hawthorne Plant? An Analysis of the Original Illumination Experiments. *American Economic Journal: Applied Economics*, *3*(1), 224–238. https://doi.org/10.1257/app.3.1.224

Lewis, J. J., & Pattanayak, S. K. (2012). Who adopts improved fuels and cookstoves? A systematic review. *Environmental Health Perspectives*, *120*(5), 637–645. https://doi.org/10.1289/ehp.1104194

Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., … Et, A. (2013). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. *The Lancet*, *380*, 2224–2260. https://doi.org/10.1016/S0140-6736(12)61766-8

Maddux, J. E. (1999). Expectancies and the social–cognitive perspective: Basic principles, processes, and variables. In *How expectancies shape experience.* (pp. 17–39). Washington: American Psychological Association. https://doi.org/10.1037/10332-001

Malakar, Y., Greig, C., & van de Fliert, E. (2018). Resistance in rejecting solid fuels: Beyond availability and adoption in the structural dominations of cooking practices in rural India. *Energy Research and Social Science*, *46*(July), 225–235. https://doi.org/10.1016/j.erss.2018.07.025

Masera, O. R., Bailis, R., Drigo, R., Ghilardi, A., & Ruiz-Mercado, I. (2015). Environmental Burden of Traditional Bioenergy Use. *Annu. Rev. Environ. Resour*, *40*, 15.15.301. https://doi.org/10.1146/annurev-environ-102014-021318

McCambridge, J., Witton, J., & Elbourne, D. R. (2014). Systematic review of the Hawthorne effect: New concepts are needed to study research participation effects. *Journal of Clinical Epidemiology*, *67*(3), 267–277. https://doi.org/10.1016/J.JCLINEPI.2013.08.015

McFadden, D. (2010). Sociality, Rationality, and the Ecology of Choice. In *Choice Modelling: The State-of-the-art and The State-of-practice* (pp. 1–17). Emerald Group Publishing Limited. https://doi.org/10.1108/9781849507738-001

Mobarak, A. M., Dwivedi, P., Bailis, R., Hildemann, L., & Miller, G. (2012). Low demand for nontraditional cookstove technologies. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(27), 10815–10820. https://doi.org/DOI 10.1073/pnas.1115571109

Moses, N. D., Pakravan, M. H., & MacCarty, N. A. (2019). Development of a practical evaluation for cookstove usability. *Energy for Sustainable Development*, *48*, 154–163. https://doi.org/10.1016/J.ESD.2018.12.003

Nederhof, A. J. (1985). Methods of coping with social desirability bias: A review. *European Journal of Social Psychology*, *15*(3), 263–280. https://doi.org/10.1002/ejsp.2420150303

Oluka, O. C., Nie, S., & Sun, Y. (2014). Quality Assessment of TPB-Based Questionnaires: A Systematic Review. *PLoS ONE*, *9*(4), e94419. https://doi.org/10.1371/journal.pone.0094419

Pakravan, M. (2018, June 8). Theory of Planned Behavior Framework and Example Survey. https://doi.org/10.5281/ZENODO.1285944

Pakravan, M. H. (2018, June 8). Decision Making Theories in both Health Related Behaviors and Environmental Behaviors. https://doi.org/10.5281/ZENODO.1285942

Parker Fiebelkorn, A., Person, B., Quick, R. E., Vindigni, S. M., Jhung, M., Bowen, A., & Riley, P. L. (2012). Systematic review of behavior change research on point-of-use water treatment interventions in countries categorized as low- to medium-development on the human development index. *Social Science & Medicine*, *75*(4), 622–633. https://doi.org/10.1016/J.SOCSCIMED.2012.02.011

Rogers, E. (2002). Diffusion of preventive innovations. *Addictive Behaviors*, *27*(6), 989–993. https://doi.org/10.1016/S0306-4603(02)00300-3

Rogers, E. M. (1995). *Diffusion of Innovations, 4th Edition.* Free Press.

Ruel, M. T., Quisumbing, A. R., & Balagamwala, M. (2018). Nutrition-sensitive agriculture: What have we learned so far? *Global Food Security*. https://doi.org/10.1016/J.GFS.2018.01.002

Ruiz-Mercado, I., Canuz, E., & Smith, K. R. (2012). Temperature dataloggers as stove use monitors (SUMs): Field methods and signal analysis. *Biomass and Bioenergy*, *47*, 459–468. https://doi.org/10.1016/J.BIOMBIOE.2012.09.003

Shankar, A., Johnson, M., Kay, E., Pannu, R., Beltramo, T., Derby, E., … Petach, H. (2014). Maximizing the benefits of improved cookstoves: moving from acquisition to correct and consistent use. *Global Health, Science and Practice*, *2*(3), 268–274. https://doi.org/10.9745/GHSP-D-14-00060

Sharma, R., & Mishra, R. (2014). *A Review of Evolution of Theories and Models of Technology Adoption Common service centres View project Common service centres View project*. Retrieved from https://www.researchgate.net/publication/295461133

Shukri, M., Jones, F., & Conner, M. (2016). Work Factors, Work-Family Conflict, the Theory of Planned Behaviour and Healthy Intentions: A Cross-Cultural Study. *Stress and Health*, *32*(5), 559–568. https://doi.org/10.1002/smi.2662

Smith, K. R., Bruce, N., Balakrishnan, K., Adair-Rohani, H., Balmes, J., Chafe, Z., … Rehfuess, E. (2014). Millions Dead: How Do We Know and What Does It Mean? Methods Used in the Comparative Risk Assessment of Household Air Pollution. *Chennai) College Park Kurt Straif (International Agency for Research on Cancer Sophie Bonjour (World Health Organization GenevaThe Health Effects Institute Annu. Rev. Public Health*, *35*, 185–206. https://doi.org/10.1146/annurev-publhealth-032013-182356

Thandapani, S., & Woodbridge, R. (2011). Assessing the Benefits of Early Stage Design Research of Rural BoP-Focused Energy Solutions in Urban Settings. In *ICoRD '11 International Conference on Research into Design*. Retrieved from http://www.ifmrlead.org/wp-content/uploads/2015/OWC/ICoRD_Assessing-the-Benefits-of-Early-Stage.pdf

Trochim, W. M. K., & Donnelly, J. P. (2008). *Research methods knowledge base*. Atomic Dog/Cengage Learning.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Webb, T. L., & Sheeran, P. (2006). Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological Bulletin*, *132*(2), 249–268. https://doi.org/10.1037/0033-2909.132.2.249

Yadav, R., & Pathak, G. S. (2016). Young consumers' intention towards buying green products in a developing nation: Extending the theory of planned behavior. *Journal of Cleaner Production*, *135*, 732–739. https://doi.org/10.1016/J.JCLEPRO.2016.06.120

# Chapter 3

## Design for clean technology adoption: integration of usage context, user behavior, and technology performance in design

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## Abstract

Clean technologies address climatic, environmental, and health concerns associated with their conventional counterparts. However, such technologies only achieve their health, environmental, and/or social goals if adopted by users and effectively replacing conventional practices. Despite the important role that users play to accomplish these goals by making decisions whether to adopt such clean alternatives or not, currently there is no systematic framework for quantitative integration of users behavioral motivations during the engineering design process for these technologies. In this study, the Theory of Planned Behavior is integrated with Usage-Context Based Design to provide a holistic approach for predicting the market share of clean versus conventional alternatives based on users' personal beliefs, social norms, and perception of behavioral control. Based on the mathematical linkage of the model components, technology design attributes can then be adjusted based on beliefs, behavioral intentions, and usage-context. As a result, the final product may be more in line with users' behavioral intentions, which leads to higher adoption rates. The developed is applied in a case study of improved cookstove adoption in a  community in Northern Uganda. Results indicate that incorporating TPB attributes into utility functions improves the prediction power of the model. In addition, the attributes that users in the studied community prioritize and expect to observe in a clean cookstove are elicited through the TPB methodology. The influence of a clean cookstove usage trial phase on households' decision-making behavior suggests that technology and marketing strategy both should systematically integrate users to optimize these priorities prior to interventions to improve the outcomes and impacts of projects.

## 3.1 Introduction

In an effort to meet global goals for sustainability, technologies are rapidly being developed to meet human needs at a lower cost to the environment and health. The majority of these clean technologies typically perform the same services for users as their conventional counterparts, but may have different costs, performance, and operational parameters associated with their use. As such, users must be in some way motivated to make the decision to change their behavior or even pay a higher price as they choose to adopt these beneficial products. Yet today there is not an integrated method to specifically "design for adoption" such that the design process for these products can sufficiently incorporate attributes that account for the user's decision-making process.

Adoption of clean energy technologies is critical at the global scale, and residential consumers play a large role in these efforts. In the United States, use of cleaner residential technologies could reduce US national carbon emissions by 7.4% (Dietz et al., 2009). Globally, nearly 40% of households rely on open burning of biomass to meet over 95% of their energy needs and suffer 4 million premature deaths each year and exacerbated effects on climate change as a result (Bond et al., 2013; International Energy Agency, 2015; N. G. Johnson and Bryden 2012a; Lim et al., 2013). While a great number of cleaner and more efficient household energy technologies have been developed to address these challenges, low adoption rates have been observed in many contexts, particularly for clean cookstove projects (M. Johnson, Edwards, and Masera, 2010; Lewis and Pattanayak, 2012; Ruiz-Mercado, Canuz, and Smith, 2012). However studies suggest that systematic integration of users in design and implementation may lead to increased uptake (Alam et al., 2014; Hanna, Duflo, and Greenstone, 2016; Jan et al., 2017), and there is significant need for research in this area.

Today there is no comprehensive approach to design clean technologies in a way to achieve environmental goals in the consumer sector through sustained technology adoption and use. Current literature in engineering design, economics, and psychology detail many of the necessary components, including work in decision-based design or choice modeling. These include methods to mathematically describe the utility of each choice based on product and user attributes, usage context, social networks, and cultural backgrounds that may lead to environmentally friendly technology adoption (Jagtap, 2018). But there are no integrated methods that include these three key areas required to understand adoption of these types of beneficial technologies, including Technology performance, User behavior and preference, and Usage context.

To find out what are the influence of user's beliefs, and context of use on her decision-making this research develops a systematic model. Drawing on interdisciplinary approaches from the literature, this study combines models of user behavior within a decision-based design framework. Along with quantitative belief based user modeling this framework further incorporates technical performance and usage context to develop a holistic utility function to predict a user's choice between available technologies. Several models are developed and explored using demographic, preference, and choice set data gathered from 175 households in Uganda in a three-part study with the global cookstove organization International Lifeline Fund. Prediction power and robustness of the models are validated based on statistical tests and theoretical basis.

## 3.2 Literature review

Clean technologies address environmental concerns only if they are adopted and permanently replace conventional practices. Therefore, such technologies must be designed in a way that addresses the technical needs and user preferences in a specific context of use. Throughout the literature, researchers have investigated contribution of each of these separately.

### 3.2.1 Technology performance

The technical performance of any technology – its efficiency, emissions, operational cost, embodied energy and emissions, and functionality – is relatively easy to describe and model. For example, there are hundreds of papers and tests conducted on biomass cookstoves. Laboratory tests investigate different aspects of technical design of improved cookstoves such as emissions, effects of fuel moisture content, and thermal efficiency (Jetter et al., 2012; Lombardi et al., 2017; MacCarty, Still, and Ogle, 2010; Smith et al., 2007; Still, Bentson, and Li, 2015; Yuntenwi et al., 2008). Field tests focus on the performance of developed technologies in actual settings using a variety of methods such as the kitchen performance test, sensor-based monitoring, and usability testing protocol ( Bailis et al., 2018; Moses and MacCarty, 2018; Eilenberg et al., 2018; Ruiz-Mercado, Canuz, and Smith, 2012; Ventrella and MacCarty, 2018). These methods have led to development of a standard performance rating framework by the International Organization of Standardization (ISO) in four categories including efficiency, emissions, indoor emissions, and safety (ISO, 2012).

These technology design and performance parameters play an important role in users' decision-making process. Such variables distinguish available alternatives from each other and provide a basis on which to choose a technology. Therefore, this is important to include the variables that provide most practical insight for designers to reflect customer preferences in technology design and performance. Previous work in this area has developed methods for systematic selection of engineering attributes that inform the utility functions in a way that technology designer could benefit the most (Arendt, McAdams, and Malak, 2012; Parker, Galvan, and Malak, 2014).

### 3.2.2 Decision-making and behavioral modeling

Technology adoption extends beyond simple performance metrics into the realm of behavior because the user must make a choice to adopt. This choice is based on a number of factors, such as social, cultural, and personal beliefs and perceptions. It is impossible to develop a choice model that captures every factor for robust prediction of choices. However, choice modeling practice can be categorized into three general approaches (Adamowicz et al., 2008). The economic approach considers choices as utility maximization efforts based on developed preferences. Adopting concepts of random utility theory developed by Thurstone (1927), preferences of decision makers are incorporated into utility functions that estimate influence of each attribute on the final utility perceived by the person (McFadden, 1981). However, the behavioral and psychological approach argues that choices are not solely based on the rational processes assumed by an economic approach. Decision making in this approach could be influenced by heuristic rules, appearance of alternatives, contextual factors, and personal sources of satisfaction (Payne, Bettman, and Johnson, 1993). Theories based on this approach consider attributes that are more latent compared to the attributes of economic models, such as social norms, personal beliefs, and perceptions. The third approach to choice modeling is solely based on the recorded choices of individuals and statistical correlation of such choices to attributes associated with choices. Bypassing efforts in modeling the reasoning and preferences that led to these choices, this approach applies statistical methods that could present significantly valid models based on the data (e.g. Kamakura et al., 2005).

In engineering design, application of the categories above have been used for a number of applications. Research in decision-based design captures the normative decision analysis process by identifying logically compelling properties that a decision should conform to. These properties are identified in three general categories including human values, uncertainties and risks (Krishnamurty, 2006). Discrete choice analysis (DCA) is among the most well-established and robust methods for customer choice modeling in marketing and engineering design. In this method, a utility function is developed to model choices of individuals based on selected attributes that are assumed to have causal relationship with choices of individuals. Using a probabilistic choice modeling approach, DCA estimates the choice probabilities for each individual and then aggregates the demand for each alternative to predict the choice share in the target market (Chen, Hoyle, and Wassenaar, 2013). DCA models generally tend to apply multinomial logit (e.g. Resende, Grace Heckmann, and Michalek, 2012), nested logit (e.g. Kumar, Chen, and Simpson, 2009), or mixed logit (e.g. Hoyle et al., 2010) analyses.

Many approaches have been integrated to improve the predictability of DCA models by integrating more aspects of decision making into the utility functions. For example, considering choices as social practices, He et al. incorporate agent based modeling and social network analysis in choice modeling for green vehicles (He et al., 2014). In another work, the compensatory and non-compensatory processes of decision making are explored (Morrow, Long, and MacDonald, 2014). Based on the assumption that individuals conduct a non-compensatory screening to reduce their choices and then select one alternative through compensatory practices, a hybrid model called consider-then-choose is integrated with DCA to improve its predictability power. Focusing on the meaning of product attributes for customers, another study proposes a feature learning method that replaces product design attributes with the features and functions of such attributes that customers perceive (Burnap et al., 2016). Results of DCA are easy to interpret when every variable associated is considered to be deterministic. However, many variables such as user preferences are inherently stochastic and therefore, their distribution influences the final design recommendations. Developing a quantitative definition for reliability of product design recommendations through uncertainty quantification, Shin and Ferguson present a multi-objective optimization problem to determine final reliable product line solutions based on DCA results (Shin and Ferguson, 2016).

In engineering application of DCA, users' role and heterogeneity is often limited to demographic data. Although demographic data play an important role in shaping decisions, there are several approaches that suggest behavior is often more nuanced and stems from a variety of psychological factors such as individual beliefs, evaluations, social norms, motivations, and perceptions. There are several approaches to model human behavior in different domains. The adoption of clean technology is most closely related to the domains of health or environmental related behavior. Thus, the chosen model should be applicable in explaining technology adoption, health behavior, and pro-environmental behavior.

An extensive review of the literature suggested that the Theory of Planned Behavior (TPB) is the most applicable model to integrate user behavior for clean technology adoption

(Pakravan and MacCarty, 2019). A variety of behavioral theories exist including The Health Belief Model (Charles Abraham and Sheeran, 2005), Transtheoretical Model (Prochaska and Velicer, 1997). Norm Activation Model (Schwartz, 1977), Value-Belief-Norm Theory (Stern 2000), and Goal framing Theory (Lindenberg and Steg, 2007), and the Theory of Planned Behavior (TPB). Of these, TPB is one of the most robust and frequently used options (Weigel et al., 2014). It provides a quantitative and comprehensive model to capture the behavioral determinants for intention to adopt clean technologies. These are based on three main derivatives including (Ajzen, 1985, 1991):

1) Attitude toward behavior (ATB) – an individual's evaluation of particular behavior in terms of value and expected outcome

2) Subjective norms (SN) – an individual's perception about the behavior influenced by her reference regarding people's opinions

3) Perceived behavioral control (PBC) – factors that may facilitate or hinder an individual's action.

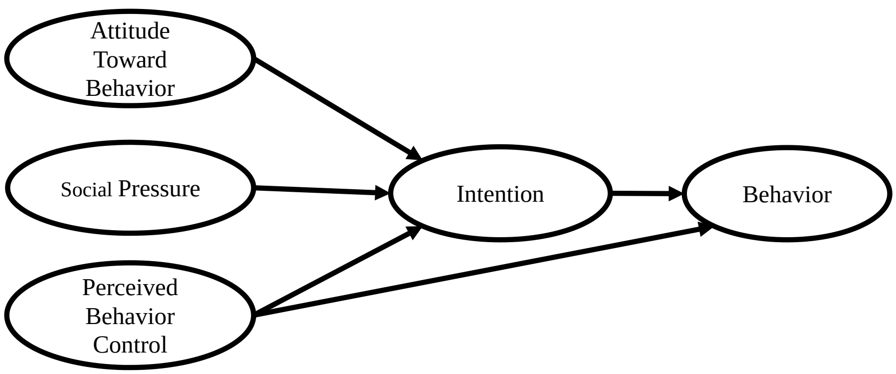


Figure 3.1. Constructs of the Theory of Planned Behavior (Ajzen 1991)

As illustrated in Figure 3.1, these elements construct a behavior intention function that determines a person's readiness to take an action. According to TPB, intention is the main determinant of behavior. Several studies have successfully applied TPB to explain environmental and health related behaviors throughout the literature. From understanding pro-environmental behavior of green buildings' occupants (Wu et al., 2017), to green purchase behavior in developing world (Yadav and Pathak 2017), to organic food consumption (Scalco et al., 2017), and behavior change by physical activity and exercise (Brooks et al., 2017), TPB is a well-established methodology environmental and health related behaviors. There are limitations to the use of TPB, including omission of the difference between value and expectancy beliefs (French and Hankins, 2003), and the influence of habits (Sniehotta, Presseau, and Araújo-Soares, 2014). However, these can be overcome with careful study design and appropriate statistical analysis (Ajzen, 2015b).

### 3.2.3 Incorporation of Usage Context

One influential factor that influences both the performance of a technology and hence user behavior and preference is the context of using the technology. Context is critical because human behavior and technology performance can vary significantly depending on the location, application, and details of product use. For example, urban or rural contexts significantly change the preferred choice of transportation method for individuals. In the context of household energy technologies, family size, energy cost and availability, and cooking practices are key drivers of choice.

One of the early works that acknowledges role of context in customer's decision making is based on the stimulus-organism-response (S-O-R) paradigm introduced by Belk (Belk, 1975). This postulates that the stimulus generated by the situation (usage context) and product influence the organism (customer) to generate a response, or choice. Here the context of user needs is defined to include the following five areas:

Physical surroundings – urban/rural, geography, climate, forest proximity, indoor/outdoor location

Social surroundings – family size and presence, privacy concerns

Temporal perspective – availability/value of performance attributes, need for faster or less tended task

Task definition – the type of technology outcomes and externalities to complete the task

Antecedent states – existing technologies, cash available

In engineering design, Green et al. focus on the importance of context by challenging successful design practices in frontier domains that are unfamiliar for the designer (Green et al., 2006; 2005; 2004). They define product design context as the collection of all the environmental factors that affect the design of a product. These factors are categorized into three groups as customer context factors, market context factors and usage context factors. Set-based design by usage coverage simulation is another methodology that applies an adaptable approach to identify a product alternative that best covers a usage scenario space that includes different context-user scenarios (Yannou et al., 2013). Another study presents a usage coverage model that develops a product family assessment based on different user-expected usage scenarios to determine whether a product family is in compliance with potential usage scenarios (Wang et al., 2013).

The Usage Context-Based Design (UCBD) framework was developed based on these ideas to focus on the importance of mathematical incorporation of context in choice modeling (He et al., 2012). UCBD has been used for applications such as illustrating how usage context influences customers' choice of hybrid electric vehicles and jigsaws (He et al., 2012). This model predicts market share of each alternative based on usage context, user preferences, technology performance and design variables. Mathematical linkage of this framework enables designers to adjust design variables to maximize the market share of desired alternative. Through DCA, UCBD records customers' choices from a choice set, which includes every product alternative that has been developed to address one specific task and available to customers. The variation of choices among individuals is modeled based on individual attributes, technology alternative attributes, and usage context attributes. The choice share estimates market share of each alternative in the studied population.

### 3.2.4 Summary of the literature

While much work in engineering design has focused on the design of technologies to achieve desired market shares in terms of purchasing products, adoption of clean technologies is not limited to the purchasing behavior of customers alone. Clean technology adoption is a continuous behavior and requires that users replace traditional practices with clean alternatives in order for such technologies to achieve their ultimate goals. Therefore, it is important to incorporate users' health and pro-environmental behavior tendencies and motivation to design residential clean technologies for adoption. Currently, there is no design framework that systematically integrates these psychological decision making and usage context attributes to design technologies for their adoptability. To address this gap, the current study integrates TPB with UCBD to quantitatively link user behavior to choice modeling. As a result, engineers can design clean technologies that are more compatible with users' health and environmental worldview and specific context of use which may lead to higher adoption rates for such products. A case study of clean cookstoves is used to highlight the application of the proposed framework because development practitioners have struggled for years to address the pervasive environmental and health issue presented by use of traditional biomass stoves and open fires on a daily basis for cooking food and warming water by 2.7 billion people (World Health Organization, 2016). International aid organizations, NGOs, and governments have been promoting use of improved biomass cookstoves for several decades, however goals for transitioning households adopt cleaner technologies to displace traditional methods have met only limited success. Therefore, a better approach to design technologies and implementation strategies is needed in this sector.

## 3.3 Methodology

The proposed platform of this research seeks to combine the three elements discussed above to predict the choice share of several cooking device alternatives in a rural market in Apac district, Uganda (Figure 3.2). In this methodology, data of users' behavior attributes and the final choices they made among the available alternatives in the choice set were recorded. These choices were regressed based on user attributes, technology attributes, and usage context attributes. This regression model serves as the utility function that estimates influence of each attribute of the model on each individual's choice. Based on the calculated weights of each attribute in the utility function, the market share of each alternative is predicted. Through this mathematical linkage, the predicted choice share of a desired alternative can be maximized by modifying relevant attributes through methods such as designing appropriate behavior change communications, adjusting design variables, or any approach that optimizes relevant explanatory variables in the model to generate the highest market share of a desired clean technology alternative.

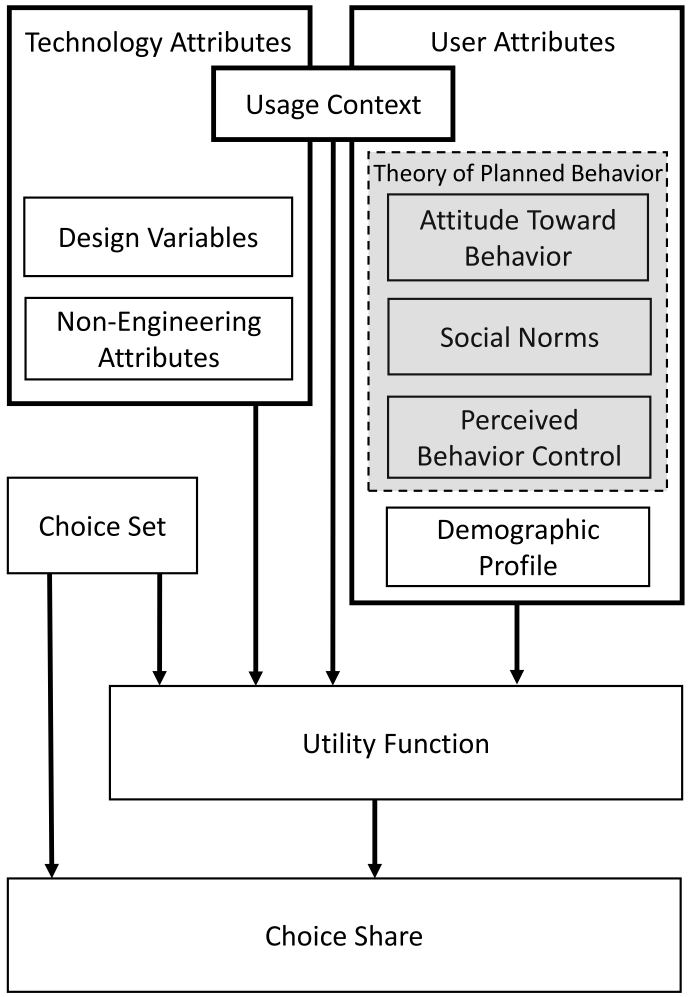


Figure 3.2 Platform for integrating user behavior, usage context and technology attributes

3.3.1 Model development

To model individual user's decision making behavior, two regression analyses were completed. The first determined the most significant behavioral attributes that explain the intention toward using a clean technology based on TPB, while the second incorporates the most significant behavioral attributes from TPB into UCBD's utility function to estimate the utility that individuals assign to choice alternatives.

To apply TPB in the domain of technology adoption, a pilot survey was first used to elicit the dominant widespread beliefs, available alternatives, and social and cultural norms of the target community. Given the results of the pilot study, a set of survey questions was designed to measure individuals' (1) attitudes toward using clean technology, (2) social norms associated with common practices and application of clean technology as an alternative practice, (3) ability to change the behavior in favor of using clean technology instead of conventional practices, and (4) intention to use the clean technology. There are two main approaches for measuring these three categories. An indirect method could be used to quantify each category's score according to expectancy-value model In this method, the final score for each attribute is derived by multiplying respondent's rating of beliefs about consequences of behavior times desirability of such consequences (French and Hankins, 2003). Using direct method questions that are designed based on global scores, combine individual beliefs and evaluations to produce a global response. As a result, answers to each global question generate one score for the relevant attribute (Ajzen, 1991).

Responses are coded as either unipolar or bipolar based on a Likert scale (Francis et al. 2004). Each category of TPB consists of questions that capture scores for more than one attribute related to that category. Therefore, each category is represented by a latent variable (with * superscript) that is formed to represent aggregated value calculated based on recorded responses to relevant survey questions. Each attribute that was elicited to be an important public concern was reflected in one or two questions in the survey. Hence, the survey included questions to quantify respondent's beliefs regarding smoke emissions, firewood consumption, safety, aesthetics, decision-making authority, ease of changing habits, role of neighbors' stove type, and other attributes detailed in (Pakravan and MacCarty, 2019). The influence of each attribute/category (α) in determining intention (*I*) is estimated through the regression analysis of Eq. (1):

$$I_i^* = I(\alpha: ATT_i^*, SN_i^*, PBC_i^*) \tag{1}$$

There are two statistical methods to analyze the data and develop the model of Eq. (1) including structural equation modeling and multiple linear regression. Either method could be used depending on the quality of data and preferences of the researcher (Hankins, French, and Horne 2000). Based on these results, the most significant attributes that have highest power to explain intention to use clean technology are selected for inclusion in the utility function.

The regression models in this research incorporate the most significant behavioral attributes from TPB into UCBD's utility function, which provides with an estimate of the utility that individuals assign to choice alternatives. True utility is not completely measurable and consists of an observed part or deterministic part (W), and an unobserved or random disturbance part (ε)  (McFadden, 1981). Equation (2) is a mathematical expression of the true utility of alternative (j) for individual (i).

$$U_{i,j} = W_{i,j} + \varepsilon_{i,j} \tag{2}$$

The deterministic part of the utility function estimates the correlation of attributes discussed above with the stated or revealed choice of the users. As shown in Equation (3), the regression model of the utility function estimates the utility of each choice (j) for each individual (i) based on technology variables (T), user attributes (U), and usage context attributes (C). In this study conditional logistic regression is used for estimating the weights of attributes in predicting stated choices of respondents. Stated choices of respondents complies with Independence of Irrelevant Alternatives (IIA) assumption that states the order of preferences for alternatives in the choice set should not change by addition or removal of one alternative. The reason that this assumption holds in this study is because of the significant differences of alternatives with each other. While Open fire is very easily accessible and free of charge, for more than a hundred years households have developed and used local mud stoves besides open fire. Hence, their preferences for mud stove versus open fire is not likely to change due to introduction of ICS. Additionally, introduction of ICS is not likely to change preferences for charcoal stoves, since the main barrier for dominant preference of charcoal stove is due to limited supply of charcoal in the rural region of the study that leads to high costs of charcoal and short amount of supplies. Therefore, IIA assumption is likely to be valid and henceforth the application of conditional logistics regression is justifiable.

$$W_{i,j} = W\left(\beta\colon T_j,\ U_i, C_{i,j}\right) \tag{3}$$

Results of Eq. (3) determines the utility of each alternative for each individual in the sample. The probability of choosing alternative (j) from available alternative in the choice set (s) for individual (i) is calculated using choice model presented in Eq. (4):

$$Pr_i(j) = \frac{e^{(W_{i,j})}}{\sum_j e^{(W_{i,s})}} \tag{4}$$

Using estimation techniques such as maximum likelihood method or least square method, the β coefficients of Eq. (3) are determined in a way that the calculated probabilities of Eq. (4) match as closely as possible to the recorded choices of individuals. In this way, the demand for each alternative is estimated at the individual scale. However, engineering design modifications such as changing technology variables, developing behavior change communication strategies, and analyzing policy implications require knowledge of the market scale demand for each alternative. Given the user heterogeneities in the market, sample size, or quality of data, the market could be categorized into different segments. Demand for each alternative could then be estimated through multiplication of number of individuals in each market segment times summation of probabilities of individuals' choices derived from Eq. (4) (Ben-Akiva and Lerman 1985).

3.3.2 Data collection

Creation of and data collection for the proposed model was implemented in five phases a rural community in Apac, Uganda in collaboration with International Lifeline Fund (ILF), an active NGO in clean cookstove development and implementation projects.

**Choice Set Development**. *Determine available options in the choice set based on clean and conventional alternatives in the local market.* Although in this area there are different types of improved stoves as well as LPG stoves in the market, rural access to these is limited. Field observations suggested that only ILF's rural wood stove, which is an improved cookstove, traditional mud stoves, and open fire are considerably available in the target community. Therefore, only these three choices were included in the choice set.

**Pilot Study and Attribute Identification**. *Conduct a pilot study from a small sample of users with a few open ended questions or a focus group discussion*. As the standard method of applying TPB (Ajzen 2013), a pilot study enables researchers to identify priorities, wide spread beliefs regarding the task, social norms, and context based preferences of users in the targeted community. A small sample of 10 households were chosen to conduct a pilot study to elicit general beliefs regarding cooking devices, important factors that community members associate with their stoves and foods, and available stove alternatives in local market using focus group discussion and open-ended surveys. Based the information provided, researchers identified the attributes presented in Table 3.1 as the most important attributes associated with cooking practices for households in the subject community.

**Data Collection**. *Develop and implement a standard survey to elicit TPB, usage context, and demographic data, as well as stated or revealed choices of participants*. The quality of designed questions and the data collection process play an important role in the model's statistical significance, thus survey techniques from social science are used in this stage (e.g. Gideon 2012). The sample size should be calculated based on the number of variables being studied in the model using design of experiment methods. A minimum of 200 observations (Chen, Hoyle, and Wassenaar 2013) or 10 observations per variable (Scott Long and Freese 2014) are rough estimates for reasonable sample size appropriate for the statistical analysis of the model. In this study, a sample of 170 households were randomly selected in the target community based on ILF's experience in the field and their available logistics for data collection process, with demographic details presented in Table 3.2. Using observations from Step 2, survey questions were designed to capture the perceivable aspects of clean cookstove adoption for users and implemented using Magpi data collection software. The baseline survey captured scores for each attribute from respondents. At the end of the baseline survey, the household's choice of stove among the three available alternatives was recorded. In the next step, ILF's improved cookstove was provided at a subsidized cost for the households that stated a clean cookstove as their choice. After a month of initial use, a follow-up survey with similar questions to the baseline survey was conducted to capture users' opinion changes and updated decisions for investigating long-term behavior analysis. The follow-up survey was conducted for both improved stove adopters and a subset of households that stated traditional stoves as their preferred choice in the baseline survey.

**Model Development and Data Analysis**. *Clean collected data and apply statistical modeling techniques to estimate each choice's market share*. Development of the TPB model and extracting most important attributes are discussed in detail in (Pakravan and MacCarty 2018). Results of these TPB models informed the utility function by incorporating the most important attributes of behavior as a group of explanatory variables in the model. Other explanatory variables include technology attributes (size, fuel type, and cost) and usage context attributes (indoor/outdoor, firewood moisture content). Stata was used to analyze the data and develop the model based on Equation 3. Table 3.3 presents results of conditional fixed effects regression analysis.

**Reliability Analysis and Model Validation**. *Validate the results using observed behavior and revealed choices to compare them with the predicted behaviors and stated preferences*. Results were validated in two separate formats. First, validity of collected data was examined by comparing responses of baseline and follow up surveys. However, responses to some questions should change due to users' updated beliefs and experiences after using the cookstove. In addition, a test-re-test reliability measure provides a rubric to compare responses to those questions that are not longitudinal. For instance, responses to a question like 'Doctors opinions are:_______’ should not change after a cookstove trial phase. Therefore, a subset of non-longitudinal questions were selected to evaluate reliability of collected responses as a test-retest reliability measure. Second, reliability of data analysis was evaluated based on cross validation (Arlot and Celisse 2010), goodness of fit measures, parallel regression assumption test, and tests for heteroscedasticity and multicollinearity. Results of these tests are presented in the results section.

Table 3.1 Attributes incorporated in the case study of clean cookstoves

| Usage context attributes | Wide spread beliefs attributes | Technology attributes |
|---|---|---|
| Indoor/Outdoor | Smoke emission | Price |
| Moisture content of firewood | Firewood consumption | Number of burners |
| | Safety | Dimension of burner |
| | Aesthetic | Fuel type |
| | Permission of family head | Thermal power |
| | Opinion of friends and family | Insulation |

Table 3.2 Demographic information of the case study's sample

| | Uganda |
|---|---|
| Sample size | 175 |
| Number of villages | 2 |
| Affected population | 581 |
| Number of children (under 17) | 204 (35% of affected population) |
| Main cook's age distribution | Minimum: 15<br>Maximum:75<br>Average:36.16<br>Std. dev.:15.32 |
| Income average (per week) | 24000 UGX<br>(~ 6.70 USD) |
| Education<br>(primary income earner) | No education 10%<br>Incomplete primary 17%<br>complete primary 28%<br>Incomplete secondary 12%<br>Complete secondary 20%<br>College/university 11% |

## 3.4 Results

Three forms of utility functions developed from the results of the study are presented in Table 3.3. Models are developed using conditional fixed-effects logistics regression under 'clogit' command in Stata 14 software. While several models were able to include both TPB constructs as well as demographic and technology attributes, no models incorporating usage context would successfully converge due to the sample size of 175 households and limitations in survey questions. Data on moisture content of firewood, and indoor versus outdoor cooking were collected, but did not achieve statistical significance in the model. Although the context based attributes are not discussed further in this case study, former studies have emphasized the significance of including them in the models (e.g. He et al. 2012; Telenko and Seepersad 2014;

Green et al. 2006). However, statistically significant models integrating the other two categories were successfully developed.

Table 3.3 Results

| Independent Variables | | Model I (Base Model) | Model II (Model I without TPB) | Model III (Model I with PBC only) |
|---|---|---|---|---|
| Price | | 0.019*** (0.003) | 0.019*** (0.003) | 0.020*** (0.003) |
| Fuel type | | -1.049*** (0.230) | -1.054*** (0.229) | -1.033*** (0.230) |
| Income | 1 | 0.071 (0.362) | 0.254 (0.403) | -0.241 (0.230) |
| | 2 | | -0.243 (0.649) | |
| | 3 | | 0.102 (0.536) | |
| ATB – importance of less fuelwood consumption | 1 | -16.686*** (1.680) | | |
| | 2 | 31.523*** (1.803) | | |
| | 3 | -2.834** (1.339) | | |
| | 4 | -1.783 (1.262) | | |
| PBC – Independence in decision making | 1 | -45.382*** (2.003) | | -13.170*** (0.513) |
| | 2 | -11.706*** (1.356) | | -0.075 (1.077) |
| | 3 | 4.105*** (1.440) | | 1.836* (1.054) |
| | 4 | 2.730*** (0.976) | | 0.780* (0.443) |
| SN – Social network's influence | 1 | 1.204 (1.710) | | |
| | 2 | -0.556 (1.074) | | |
| | 3 | -0.551 (0.954) | | |
| N | | 685 | 687 | 687 |
| AIC | | 376.61 | 385.62 | 384.30 |
| BIC | | 440.02 | 408.28 | 416.02 |
| Goodness of fit - $\rho^2$(%) | | 27.02 | 21.55 | 22.66 |
| Hit rate (%) | | 47.23 | 61.8 | 52.47 |
| Log-Likelihood (zero) | | -239.70 | -239.70 | -239.70 |
| Log-Likelihood (convergence) | | -174.31 | -187.81 | -185.15 |
| $\chi^2$ test (DoF) | | 2867.01*** (14) | 103.20*** (5) | 1429.24*** (7) |

Robust standard errors in parenthesis. * p-value <0.1 , ** p-value < 0.05 , *** p-value < 0.01

Model I is the base model that includes attributes representing all three TPB constructs that formulate the intention. Statistical significance of the multiple levels of ATB and PBC attributes suggest that including such independent variables improves the estimation power of the model as measured by likelihood ratio test (Presented in Table 3.2), Pseudo R-square $\rho^2$ (27% in Model I compared to 21% in Model II), and lower AIC value (376.61 in Model I compared to 385.62 in Model II). In addition, the SN attribute is likely to have no statistically significant contribution to the respondents' choice of stove. Although it might be counter intuitive, lack of statistical significance of SN does not mean that social norms have no effect in households' choices. Since TPB constructs are interconnected, SN influences may be channeled through other two constructs by either influencing ATB or PBC or both. However, SN is not likely to directly inform the decision of households. This finding is in line with field observations. Because the data is for the baseline study before households purchase the ICS, community members had no widespread opinion about the new stove that was presented to them right before the baseline survey. In terms of influence of ATB attribute in predicting choices, Model I suggests that considering firewood conservation less important is likely to influence the overall choice of stove significantly toward not choosing the ICS. Similarly, the PBC attribute has a significant negative correlation with choice of ICS when households perceive less independence in deciding what stove to use. The value of coefficients suggest that the influence of perceiving less independence in decision making which is represented by levels 1 and 2 of this attribute is considerably stronger than the influence of perceiving more independency represented by levels 3 and 4. This suggests that gender plays a role in decision-making behavior. Since majority of women in the target community are main cooks, they are exposed to the problems associated with traditional methods more than male heads of families. Therefore, it's likely that their priorities are not necessarily reflected in the decisions of the male family heads. As a result, the more power they perceive in independent decision-making, the more likely they will use ICS for cooking main meals.

Model II estimates the choices of customers based on conventional attributes for describing the utility of each alternative. Similar to all other models, in this model fuel type and income have statistically significant correlation with respondents' choices. Four alternative devices in this study burn either charcoal (coded as 1) or biomass firewood (coded as 0). The negative sign of fuel type indicates that alternative devices that rely on charcoal have less likelihood to be adopted than firewood based counterparts. This estimation is in line with field observations. Due to lack of reliable and consistent supply chain for charcoal to the study area, households are less likely to cook with charcoal stoves. Price, income, and fuel type are normalized in Model II. Therefore, a comparison of magnitude of influence of price (0.019) relative to fuel type (-1.049) and income (0.071) suggests that this attribute is not likely to have major influence on choices of households. One potential explanation for the small contribution of price of alternatives to inform the decision of households is that among four alternative devices in the study (open fire, local mud stove, ICS, and charcoal stove) households construct the first two without any payment from locally available material. In addition, the ICS for participants in this study was considerably subsidized from its original market price. As a result, households' decision magnify the importance of other attributes in decision making related to price.

Model III includes only one category of TPB instead of all TPB constructs in addition to the conventional attributes of utility function. This model presents partial application of TPB in predicting users' choices that could improve prediction power and market share estimations without full implementation of TPB. Similar to the base model (Model I), this model suggests that the likelihood of choice of ICS is significantly correlated with higher levels of perceived independency in decision-making.

The results of the Likelihood Ratio (LR) test are presented in Table 3.4. Hypothesis I compares the utility function without any TPB variables (Model II in Table 3.3) with the base model (Model I in Table 3.3). Similarly, Hypothesis II evaluates the utility function with one TPB construct (Model III in Table 3.3) with the base model (Model I in Table 3.3). Results of the LR test suggests that both hypotheses could be rejected at 90% confidence level. Therefore, TPB attributes are likely to have statistically significant contribution in explaining users' choices of stove.

Table 3.4 Likelihood Ratio Test for Hypothesis I and II

| Variables | Test for Hypothesis I $H_I: \ \beta_{ATB} = \beta_{PBC} = \beta_{SN} = 0$ | Test for Hypothesis II $H_{II}: \ \beta_{ATB} = \beta_{SN} = 0$ |
|---|---|---|
| Log-Likelihood of Unrestricted Model ($LL_U$) | -174.31 | -174.31 |
| Log-Likelihood of Restricted Model ($LL_R$) | -187.81 | -185.15 |
| Test Statistics [-2($LL_R$-$LL_U$)] | 27 | 21.68 |
| Number of Restrictions | 3 | 2 |
| Critical Chi-Squared Value at 90% Confidence | 6.25 | 4.61 |
| Rejection Confidence | 90% | 90% |
| Rejection Significance | 0.000 | 0.001 |

## 3.5 Conclusions and future work

Clean technologies should be designed with an emphasis on their adoption and successful replacement of conventional inefficient practices. One important aspect of technology adoption is that of user's beliefs and behavioral attributes. Therefore, it is important to systematically incorporate attributes of behavior and beliefs in the engineering design. So that the designed product or service can achieve higher market share in a sustainable way. This proposed methodology that integrates UCBD with TPB in a DCA platform reveals that conducting a survey from a sample of the target population could help improve compatibility of designed products or services with user needs. The main contribution of the presented methodology in this study is the systematic integration of theories and models that independently have been established in literature to describe behaviors that could be aggregated to explain clean technology adoption in low-resource regions including, developed settings, environmentally responsible behaviors, health related behavior, and rational decision-making.

The framework presented in this is study is developed based on three criteria to improve its practicality for future applications. First, the integrated method is holistic in terms of including attributes from user behaviors to usage context, and to technology design. This allows the framework to provide insights that systematically improve intervention strategies, highlighting the roles of user, technology and context of use. Second, the model is parsimonious meaning that gathering key input data that leads to insightful results is reflective of the high costs and level of efforts associated with data scarce settings. Therefore, the model setup relies on pilot study results for selecting the most important attributes and variables for further data collection and analysis to achieve actionable and reliable results. Third, the framework is developed based on valid and well-established theories that have been applied successfully throughout the literature.

A case study of improved cookstoves adoption is presented to demonstrate how the prediction power of decision-based design approaches improves by integrating attributes of user behavior based on TPB into utility functions. Results present statistically significant measures of the influence of behavioral attributes such as individuals' attitude toward less firewood consumption and their perception of the authority they have in making decisions in households' choices of stove. Such findings suggest that in the target community of the case study, ICS should be designed to prioritize firewood savings over other attributes to improve intention to replace their traditional stoves. Similarly, findings suggest that main cooks do not necessarily have enough authority to make decisions regarding the choice of stove independently. Therefore, appropriate information campaigns should be utilized to increase awareness for necessity of such behavior changes throughout community for both husbands (generally main decision makers of households) as well as the main cooks. Applying findings of this case study is likely to increase the intention of households throughout the community to choose ICS for cooking more frequently that gradually could shift their long-term behavior of using inefficient cooking practices.

Such models could be integrated in large scale intervention models for international development. In addition, this framework provides insight for design of appropriate macroscale information campaigns and behavior change communications that target main hindrances against higher intentions to use clean technologies. Policy makers may utilize this model to design education policies and intervention criteria for international development stakeholders to develop and distribute products that are reflective of usage context and user behavior. As a result, the efficacy of resources allocated to development projects could improve through higher adoption rates.

Future work regarding effective incorporation of usage context attributes is recommended to present the model's performance based on variable usage context attributes to predict choices preferred by users in different use situations. Developed model in this study provides the opportunity for practitioners to draw systematic conclusions related to users' beliefs and behaviors in target communities through a pilot study and TPB based survey. Further studies can be undertaken to include a greater number of contextual, technological, and behavioral variables to answer questions that improve international development interventions. In addition, such decision-making model could represent the decision criteria in adoption studies that investigate community scale emerging adoption patterns using agent based modeling ( Pakravan and MacCarty, 2019).

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## References

Abraham, C., & Sheeran, P. (2005). The Health Belief Model. In M. Conner & P. Norman (Eds.), *Predicting Health Behavior* (p. 385). McGraw-Hill.

Adamowicz, W., Bunch, D., Cameron, T. A., Dellaert, B. G. C., Hanneman, M., Keane, M., … Swait, J. (2008). Behavioral frontiers in choice modeling. *Marketing Letters*, *19*(3–4), 215–228. https://doi.org/10.1007/s11002-008-9038-1

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. In *Action Control* (pp. 11–39). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-69746-3_2

Ajzen, I. (1991). The theory of planned behavior. *Orgnizational Behavior and Human Decision Processes*, *50*, 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2013). Theory of Planned Behaviour Questionnaire . Measurement Instrument Database for the Social Science. Retrieved from http://www.midss.org/sites/default/files/tpb.construction.pdf

Ajzen, I. (2015). The theory of planned behaviour is alive and well, and not ready to retire: a commentary on Sniehotta, Presseau, and Araújo-Soares. *Health Psychology Review*, *9*(2), 131–137. https://doi.org/10.1080/17437199.2014.883474

Alam, S. S., Nik Hashim, N. H., Rashid, M., Omar, N. A., Ahsan, N., & Ismail, M. D. (2014). Small-scale households renewable energy usage intention: Theoretical development and empirical settings. *Renewable Energy*, *68*, 255–263. https://doi.org/10.1016/J.RENENE.2014.02.010

Arendt, J. L., McAdams, D. A., & Malak, R. J. (2012). Uncertain Technology Evolution and Decision Making in Design. *Journal of Mechanical Design*, *134*(10), 100904. https://doi.org/10.1115/1.4007396

Arlot, S., & Celisse, A. (2010). A survey of cross-validation procedures for model selection. *Statistics Surveys*, *4*(0), 40–79. https://doi.org/10.1214/09-SS054

Bailis, R., Thompson, R., Lam, N., Berrueta, V., Muhwezi, G., & Adams, E. (2018). *Kitchen Performance Test (KPT) Overview: Household Surveys and Fuel Consumption Measurements*. Retrieved from http://cleancookstoves.org/technology-

Belk, R. W. (1975). Situational Variables and Consumer Behavior. *Journal of Consumer Research*, *2*(3), 157. https://doi.org/10.1086/208627

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis : theory and application to travel demand*. MIT Press. Retrieved from https://books.google.com/books?id=oLC6ZYPs9UoC&dq=ben+akiva+lerman+1985&lr=&source=gbs_navlinks_s

Bond, T. C., Doherty, S. J., Fahey, D. W., Forster, P. M., Berntsen, T., DeAngelo, B. J., … Zender, C. S. (2013). Bounding the role of black carbon in the climate system: A scientific assessment. *Journal of Geophysical Research: Atmospheres*, *118*(11), 5380–5552. https://doi.org/10.1002/jgrd.50171

Brooks, J. M., Iwanaga, K., Chiu, C.-Y., Cotton, B. P., Deiches, J., Morrison, B., … Chan, F. (2017). Relationships between self-determination theory and theory of planned behavior applied to physical activity and exercise behavior in chronic pain. *Psychology, Health & Medicine*, *22*(7), 814–822. https://doi.org/10.1080/13548506.2017.1282161

Burnap, A., Pan, Y., Liu, Y., Ren, Y., Lee, H., Gonzalez, R., & Papalambros, P. Y. (2016). Improving Design Preference Prediction Accuracy Using Feature Learning. *Journal of Mechanical Design*, *138*(7), 071404. https://doi.org/10.1115/1.4033427

Chen, W., Hoyle, C., & Wassenaar, H. J. (2013). *Decision-based design integrating consumer preferences into engineering design*. Springer.

Dietz, T., Gardner, G. T., Gilligan, J., Stern, P. C., & Vandenbergh, M. P. (2009). Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(44), 18452–18456. https://doi.org/10.1073/pnas.0908738106

Francis, J., Eccles, M. P., Johnston, M., Walker, A., Grimshaw, J., Foy, R., … Bonetti, D. (2004). Constructing Questionnaire Based on The Theory of Planned Behaviour, A Manual for Health Services Researchers. *ReBEQI WP2 Theory of Planned Behaviour Questionnaires: Manual for Researchers FOREWORD*, 42. https://doi.org/0-9540161-5-7

French, D. P., & Hankins, M. (2003). The expectancy-value muddle in the theory of planned bheavior - and some proposed solutions. *British Journal of Health Psychology*, *8*, 37–55. https://doi.org/https://doi.org/10.1348/135910703762879192

Gideon, L. (Ed.). (2012). *Handbook of Survey Methodology for the Social Sciences*. New York, NY: Springer New York. https://doi.org/10.1007/978-1-4614-3876-2

Green, M. G., Linsey, J. S., Seepersad, C. C., Wood, K. L., & Jensen, D. J. (2006). Frontier Design: A Product Usage Context Method. In *Volume 4a: 18th International Conference on Design Theory and Methodology* (Vol. 2006, pp. 99–113). ASME. https://doi.org/10.1115/DETC2006-99608

Green, M. G., Palani Rajan, P. K., & Wood, K. L. (2004). Product Usage Context: Improving Customer Needs Gathering and Design Target Setting. In *Volume 3a: 16th International Conference on Design Theory and Methodology* (Vol. 2004, pp. 393–403). ASME. https://doi.org/10.1115/DETC2004-57498

Green, M. G., Tan, J., Linsey, J. S., Seepersad, C. C., & Wood, K. L. (2005). Effects of Product Usage Context on Consumer Product Preferences. In *Volume 5a: 17th International Conference on Design Theory and Methodology* (Vol. 2005, pp. 171–185). ASME. https://doi.org/10.1115/DETC2005-85438

Hankins, M., French, D., & Horne, R. (2000). Statistical guidelines for studies of the theory of reasoned action and the theory of planned behaviour. *Psychology & Health*, *15*(2), 151–161. https://doi.org/10.1080/08870440008400297

Hanna, R., Duflo, E., & Greenstone, M. (2016). Up in smoke: The influence of household behavior on the long-run impact of improved cooking stoves. *American Economic Journal: Economic Policy*, *8*(1), 80–114. https://doi.org/10.1257/pol.20140008

He, L., Chen, W., Hoyle, C., & Yannou, B. (2012). Choice Modeling for Usage Context-Based Design. *Journal of Mechanical Design*, *134*(3), 031007. https://doi.org/10.1115/1.4005860

He, L., Wang, M., Chen, W., & Conzelmann, G. (2014). Incorporating social impact on new product adoption in choice modeling: A case study in green vehicles. *Transportation Research Part D: Transport and Environment*, *32*, 421–434. https://doi.org/10.1016/J.TRD.2014.08.007

Hoyle, C., Chen, W., Wang, N., & Koppelman, F. S. (2010). Integrated Bayesian Hierarchical Choice Modeling to Capture Heterogeneous Consumer Preferences in Engineering Design. *Journal of Mechanical Design*, *132*(12), 121010. https://doi.org/10.1115/1.4002972

International Energy Agency. (2015). World Energy Outlook 2015 - Biomass database. Retrieved from http://www.worldenergyoutlook.org/media/weowebsite/WEO2015Biomassdatabase.xlsx

International Standard Organization. (2012). *ISO/IWA 11:2012 Guidelines for evaluating* *cookstove performance*. Retrieved from https://www.iso.org/obp/ui/#iso:std:iso:iwa:11:ed-1:v1:en

Jagtap, S. (2018). Design and poverty: a review of contexts, roles of poor people, and methods. *Research in Engineering Design*, 1–22. https://doi.org/10.1007/s00163-018-0294-7

Jan, I., Ullah, S., Akram, W., Khan, N. P., Asim, S. M., Mahmood, Z., … Ahmad, S. S. (2017). Adoption of improved cookstoves in Pakistan: A logit analysis. *Biomass and Bioenergy*, *103*, 55–62. https://doi.org/10.1016/J.BIOMBIOE.2017.05.014

Jetter, J., Zhao, Y., Smith, K. R., Khan, B., Yelverton, T., Decarlo, P., & Hays, M. D. (2012). Pollutant emissions and energy efficiency under controlled conditions for household biomass cookstoves and implications for metrics useful in setting international test standards. *Environmental Science and Technology*, *46*(19), 10827–10834. https://doi.org/10.1021/es301693f

Johnson, M., Edwards, R., & Masera, O. (2010). Improved stove programs need robust methods to estimate carbon offsets. *Climatic Change*, *102*(3–4), 641–649. https://doi.org/10.1007/s10584-010-9802-0

Johnson, N. G., & Bryden, K. M. (2012). Energy supply and use in a rural West African village. *Energy*, *43*(1), 283–292. https://doi.org/10.1016/j.energy.2012.04.028

Kamakura, W., Mela, C. F., Ansari, A., Bodapati, A., Fader, P., Iyengar, R., … Wilcox, R. (2005). Choice Models and Customer Relationship Management. *Marketing Letters*, *16*(3–4), 279–291. https://doi.org/10.1007/s11002-005-5892-2

Krishnamurty, S. (2006). Normative Decision Analysis in Engineering Design. In *Decision Making in Engineering Design* (pp. 21–33). Three Park Avenue New York, NY 10016-5990: ASME. https://doi.org/10.1115/1.802469.ch4

Kumar, D., Chen, W., & Simpson, T. W. (2009). A market-driven approach to product family design. *International Journal of Production Research*, *47*(1), 71–104. https://doi.org/10.1080/00207540701393171

Lewis, J. J., & Pattanayak, S. K. (2012). Who adopts improved fuels and cookstoves? A systematic review. *Environmental Health Perspectives*, *120*(5), 637–645. https://doi.org/10.1289/ehp.1104194

Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., … Et, A. (2013). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010. *The Lancet*, *380*, 2224–2260. https://doi.org/10.1016/S0140-6736(12)61766-8

Lindenberg, S., & Steg, L. (2007). Normative, Gain and Hedonic Goal Frames Guiding Environmental Behavior. *Journal of Social Issues*, *63*(1), 117–137. https://doi.org/10.1111/j.1540-4560.2007.00499.x

Lombardi, F., Riva, F., Bonamini, G., Barbieri, J., & Colombo, E. (2017). Laboratory protocols for testing of Improved Cooking Stoves (ICSs): A review of state-of-the-art and further developments. *Biomass and Bioenergy*, *98*, 321–335. https://doi.org/10.1016/J.BIOMBIOE.2017.02.005

MacCarty, N., Still, D., & Ogle, D. (2010). Fuel use and emissions performance of fifty cooking stoves in the laboratory and related benchmarks of performance. *Energy for Sustainable Development*, *14*(3), 161–171. https://doi.org/10.1016/j.esd.2010.06.002

McFadden, D. (1981). Econometric Models of Probabilistic Choice. In Manski C. & D. McFadden (Eds.), *Structural Analysis of Discrete Data* (pp. 198–272). Cambridge, Mass.:

MIT Press. Retrieved from https://elsa.berkeley.edu/~mcfadden/discrete/ch5.pdf

Moses, N. D., & MacCarty, N. A. (2018). A Practical Evaluation For Cookstove Usability. In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. Quebec: ASME.

Pakravan, M. H., & MacCarty, N. (2018). Evaluating User Intention for Uptake of Clean Technologies Using the Theory of Planned Behavior. In *Volume 2A: 44th Design Automation Conference* (p. V02AT03A047). ASME. https://doi.org/10.1115/DETC2018-85992

Pakravan, M. H., & MacCarty, N. A. (2019). Analysis of user intentions to adopt clean energy technologies in low resource settings using the theory of planned behavior. *Energy Research and Social Science*, (In review).

Pakravan, M. H., & MacCarty, N. A. (2019). An Agent-Based Model for Diffusion of Clean Technology using the Theory of Planned Behavior. In *Submitted to: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference IDETC/CIE2019* (pp. 1–10).

Parker, R. R., Galvan, E., & Malak, R. J. (2014). Technology Characterization Models and Their Use in Systems Design. *Journal of Mechanical Design*, *136*(7), 071003. https://doi.org/10.1115/1.4025960

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press. Retrieved from https://books.google.com/books?id=QzXFqwrPLXkC&dq=Payne+et+al.+1993&lr=&source=gbs_navlinks_s

Prochaska, J. O., & Velicer, W. F. (1997). The Transtheoretical Model of Health Behavior Change. *American Journal of Health Promotion*, *12*(1), 38–48. https://doi.org/10.4278/0890-1171-12.1.38

Resende, C. B., Grace Heckmann, C., & Michalek, J. J. (2012). Robust Design for Profit Maximization With Aversion to Downside Risk From Parametric Uncertainty in Consumer Choice Models. *Journal of Mechanical Design*, *134*(10), 100901. https://doi.org/10.1115/1.4007533

Rose Eilenberg, S., Bilsback, K. R., Johnson, M., Kodros, J. K., Lipsky, E. M., Naluwagga, A., … Robinson, A. L. (2018). Field measurements of solid-fuel cookstove emissions from uncontrolled cooking in China, Honduras, Uganda, and India. *Atmospheric Environment*, *190*, 116–125. https://doi.org/10.1016/J.ATMOSENV.2018.06.041

Ross Morrow, W., Long, M., & MacDonald, E. F. (2014). Market-System Design Optimization With Consider-Then-Choose Models. *Journal of Mechanical Design*, *136*(3), 031003. https://doi.org/10.1115/1.4026094

Ruiz-Mercado, I., Canuz, E., & Smith, K. R. (2012). Temperature dataloggers as stove use monitors (SUMs): Field methods and signal analysis. *Biomass and Bioenergy*, *47*, 459–468. https://doi.org/10.1016/J.BIOMBIOE.2012.09.003

Scalco, A., Noventa, S., Sartori, R., & Ceschi, A. (2017). Predicting organic food consumption: A meta-analytic structural equation model based on the theory of planned behavior. *Appetite*, *112*, 235–248. https://doi.org/10.1016/J.APPET.2017.02.007

Schwartz, S. H. (1977). Normative Influences on Altruism. *Advances in Experimental Social Psychology*, *10*, 221–279. https://doi.org/10.1016/S0065-2601(08)60358-5

Scott Long, J., & Freese, J. (2014). Models for ordinal outcomes. In *Regression Models for Categorical Dependent Variables Using Stata* (3rd ed., p. 589). Stata Press. Retrieved from

https://www.stata.com/bookstore/regression-models-categorical-dependent-variables/
Shin, J., & Ferguson, S. (2016). Product Line Design Search Considering Reliability and Robustness Under Uncertainty in Discrete Choice Methods. In *Volume 2A: 42nd Design Automation Conference* (p. V02AT03A039). ASME. https://doi.org/10.1115/DETC2016-59535
Smith, K. R., Dutta, K., Chengappa, C., Gusain, P. P. S., Berrueta, O. M. and V., Edwards, R., … Shields, K. N. (2007). Monitoring and evaluation of improved biomass cookstove programs for indoor air quality and stove performance: conclusions from the Household Energy and Health Project. *Energy for Sustainable Development*, *11*(2), 5–18. https://doi.org/10.1016/S0973-0826(08)60396-8
Sniehotta, F. F., Presseau, J., & Araújo-Soares, V. (2014). Time to retire the theory of planned behaviour. *Health Psychology Review*, *8*(1), 1–7. https://doi.org/10.1080/17437199.2013.869710
Stern, P. C. (2000). New Environmental Theories: Toward a Coherent Theory of Environmentally Significant Behavior. *Journal of Social Issues*, *56*(3), 407–424. https://doi.org/10.1111/0022-4537.00175
Still, D., Bentson, S., & Li, H. (2015). Results of Laboratory Testing of 15 Cookstove Designs in Accordance with the ISO/IWA Tiers of Performance. *EcoHealth*, *12*(1), 12–24. https://doi.org/10.1007/s10393-014-0955-6
Telenko, C., & Seepersad, C. (2014). Scoping Usage Contexts and Scenarios in Eco-Design. In *Volume 4: 19th Design for Manufacturing and the Life Cycle Conference; 8th International Conference on Micro- and Nanosystems* (p. V004T06A055). ASME. https://doi.org/10.1115/DETC2014-34846
Thurstone, L. L. (1927). A law of comparative judgment. *Psychological Review*, *34*(4), 273–286. https://doi.org/10.1037/h0070288
Ventrella, J., & Maccarty, N. A. (2018). Development and Pilot Study of an Integrated Sensor System to Measure Fuel Consumption and Cookstove Use in Rural Households. In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. Quebec, Canada: ASME.
Wang, J., Yannou, B., Alizon, F., & Yvars, P.-A. (2013). A usage coverage-based approach for assessing product family design. *Engineering with Computers*, *29*(4), 449–465. https://doi.org/10.1007/s00366-012-0262-1
Weigel, F. K., Hazen, B. T., Cegielski, C. G., & Hall, D. J. (2014). Diffusion of Innovations and the Theory of Planned Behavior in Information Systems Research: A Metaanalysis. *Communications of the Association for Information Systems*, *34*(31), 619–636. Retrieved from http://aisel.aisnet.org/cais/vol34/iss1/31
World Health Organization. (2016). *Burning Opportunity: Clean Household Energy for Health, Sustainable Development, and Wellbeing of Women and Children*. *WHO*. World Health Organization. Retrieved from http://www.who.int/indoorair/publications/burning-opportunities/en/
Wu, S. R., Greaves, M., Chen, J., & Grady, S. C. (2017). Green buildings need green occupants: a research framework through the lens of the Theory of Planned Behaviour. *Architectural Science Review*, *60*(1), 5–14. https://doi.org/10.1080/00038628.2016.1197097
Yadav, R., & Pathak, G. S. (2017). Determinants of Consumers' Green Purchase Behavior in a Developing Nation: Applying and Extending the Theory of Planned Behavior. *Ecological Economics*, *134*, 114–122. https://doi.org/10.1016/J.ECOLECON.2016.12.019

Yannou, B., Yvars, P.-A., Hoyle, C., & Chen, W. (2013). Set-based design by simulation of usage scenario coverage. *Journal of Engineering Design*, *24*(8), 575–603. https://doi.org/10.1080/09544828.2013.780201

Yuntenwi, E. A. T., MacCarty, N., Still, D., & Ertel, J. (2008). Laboratory study of the effects of moisture content on heat transfer and combustion efficiency of three biomass cook stoves. *Energy for Sustainable Development*, *12*(2), 66–77. https://doi.org/10.1016/S0973-0826(08)60430-5

# Chapter 4

## An Agent-Based Modeling approach for adoption of clean technologies using the Theory of Planned Behavior

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## Abstract

Technology adoption in low-resource regions is among the key challenges facing international development projects. Nearly 40% of the world's population relies on open fires and rudimentary cooking devices exacerbating health outcomes, deforestation, and climatic impacts of inefficient biomass burning. Clean technology alternatives such as clean cookstoves are among the most challenging technologies to approach their target goals through sustainable adoption due to lack of systematic market-driven design for adoption. Thus, a method is needed to provide insight regarding how target customers evaluate and perceive causes for adopting a clean technology. The holistic approach of this study captures the three main aspects of technology adoption through lenses of social networks, individual and society scale beliefs, and rational decision-making behavior. Based on data collected in the Apac region in Northern Uganda, an Agent-Based Model is developed to simulate emerging adoption behavior in a community. Then, four different scenarios investigate how adoption patterns change due to potential changes in technology or intervention strategy. These scenarios include influence of stove malfunctions, price elasticity, information campaigns, and strength of social network. Results suggest that higher adoption rates are achievable if designed technologies are more durable, information campaigns provide realistic expectations for users, policy makers and education programs work toward women's empowerment, and communal social ties are recognized for influence maximization. Application of this study provides insight for technology designers, project implementers, and policy makers to update their practices for achieving sustainable and to the scale clean technology adoption rates.

## 4.1 Introduction

Technologies created to address needs in low-resource regions play a crucial role in community development and empowerment. Ten out of the seventeen Sustainable Development Goals can be met through successful adoption of appropriate technologies like clean cookstoves, water filtration systems, renewable energy technologies, and waste management processes (United Nations, 2015). Technology adoption is particularly important for clean technologies because ultimate goals will be achieved only if inefficient, conventional practices are successfully displaced by new technologies. Therefore, it is important to study the determinants of adoption of such technologies in the early phases of design. The information provided by investigating the adoption behavior of clean technology users can enable technology designers and project implementers to effectively reshape their approaches to achieve higher market penetration and technology usability.

The decision to adopt is a complex process that involves individual attitudes toward specific behavior, beliefs about personal ability to control that behavior, and perceptions of social pressures for or against certain behaviors. Systematic integration of these three categories of beliefs with utility maximization theory could lead to better understanding of user decision-making behavior in terms of clean technology adoption. Therefore, in this work, individual scale utility functions based on personal beliefs, evaluations, and perceptions are formulated according to the Theory of Planned Behavior (TPB). Then, the developed utility functions are applied to an Agent-Based Modeling (ABM) system to simulate community-scale emerging adoption patterns within social networks. This model is then used to simulate the impacts of various technology design and policy decisions for a clean cookstove project in a rural community based on data from Apac, Uganda.

## 4.2 Background

Community scale technology adoption is a phenomenon that emerges from individual households' decision-making behavior. There are two main attributes that distinguish technology adoption in groups of people and hence should be taken into account in the models. First, households independently make a volitional decision whether to adopt an available technology or not. Therefore, each household is an autonomous decision-making agent. Second, households communicate their decisions within their networks and throughout their communities. One main reason for such communication is that humans' choices are social, meaning that social contexts are likely to influence choice behavior of individuals (He et al., 2014). To recognize both these conditions, ABM can be used. Agent-based simulations provide a unique opportunity to draw community scale conclusions based on individual decisions. Such simulations are dynamic, hence long term behavior of agents could be traced through time as their behaviors may update or technologies change (Macal and North, 2009). In addition, ABM provides the structure for agents to communicate through their social networks and update their decisions based on their peers' decisions. Throughout the literature, ABM is among frequently applied simulations for analyzing coupled human and natural systems (An, 2012).

Models for the behavior of agents to reflect the process of technology adoption within ABMs can be described in a variety of ways. The Diffusion of Innovation (DoI) theory developed by Everett Rogers is among the well-known theories that captures multiple aspects of adoption from technology itself to methods of communication, adoption timing and attributes of the adopters. In terms of technological innovation, key factors that influence adoption according to DoI include comparative advantage, compatibility, complexity, trialability, and observability (E. M. Rogers, 2010). Rogers further expands drivers of adoption to people through a five stage decision making process described by knowledge, persuasion, decision, implementation and confirmation. As a result, every decision maker ends up being a member of one of four general groups that forms the society based on when they may adopt a technology, including early adopters, early majority, late majority, and laggards (E. M. Rogers, 2010). DoI is among the widely used models across several branches of science since its introduction in 1962 (Sahin, 2006). Although DoI is among robust theories for technology adoption, its focus is more toward technology (innovation) rather than decision-maker's intentions (Weigel et al., 2014).

Focusing on the role of users in technology adoption, the Technology Acceptance Model (TAM) developed by Davis relies only on two factors to describe adoption behavior including perceived usefulness and perceived ease of use (Davis, 1989). Perceived usefulness refers to the level at which individuals perceive a technology would enhance their performances. Perceived ease of use is defined as an individual's perception regarding how easy it is to use a technology. A meta-analysis of TAM suggests that the theory provides valid and robust models of adoption and has the potential to be expanded for a wider domain of applications in different branches of science (King and He 2006). One of the main limitations of TAM is capturing social effects on decision-making for technology adoption (Hwang, Al-Arabiat, and Shin, 2016). Further works on robustness of TAM model led to an extended version of TAM called TAM2. In this version two general categories are added to the original TAM model to capture social influence process such as social norms and cognitive instrumental processes like results demonstrability (V. Venkatesh and Davis, 2000).  A comparison between TAM2 and TPB suggest that TAM2's attributes are captured by TPB which is more parsimonious than TAM2 (Benbasat and Barki, 2007).

Inspired by categories of attributes that are utilized in DoI, and TAM as well as other models of technology adoption, the Unified Theory of Acceptance and Use of Technology (UTAUT) is developed as a holistic approach (Viswanath Venkatesh et al., 2003). The attributes that determine adoption in UTAUT include performance expectancy, effort expectancy, social influences and facilitating conditions. A literature review on 450 applications of UTAUT suggests that although the model is robust to predict adoption behavior, the complexity of the model components are a barrier for many case studies(Williams, Rana, and Dwivedi, 2015). Computational efficiency of the model is particularly important for investigating adoption in data scarce settings, so a more resource-efficient model is needed.

One of the most parsimonious models of behavior modeling is the Theory of Planned Behavior (TPB). Developed by Ajzen (Ajzen, 1991), TPB explores the belief-based factors that formulate intentions of individuals to make a choice. According to TPB, three categories of attributes, referred to as TPB constructs, determine intention, which is main factor that leads to behavior. These three constructs are a user's Attitude Toward the Behavior (ATB) based on behavioral beliefs, Social Norms (SN) surrounding perceptions of a behavior based on normative beliefs, and Perceived Behavioral Control (PBC) to conduct an action based on control beliefs (Ajzen, 2013). TPB is one of the well-established models in the literature for investigating the human side of adoption for technologies that are already in the market and social influences that could contribute to their adoption (Lai, 2017).

TPB has been integrated with ABM for studying technology adoption in domains such as organic farming practices (Kaufmann, Stagl, and Franks, 2009), environmental innovations (Schwarz and Ernst, 2009), natural gas vehicles (Sopha, Klöckner, and Febrianti, 2017), and smart residential electricity meters (Zhang and Nuttall, 2012). A review of the literature suggests that TPB is among the most robust models for analyzing adoption behavior from the user acceptance perspective (Hwang, Al-Arabiat, and Shin, 2016). In addition, previous works of authors present successful application of TPB to explain user behavior with respect to ICS adoption in low-resource contexts ( Pakravan and MacCarty, 2018; Pakravan and MacCarty, 2019).

It is conventional wisdom that society plays an important role in shaping individuals' behaviors. Many technology adoption theories, such as DoI, TPB, and UTAUT, reflect the role of society in their models. Rogers presents the role of social networks in DoI through influences of opinion leaders and critical mass. He further explains why the adoption curve, oftentimes represented by an S-shape results from the assumption that if opinion leaders adopt a technology, the adoption reaches a critical mass after which other society members adopt the technology in an exponential rate (E. M. Rogers, 2010). In addition to role of opinion leaders, Rogers presents close spatial proximity to technology adoption leads to “neighborhood effect” which increases the likelihood of adoption. According to TPB, social norms are one of the main determinants of behavioral intentions. Formed by normative beliefs social norms highlight individual’s evaluation regarding society’s norms and the importance of complying with them (Ajzen, 1991).

Researchers have emphasized using social networks to describe the role of society in technology adoption (Kempe, Kleinberg, and Tardos, 2005). A review of literature related to characteristics of social networks for investigating technology adoption using ABM suggests that adoption networks follow small-world network characteristics (Kiesling et al., 2012). Small-world networks, as opposed to completely regular and completely random networks, capture how the randomness of connecting nodes could be clustered by network parameters like characteristic path length (Watts and Strogatz, 1998). The path length and dynamic properties of small-world networks presented by Watts and Strogatz could convey two important aspects of technology adoption. First, path lengths could represent proximity of households and neighborhood effects. Second, the network is dynamic based on a network update probability attribute that could represent households’ changes in peers, preferences and intra-communal communications. These two main characteristics have led multiple technology adoption studies using ABM to implement small-world network (Sopha, Klöckner, and Febrianti, 2017; Zhang and Nuttall, 2012).

In addition to making decision based on the influence of society, the idea that individuals choose alternatives that maximizes their utility is widely regarded in neo-classical economic theories. In this study Discrete Choice Analysis (DCA) is used to model choice behavior from a set of mutually exclusive alternative technologies using the principle of utility maximization (Ben-Akiva and Lerman, 1985). The rational process of utility maximization is analyzed based on different attributes incorporated form multiple disciplines. Psychological approaches in calculating utility often fall short in terms of providing quantitative insights in terms of technology related attributes (Maya Sopha, Klöckner, and Hertwich, 2011), while engineering approaches lack systematic incorporation of users’ behavioral elements for robust choice modeling (Shafiei et al., 2012).

Despite these tools and advances, there is not currently a methodology that integrates rational decision making with behavioral models to simulate the process of technology adoption through a social network in low resource settings. At the individual scale, this research seeks to incorporate both rational and psychological aspects of decision-making to describe households' autonomous decisions. At the community level, a social network based on small-world networks provides the communication links among agents that leads to capture emerging adoption behavior using an ABM.

## 4.3 Methodology

In this study, an ABM approach is developed for a rural community based on the information collected during a two-phase field study in Apac, Uganda. The model investigates the proliferation of ICS adoption in households through a theoretical community. Diffusion and the decision to adopt is based on a combination of the social influences of peers and the individual decision-making behavior based on utility maximization theory. The DCA representing utility maximization theory is integrated with TPB to improve predictability power of the utility function by capturing attributes related to beliefs and psychological process related to adopting a clean technology. The data collection for TPB attributes of clean technology adoption in the Ugandan community is presented in (Pakravan, 2018; Pakravan and MacCarty, 2019). The development of utility functions based on these are presented in( Pakravan and MacCarty, 2019).

In the ABM, households in the community are represented by agents that individually make decisions to maximize their utility regarding their choices of cooking stove. The attributes that inform the utility function based on TPB include ATB, SN, PBC, and income for capturing user heterogeneity, while available choices of cookstoves in the local market of the case study are represented by technology price, and fuel type.  Agents communicate their decisions through their community based on a small-world network. Learning from decisions of peers in the community and stove performance, agents update their decision about adopting improved cookstoves over time. As a result, the community scale adoption behavior is elicited. The model is used to simulate four different scenarios of technology adoption to inform technology designers and project implementers to gain insight into how product features and services can help achieve higher adoption rates. All research with human subjects was overseen by the Oregon State University Institutional Review Board under study number 7257.

The village-level progression of ICS adoption is represented as a flowchart in Figure 1. This model is developed in Mesa, a platform for ABM analysis using Python (Masad and Kazil, 2015). Based on this framework, a theoretical community was created. Each household is represented as an autonomous agent with heterogeneous attributes of behavior and income based on the sample data. Agents communicate with other agents in their network (peers) regarding their choice of stoves and report if their stoves do not work properly. In each time step of the model, attributes that inform stove choice are updated based on agent communications and a dynamic network of peer updates. At the end of each time step, the overall number of ICS adopters relative to the total number of households is calculated and referred to as the adoption rate. Variables used in the analysis are presented in the Table 1.

### 4.3.1 Model initialization

The developed model extends characteristics of households that were surveyed in a representative rural community in Apac, Uganda. The stated stove preferences of these 175 randomly selected households informed the utility function of the model (Pakravan and MacCarty 2019). Results of regressions on the collected data determined weights of influences of attributes presented in the utility function. Characteristics of the collected data are presented in Table 1. Data collected form the sample were scaled up using linear expansion to represent a reasonable estimate of population of the community. For this purpose, the distribution of surveyed household attributes informed attributes of every household in a community of 1045 households (Table 2). In the community, it is assumed that 40% of households have a stove at time=0, which comes from survey results.

### 4.3.2 Social influence

The model in this study assumes that households in the community exhibit small-world network characteristics. Therefore, the social network was developed following recommendations of Watts and Strogatz (Watts and Strogatz, 1998). In the model, each agent is connected to its neighbor agents that represent neighborhoods as well as some agents in the community that exhibit social status proximity instead of physical proximity. The network has a network update probability attribute to capture the dynamic aspect of such social networks. The network update probability changes 20% of agents' links in each time step of the model. Such link changes represents the fact that people change their preferences, social ties, and meet new community members, and are exposed to new opinions through day to day life.

To capture choices that are made based on strong influence of peers through word-of-mouth or social need motivation this study incorporates imitation process of decision making based on the Consumat approach (Jager and Janssen, 2012). This approach covers four main behavioral rules that dominantly explain agent decision-making. Imitation is the process of decision making as a result of peers' behaviors. Through imitation, agent copies the choice that majority of her peers successfully make. To define the threshold that determines majority of peers, this model follows the recommendations of Kempe et al. (Kempe, Kleinberg, and Tardos, 2005). In their work, the maximum influence from spread of information through social network occurs when (63%) of the links are activated (Kempe, Kleinberg, and Tardos, 2003). Therefore, in this model we assume imitation leads the agents to copy their peers' choice of stove if more than 63% of them have adopted an ICS, bypassing utility analysis.

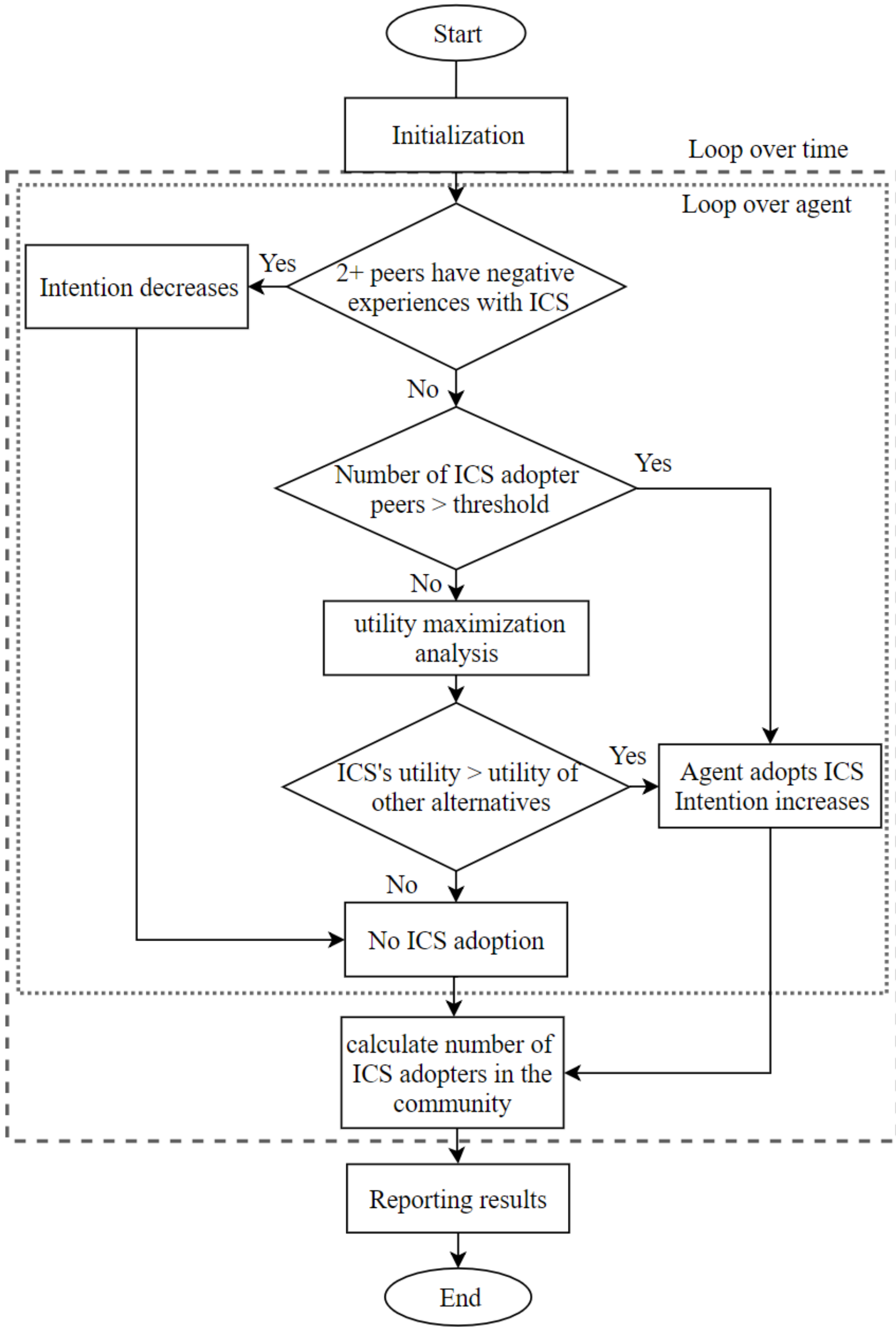


Figure 4.1 Flowchart of the model

4.3.3 Decision-making based on DCA

In addition to the direct social influence, the decision to adopt also includes the utility maximization theory, including TPB. Equation (1) illustrates the integration of TPB attributes along with technological attributes that predict choices of agent (i) for technology alternative (n) as the deterministic part of utility function. The three TPB constructs included in the utility function are attitude toward behavior (ATB), social norms (SN), and perceived behavior control (PBC) (Pakravan and MacCarty, 2019).

$$W_{in} = \beta_{0,i} + \beta_{Price,n}\, Price_n + \beta_{Fuel,n}\, Fuel_n + \beta_{income,i}\, Inc._i + \beta_{ATB,i}\, ATB_i + \beta_{SN,i}\, SN_i + \beta_{PBC,i}\, PBC_i \qquad (1)$$

TPB analysis of data collected from the sample suggests that most important representative of ATB attribute is individual’s evaluation of importance of firewood consumption. Similarly, evaluation of individuals regarding the importance of the opinion of friends and family about choice of stove represents the SN attribute and the perception of authority in making the decision for stove type to use represents the PBC attribute in this study (Pakravan and MacCarty, 2019).

### 4.3.4 Post-adoption behavior updates

Adopting a new stove provides users with experiences that influence their evaluations and behavioral attributes. To capture post adoption experiences, this study models two general cases. The first case is based on the assumption that the user’s need is satisfied and she has a pleasant experience with the new technology. As a result, the TPB attributes improve in favor of the new technology, which leads to higher intentions for the user to keep using the technology. The second case corresponds to negative experiences based on the assumption that new technology is not fulfilling agent’s expectations. This is often the case in projects due to stove break down and malfunction. The model is developed to reflect such experiences by decreasing behavioral attributes indicating that the person is less likely to keep using the new technology.

### 4.3.5 Time steps

Although the time steps are not intended to represent a fixed increment of real time, each time step of the model represents a full model utilization and transfer of information across the social network. As a result, at each time step, the choices of stove are updated either through a social influence or utility maximization process, and households opinions about cookstoves are updated based on their satisfying or dissatisfying experiences. The updated choice of stove, as well as the agent’s dynamic attributes inform the next time step updating the social network setup according to the network update probability. Since the stove choice of agents have changed from the previous time step, agents decisions are updated again to inform the next run, as illustrated with the gray box in Figure 1.

Table 4.1 ABM input data

| **Variable** | **Level** | **Type** | **Initial value** |
|---|---|---|---|
| ATB - Attitude toward saving firewood | Agent | Dynamic | Extended from survey results[a] in Likert scale from 1 to 4 |
| SN - Evaluation of social ties' ICS opinion | Agent | Dynamic | Extended from survey results[a] in Likert scale from 1 to 4 |
| PBC - Perception of authority in making decision | Agent | Dynamic | Extended from survey results[a] in Likert scale from 1 to 4 |
| Income | Agent | Static | From survey results[a]<br>- < 25,000 UGX,<br>- 25,000 < <50,000<br>- > 50,000 UGX |
| Fuel type | Tech. | Static | Field observation (0 for firewood, 1 for charcoal) |
| Stove price | Tech. | Static | Field staff's experience (Normalized as 5: open fire, 25: mud stove, 75: charcoal stoves,100: ICS) |
| Stove type | Tech. | Static | Field observation (open fire, mud stove, charcoal stove, ICS) |
| Number of peers | Model | Static | Assumption based on literature[b]– from 6to12 |
| Network updating probability | Model | Dynamic | Assumption based on literature[b]– 20% |
| Technology degradation rate | Model | Static | Assumption based on field observation (4% - 8% -10% - 18%) |
| Adoption rate | Model | Dynamic | Ratio of households with ICS to all households |
| Stove choice | Agent | Dynamic | Extended from survey results (At the baseline: open fire: 18%, mud stove: 42% , ICS: 40% ) |
| $\beta^{ATB}$ | Agent | Static | 1: -16.686 , 2: 31.523, 3: -2.834 , 4: -1.783[a] |
| $\beta^{SN}$ | Agent | Static | 1: 1.204, 2: -0.556 , 3: -0.551[a] |
| $\beta^{PBC}$ | Agent | Static | 1: -45.382 ,2: -11.706, 3: 4.105 ,4: 2.730[a] |
| $\beta^{Income}$ | Agent | Static | 0.071[a] |
| $\beta^{Fuel}$ | Agent | Static | -1.049[a] |
| $\beta^{Price}$ | Agent | Static | 0.019[a] |

[a] (Pakravan and MacCarty, 2019)[b](Sopha, Klöckner, and Febrianti, 2017)

Table 4.2 TPB attribute distribution in sample and projected population [30]

| | Sample (collected) N = 175 | | Population (estimated) N=1045 | |
|---|---|---|---|---|
| **Attribute** | **Mean** | **Standard Deviation** | **Mean** | **Standard Deviation** |
| ATB | 3.54 | 0.68 | 3.52 | 0.70 |
| SN | 3.60 | 0.91 | 3.59 | 0.93 |
| PBC | 3.12 | 1.44 | 3.12 | 1.44 |
| Income | 1.76 | 0.85 | 1.77 | 0.86 |

## 4.4 Results and discussion

Four scenarios are investigated against the baseline analysis discussed in section 3 to reflect real-world situations that may occur, and policy implications of each scenario are explored.

### 4.4.1 Scenario I: Price elasticity

One of the key factors in decision-making is the price of available alternatives (Levine et al. 2012). The ICS owners in this study received their cookstoves fully subsidized. As a result,

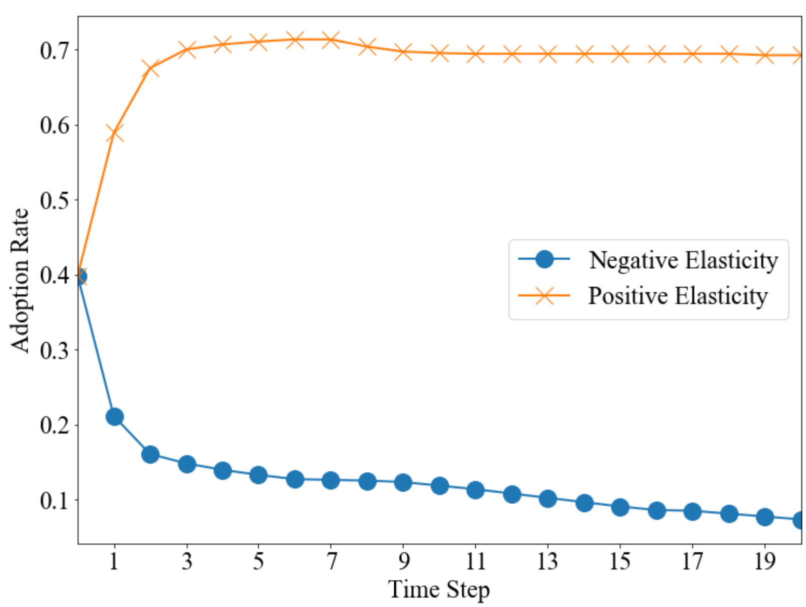


Figure 4.2 Price elasticity’s impact in community scale ICS adoption

their decisions of whether or not to adopt the ICS were not significantly influenced by the price of the technology. To investigate how price changes influence the technology adoption pattern, the model was used to simulate the *ceteris paribus* effect of positive and negative price elasticity of demand for ICS. Price elasticity of demand is an economic term referring to the rate at which demand for a product changes due to product price changes. Negative elasticity is based on the assumption that as the price of an ICS increases its demand decreases (ICS is normal good as defined in microeconomics). Positive elasticity means that as the price of an ICS increases, demand for it increases by some ratio.

Since real choices of households (revealed preferences) were not recorded, utilities calculated based on stated preferences are used to approximate demand. The adoption rate simulated in Figure 4.2 suggests that if households consider ICS as a normal good, adoption of cookstoves is not likely to approach satisfactory scales through time. Even though the value of negative elasticity in the model is set to (-0.001) compared to the value from Table 4.1 (0.019) for positive price elasticity, results of simulations suggest that even a slightly negative influence of price on utility significantly reduces the adoption rate in the community. Regression results of the sampled households suggest that the price has a small positive influence in the utility perceived by users in the community, as evidenced by the positive price elasticity of utility (0.019) in the sample size. That means the higher the price, the utility that households assign to the ICS increases. It is important to mention that approximately 40% of the households in the survey already owned a fully subsidized ICS. Therefore, their price sensitivity is prone to be unrealistic. Another potential explanation for assigning higher utility to a technology as its price increases could be due to the social status that ownership of the technology provides for the household, referred to as Giffen goods in economics (Masuda and Newman 1981). Although the discussion regarding causes of positive price elasticity of demand are beyond the scope of this study, the model suggests that having positive price responsiveness is likely to improve technology adoption considerably holding all other variables constant.

4.4.2 Scenario II: Influence of household's psychological attributes of behavior

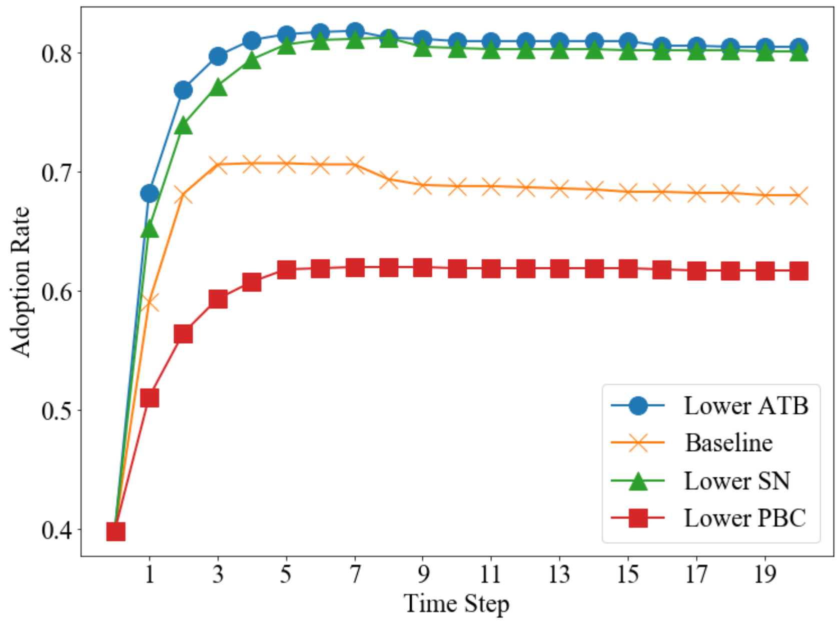


Figure 4.3 Influences of changes in TPB attributes on community scale ICS adoption

As discussed above, according to TPB, three categories of attributes formulate intention. In Figure 4.3, the influence of changes in each of these categories on overall adoption behavior are presented with respect to the baseline. The baseline refers to the values of TPB attributes that were assigned based on survey data and extended through all community members, reported in Table 1. Any consistent change in widespread beliefs in the community may lead to higher or lower adoption rates than baseline. Information campaigns, and behavior change communications are two examples of the methods that could influence such attributes in a consistent way throughout the community.

Results of the analysis suggest that a uniform decrease in households' perception of their independence in making decisions, or PBC, regarding choice of stove decreases ICS adoption rate in the community. This finding matches with results of (Miller and Mobarak 2013), which found that women being more exposed to risks associated with inefficient cooking are more likely to adopt ICS. However, in many contexts they have lack of authority to purchase such stoves.

Lowering households' ATB regarding the importance of firewood consumption increases the adoption rates through time. This counterintuitive finding suggests that the current technology's performance is not fulfilling expectations of those households that consider less firewood consumption more important than other community members. A household with strong beliefs regarding reducing firewood consumption may stop using ICS because despite the efforts to change their behavior and the cost of acquiring an ICS, the technology does not reduce their firewood consumption as expected. Therefore, it is important that information campaigns reflect the actual performance of the technology instead of exaggerating it.

Assigning less value to the importance of opinions of friends and family is likely to increase technology adoption over time. This finding suggests that behavior change communications that improve community scale beliefs regarding ICS play an important role in the overall adoption pattern. Other literature in social capital and the influence of word of mouth in technology adoption validate this finding. For example, a study in Northern Peruvian Andes found that households are more likely to follow the widespread behavior in the community if the social bonds are strong (Adrianzén 2014). Another study in western Honduras apply social network analysis to describe how spread of information solely through word-of-mouth by active community members led to a successful ICS intervention (Ramirez et al. 2014).

### 4.4.3 Scenario III: Degree centrality of households

This scenario studies the influence of social network on adoption based on degree centrality. Degree centrality is the number of households each agent is connected with, essentially representing the number of peers with which information is exchanged. Degree centrality of the network represents the overall social capital of the community. Social capital is referred to as a measure for intra-communal link strength (Adrianzén 2014). Social capital provides the capacity within a social network for collective actions (Robins 2015). Thus, strength of social capital impacts on adoption pattern can be simulated in the model through varying the degree centrality modeled as the number of peers connected to each agent varies from 6 to 12 households.

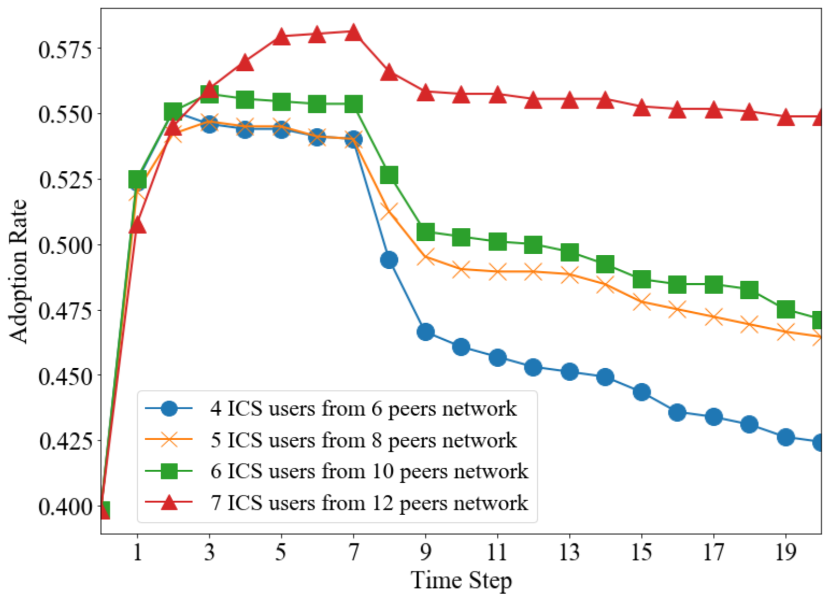


Figure 4.4 Influences of degree centrality on community scale ICS adoption

Results suggest that the stronger the social capital, adoption rates improve *ceteris paribus*. However, the strength of social networks facilitates the spread of both positive and negative feedback. As a result, although adoption rates improves initially, negative feedback leads to decreasing long-term adoption behavior for a network with less degree centrality. If a household is connected to only five other households and two of them have negative experiences with ICS, this household is surrounded by negative feedback from one-third of her peers. While a household that is connected to eleven other households, only two of which have negative experiences with their ICSs, is affected by negative feedback of only one-sixth of her peers. Such change in weight of influence of peers leads to decreasing adoption rate in the community if the communal ties are not relatively strong.

### 4.4.4 Scenario IV: Rate of ICS malfunction

The durability of ICS is among the major challenges that impact adoption rates (Hanna, Duflo, and Greenstone, 2016). While these cookstoves optimize combustion to reduce firewood

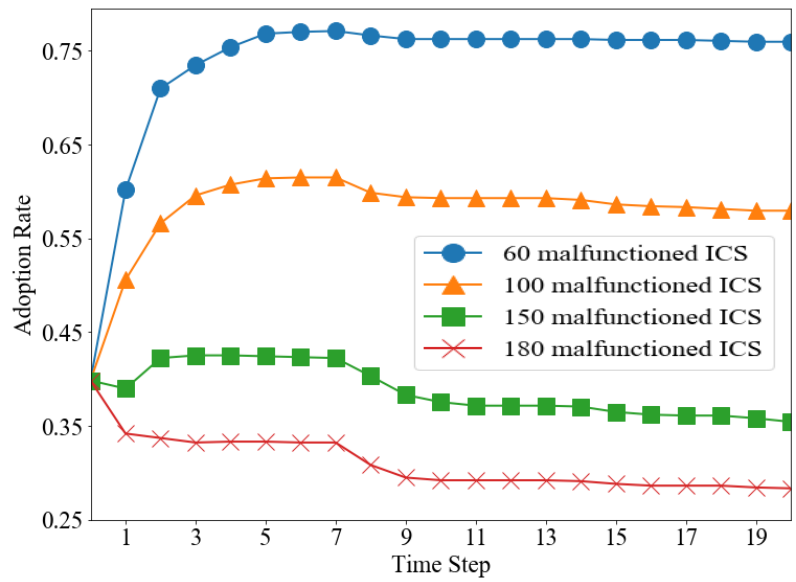


Figure 4.5 Influences of stove malfunction on community scale ICS adoption

consumption and smoke emissions, high temperatures, corrosive environmental, material limitations, and cost constraints are some challenges that could lead to stove failure from continuous use. Therefore, it is important to capture the effect of stove failure on community scale adoption pattern.

Figure 4.5 illustrates the adoption rates in the community with respect to four scenarios based on number of ICSs that fail to work properly due to durability issues. This is modeled by randomly assigning 60 to 180 malfunctioning stoves among all ICS owners. These households disseminate negative feedback regarding their broken stove. Having two or more peers with negative experiences lowers the agent's intention to choose ICS. Results suggest that durability significantly influences the adoption pattern in the community in the long term. As the number of malfunctioning stoves increases, the spread of negative feedback throughout the community negatively decreases peers' behavioral attributes. Throughout time such negative influences are likely to lower intention of households who are not experiencing any issues with their ICSs to cook fewer meals with it. Therefore, it is important for stove designers and project implementers to provide ongoing maintenance and repair services through the community to improve the durability and operation of designed technologies.

## 4.5 Verification and validation

Verification refers to the process that examines models performance against intended designed study while, validation evaluates to what extend the model explains the real-world system. Following recommendations of Macal and North (North and Macal, 2007) the model in this study has been verified to implement the designed study illustrated in Figure 4.1. Macal and North present multiple types of validation for ABM including requirement validation, data validation, face validation, process validation, theory validation, agent validation, and model output validation. This work captures four types of validations, including:

(1) *Data validation*: The data collected to represent agents in this study are based on a standard survey method in a real-world setting. Participants in the survey were randomly selected and survey questions were carefully designed to avoid inherent biases associated with survey questions. Surveyors were trained to avoid potential implications during the data collection process. Full discussion on the survey procedure is presented in ( Pakravan and MacCarty, 2019).

(2) *Theory validation*: The theories implemented in this study are among well-established theories in the literature. The DCA, TPB, Social Networks, and DoI methods have been reviewed extensively and applied in different domains of technology adoption using ABM through literature as discussed in the background.

(3) *Model output validation*: The output of the model in scenarios II, III, and IV agree with independent analytical work discussed at the end of each scenario. Therefore, output of the model reinforces the conclusions of independent researchers that have applied different analytical techniques for similar research questions.

(4) *Requirements validation*: The requirements that have been integrated into the model are selected based on DoI theory and field observations. To ensure the model captures the correct elements to address the research questions, a pilot study that included open-ended questions was implemented from a group of five community members and field staff. Results of the pilot study guided this research to reflect widespread beliefs in the community and incorporate techniques based on literature that could provide quantitative and systematic insight based on such beliefs and context-specific attributes.

## 4.6 Conclusions and future work

In this study, the long-term technology adoption behavior in a community is studied based on emerging patterns of household decision-making accounting for utility maximization and influence of social networks. Households' decisions and their peers' choice of stove updates their TPB-based behavioral attributes through time. The dynamic ABM platform provides the opportunity to study impacts of different scenarios related to clean cookstove adoption in the community. The four scenarios investigated in this research highlight the importance of systematic integration of users' behavioral attributes and having a long-term perspective for technology designers and project implementers to achieve higher impacts in the context of international development.

Results indicate that technology degradation and malfunction is one of the key factors that could define whether an intervention will be successful or not. One implication of this finding is that providing long-term customer service and scheduled maintenance programs are essential for scalable technology adoption. Information campaigns and behavior change communications that target mass populations should be carefully designed to avoid inflated expectations about technology performance, while realistically informing communities regarding the challenges associated with conventional inefficient practices. In addition, the messages of such public awareness programs should reflect wide-spread community beliefs and recognize the power and level of authority in changing behaviors. For instance, in a community where husbands and male family heads are the main decision makers, informing wives and female cooks about the benefits of using ICS may not lead to successful adoption patterns due to lack of enough authority to make such decisions.

The role of society and intra-communal ties is significant in adoption patterns. Recognizing the strength of social capital in a target community could help project implementers to appropriately focus on influence maximization through the spread of information in the social network of the community. For this purpose, further studies should incorporate different household types according to DoI theory for investigating how identifying households with higher social reputation could influence adoption behavior of the community.

Households' sensitivity to price significantly influences technology adoption. While negative and positive price elasticity of ICS demand is shown to be strongly correlated with technology adoption behavior, future work is needed to determine whether an ICS is a normal good or Giffen good. The difference between these two types of goods may depend on how ICS ownership is regarded in the community. If ICS is a normal good, increasing its price will lead to less ICS demand and project implementers should consider the price sensitivity of households as a key determinant of adoption. In the case of a Giffen good, ICS could be regarded as a social status product. As a result, increases in its price may lead to higher demand for it.

Results of this study could be improved based on the fact that community members have different levels of influence based on their social status. Therefore, designing the social network of target community through reflecting the weight of influences for households that are naturally more influential in community could improve the robustness of the model.

Applying this model to different types of technologies that aim to address challenges of bottom of pyramid based on appropriate user heterogeneity attributes could lead future works toward more successful projects. In larger scale, integrating such adoption behavior model to extended village scale models, policy level toolkits for international development, and macro scale energy policy systems could improve the overall approach to energy aspects of international development.

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References

Adrianzén, M. A. (2014). Social Capital and Improved Stoves Usage Decisions in the Northern Peruvian Andes. *World Development*, *54*, 1–17. https://doi.org/10.1016/j.worlddev.2013.07.004

Ajzen, I. (1991). The theory of planned behavior. *Orgnizational Behavior and Human Decision Processes*, *50*, 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2013). Theory of Planned Behaviour Questionnaire . Measurement Instrument Database for the Social Science. Retrieved from http://www.midss.org/sites/default/files/tpb.construction.pdf

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling*, *229*, 25–36. https://doi.org/10.1016/j.ecolmodel.2011.07.010

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis : theory and application to travel demand*. MIT Press. Retrieved from https://books.google.com/books?id=oLC6ZYPs9UoC&dq=ben+akiva+lerman+1985&lr=&source=gbs_navlinks_s

Benbasat, I., & Barki, H. (2007). Quo vadis, TAM? *Journal of the Association for Information Systems*, *8*(4), 211–218. Retrieved from https://aisel.aisnet.org/cgi/viewcontent.cgi?referer=&httpsredir=1&article=1410&context=jais

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Hanna, R., Duflo, E., & Greenstone, M. (2016). Up in smoke: The influence of household behavior on the long-run impact of improved cooking stoves. *American Economic Journal: Economic Policy*, *8*(1), 80–114. https://doi.org/10.1257/pol.20140008

He, L., Wang, M., Chen, W., & Conzelmann, G. (2014). Incorporating social impact on new product adoption in choice modeling: A case study in green vehicles. *Transportation Research Part D: Transport and Environment*, *32*, 421–434. https://doi.org/10.1016/J.TRD.2014.08.007

Hwang, Y., Al-Arabiat, M., & Shin, D.-H. (2016). Understanding technology acceptance in a mandatory environment: A literature review. *Journal of Information Development,* Vol 32 issue 4, https://doi.org/10.1177/0266666915593621

Jager, W., & Janssen, M. (2012). *An updated conceptual framework for integrated modeling of human decision making: The Consumat II*. Retrieved from https://www.rug.nl/staff/w.jager/jager_janssen_eccs_2012.pdf

Kaufmann, P., Stagl, S., & Franks, D. W. (2009). Simulating the diffusion of organic farming practices in two New EU Member States. *Ecological Economics*, *68*(10), 2580–2593. https://doi.org/10.1016/J.ECOLECON.2009.04.001

Kempe, D., Kleinberg, J., & Tardos, É. (2003). Maximizing the spread of influence through a social network. *Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '03*, 137. https://doi.org/10.1145/956755.956769

Kempe, D., Kleinberg, J., & Tardos, É. (2005). Influential Nodes in a Diffusion Model for Social Networks (pp. 1127–1138). Springer Berlin Heidelberg. https://doi.org/10.1007/11523468_91

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research*, *20*(2), 183–230. https://doi.org/10.1007/s10100-011-0210-y

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740–755. https://doi.org/10.1016/J.IM.2006.05.003

Lai, P. (2017). The Literature Review of Technology Adoption Models and Theories for the Novelty Technology. *Journal of Information Systems and Technology Management*, *14*(1), 21–38. https://doi.org/10.4301/S1807-17752017000100002

Levine, D., Cotterman, C., Levine, D., & Cotterman, C. (2012). What Impedes Efficient Adoption of Products? Evidence from Randomized Variation in Sales Offers for Improved Cookstoves in Uganda.

Macal, C. M., & North, M. J. (2009). Agent-based modeling and simulation. In *Proceedings of the 2009 Winter Simulation Conference (WSC)* (pp. 86–98). IEEE. https://doi.org/10.1109/WSC.2009.5429318

Masad, D., & Kazil, J. (2015). Mesa: An Agent-Based Modeling Framework. In *14th Python In Science Conference (SCIPY 2015)* (p. 51). Retrieved from https://github.com/projectmesa/mesa

Masuda, E., & Newman, P. (1981). Gray and Giffen Goods. *The Economic Journal*, 1011–1014. Retrieved from https://academic.oup.com/ej/article-abstract/91/364/1011/5219928

Maya Sopha, B., Klöckner, C. A., & Hertwich, E. G. (2011). Exploring policy options for a transition to sustainable heating system diffusion using an agent-based simulation. *Energy Policy*, *39*(5), 2722–2729. https://doi.org/10.1016/j.enpol.2011.02.041

Miller, G., & Mobarak, A. M. (2013). Intra-household externalities and low demand for a new technology: experimental evidence on improved cookstoves. *NBER Working Paper Series*, *Working Pa*(January), 1–58. https://doi.org/10.3386/w18964

North, M. J., & Macal, C. M. (2007). ABMS Verification and Validation. In *Managing Business Complexity* (pp. 221–234). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195172119.003.0011

Pakravan, Mohammad H., N. A. M. (2018). Evaluating User Intention For Uptake Of Clean Technologies Using The Theory Of Planned Behavior. In *Proceedings to ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*.

Pakravan, M. H., & MacCarty, N. (2018). Evaluating User Intention for Uptake of Clean Technologies Using the Theory of Planned Behavior. In *Volume 2A: 44th Design Automation Conference* (p. V02AT03A047). ASME. https://doi.org/10.1115/DETC2018-85992

Pakravan, M. H., & MacCarty, N. A. (2019). Design for clean technology adoption: integration of usage context, user behavior and technology performance in design. *Journal of Mechanical Design*, (In review).

Pakravan, M. H., & MacCarty, N. A. (2019). Analysis of user intentions to adopt clean energy technologies in low resource settings using the theory of planned behavior. *Energy Research and Social Science*, (In review).

Ramirez, S., Dwivedi, P., Ghilardi, A., & Bailis, R. (2014). Diffusion of non-traditional cookstoves across western Honduras: A social network analysis. *Energy Policy*, *66*, 379–389. https://doi.org/10.1016/j.enpol.2013.11.008

Robins, G. (2015). *Doing social network research : network-based research design for social scientists*.

Rogers, E. M. (2010). *Diffusion of Innovations, 4th Edition.* Free Press.

Sahin, I. (2006). Detailed Review of Rogers' Diffusion of Innovations Theory and Educational Technology-Related Studies based on Rogers' Theory. *The Turkish Online Journal of Educational Technology*, *5*(2), 14–23. https://doi.org/10.1287/mnsc.43.7.934

Schwarz, N., & Ernst, A. (2009). Agent-based modeling of the diffusion of environmental innovations - An empirical approach. *Technological Forecasting and Social Change*, *76*(4), 497–511. https://doi.org/10.1016/j.techfore.2008.03.024

Shafiei, E., Thorkelsson, H., Ásgeirsson, E. I., Davidsdottir, B., Raberto, M., & Stefansson, H. (2012). An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. *Technological Forecasting and Social Change*, *79*(9), 1638–1653. https://doi.org/10.1016/J.TECHFORE.2012.05.011

Sopha, B. M., Klöckner, C. A., & Febrianti, D. (2017). Using agent-based modeling to explore policy options supporting adoption of natural gas vehicles in Indonesia. *Journal of Environmental Psychology*, *52*, 149–165. https://doi.org/10.1016/j.jenvp.2016.06.002

United Nations. (2015). *Transforming Our World: The 2030 Agenda for Sustainable Development*. New York, New York, USA: UN Publishing.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204. https://doi.org/http://dx.doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Watts, D. J., & Strogatz, S. H. (1998). Watts-1998-Collective dynamics of 'small-world. *Nature*, *393*(June), 440–442. https://doi.org/Doi 10.1038/30918

Weigel, F. K., Hazen, B. T., Cegielski, C. G., & Hall, D. J. (2014). Diffusion of Innovations and the Theory of Planned Behavior in Information Systems Research: A Metaanalysis. *Communications of the Association for Information Systems*, *34*(31), 619–636. Retrieved from http://aisel.aisnet.org/cais/vol34/iss1/31

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. *Journal of Enterprise Information Management*, *28*(3), 443–488.

Zhang, T., & Nuttall, W. J. (2012). An agent-based simulation of smart metering technology adoption. *International Journal of Agent Technologies and Systems (IJATS)*, *4*(1), 17–38.

# Chapter 5 – General Conclusion

Technology adoption is a complicated function of technology, user, and usage-context attributes. This three-fold challenge is eminent in the domain of clean technologies, particularly in frontier contexts where a technology designer is not well aware of the users' behaviors and widespread beliefs, as well as contextual elements. In terms of engineering design, clean technologies should compete with traditional or inefficient practices with regard to performance, price, durability and similar attributes while providing a less environmentally burdensome footprint. Although this is in itself a challenge, clean technologies may not reach their ultimate goals if they do not effectively replace inefficient practices. Therefore, it is important to understand the drivers of users' decision-making with respect to such technologies.

The framework presented in this research integrated TPB with technology design attributes, usage context attributes, and users' beliefs and demographic attributes in a DCA platform. The framework was evaluated in two case studies of ICS adoption in low-resource regions in Honduras and Uganda. Three separate studies form this research were described in Chapters 2, 3 and 4. First, the application of TPB in data-scarce settings was investigated. Learning from the challenges of the first round of data collection in Honduras, methods and data quality were improved in the second study in Uganda. Chapter 2 provided details of the process for successful TPB implementation practices in these low-resource settings. Then, using data collected in Uganda, the framework was evaluated as discussed in Chapter 3. Results of cross comparison of utility functions that include TPB indicate that inclusion of TPB in conventional decision-based design utility functions improves the models' robustness and predictability power. Considering that such utility functions represent individuals' decision-making behavior, the collective adoption behavior of a community was investigated in Chapter 4. For this purpose, an ABM environment of 1050 agents was created that modeled a village. Each village household is represented by an agent that makes decision based on either the utility function developed in Chapter 3 or peer influences. This model shed light into long-term adoption patterns at the community scale.

Results of this research could provide insight for practitioners to improve intervention strategies. Using the findings of this study, technology designers may achieve higher user acceptability and compatibility rates by systematically eliciting details about widespread beliefs and user priorities in a given community. Capturing contextual elements may lead to performance improvement in technology design as well as better compliance with user preferences. Both of these impacts are likely to improve the technology's usability and adoption. In terms of intervention strategies, the methodology presented in this work provides a method for quantification of user behavior that informs project implementers for best practices regarding behavior change communication, messaging in information campaigns, and customer service requirements. Policy makers can benefit from this work by prioritizing verification of adoption prior to mass distribution.

Future work in this area may incorporate the models developed into larger scale village-level behavior analysis and technology choice models for comprehensive international development planning. In addition, it would be valuable to explore performance of the model in cases of other technologies with additional detail regarding the contextual attributes that are most relevant to designers and practitioners.

# References


Abraham, C., P. Sheeran, and M. Johnston. 1998. “From Health Beliefs to Self-Regulation: Theoretical Advances in the Psychology of Action Control.” *Psychology & Health* 13(4): 569–91. http://www.tandfonline.com/doi/abs/10.1080/08870449808407420 (February 2, 2018).

Abraham, Charles, and Paschal Sheeran. 2005. “The Health Belief Model.” In *Predicting Health Behavior*, eds. Mark Conner and Paul Norman. McGraw-Hill, 385.

Adamowicz, Wiktor et al. 2008. “Behavioral Frontiers in Choice Modeling.” *Marketing Letters* 19(3–4): 215–28. http://link.springer.com/10.1007/s11002-008-9038-1 (August 9, 2018).

Adrianzén, Marcos Agurto. 2014. “Social Capital and Improved Stoves Usage Decisions in the Northern Peruvian Andes.” *World Development* 54: 1–17.

Ajzen, Icek. 1985. “From Intentions to Actions: A Theory of Planned Behavior.” In *Action Control*, Berlin, Heidelberg: Springer Berlin Heidelberg, 11–39. http://www.springerlink.com/index/10.1007/978-3-642-69746-3_2 (November 29, 2016).

Ajzen, Icek. 1991. “The Theory of Planned Behavior.” *Orgnizational Behavior and Human Decision Processes* 50: 179–211.

Ajzen, Icek. 2013. “Theory of Planned Behaviour Questionnaire . Measurement Instrument Database for the Social Science.” http://www.midss.org/sites/default/files/tpb.construction.pdf (November 18, 2016).

Ajzen, Icek. 2015a. “Consumer Attitudes and Behavior: The Theory of Planned Behavior Applied to Food Consumption Decisions.” *Italian Review of Agricultural Economics* 70(2): 121–38. http://fupress.net/index.php/rea/article/view/18003 (February 13, 2018).

Ajzen, Icek. 2015b. “The Theory of Planned Behaviour Is Alive and Well, and Not Ready to Retire: A Commentary on Sniehotta, Presseau, and Araújo-Soares.” *Health Psychology Review* 9(2): 131–37. http://www.tandfonline.com/doi/full/10.1080/17437199.2014.883474 (June 26, 2018).

Alam, Syed Shah et al. 2014. “Small-Scale Households Renewable Energy Usage Intention: Theoretical Development and Empirical Settings.” *Renewable Energy* 68: 255–63. https://www.sciencedirect.com/science/article/pii/S0960148114000901 (February 9, 2018).

Albarracín, Dolores, Blair T. Johnson, Martin Fishbein, and Paige A. Muellerleile. 2001. “Theories of Reasoned Action and Planned Behavior as Models of Condom Use: A Meta-Analysis.” *Psychological Bulletin* 127(1): 142–61. http://doi.apa.org/getdoi.cfm?doi=10.1037/0033-2909.127.1.142 (December 18, 2017).

Albert, A., and J. A. Anderson. 1984. “On the Existence of Maximum Likelihood Estimates in Logistic Regression Models.” *Biometrika* 71(1): 1–10. https://academic.oup.com/biomet/article-lookup/doi/10.1093/biomet/71.1.1 (December 19, 2018).

Albertyn, R., H. Rode, A.J.W. Millar, and M.D. Peck. 2012. “The Domestication of Fire: The Relationship between Biomass Fuel, Fossil Fuel and Burns.” *Burns* 38(6): 790–95. https://www.sciencedirect.com/science/article/pii/S0305417912001039 (February 27, 2019).

An, Li. 2012. “Modeling Human Decisions in Coupled Human and Natural Systems: Review of Agent-Based Models.” *Ecological Modelling* 229: 25–36.

Arendt, Jonathan L., Daniel A. McAdams, and Richard J. Malak. 2012. “Uncertain Technology Evolution and Decision Making in Design.” *Journal of Mechanical Design* 134(10): 100904. http://mechanicaldesign.asmedigitalcollection.asme.org/article.aspx?articleid=1484825.

Arlot, Sylvain, and Alain Celisse. 2010. “A Survey of Cross-Validation Procedures for Model Selection.” *Statistics Surveys* 4(0): 40–79. http://projecteuclid.org/euclid.ssu/1268143839 (July 9, 2018).

Armitage, Christopher J., and Mark Conner. 2001. "Efficacy of the Theory of Planned Behaviour: A Meta-Analytic Review." *British Journal of Social Psychology* 40(4): 471–99. http://doi.wiley.com/10.1348/014466601164939 (November 22, 2017).

Bailis, Rob et al. 2018. *Kitchen Performance Test (KPT) Overview: Household Surveys and Fuel Consumption Measurements*. http://cleancookstoves.org/technology- (August 9, 2018).

Bailis, Robert, Rudi Drigo, Adrian Ghilardi, and Omar Masera. 2015. "The Carbon Footprint of Traditional Woodfuels." *Nature Climate Change* 5(3): 266–72. http://www.nature.com/doifinder/10.1038/nclimate2491 (February 23, 2017).

Bandura, Albert, and Daniel Cervone. 1986. "Differential Engagement of Self-Reactive Influences in Cognitive Motivation." *Organizational Behavior and Human Decision Processes* 38(1): 92–113. https://www.sciencedirect.com/science/article/pii/0749597886900282 (August 15, 2018).

Barnes, Douglas F, Keith Openshaw, Kirk R Smith, and Robert Van Der Plas. 1994. *What Makes People Cook with Improved Biomass Stoves? A Comparative International Review of Stove Programs*. http://documents.worldbank.org/curated/en/738011468766789505/pdf/multi-page.pdf (November 10, 2017).

Belk, Russell W. 1975. "Situational Variables and Consumer Behavior." *Journal of Consumer Research* 2(3): 157. https://academic.oup.com/jcr/article-lookup/doi/10.1086/208627 (June 26, 2018).

Ben-Akiva, Moshe E., and Steven R. Lerman. 1985. *Discrete Choice Analysis : Theory and Application to Travel Demand*. MIT Press. https://books.google.com/books?id=oLC6ZYPs9UoC&dq=ben+akiva+lerman+1985&lr=&source=gbs_navlinks_s (March 31, 2018).

Benbasat, Izak, and Henri Barki. 2007. "Quo Vadis, TAM?" *Journal of the Association for Information Systems* 8(4): 211–18. https://aisel.aisnet.org/cgi/viewcontent.cgi?referer=&httpsredir=1&article=1410&context=jais (February 21, 2019).

Bond, T. C. et al. 2013. "Bounding the Role of Black Carbon in the Climate System: A Scientific Assessment." *Journal of Geophysical Research: Atmospheres* 118(11): 5380–5552. http://doi.wiley.com/10.1002/jgrd.50171 (November 10, 2017).

Botetzagias, Iosif, Andora-Fani Dima, and Chrisovaladis Malesios. 2015. "Extending the Theory of Planned Behavior in the Context of Recycling: The Role of Moral Norms and of Demographic Predictors." *Resources, Conservation and Recycling* 95: 58–67. https://www.sciencedirect.com/science/article/pii/S0921344914002663 (February 13, 2018).

Bouzarovski, Stefan, and Saska Petrova. 2015. "A Global Perspective on Domestic Energy Deprivation: Overcoming the Energy Poverty-Fuel Poverty Binary." *Energy Research and Social Science* 10: 31–40.

Briscoe, Ciara, and Frances Aboud. 2012. "Behaviour Change Communication Targeting Four Health Behaviours in Developing Countries: A Review of Change Techniques." *SSM* 75: 612–21. https://ac.els-cdn.com/S0277953612002614/1-s2.0-S0277953612002614-main.pdf?_tid=89e5a8ec-1aa1-4c89-96ce-08ce10ffcca5&acdnat=1520026933_e894261df19f22848fbda2461ecc819d (March 2, 2018).

Brooks, Jessica M. et al. 2017. "Relationships between Self-Determination Theory and Theory of Planned Behavior Applied to Physical Activity and Exercise Behavior in Chronic Pain." *Psychology, Health & Medicine* 22(7): 814–22. https://www.tandfonline.com/doi/full/10.1080/13548506.2017.1282161 (June 25, 2018).

Brown, Tim, and Barry Katz. 2011. "Change by Design." *Journal of Product Innovation*

*Management* 28(3): 381–83. http://doi.wiley.com/10.1111/j.1540-5885.2011.00806.x (February 20, 2018).

Bryden, Mark et al. 2006. “Design Principles for Wood Burning Cook Stoves.” : 38.

Burnap, Alex et al. 2016. “Improving Design Preference Prediction Accuracy Using Feature Learning.” *Journal of Mechanical Design* 138(7): 071404. http://mechanicaldesign.asmedigitalcollection.asme.org/article.aspx?doi=10.1115/1.4033427 (August 13, 2018).

Chen, Wei, Christopher. Hoyle, and Henk Jan. Wassenaar. 2013. *Decision-Based Design Integrating Consumer Preferences into Engineering Design*. Springer.

Conner, Mark, and Christopher J Armitage. 1998. “Extending the Theory of Planned Behavior: A Review and Avenues for Further Research.” *Journal of Applied Social Psychology* 28: 1429–64. http://doi.wiley.com/10.1111/j.1559-1816.1998.tb01685.x.

Conner, Mark, and Paul Norman. 1996. *Predicting Health Behaviour : Research and Practice with Social Cognition Models*. Open University Press. http://psycnet.apa.org/record/1996-97268-001 (February 2, 2018).

Davis, Fred D. 1989. “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology.” *MIS Quarterly* 13(3): 319. https://www.jstor.org/stable/249008?origin=crossref (August 15, 2018).

Dietz, Thomas et al. 2009. “Household Actions Can Provide a Behavioral Wedge to Rapidly Reduce US Carbon Emissions.” *Proceedings of the National Academy of Sciences of the United States of America* 106(44): 18452–56. http://www.ncbi.nlm.nih.gov/pubmed/19858494 (July 31, 2018).

Dodou, D., and J.C.F. de Winter. 2014. “Social Desirability Is the Same in Offline, Online, and Paper Surveys: A Meta-Analysis.” *Computers in Human Behavior* 36: 487–95. https://www.sciencedirect.com/science/article/pii/S0747563214002143 (December 21, 2018).

Evans, William et al. 2017. “Evaluation of Behavior Change Communication Campaigns to Promote Modern Cookstove Purchase and Use in Lower Middle Income Countries.” *International Journal of Environmental Research and Public Health* 15(1): 11. http://www.mdpi.com/1660-4601/15/1/11 (January 1, 2018).

Francis, JJ. et al. 2004. “Constructing Questionnaire Based on The Theory of Planned Behaviour, A Manual for Health Services Researchers.” *ReBEQI WP2 Theory of Planned Behaviour Questionnaires: Manual for Researchers FOREWORD*: 42. http://openaccess.city.ac.uk/1735/1/TPB Manual FINAL May2004.pdf (June 11, 2017).

French, David P, and Mathew Hankins. 2003. “The Expectancy-Value Muddle in the Theory of Planned Bheavior - and Some Proposed Solutions.” *British Journal of Health Psychology* 8: 37–55.

Gideon, Lior, ed. 2012. *Handbook of Survey Methodology for the Social Sciences*. New York, NY: Springer New York. http://link.springer.com/10.1007/978-1-4614-3876-2 (August 2, 2018).

Gifford, Robert, Linda Steg, and Joseph P Reser. 2011. “Environmental Psychology.” In *The IAAP Handbook of Applied Psychology*, Blackwell Publishing Ltd., 440–70. https://www.rug.nl/staff/e.m.steg/giffordstegreser2011.pdf (February 13, 2018).

Green, Matthew G. et al. 2005. “Effects of Product Usage Context on Consumer Product Preferences.” In *Volume 5a: 17th International Conference on Design Theory and Methodology*, ASME, 171–85. http://proceedings.asmedigitalcollection.asme.org/proceeding.aspx?articleid=1572118 (November 27, 2016).

Green, Matthew G. et al. 2006. “Frontier Design: A Product Usage Context Method.” In *Volume 4a: 18th International Conference on Design Theory and Methodology*, ASME, 99–113. http://proceedings.asmedigitalcollection.asme.org/proceeding.aspx?articleid=1595465 (November 27, 2016).

Green, Matthew G., Palanisamy Kuppuraj Palani Rajan, and Kristin L. Wood. 2004. “Product Usage Context: Improving Customer Needs Gathering and Design Target Setting.” In *Volume 3a: 16th International Conference on Design Theory and Methodology*, ASME, 393–403. http://proceedings.asmedigitalcollection.asme.org/proceeding.aspx?articleid=1651509 (November 27, 2016).

Hankins, Matthew, David French, and Rob Horne. 2000. “Statistical Guidelines for Studies of the Theory of Reasoned Action and the Theory of Planned Behaviour.” *Psychology & Health* 15(2): 151–61. http://www.tandfonline.com/doi/abs/10.1080/08870440008400297 (November 15, 2017).

Hanna, Rema, Esther Duflo, and Michael Greenstone. 2016. “Up in Smoke: The Influence of Household Behavior on the Long-Run Impact of Improved Cooking Stoves.” *American Economic Journal: Economic Policy* 8(1): 80–114.

He, Lin, Wei Chen, Christopher Hoyle, and Bernard Yannou. 2012. “Choice Modeling for Usage Context-Based Design.” *Journal of Mechanical Design* 134(3): 031007.

He, Lin, Mingxian Wang, Wei Chen, and Guenter Conzelmann. 2014. “Incorporating Social Impact on New Product Adoption in Choice Modeling: A Case Study in Green Vehicles.” *Transportation Research Part D: Transport and Environment* 32: 421–34. https://www.sciencedirect.com/science/article/pii/S1361920914001084 (June 5, 2018).

Heinze, Georg, and Michael Schemper. 2002. “A Solution to the Problem of Separation in Logistic Regression.” *Statistics in Medicine* 21(16): 2409–19. http://doi.wiley.com/10.1002/sim.1047 (December 19, 2018).

Hoyle, Christopher, Wei Chen, Nanxin Wang, and Frank S. Koppelman. 2010. “Integrated Bayesian Hierarchical Choice Modeling to Capture Heterogeneous Consumer Preferences in Engineering Design.” *Journal of Mechanical Design* 132(12): 121010. http://mechanicaldesign.asmedigitalcollection.asme.org/article.aspx?articleid=1450441 (August 14, 2018).

Huda, Tarique Md. Nurul et al. 2012. “Interim Evaluation of a Large Scale Sanitation, Hygiene and Water Improvement Programme on Childhood Diarrhea and Respiratory Disease in Rural Bangladesh.” *Social Science & Medicine* 75(4): 604–11. https://www.sciencedirect.com/science/article/pii/S0277953611007222 (March 2, 2018).

Hwang, Yujong, Mohanned Al-Arabiat, and Dong-Hee Shin. “Understanding Technology Acceptance in a Mandatory Environment: A Literature Review.” https://journals-sagepub-com.ezproxy.proxy.library.oregonstate.edu/doi/pdf/10.1177/0266666915593621 (February 18, 2019).

Iarossi, Giuseppe. 2006. *The Power of Survey Design A User’s Guide for Managing Surveys, Interpreting Results, and Influencing Respondents*. The World Bank. www.worldbank.org (December 19, 2018).

International Energy Agency. 2015. “World Energy Outlook 2015 - Biomass Database.” http://www.worldenergyoutlook.org/media/weowebsite/WEO2015Biomassdatabase.xlsx.

International Standards Organization. 2012. *ISO/IWA 11:2012 Guidelines for Evaluating Cookstove Performance*. https://www.iso.org/obp/ui/#iso:std:iso:iwa:11:ed-1:v1:en.

Jager, Wander, and Marco Janssen. 2012. *An Updated Conceptual Framework for Integrated*

*Modeling of Human Decision Making: The Consumat II*. https://www.rug.nl/staff/w.jager/jager_janssen_eccs_2012.pdf (February 19, 2019).

Jagtap, Santosh. 2018. "Design and Poverty: A Review of Contexts, Roles of Poor People, and Methods." *Research in Engineering Design*: 1–22. http://link.springer.com/10.1007/s00163-018-0294-7 (August 9, 2018).

Jan, Inayatullah et al. 2017. "Adoption of Improved Cookstoves in Pakistan: A Logit Analysis." *Biomass and Bioenergy* 103: 55–62. https://www.sciencedirect.com/science/article/pii/S0961953417301708 (June 27, 2018).

Jetter, James et al. 2012. "Pollutant Emissions and Energy Efficiency under Controlled Conditions for Household Biomass Cookstoves and Implications for Metrics Useful in Setting International Test Standards." *Environmental Science and Technology* 46(19): 10827–34.

Jeuland, M. A. et al. 2015. "Preferences for Improved Cook Stoves: Evidence from Rural Villages in North India." *Energy Economics* 52: 287–98. http://dx.doi.org/10.1016/j.eneco.2015.11.010.

Johnson, Michael, Rufus Edwards, and Omar Masera. 2010. "Improved Stove Programs Need Robust Methods to Estimate Carbon Offsets." *Climatic Change* 102(3–4): 641–49. http://link.springer.com/10.1007/s10584-010-9802-0 (March 6, 2018).

Johnson, Nathan G., and Kenneth M. Bryden. 2012a. "Energy Supply and Use in a Rural West African Village." *Energy* 43(1): 283–92. http://dx.doi.org/10.1016/j.energy.2012.04.028.

Johnson, Nathan G., and Kenneth M. Bryden. 2012a. 2012b. "Factors Affecting Fuelwood Consumption in Household Cookstoves in an Isolated Rural West African Village." *Energy* 46(1): 310–21. http://dx.doi.org/10.1016/j.energy.2012.08.019.

Jürisoo, Marie, Fiona Lambe, and Matthew Osborne. 2018. "Beyond Buying: The Application of Service Design Methodology to Understand Adoption of Clean Cookstoves in Kenya and Zambia." *Energy Research & Social Science* 39: 164–76. http://linkinghub.elsevier.com/retrieve/pii/S2214629617304383 (January 1, 2018).

Kamakura, Wagner et al. 2005. "Choice Models and Customer Relationship Management." *Marketing Letters* 16(3–4): 279–91. http://link.springer.com/10.1007/s11002-005-5892-2 (August 10, 2018).

Kaufmann, Peter, Sigrid Stagl, and Daniel W. Franks. 2009. "Simulating the Diffusion of Organic Farming Practices in Two New EU Member States." *Ecological Economics* 68(10): 2580–93. https://www.sciencedirect.com/science/article/pii/S0921800909001372 (February 16, 2019).

Kempe, David, Jon Kleinberg, and Éva Tardos. 2003. "Maximizing the Spread of Influence through a Social Network." *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '03*: 137. http://portal.acm.org/citation.cfm?doid=956750.956769.

Kempe, David, Jon Kleinberg, and Éva Tardos. 2005. "Influential Nodes in a Diffusion Model for Social Networks." In Springer Berlin Heidelberg, 1127–38. http://link.springer.com/10.1007/11523468_91 (October 29, 2016).

Kiesling, Elmar, Markus Günther, Christian Stummer, and Lea M. Wakolbinger. 2012. "Agent-Based Simulation of Innovation Diffusion: A Review." *Central European Journal of Operations Research* 20(2): 183–230. http://link.springer.com/10.1007/s10100-011-0210-y (February 13, 2019).

King, William R., and Jun He. 2006. "A Meta-Analysis of the Technology Acceptance Model." *Information & Management* 43(6): 740–55. https://www.sciencedirect.com/science/article/pii/S0378720606000528 (February 11, 2019).

Klöckner, Christian A. 2015. "Decision Models — What Psychological Theories Teach Us about

People's Behaviour." In *The Psychology of Pro-Environmental Communication*, London: Palgrave Macmillan UK, 69–102. http://link.springer.com/10.1057/9781137348326_4 (November 29, 2016).

Krishnamurty, Sundar. 2006. "Normative Decision Analysis in Engineering Design." In *Decision Making in Engineering Design*, Three Park Avenue New York, NY 10016-5990: ASME, 21–33. http://ebooks.asmedigitalcollection.asme.org/content.aspx?bookid=261&sectionid=38776931 (August 10, 2018).

Kumar, Deepak, Wei Chen, and Timothy W. Simpson. 2009. "A Market-Driven Approach to Product Family Design." *International Journal of Production Research* 47(1): 71–104. https://www.tandfonline.com/doi/full/10.1080/00207540701393171 (August 14, 2018).

Kumar, Praveen, and Leah Igdalsky. 2019. "Sustained Uptake of Clean Cooking Practices in Poor Communities: Role of Social Networks." *Energy Research and Social Science* 48(February 2018): 189–93.

Kumar, Praveen, and Sumi Mehta. 2016. "Poverty, Gender, and Empowerment in Sustained Adoption of Cleaner Cooking Systems: Making the Case for Refined Measurement." *Energy Research and Social Science* 19: 48–52.

Lai, PC. 2017. "The Literature Review of Technology Adoption Models and Theories for the Novelty Technology." *Journal of Information Systems and Technology Management* 14(1): 21–38. http://www.jistem.fea.usp.br/index.php/jistem/article/view/10.4301%25S1807-17752017000100002 (August 15, 2018).

Legros, Gwenaelle, Ines Havet, Nigel Bruce, and Sophie Bonjour. 2009. UNDP WHO New York *The Energy Access Situation in Developing Countries, A Review Focusing on the Least Developed Countries and Sub-Saharan Africa*. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:THE+ENERGY+ACCESS+SITUATION+IN+DEVELOPING+COUNTRIES+A+Review+Focusing+on+the#0 (November 1, 2016).

Levine, David, Carolyn Cotterman, David Levine, and Carolyn Cotterman. 2012. "What Impedes Efficient Adoption of Products? Evidence from Randomized Variation in Sales Offers for Improved Cookstoves in Uganda."

Levitt, Steven D, and John A List. 2011. "Was There Really a Hawthorne Effect at the Hawthorne Plant? An Analysis of the Original Illumination Experiments." *American Economic Journal: Applied Economics* 3(1): 224–38. http://pubs.aeaweb.org/doi/10.1257/app.3.1.224 (December 19, 2018).

Lewis, Jessica J, and Subhrendu K Pattanayak. 2012. "Who Adopts Improved Fuels and Cookstoves? A Systematic Review." *Environmental health perspectives* 120(5): 637–45. http://www.ncbi.nlm.nih.gov/pubmed/22296719 (December 16, 2017).

Lim, Stephen S et al. 2013. "A Comparative Risk Assessment of Burden of Disease and Injury Attributable to 67 Risk Factors and Risk Factor Clusters in 21 Regions, 1990–2010: A Systematic Analysis for the Global Burden of Disease Study 2010." *The Lancet* 380: 2224–60. http:// (November 10, 2017).

Lindenberg, Siegwart, and Linda Steg. 2007. "Normative, Gain and Hedonic Goal Frames Guiding Environmental Behavior." *Journal of Social Issues* 63(1): 117–37. http://doi.wiley.com/10.1111/j.1540-4560.2007.00499.x (August 14, 2018).

Lombardi, Francesco et al. 2017. "Laboratory Protocols for Testing of Improved Cooking Stoves (ICSs): A Review of State-of-the-Art and Further Developments." *Biomass and Bioenergy* 98:

321–35. https://www.sciencedirect.com/science/article/pii/S096195341730065X (August 9, 2018).

Macal, Charles M., and Michael J. North. 2009. "Agent-Based Modeling and Simulation." In *Proceedings of the 2009 Winter Simulation Conference (WSC)*, IEEE, 86–98. http://ieeexplore.ieee.org/document/5429318/ (February 18, 2019).

MacCarty, Nordica, Dean Still, and Damon Ogle. 2010. "Fuel Use and Emissions Performance of Fifty Cooking Stoves in the Laboratory and Related Benchmarks of Performance." *Energy for Sustainable Development* 14(3): 161–71. http://dx.doi.org/10.1016/j.esd.2010.06.002.

Maddux, James E. 1999. "Expectancies and the Social–cognitive Perspective: Basic Principles, Processes, and Variables." In *How Expectancies Shape Experience.*, Washington: American Psychological Association, 17–39. http://content.apa.org/books/10332-001 (February 2, 2018).

Malakar, Yuwan, Chris Greig, and Elske van de Fliert. 2018. "Resistance in Rejecting Solid Fuels: Beyond Availability and Adoption in the Structural Dominations of Cooking Practices in Rural India." *Energy Research and Social Science* 46(July): 225–35.

Masad, David, and Jacqueline Kazil. 2015. "Mesa: An Agent-Based Modeling Framework." In *14th Python In Science Conference (SCIPY 2015)*, , 51. https://github.com/projectmesa/mesa (February 18, 2019).

Masera, Omar R et al. 2015. "Environmental Burden of Traditional Bioenergy Use." *Annu. Rev. Environ. Resour* 40: 15.15.301.

Masuda, Etsusuke, and Peter Newman. 1981. "Gray and Giffen Goods." *The Economic Journal*: 1011–14. https://academic.oup.com/ej/article-abstract/91/364/1011/5219928 (February 19, 2019).

Maya Sopha, Bertha, Christian A. Klöckner, and Edgar G. Hertwich. 2011. "Exploring Policy Options for a Transition to Sustainable Heating System Diffusion Using an Agent-Based Simulation." *Energy Policy* 39(5): 2722–29.

McCambridge, Jim, John Witton, and Diana R. Elbourne. 2014. "Systematic Review of the Hawthorne Effect: New Concepts Are Needed to Study Research Participation Effects." *Journal of Clinical Epidemiology* 67(3): 267–77. https://www.sciencedirect.com/science/article/pii/S0895435613003545 (December 21, 2018).

McFadden, Daniel. 1981. "Econometric Models of Probabilistic Choice." In *Structural Analysis of Discrete Data*, eds. Manski C. and D. McFadden. Cambridge, Mass.: MIT Press, 198–272. https://elsa.berkeley.edu/~mcfadden/discrete/ch5.pdf (July 16, 2018).

McFadden, Daniel. 2010. "Sociality, Rationality, and the Ecology of Choice." In *Choice Modelling: The State-of-the-Art and The State-of-Practice*, Emerald Group Publishing Limited, 1–17. http://www.emeraldinsight.com/doi/10.1108/9781849507738-001 (August 27, 2018).

Miller, Grant, and A Mushfiq Mobarak. 2013. "Intra-Household Externalities and Low Demand for a New Technology: Experimental Evidence on Improved Cookstoves." *NBER Working Paper Series* Working Pa(January): 1–58.

Mobarak, A M et al. 2012. "Low Demand for Nontraditional Cookstove Technologies." *Proceedings of the National Academy of Sciences of the United States of America* 109(27): 10815–20.

Moses, Nicholas D., Mohammad H. Pakravan, and Nordica A. MacCarty. 2019. "Development of a Practical Evaluation for Cookstove Usability." *Energy for Sustainable Development* 48: 154–63. https://www.sciencedirect.com/science/article/pii/S0973082618308196?dgcid=author (January 11, 2019).

Moses, Nicholas D, and Nordica A MacCarty. 2018. "A Practical Evaluation For Cookstove Usability." In *International Design Engineering Technical Conferences and Computers and*

*Information in Engineering Conference*, Quebec: ASME.

Nederhof, Anton J. 1985. "Methods of Coping with Social Desirability Bias: A Review." *European Journal of Social Psychology* 15(3): 263–80. http://doi.wiley.com/10.1002/ejsp.2420150303 (December 21, 2018).

North, Michael J., and Charles M. Macal. 2007. "ABMS Verification and Validation." In *Managing Business Complexity*, Oxford University Press, 221–34. http://www.oxfordscholarship.com/view/10.1093/acprof:oso/9780195172119.001.0001/acprof-9780195172119-chapter-11 (February 19, 2019).

OECD/IEA. 2017. Energy Access Outlook *World Energy Outlook Special Report: From Poverty to Prosperity*.

Oluka, Obiageli Crystal, Shaofa Nie, and Yi Sun. 2014. "Quality Assessment of TPB-Based Questionnaires: A Systematic Review" ed. Hamid Reza Baradaran. *PLoS ONE* 9(4): e94419. http://dx.plos.org/10.1371/journal.pone.0094419 (August 15, 2018).

Pakravan, Mohammad H., Nordica A. MacCarty. 2018. "Evaluating User Intention For Uptake Of Clean Technologies Using The Theory Of Planned Behavior." In *Proceedings to ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*,.

Pakravan, Mohammad H. 2018. "Decision Making Theories in Both Health Related Behaviors and Environmental Behaviors." *Zenodo*. https://doi.org/10.5281/zenodo.1285942# (June 8, 2018).

Pakravan, Mohammad H., and Nordica MacCarty. 2018. "Evaluating User Intention for Uptake of Clean Technologies Using the Theory of Planned Behavior." In *Volume 2A: 44th Design Automation Conference*, ASME, V02AT03A047. http://proceedings.asmedigitalcollection.asme.org/proceeding.aspx?doi=10.1115/DETC2018-85992 (February 18, 2019).

Pakravan, Mohammad H., and Nordica A. MacCarty. 2019. "An Agent-Based Model for Diffusion of Clean Technology Using the Theory of Planned Behavior." In *Submitted to: International Design Engineering Technical Conferences and Computers and Information in Engineering Conference IDETC/CIE2019*, , 1–10.

Pakravan, Mohammad H., and Nordica A MacCarty. "Design for Clean Technology Adoption: Integration of Usage Context, User Behavior and Technology Performance in Design." *Journal of Mechanical Design* (In review).

Pakravan, Mohammad Hossein, and Nordica A MacCarty. 2019. "Analysis of User Intentions to Adopt Clean Energy Technologies in Low Resource Settings Using the Theory of Planned Behavior." *Energy Research and Social Science* (In review).

Parker Fiebelkorn, Amy et al. 2012. "Systematic Review of Behavior Change Research on Point-of-Use Water Treatment Interventions in Countries Categorized as Low- to Medium-Development on the Human Development Index." *Social Science & Medicine* 75(4): 622–33. https://www.sciencedirect.com/science/article/pii/S0277953612001815 (March 2, 2018).

Parker, Robert R., Edgar Galvan, and Richard J. Malak. 2014. "Technology Characterization Models and Their Use in Systems Design." *Journal of Mechanical Design* 136(7): 071003. http://mechanicaldesign.asmedigitalcollection.asme.org/article.aspx?doi=10.1115/1.4025960 (February 18, 2019).

Payne, John W., James R. Bettman, and Eric J. Johnson. 1993. *The Adaptive Decision Maker*. Cambridge University Press. https://books.google.com/books?id=QzXFqwrPLXkC&dq=Payne+et+al.+1993&lr=&source=gbs_navlinks_s (August 10, 2018).

Prochaska, James O., and Wayne F. Velicer. 1997. "The Transtheoretical Model of Health Behavior Change." *American Journal of Health Promotion* 12(1): 38–48. http://journals.sagepub.com/doi/10.4278/0890-1171-12.1.38 (August 14, 2018).

Ramanathan, V., and G. Carmichael. 2008. "Global and Regional Climate Changes Due to Black Carbon." *Nature Geoscience* 1(4): 221–27. http://www.nature.com/doifinder/10.1038/ngeo156 (November 10, 2017).

Ramirez, Sebastian, Puneet Dwivedi, Adrian Ghilardi, and Robert Bailis. 2014. "Diffusion of Non-Traditional Cookstoves across Western Honduras: A Social Network Analysis." *Energy Policy* 66: 379–89. http://dx.doi.org/10.1016/j.enpol.2013.11.008.

Resende, Camilo B., C. Grace Heckmann, and Jeremy J. Michalek. 2012. "Robust Design for Profit Maximization With Aversion to Downside Risk From Parametric Uncertainty in Consumer Choice Models." *Journal of Mechanical Design* 134(10): 100901. http://mechanicaldesign.asmedigitalcollection.asme.org/article.aspx?articleid=1484822 (August 14, 2018).

Robins, Garry. 2015. *Doing Social Network Research : Network-Based Research Design for Social Scientists*.

Rogers, Everett. 2002. "Diffusion of Preventive Innovations." *Addictive Behaviors* 27(6): 989–93. http://www.sciencedirect.com/science/article/pii/S0306460302003003 (November 10, 2017).

Rogers, Everett M. 1995. *Diffusion of Innovations, 4th Edition.* Free Press.

Rogers, Everett M. 2010. *Diffusion of Innovations, 4th Edition.* Free Press.

Rose Eilenberg, S. et al. 2018. "Field Measurements of Solid-Fuel Cookstove Emissions from Uncontrolled Cooking in China, Honduras, Uganda, and India." *Atmospheric Environment* 190: 116–25. https://www.sciencedirect.com/science/article/pii/S1352231018304321 (August 9, 2018).

Ross Morrow, W., Minhua Long, and Erin F. MacDonald. 2014. "Market-System Design Optimization With Consider-Then-Choose Models." *Journal of Mechanical Design* 136(3): 031003. http://mechanicaldesign.asmedigitalcollection.asme.org/article.aspx?doi=10.1115/1.4026094 (June 26, 2018).

Ruel, Marie T., Agnes R. Quisumbing, and Mysbah Balagamwala. 2018. "Nutrition-Sensitive Agriculture: What Have We Learned so Far?" *Global Food Security*. https://www.sciencedirect.com/science/article/pii/S221191241730127X (March 2, 2018).

Ruiz-Mercado, Ilse, Eduardo Canuz, and Kirk R. Smith. 2012. "Temperature Dataloggers as Stove Use Monitors (SUMs): Field Methods and Signal Analysis." *Biomass and Bioenergy* 47: 459–68. https://www.sciencedirect.com/science/article/pii/S096195341200342X (March 6, 2018).

Sahin, Ismail. 2006. "Detailed Review of Rogers' Diffusion of Innovations Theory and Educational Technology-Related Studies Based on Rogers' Theory." *The Turkish Online Journal of Educational Technology* 5(2): 14–23.

Scalco, Andrea, Stefano Noventa, Riccardo Sartori, and Andrea Ceschi. 2017. "Predicting Organic Food Consumption: A Meta-Analytic Structural Equation Model Based on the Theory of Planned Behavior." *Appetite* 112: 235–48. https://www.sciencedirect.com/science/article/pii/S0195666317301939 (June 25, 2018).

Schwartz, Shalom H. 1977. "Normative Influences on Altruism." *Advances in Experimental Social Psychology* 10: 221–79.

Schwarz, Nina, and Andreas Ernst. 2009. "Agent-Based Modeling of the Diffusion of Environmental Innovations - An Empirical Approach." *Technological Forecasting and Social Change* 76(4):

497–511.
Scott Long, J, and Jeremy Freese. 2014. "Models for Ordinal Outcomes." In *Regression Models for Categorical Dependent Variables Using Stata*, Stata Press, 589. https://www.stata.com/bookstore/regression-models-categorical-dependent-variables/ (March 8, 2018).
Shafiei, Ehsan et al. 2012. "An Agent-Based Modeling Approach to Predict the Evolution of Market Share of Electric Vehicles: A Case Study from Iceland." *Technological Forecasting and Social Change* 79(9): 1638–53. https://www.sciencedirect.com/science/article/pii/S0040162512001412 (February 13, 2019).
Shankar, Anita et al. 2014. "Maximizing the Benefits of Improved Cookstoves: Moving from Acquisition to Correct and Consistent Use." *Global health, science and practice* 2(3): 268–74. http://www.ncbi.nlm.nih.gov/pubmed/25276586 (November 10, 2017).
Sharma, Rajesh, and Rajhans Mishra. 2014. *A Review of Evolution of Theories and Models of Technology Adoption Common Service Centres View Project Common Service Centres View Project*. https://www.researchgate.net/publication/295461133 (August 15, 2018).
Shin, Jaekwan, and Scott Ferguson. 2016. "Product Line Design Search Considering Reliability and Robustness Under Uncertainty in Discrete Choice Methods." In *Volume 2A: 42nd Design Automation Conference*, ASME, V02AT03A039. http://proceedings.asmedigitalcollection.asme.org/proceeding.aspx?doi=10.1115/DETC2016-59535 (August 14, 2018).
Shukri, Madihah, Fiona Jones, and Mark Conner. 2016. "Work Factors, Work-Family Conflict, the Theory of Planned Behaviour and Healthy Intentions: A Cross-Cultural Study." *Stress and Health* 32(5): 559–68. http://doi.wiley.com/10.1002/smi.2662 (February 13, 2018).
Smith, Kirk R. et al. 2007. "Monitoring and Evaluation of Improved Biomass Cookstove Programs for Indoor Air Quality and Stove Performance: Conclusions from the Household Energy and Health Project." *Energy for Sustainable Development* 11(2): 5–18. https://www.sciencedirect.com/science/article/pii/S0973082608603968 (April 30, 2018).
Smith, Kirk R et al. 2014. "Millions Dead: How Do We Know and What Does It Mean? Methods Used in the Comparative Risk Assessment of Household Air Pollution." *Chennai) College Park Kurt Straif (International Agency for Research on Cancer Sophie Bonjour (World Health Organization GenevaThe Health Effects Institute Annu. Rev. Public Health* 35: 185–206. www.annualreviews.org (November 10, 2017).
Sniehotta, Falko F., Justin Presseau, and Vera Araújo-Soares. 2014. "Time to Retire the Theory of Planned Behaviour." *Health Psychology Review* 8(1): 1–7. http://www.tandfonline.com/doi/abs/10.1080/17437199.2013.869710 (June 26, 2018).
Sopha, Bertha Maya, Christian A. Klöckner, and Dona Febrianti. 2017. "Using Agent-Based Modeling to Explore Policy Options Supporting Adoption of Natural Gas Vehicles in Indonesia." *Journal of Environmental Psychology* 52: 149–65.
Stern, Paul C. 2000. "New Environmental Theories: Toward a Coherent Theory of Environmentally Significant Behavior." *Journal of Social Issues* 56(3): 407–24. http://doi.wiley.com/10.1111/0022-4537.00175 (December 14, 2016).
Still, Dean, Samuel Bentson, and Haixi Li. 2015. "Results of Laboratory Testing of 15 Cookstove Designs in Accordance with the ISO/IWA Tiers of Performance." *EcoHealth* 12(1): 12–24. http://dx.doi.org/10.1007/s10393-014-0955-6.
Telenko, Cassandra, and Carolyn Seepersad. 2014. "Scoping Usage Contexts and Scenarios in Eco-Design." In *Volume 4: 19th Design for Manufacturing and the Life Cycle Conference; 8th*

*International Conference on Micro- and Nanosystems*, ASME, V004T06A055. http://proceedings.asmedigitalcollection.asme.org/proceeding.aspx?doi=10.1115/DETC2014-34846 (August 16, 2018).

Thandapani, Selvan, and Richard Woodbridge. 2011. "Assessing the Benefits of Early Stage Design Research of Rural BoP-Focused Energy Solutions in Urban Settings." In *ICoRD '11 International Conference on Research into Design*, http://www.ifmrlead.org/wp-content/uploads/2015/OWC/ICoRD_Assessing-the-Benefits-of-Early-Stage.pdf (February 13, 2018).

Thurstone, L. L. 1927. "A Law of Comparative Judgment." *Psychological Review* 34(4): 273–86. http://content.apa.org/journals/rev/34/4/273 (August 9, 2018).

Trochim, William M. K., and James P. Donnelly. 2008. *Research Methods Knowledge Base*. Atomic Dog/Cengage Learning.

United Nations. 2015. *Transforming Our World: The 2030 Agenda for Sustainable Development*. New York, New York, USA: UN Publishing.

Venkatesh, V., and F. D. Davis. 2000. "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies." *Management Science* 46(2): 186–204.

Venkatesh, Viswanath, Michael G. Morris, Gordon B. Davis, and Fred D. Davis. 2003. "User Acceptance of Information Technology: Toward a Unified View." *MIS Quarterly* 27(3): 425. https://www.jstor.org/stable/10.2307/30036540 (August 15, 2018).

Ventrella, Jennifer, and Nordica A MacCarty. 2018. "Development and Pilot Study of an Integrated Sensor System to Measure Fuel Consumption and Cookstove Use in Rural Households." In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Quebec, Canada: ASME.

Wang, Jiliang, Bernard Yannou, Fabrice Alizon, and Pierre-Alain Yvars. 2013. "A Usage Coverage-Based Approach for Assessing Product Family Design." *Engineering with Computers* 29(4): 449–65. http://link.springer.com/10.1007/s00366-012-0262-1 (August 16, 2018).

Watts, Duncan J, and Steven H Strogatz. 1998. "Watts-1998-Collective Dynamics of 'small-World." *Nature* 393(June): 440–42.

Webb, Thomas L., and Paschal Sheeran. 2006. "Does Changing Behavioral Intentions Engender Behavior Change? A Meta-Analysis of the Experimental Evidence." *Psychological Bulletin* 132(2): 249–68. http://doi.apa.org/getdoi.cfm?doi=10.1037/0033-2909.132.2.249 (February 2, 2018).

Weigel, Fred K, Benjamin T Hazen, Casey G Cegielski, and Dianne J Hall. 2014. "Diffusion of Innovations and the Theory of Planned Behavior in Information Systems Research: A Metaanalysis." *Communications of the Association for Information Systems* 34(31): 619–36. http://aisel.aisnet.org/cais/vol34/iss1/31 (August 15, 2018).

Williams, Michael D, Nripendra P Rana, and Yogesh K Dwivedi. 2015. "The Unified Theory of Acceptance and Use of Technology (UTAUT): A Literature Review." *Journal of Enterprise Information Management* 28(3): 443–88.

Winijkul, Ekbordin, Laura Fierce, and Tami C. Bond. 2016. "Emissions from Residential Combustion Considering End-Uses and Spatial Constraints: Part I, Methods and Spatial Distribution." *Atmospheric Environment* 125: 126–39. https://www.sciencedirect.com/science/article/pii/S1352231015304313 (February 27, 2019).

World Health Organization. 2016. WHO *Burning Opportunity: Clean Household Energy for Health, Sustainable Development, and Wellbeing of Women and Children*. World Health Organization. http://www.who.int/indoorair/publications/burning-opportunities/en/ (October 14, 2016).

Wu, Susie R., Martin Greaves, Jiquan Chen, and Sue C. Grady. 2017. "Green Buildings Need Green Occupants: A Research Framework through the Lens of the Theory of Planned Behaviour." *Architectural Science Review* 60(1): 5–14. https://www.tandfonline.com/doi/full/10.1080/00038628.2016.1197097 (June 25, 2018).

Yadav, Rambalak, and Govind S. Pathak. 2017. "Determinants of Consumers' Green Purchase Behavior in a Developing Nation: Applying and Extending the Theory of Planned Behavior." *Ecological Economics* 134: 114–22. https://www.sciencedirect.com/science/article/pii/S0921800916307613 (June 25, 2018).

Yadav, Rambalak, and Govind Swaroop Pathak. 2016. "Young Consumers' Intention towards Buying Green Products in a Developing Nation: Extending the Theory of Planned Behavior." *Journal of Cleaner Production* 135: 732–39. https://www.sciencedirect.com/science/article/pii/S0959652616307971 (February 13, 2018).

Yannou, Bernard, Pierre-Alain Yvars, Chris Hoyle, and Wei Chen. 2013. "Set-Based Design by Simulation of Usage Scenario Coverage." *Journal of Engineering Design* 24(8): 575–603. http://www.tandfonline.com/doi/abs/10.1080/09544828.2013.780201 (August 16, 2018).

Yuntenwi, E. A T, Nordica MacCarty, Dean Still, and Jürgen Ertel. 2008. "Laboratory Study of the Effects of Moisture Content on Heat Transfer and Combustion Efficiency of Three Biomass Cook Stoves." *Energy for Sustainable Development* 12(2): 66–77. http://dx.doi.org/10.1016/S0973-0826(08)60430-5.

Zhang, Tao, and William J Nuttall. 2012. "An Agent-Based Simulation of Smart Metering Technology Adoption." *International Journal of Agent Technologies and Systems (IJATS)* 4(1): 17–38.

# Appendix I – Survey questions

Honduras - Baseline

How much do you trust following:

1. Your village neighbors

   Do not trust -2 -1 0 +1 +2 trust

2. Your local organizations

   Do not trust -2 -1 0 +1 +2 trust

3. People from other villages

   Do not trust -2 -1 0 +1 +2 trust

4. Stranger

   Do not trust -2 -1 0 +1 +2 trust

5. How many meals do you expect to cook each day with the ecocina?

   None 1 2 3 4 5

6. How much do you value NGO/Government officials' opinion about using ecocina?

   A lot, try to comply

   I respect their opinion, but it doesn't influence me

   I don't pay attention

   I ignore them

   I try the opposite

7. Consuming less fuelwood is :______________

   Very important important Doesn't matter not important Not important at all

8. How much do you think less fire smoke is important?

   Not important moderately important I don't know important very important

9. How much do you think cooking meal with ecocina changes the taste of the food?

   no change a little bit I don't know considerably a lot

10. How difficult do you think it will be to not use your traditional stove?

    very hard Hard I don't know easy very easy

11. How much do you value doctors' opinion about using ecocina?

    A lot, try to comply

    I respect their opinion, but it doesn't influence me

    I don't pay attention

    I ignore them

I try the opposite

12. Can you decide to use ecocina or do you need to consult someone?

    I can decide myself

    I feel I can decide by myself

    I don’t know

    I prefer to consult

    I need to consult

13. Doctors opinions are: ___________

    Important and correct good to consider I don’t know not important incorrect

14. How much do you think less fuelwood consumption is important?

    Not important moderately important I don’t know important very important

15. NGOs/government officials opinions are:_____________

    Important and correct good to consider I don’t know not important incorrect

16. How much do you value the opinion of people that are important to you about your decision on using ecocina?

    Very much a little bit I don’t know not particularly

    I don’t care what they think

17. How much do you think ecocina is designed to meet your needs?

    Very good designed Its OK I don’t know I’m not confident it’s a good design

    Its not designed based on what I need

18. For the people who are important to you do you think that for them it s important that you adopt ecocina?

    They discourage They don’t feel good Indifferent they feel good they encourage

19. Do you think you will cook all of your meals with ecocina?

    Not at all not likely Maybe most likely Yes for sure

20. How much do you value teachers' opinion about using ecocina?

    A lot, try to comply

    I respect their opinion, but it doesn’t influence me

    I don’t pay attention

    I ignore them

    I try the opposite

21. How much do you think cooking meal with ecocina is beneficial?

    Detrimental somewhat harmful neutral somewhat beneficial beneficial

22. Are you confident that you can use ecocina?

    Not at all I'm not sure I don't know I am confident I'm very confident

23. Spending less time for cooking is: __________

    Very important important doesn't matter not important not important at all

24. Teachers opinions are:___________

    Important and correct good to consider I don't know not important incorrect

25. Emitting less smoke is:___________

    Not important moderately important I don't know important very important

26. Will you cook your principal meals mainly with the ecocina?

    Not at all not likely maybe most likely yes for sure

27. How much do you think replacing your current stove with ecocina is feasible?

    Its very hard to change

    It's a little hard to change current stove

    I don't know

    Its easy to change current stove

    Its necessary to change current stove

28. How much do you think cooking meal with ecocina is easy?

    Very easy somewhat easy I don't know hard very hard

29. For the people who are important to you do you think that for them it s important that you adopt ecocina?

    Not at all they feel good they encourage you they don't feel good they discourage

30. How much do you think the time it will take to learn how to use ecocina is a problem?

    Not a problem at all could be a problem I don't know challenging very problematic

31. How much do you value cooking your meals faster?

    Not important moderately important I don't know important very important

Honduras- Follow-up

1- How many meals do you cook each day with the ecocina?

None 1 2 3 4

2- How much do you value NGO/Government officials' opinion about using ecocina?

A lot, try to comply I respect their opinion, but it doesn't influence me

I don't pay attention I ignore them I try the opposite

3. Consuming less fuelwood is :______________

Very important Important Doesn't matter Not important Not important at all

4. When you want to cook for more people than usual, which stove is better for you?

Ecocina is much better Ecocina is somewhat better No difference Traditional stove is somewhat better Traditional stove is much better

5. How much do you think cooking meal with Ecocina changes the taste of the food?

No change A little bit I don't know Considerably A lot

6. How much do you value doctors' opinion about using ecocina?

A lot, try to comply I respect their opinion, but it doesn't influence me

I don't pay attention I ignore them I try the opposite

7. How much do you think less fire smoke is important?

Very important Important Doesn't matter Not important Not important at all

8. Is it your decision to keep using your Ecocina or do you need to consult someone?

I can decide myself I feel I can decide by myself I don't know I prefer to consult

I need to consult

9. When you have less fuelwood than usual cooking with Ecocina is:

Very difficult Difficult I don't know Easy Very easy

10. Doctors opinions are: ___________

Important and correct Good to consider I don't know Not important Incorrect

11. When you have a low supply of fuelwood which stove is better for you?

Ecocina is much better Ecocina is somewhat better No difference

Traditional stove is somewhat better Traditional stove is much better

12. How much do you think less fuelwood consumption is important?

Very important Important Doesn't matter Not important Not important at all

13. NGOs/government officials opinions are:____________

Important and correct Good to consider I don't know Not important Incorrect

14. How much do you value the opinion of people that are important to you about your decision on using Ecocina?

Very much A little bit I don't know Not particularly

I don't care what they think

15. How much do you think Ecocina is designed to meet your needs?

Very well designed Its fine I don't know It's not the best design for my need

It's not designed based on what I need

16. For the people who are important to you do you think that for them it is important that you adopt Ecocina?

They discourage They don't feel good Indifferent They feel good

They encourage

17. Do you think you will cook all of your meals with Ecocina?

Not at all Not likely Maybe Most likely Yes for sure

18. How much do you value teachers' opinion about using Ecocina?

A lot, try to comply I respect their opinion, but it doesn't influence me

I don't pay attention I ignore them I try the opposite

19. How much do you think cooking meal with Ecocina is beneficial?

Detrimental Somewhat harmful Neutral Somewhat beneficial beneficial

20. Cooking a meal quickly with the Ecocina is:

Very difficult Difficult I don't know Easy Very easy

21. Spending less time for cooking is: __________

Very important Important Doesn't matter Not important Not important at all

22. teachers opinions are:___________

Important and correct Good to consider I don't know Not important Incorrect

23. Emitting less smoke is:___________

Very important Important Doesn't matter Not important Not important at all

24. Do you cook your principal meals mainly with the Ecocina?

Never Rarely Sometimes Often Always

25. When you want to cook for more people than usual, using the Ecocina is:

Very difficult Difficult I don't know Easy Very easy

26. How much do you value other people's experience using Ecocina over your experience?

Very much A little bit I don't know Not particularly

I don't care what they think

27. When you want to cook something fast which stove is better for you?

Ecocina is much better Ecocina is somewhat better No difference

Traditional stove is somewhat better Traditional stove is much better

28. How much do you value cooking your meals faster?

Very important Important Doesn't matterNot important Not important at all

Uganda - Baseline

Please read this to the respondent: Now I want to ask your opinion about improved cookstoves. I know you may not have cooked with any of the improved cookstoves yet. You can answer based on whatever you think could be possibly correct about an improved cookstove. The questions have five different choices with different intensity. Depend on how strong you feel you can pick one choice.

1. How many meals do you want to cook each day with your improved cookstove?
   - None
   - 1
   - 2
   - 3
   - 4
2. If you buy an improved cookstove, how likely is it to cook your principal meals with it.
   - Very unlikely
   - A little unlikely
   - Neutral
   - Somewhat likely
   - Very likely
3. How much do you agree or disagree with the following sentence: I will use an improved cookstove more, if it looks beautiful.
   - Strongly disagree
   - Disagree
   - Neither agree or disagree
   - Agree
   - Strongly agree
4. How much do you think cooking meals with an improved cookstove changes the fuelwood consumption?
   - Burns significantly more fuelwood
   - Burns a little more fuelwood
   - No difference

- Burns a little less fuel wood
- Burns significantly less fuelwood

5. Compared to cooking with traditional stoves, how safe or dangerous is it to use an improved cookstove?
   - Improved cookstove is a lot more dangerous
   - Improved cookstove is a little more dangerous
   - No difference
   - Improved cookstove is a little more safe
   - Improved cookstove is a lot more safe
6. How much do you think cooking meals with an improved cookstove is easy or hard?
   - It’s very hard
   - It’s a little difficult
   - No difference
   - It’s a little easy
   - It’s very easy
7. What do you think about the smoke an improved cookstove emits?
   - Too much more than traditional stove
   - A little more than traditional stove
   - No difference
   - A little less than traditional stove
   - Significantly less than traditional stove
8. How much do you think cooking with an ICS changes the amount of charcoal/fuel you buy?
   - Significantly increases what I currently buy
   - A little increases what I currently buy
   - Does not change
   - A little bit reduces what I currently buy
   - Significantly reduces what I currently buy
9. How many of your friends and family use an improved cookstove themselves?
   - None of them

- Less than 4
- Between 4 to 7
- Between 7 to 10
- More than 10 (all of them)

10. If you use an improved cookstove, do you think your friends and family support you or discourage you?

    - Very discouraging
    - A little discouraging
    - Neither supportive or discouraging
    - A little supportive
    - Very supportive

11. How much do you agree or disagree with the following sentence: my friends and family expect me to use traditional stove.

    - Strongly disagree
    - Disagree
    - Neither agree or disagree
    - Agree
    - Strongly agree

12. Do you need to ask permission or consult with someone for using an improved cookstove?

    - My husband decides about it
    - My husband decides after consulting with me
    - We consult and decide together
    - I decide after consulting with my husband
    - It’s completely up to me

13. Overall, how easy or hard do you think it is to use an improved cookstove instead of your mud stove/metallic charcoal stove?

    - Very hard
    - A little difficult
    - Neither hard nor easy
    - easy
    - Very easy

14. How much do you agree or disagree with the following sentence: I am the only person who can decide whether to use an improved cookstove or not.

- Strongly disagree
- Disagree
- Neither agree or disagree
- Agree
- Strongly agree

15. How many meals do you think you will cook with the improved cookstove during each week?

- Less than 3
- Between 3 to 5 meals
- Between 5 to 7 meals
- Between 7 to 10
- More than 10 meals] (4)

16. How does an improved cookstove compare to your traditional stove in general?

- Much worse
- Somewhat worse
- No difference
- Somewhat better
- Much better

17. How much do you value opinion of the people whom are important to you about your cookstove?

- Not at all important
- Neutral
- Slightly important
- Important
- Very important

18. How much are you confident that you will use an improved cookstove regularly to cook your meals?

- Very uncertain

- Slightly uncertain
- Neither confident nor uncertain
- Slightly confident
- Very confident

19. Emitting less smoke is: ____________
    - Very bad
    - A little bad
    - Not a problem
    - A little good
    - Very good

Uganda - Follow-up

Please read this to the respondent: Now that you have used ILF woodstove for a couple of weeks, I want to ask your opinion about it. The following questions have five different choices with different intensity. We would like to hear your opinion based on how strong you believe in your answer. That is why there is a range with different intensity. Please select the choice that reflects strength of your belief regarding your answer.

1. Now that we are removing sensors and you have experienced ILF woodstove, how likely is it that you cook all your main meals with ILF woodstove?
   - Extremely unlikely
   - Unlikely
   - Neutral
   - Likely
   - Extremely likely
2. How often do you cook your main meals with your improved cookstove?
   - Never
   - Seldom
   - About half the time
   - Usually
   - Always
3. How much do you agree or disagree with the following sentence: I will use an improved cookstove more, if it looks beautiful.
   - Strongly disagree
   - Disagree
   - Neither agree or disagree
   - Agree
   - Strongly agree
4. How much do you agree or disagree with the following sentence: The most important reason that I use ILF woodstove because it uses less firewood.
   - Strongly disagree
   - Disagree

- Neither agree or disagree
- Agree
- Strongly agree

5. Compared to cooking with traditional stoves, how safe or dangerous is it to use ILF woodstove?
    - Improved cookstove is a lot more dangerous
    - Improved cookstove is a little more dangerous
    - No difference
    - Improved cookstove is a little more safe
    - Improved cookstove is a lot more safe
6. How much do you think cooking meals with ILF woodstove is easy or hard?
    - It’s very hard
    - It’s a little difficult
    - No difference
    - It’s a little easy
    - It’s very easy
7. How much do you agree or disagree with this sentence: Less smoke emission is the most important reason that you use improved cookstove.
    - Strongly disagree
    - Disagree
    - Neither disagree or agree
    - Agree
    - Strongly agree
8. How many of your friends and family use an improved cookstove themselves?
    - None of them
    - Less than 4
    - between 4 to 7
    - between 7 to 10
    - more than 10 (all of them)
9. To what extend do you think your friends and family encourage or discourage you to cook main meals with ILF woodstove?

- very discouraging
- A little discouraging
- Neither supportive or discouraging
- A little supportive
- Very supportive

10. How much do you care or don't care about the stove type that your neighbors use?
    - Not at all important
    - A little important
    - Slightly important
    - Important
    - Very important
11. Do you need to ask permission or consult with someone for using ILF woodstove?
    - My husband decides about it
    - My husband decides after consulting with me
    - We consult and decide together
    - I decide after consulting with my husband
    - It's completely up to me
12. How easy or hard do you think it is to use an improved cookstove instead of your traditional stove?
    - Very hard
    - A little difficult
    - Neither hard nor easy
    - Easy
    - Very easy
13. How much do you agree or disagree with the following sentence: I am the only person who can decide whether to use an improved cookstove or not.
    - Strongly disagree
    - Disagree
    - Neither agree or disagree
    - Agree
    - Strongly agree

14. How often do you think you will use ILF woodstove in next few months to cook your main meals?

- Never
- Seldom
- Sometimes
- Usually
- Almost always

15. How much do you value opinion of the people whom are important to you about your cookstove?

- Not at all important
- Neutral
- Slightly important
- Important
- Very important

16. How hard or easy is it to use improved cookstove instead of your traditional stove regularly?

- Very hard
- A little difficult
- neither hard nor easy
- Somewhat easy
- Very easy

17. Generally what do you think about emission of less smoke?------------

- Very bad
- A little bad
- Not a problem
- A little good
- Very good

18. Less firewood burning is :What do you think about less firewood burning

- Not important at all
- A little important
- Fairly important

- Important
- Very important

# Appendix II – ABM code

```
import math
from enum import Enum
import networkx as nx
from mesa import Agent, Model
from mesa.time import RandomActivation
from mesa.datacollection import DataCollector
import pandas as pd
import random
from mesa.space import NetworkGrid
import matplotlib.pyplot as plt
from pandas import ExcelWriter
from matplotlib.pyplot import figure
from mesa.batchrunner import BatchRunner
```

In [2]:

```
# Loading data in the model

df = pd.read_csv('virtual_village_1.csv')




beta_price = 0.019501
beta_ft = -1.04942
beta_income = 0.071442
price_of = 5
price_ics = 100
price_cs = 75
price_ms = 25
```

In [34]:

```
# Defining each agent's behavior and attributes

class household(Agent):
    def __init__(self, Household_ID, model):
        super().__init__(Household_ID, model)
        self.income = df.at[Household_ID, 'income']
        self.att = df.at[Household_ID, 'Att2']
```

```
        self.sn = df.at[Household_ID, 'SN2']
        self.pbc = df.at[Household_ID, 'PBC1']
        self.age = df.at[Household_ID, 'age']
        self.edu = df.at[Household_ID, 'edumax']
        self.stv = df.at[Household_ID, 'stove0']
        self.beta_att = df.at[Household_ID, 'beta_att']
        self.beta_sn = df.at[Household_ID, 'beta_sn']
        self.beta_pbc = df.at[Household_ID, 'beta_pbc']
        self.influence = df.at[Household_ID, 'influence']


    def utility(self):
        util=[]
        util_of = beta_income * self.income +  beta_price * price_of
        util.append(util_of)
        util_ms = beta_income * self.income + self.beta_att * self.att + self.beta_sn
* self.sn + self.beta_pbc * self.pbc + beta_price * price_ms
        util.append(util_ms)
        util_ics = beta_income * self.income + self.beta_att * self.att + self.beta_sn
* self.sn + self.beta_pbc * self.pbc + beta_price * price_ics
        util.append(util_ics)
        util_cs = beta_income * self.income + self.beta_att * self.att + self.beta_sn
* self.sn + self.beta_pbc * self.pbc + beta_price * price_cs + beta_ft
        util.append(util_ms)
        #print (util)
        #self.stv = util.index(max(util))+1
        #self.sn +=0.1
        #self.att +=0.1
        #self.pbc +=0.1
        #stove.append(self.util.index(max(util)))
        #self.stv=1
        #print(util)
        self.pr=[]
        self.pr_of = (math.exp(util_of))/(math.exp(util_ms)+math.exp(util_of)+math.exp
(util_ics)+math.exp(util_cs))
        self.pr.append(self.pr_of)
        self.pr_ms = (math.exp(util_ms))/(math.exp(util_ms)+math.exp(util_of)+math.exp
(util_ics)+math.exp(util_cs))
        self.pr.append(self.pr_ms)
        self.pr_ics = (math.exp(util_ics))/(math.exp(util_ms)+math.exp(util_of)+math.e
xp(util_ics)+math.exp(util_cs))
```

```
        self.pr.append(self.pr_ics)

        self.pr_cs = (math.exp(util_cs))/(math.exp(util_ms)+math.exp(util_of)+math.exp
(util_ics)+math.exp(util_cs))

        self.pr.append(self.pr_cs)

        self.stv = self.pr.index(max(self.pr))+1

        if self.stv == 3:

            self.sn +=0.5

            self.att +=0.5

            self.pbc +=0.5



    def step(self):


        social_ties_nodes = self.model.grid.get_neighbors(self.pos, include_center=Fal
se)

        adopted_social_ties = [agent for agent in self.model.grid.get_cell_list_conten
ts(social_ties_nodes) if agent.stv ==3]


        num_adopters = 7

        #num_adopters = 6

        #num_adopters = 4  #baseline

        #num_adopters = 5


        influenced = [agent for agent in self.model.grid.get_cell_list_contents(social
_ties_nodes) if agent.influence ==0]



        if len(influenced) < 2:   #baseline


            if len(adopted_social_ties) > num_adopters:

                self.stv = 3

            #self.pbc += 0.5

            #self.sn += 0.5

            #print (self.stv)

            else:

        #stove = []

                self.utility()

        #stove.append(self.stv)
```

```
        else:


            #self.stv = 2


            self.sn -=1
            self.att -=1
            self.pbc -=1
    def stovechoice(model):
        stove_choice = [agent.stv for agent in model.schedule.agents]
        #stove =[]
        #stove.append(stove_choice)
```

In [35]:

```
#Defining the space, network, and population scale behavior and attributes


class village(Model):


    def __init__(self, degradation_rate = 20):
        self.running = True
        self.schedule = RandomActivation(self)
        self.num_agents = len(df.index)
        #self.G = nx.watts_strogatz_graph(len(df.index),8,0.2,seed=None)   #baseline
        #self.G = nx.watts_strogatz_graph(len(df.index),10,0.2,seed=None)
        self.G = nx.watts_strogatz_graph(len(df.index),12,0.2,seed=None)
        #self.G = nx.watts_strogatz_graph(len(df.index),6,0.2,seed=None)



        self.grid = NetworkGrid(self.G)
        self.malfunction_rate = degradation_rate


        for k, node in enumerate(self.G.nodes()):
            a = household(k, self)
            self.schedule.add(a)
            self.grid.place_agent(a, node)


        malfunction_stoves = self.random.sample(self.G.nodes(), self.malfunction_rate)
        for a in self.grid.get_cell_list_contents(malfunction_stoves):
```

```
            a.influence = 0

        self.datacollector = DataCollector(model_reporters={"Adoption Rate":adoption_r
ate}, agent_r    eporters={"stove":lambda a: a.stv})



        self.datacollector.collect(self)

    def step(self):

        self.schedule.step()

        self.datacollector.collect(self)
```

In [36]:

```
# Calculation of number of ICS adopters over the village population


def adoption_rate(model):

    ics_owners = [agent.stv for agent in model.schedule.agents if agent.stv ==3]

    #print(len(ics_owners))

    c = len(ics_owners)

    d = len(df.index)

    return (c/d)
```

In [37]:

```
# Running the model


model = village(100)

for i in range(20):

    model.step()
```

In [38]:

```
#Plotting results


stove_choice = model.datacollector.get_agent_vars_dataframe()

adoption_plot = model.datacollector.get_model_vars_dataframe()

adoption_plot.plot()


#adoption_plot.to_csv('SN_6nodes_3adopter.csv',encoding='utf-8')

#adoption_plot.to_csv('SN_8nodes_5adopter.csv',encoding='utf-8')

#adoption_plot.to_csv('SN_10nodes_7adopter.csv',encoding='utf-8')
```

```
adoption_plot.to_csv('SN_12nodes_8adopter.csv',encoding='utf-8')


fig_size = plt.rcParams["figure.figsize"]


fig_size[0] = 12
fig_size[1] = 9
plt.rcParams["figure.figsize"] = fig_size
#figure(num=None ,figsize=(8,6), dpi=80, facecolor='w', edgecolor='k')
#writer = ExcelWriter('virtual_village_results_15.xlsx')
#stove_choice.to_excel(writer,'Sheet1')
#writer.save()
```

In [23]:

```
# generating the plot with multiple model setups for stove degradation rates
from matplotlib.ticker import FormatStrFormatter
import numpy as np
adrate_SN_6nodes_3adopter = pd.read_csv('SN_6nodes_3adopter.csv')
adrate_SN_8nodes_5adopter = pd.read_csv('SN_8nodes_5adopter.csv')
adrate_SN_10nodes_7adopter = pd.read_csv('SN_10nodes_7adopter.csv')
adrate_SN_12nodes_8adopter = pd.read_csv('SN_12nodes_8adopter.csv')



#results.info()
adrate_SN_6nodes_3adopter.rename(columns={'Adoption Rate':'SN_6nodes_3adopter'},inplac
e=True)
adrate_SN_8nodes_5adopter.rename(columns={'Adoption Rate':'SN_8nodes_5adopter'},inplac
e=True)
adrate_SN_10nodes_7adopter.rename(columns={'Adoption Rate':'SN_10nodes_7adopter'},inpl
ace=True)
adrate_SN_12nodes_8adopter.rename(columns={'Adoption Rate':'SN_12nodes_8adopter'},inpl
ace=True)



frames = [adrate_SN_6nodes_3adopter, adrate_SN_8nodes_5adopter, adrate_SN_10nodes_7ado
pter, adrate_SN_12nodes_8adopter]
results = pd.concat(frames, axis=1)
t = results[['SN_6nodes_3adopter','SN_8nodes_5adopter', 'SN_10nodes_7adopter', 'SN_12n
odes_8adopter' ]]
#print(t)
#t.plot()
```

```
#t = results[['negative elasticity','50% positive elasticity', 'twice positive elastic
ity', 'Original price elasticity' ]]


t1 = results['SN_6nodes_3adopter']#, label = "Negative Elasticity"]
t2 = results['SN_8nodes_5adopter']#, label = "50% Positive Elasticity"]
t3 = results['SN_10nodes_7adopter']#, label = "Twice Positive Elasticity" ]


t4 = results['SN_12nodes_8adopter']#, label = "Original Price Elasticity"]
#print(t)
#t.plot(marker='o')
import matplotlib as mpl
mpl.rc('font', family='Times New Roman', size=23)
plt.plot(t1, 'o', t2, 'x', t3,'s', t4, '^',markersize=16,linewidth =2 , linestyle = 's
olid')
#plt.title("Influence of price elasticity in ICS adoption")
plt.xlabel("Time Step", fontname="Times New Roman", fontsize =23)
plt.ylabel("Adoption Rate",fontname="Times New Roman", fontsize=23)
ax = plt.gca()
plt.legend(('4 ICS users from 6 peers network','5 ICS users from 8 peers network','6 I
CS users from 10 peers network','7 ICS users from 12 peers network'),bbox_to_anchor=
(1.6, 1.33), bbox_transform=ax.transData)
#ax = plt.gca()
#plt.legend(('60 malfunctioned ICS','100 malfunctioned ICS','150 malfunctioned ICS','1
80 malfunctioned ICS'),fontsize=20, bbox_to_anchor=(1.6, 1.33)


plt.xlim(0,20)
plt.xticks(np.arange(1,21,2))


plt.show()
fig_size = plt.rcParams["figure.figsize"]
fig_size[0] = 12
fig_size[1] = 9
plt.rcParams["figure.figsize"] = fig_size
```