Design for Clean Technology Adoption: Integration of Usage Context, User Behavior, and Technology Performance in Design

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Clean technologies aim to address climatic, environmental, and health concerns associated with their conventional counterparts. However, such technologies achieve these goals only if they are adopted by users and effectively replace 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 the behavioral motivations of users during the design process for these technologies. In this study, the theory of planned behavior (TPB) is integrated with usage-context-based design to provide a holistic approach for predicting the market share of clean versus conventional product 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, resulting in the design of products that are more in line with users' behavioral intentions, which can lead to higher adoption rates. The developed framework is applied in a case study of adoption of improved cookstoves in a community in Northern Uganda. Results indicate that incorporating TPB attributes into utility functions improves the prediction power of the model and that the attributes that users in the subject community prioritize in a clean cookstove are elicited through the TPB. Households' decision-making behavior before and after a trial period suggests that design and marketing strategy should systematically integrate user's behavioral tendencies prior to interventions to improve the outcomes of clean technology implementation projects. [DOI: 10.1115/1.4046236]

Keywords: conceptual design, design process, energy systems design, multidisciplinary design and optimization, user-centered design

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. Many 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. The adoption of clean technology in this context is defined as an effective and systematic change toward using clean technology instead of the traditional, inefficient counterpart. In some cases, traditional methods may have considerable social and/or cultural ties with users. In these scenarios, adopting cleaner practices may not be an instant and complete shift, but rather a gradual replacement and regular choice to opt for the cleaner alternative [1]. Despite the importance of replacing inefficient practices with clean alternatives, 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 priorities and behaviors in the decision-making process. Compared to the traditional methods in decision-based design which account for user demographics, price, technology, or alternative related variables, design for adoption must also bring in the quantification of user behavior through lenses of individual beliefs, social norms, and ability to change certain behaviors. The proposed approach in this study incorporates such attributes in a utility function applied for users' choice modeling.

The 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, the use of cleaner residential technologies could reduce US national carbon emissions by 7.4% [2]. And globally, nearly 40% of households rely on open burning of biomass to meet over 95% of their energy needs, and as a result, 4×10^6 premature deaths occur each year while the effects on climate change are exacerbated [3–6]. 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, with clean cookstove projects being a leading example [1,7,8]. However, studies suggest that the systematic integration of users in design and implementation may lead to increased uptake [9–11], and there is a significant need for research in this area. The proposed framework for clean technology adoption developed in this research has been applied to a case study of improved cookstove adoption to evaluate the performance of the theoretical framework. It is hoped that the application of the developed framework is extensible to the adoption behavior for any clean technology or service.

Today, there is no comprehensive approach to design clean technologies in a way to achieve environmental goals in the consumer

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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 [12]. However, today, there are no integrated methods that include these three key areas required to understand the adoption of these types of beneficial technologies, including (1) technology performance, (2) user behavior and preference, and (3) usage context.

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 systematic model 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. The predictive power and robustness of the models are compared and validated on a theoretical basis.

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 (a) technical needs and (b) user preferences in a (c) specific context of use. Throughout the literature, researchers have investigated the contribution of each of these separately.

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 detailing tests conducted on biomass cookstoves. Laboratory tests investigate different aspects of the technical design of improved cookstoves such as emissions, effects of fuel moisture content, and thermal efficiency [13–18]. 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 the usability testing protocol [8,19–22]. These methods have led to the development of a standard performance rating framework by the International Organization of Standardization standard number 19867-1 in four categories including efficiency, emissions, indoor emissions, and safety [23].

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, it is important to include the variables that provide the most practical insight for designers to reflect customer preferences in technology design and performance. A previous work in this area has developed methods for the systematic selection of engineering attributes that inform the utility functions in a way that technology designers could benefit the most [24,25].

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 a robust prediction of choices. However, choice modeling practice can be categorized into three general approaches [26]. The economic approach considers choices as utility maximization efforts based on developed preferences. Adopting concepts of random utility theory developed by Thurstone [27], preferences of decision-makers are incorporated into utility functions that estimate the influence of each attribute on the final utility perceived by the person [28]. 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 [29]. 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 statistical approach to choice modeling is solely based on the recorded choices of individuals and statistical correlation of such choices to hypothesized attributes associated with choices given the purpose of the model. 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 [30].

In engineering design, the application of the categories above has been used for a number of applications. Research on 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 [31]. Discrete choice analysis (DCA) is among the most well-established and robust methods for the 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 a causal relationship with the 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 [32]. DCA models generally tend to apply multinomial logit [33], nested logit [34], or mixed logit [35] 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 [36]. In another study, the compensatory and non-compensatory processes of decision-making are explored [37]. 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 [38]. 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 the 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 [39].

In the 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 environment-related behavior. Thus, a relevant model should be applicable in explaining technology adoption, health behavior, and pro-environmental behavior.

There is a plethora of methods and theories in the literature to explain human behavior in a variety of contexts. Among well-established and frequently used frameworks in environmental and health-related behaviors are the theory of planned behavior (TPB), norm activation theory, value-belief-norm theory, goal framing theory, and health belief model [40,41]. A review of these theories and the variables that are incorporated in each one to partially explain environmental and/or health behavior suggest that TPB is not only parsimonious but also robust in terms of explaining behavior in domains of both health and environment. Therefore, for this study, TPB is selected to capture behavioral aspects of clean technology adoption. TPB 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 [42,43]

(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.

As illustrated in Fig. 1, these elements construct a behavior intention function that determines a person's readiness to take action. According to TPB, the intention is the main determinant of behavior. PBC is another determinant of behavior that captures the physical limitations to conduct a certain behavior despite having the intention to do so. For example, lack of access to a clean technology alternative prevents the adoption behavior even if the user has an intention to use clean technology. 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 [44], to green purchase behavior in the developing world [45], to organic food consumption [46], and the behavior change by physical activity and exercise [47], TPB is a well-established framework for environmental and health-related behaviors. There are limitations to the use of TPB, including the omission of the difference between value and expectancy beliefs [48], and the influence of habits [49]. However, these can be overcome with careful study design and appropriate statistical analysis [50].

Incorporation of Usage Context. One factor that influences both the performance of technology and hence user behavior and preference is the context of using the technology. The context is critical because human behavior and technology performance can vary significantly depending on the location, application, and details of the product use. For example, urban or rural contexts significantly change the preferred choice of the 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.

Early research that acknowledges the role of context in the customer's decision-making is based on the stimulus-organism-response

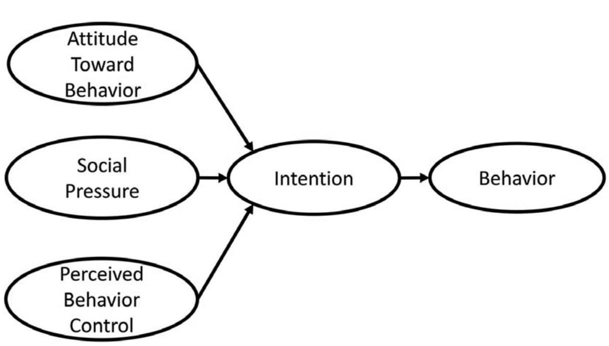

Fig. 1 Constructs of the theory of planned behavior [43]

(S-O-R) paradigm introduced by Belk [51]. 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; and
- 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 [52–54]. 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 framework that applies an adaptable approach to identify a product alternative that best covers a usage scenario space that includes different context-user scenarios [55]. 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 [56].

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 [57]. UCBD has been used for applications such as illustrating how usage context influences customers' choice of hybrid electric vehicles and jigsaws [57]. This model predicts the market share of each alternative based on the usage context, user preferences, technology performance, and design variables. The mathematical linkage of this framework enables designers to adjust design variables to maximize the market share of the 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 in choices among individuals is modeled based on individual attributes, technology alternative attributes, and usage context attributes. The choice share estimates the market share of each alternative in the studied population.

Summary of the Literature. While much work in the engineering design has focused on the design of technologies to achieve desired market shares in terms of purchasing products, the 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 attributes along with usage context attributes to design technologies for their adaptability. 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 the use of traditional biomass stoves and open fires on a daily basis for cooking food and warming water by 2.7×10^9 people [58]. International aid organizations, NGOs, and governments have been promoting the use of improved biomass cookstoves for several decades; however, goals for transitioning households to 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.

Methodology

The proposed framework 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 (Fig. 2). In this framework, the data regarding 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 the 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 utility function model to generate the highest market share of a desired clean technology alternative.

Model Development. To model the 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 the TPB, while the second incorporates the most significant behavioral attributes from the TPB into UCBD's utility function to estimate the utility that individuals assign to choice alternatives.

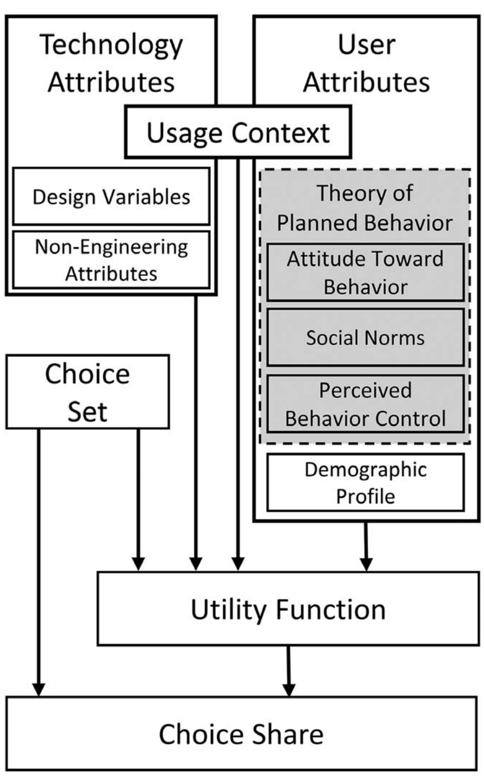

Fig. 2 Platform for integrating user behavior, usage context, and technology attributes

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 four categories. An indirect method could be used to quantify each category's score according to the expectancy-value model. In this method, the final score for each attribute is derived by multiplying the respondent's rating of beliefs about the consequences of behavior times desirability of such consequences [48]. Using the 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 [43].

Responses are coded as either unipolar or bipolar based on a Likert scale [59]. 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 the 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, esthetics, decision-making authority, ease of changing habits, role of neighbors' stove type, and other attributes detailed in Ref. [60]. The weight of each attribute that represents each category (α) in determining intention (Int) for each individual main cook of the household, also referred to as household, (i) is estimated through the regression analysis of Eq. (1)

$$Int_i^* = Int(\alpha : ATB_i^*,\ SN_i^*,\ PBC_i^*) \tag{1}$$

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 [61]. Based on these results, the most significant attributes that have the highest power to explain the 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 an estimate of the utility that individuals assign to choice alternatives. According to random utility theory, the true utility is not completely measurable and consists of an observed part or deterministic part (W), and an unobserved or random disturbance part (ε) [28]. Equation (2) is a mathematical expression of the true utility of alternative (j) for individual/household (i)

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

$$W_{i,j} = W(\beta : T_j,\ TPB_i,\ U_i,\ C_{i,j}) \tag{3}$$

The deterministic part of the utility function estimates the correlation of attributes discussed above with the stated or revealed the choice of the users. As shown in Eq. (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 addition, the most significant attributes that describe the intention based on the results of the Eq. (1) are included as TPB attributes to partially explain the utility of each choice for each individual, TPB_i. The weight of the influence of each independent variable in explaining the deterministic part of utility is captured by (β) based on the regression analysis. In this study, a conditional logistic regression is used for estimating the weights of attributes in predicting the stated choices of respondents. Stated choices of respondents comply with the independence of irrelevant alternatives (IIA) assumption that states the order of preferences for alternatives in the choice set should not change by the addition or the 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 the open fire is very easily accessible and free of charge, for more than a hundred years, households in the subject region have developed and used local mud stoves besides the open fire. Hence, their preferences for mud stove versus open fire is not likely to change due to the introduction of improved cookstoves (ICS). Additionally, the introduction of ICS is not likely to change preferences for charcoal stoves, since the main barrier to a dominant preference for charcoal stoves is due to the limited supply of charcoal in the region, leading to high costs of charcoal and short amount of supplies. Therefore, the IIA assumption is likely to be valid, and henceforth, the application of conditional logistics regression is justifiable.

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

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

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. The demand for each alternative could then be estimated through the multiplication of the number of individuals in each market segment times summation of probabilities of individuals' choices derived from Eq. (4) [62].

Data Collection. Data collection for the proposed model was implemented in five phases in a rural community in Apac, Uganda, in collaboration with International Lifeline Fund (ILF), a nongovernmental organization (NGO) active in clean cookstove development and implementation projects. All data were collected with oversight from the Oregon State University Institutional Review Board under study number 7257.

- **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 liquid petroleum gas (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 consistently 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 [63], a pilot study enables researchers to identify priorities, widespread beliefs regarding the task, social norms, and context-based preferences of users in the targeted community. A small convenience-based sample of 10 households along with the local staff of the partner NGO was chosen to conduct a pilot study to elicit general beliefs regarding cooking devices, important factors that community members associated with their stoves and foods, and available stove alternatives in the local market using focus group discussion and open-ended surveys. The open-ended questions for the pilot study were developed based on the discussion between researchers and local NGO staff and implemented in a set of ten convenience-sampled representative households. These general questions capture a spectrum of responses and opinions so that survey questions can be more targeted. For example, one question in the pilot study was "What would you like to change in your cooking practice if there was no financial or technical limitation and why?" Answers informed the researchers about the attributes that formulate opinions in the target community. For example, the answers that have a direct correlation with the necessity of smoke reduction are different from the answers that have a direct correlation with the firewood consumption, durability, or portability. Based on the information provided, researchers identified the attributes presented in Table 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., Ref. [64]). The sample size should be calculated based on the number of variables being studied in the model using the design of experiment methods. A target of 200 observations [32] or 10 observations per variable [65] are rough estimates for a reasonable sample size appropriate for the statistical analysis of the model. Therefore, a sample of 175 households was randomly selected in the target community based on ILF's experience in the field and their available logistics for the data collection process. The local staff for the NGO were trained to improve the quality of the collected data and reduce the potential bias by making sure to provide enough time for the respondent to think and answer, repeating questions and reading them without any emphasis on one response or one part of the question, learning the purpose of the survey and research, contributing to improving survey quality in the local language, and providing an explanation of the purpose of the study to respondents. Surveyors were also asked to make it clear that the study was to help improve cookstove program design so honest opinions were preferred to reduce social desirability bias. They also ensured the participants that their responses would in no way affect their relationship with ILF or their ability to receive stoves or other items/assistance in the future. The demographic details of the sample are presented in Table 2. Using observations from Step 2, survey

Table 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 Safety	Number of burners Dimension of burner
	Aesthetic Permission of family head Opinion of friends and family	Fuel type Thermal power Insulation

Table 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 the affected population)
Main cook's age distribution	Minimum: 15 Maximum: 75 Average: 36.16 Std. dev.: 15.32
Income average (per week)	24,000 UGX (~6.70 USD)
Education (primary income earner)	No education, 10% Incomplete primary, 17% Complete primary, 28% Incomplete secondary, 12% Complete secondary, 20% College/university, 11%

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 the 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 the 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. In addition, households were not notified that there would be another follow-up survey by the time they were offered with the improved cookstove.

- **Model Development and Data Analysis**. *Clean collected data and apply statistical modeling techniques to estimate each choice's market share*. The development of the TPB model and extracting the most important attributes are discussed in detail in Refs. [60,66]. The 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 included technology attributes (size, fuel type, and cost) and usage context attributes (indoor/outdoor, and firewood moisture content). Stata was used to analyze the data and develop the model based on Eq. (3). Table 3 presents the 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, the validity of the 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–retest reliability measure provides a rubric to compare responses with 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 the reliability of collected responses as a test–retest reliability measure. Second, the reliability of the data analysis was evaluated based on the cross-validation [67], goodness of fit measures, parallel regression assumption test, and tests for heteroscedasticity and multicollinearity. The results of these tests are presented in the results section.

Results

Three forms of utility functions were developed from the results presented in Table 3. While several models were able to include

Table 3 Results of developed utility functions with different levels of integrating user behavior attributes

Independent variables		Utility Function I (base utility function)	Utility Function II (base utility function without TPB)	Utility Function III (base utility function 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—ρ^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
χ^2 test (degree-of-freedom)		2867.01*** (14)	103.20*** (5)	1429.24*** (7)

Note: Robust standard errors in parenthesis. *p-value < 0.1; **p-value < 0.05; and ***p-value < 0.01.

both TPB constructs as well as demographic and technology attributes, the incorporation of usage context attributes led to erroneous utility function models due to the small sample size and lack of data variation in the sample. Therefore, data collected on the moisture content of firewood and indoor versus outdoor cooking as variables of the usage context are omitted from the utility function models presented in Table 3. Although the context-based attributes are not discussed further in this case study, former studies have emphasized the significance of including them in the utility function models (e.g., Refs. [54,57,68]). Therefore, future works should collect contextual data with a large enough sample size to capture its effect on the utility function. Nevertheless, statistically significant models integrating the other two categories were successfully developed.

Utility Function I is the base model that includes attributes representing all three TPB constructs that formulate the intention. The statistical significance of the multiple levels of ATB and PBC attributes suggests that including such independent variables improves the estimation power of the model as measured by the likelihood ratio test (presented in Table 4), pseudo R-square ρ^2 (27% in Utility Function I compared to 21% in Utility Function II), and lower Akaike information criterion (AIC) value (376.61 in Utility Function I compared to 385.62 in Utility Function II).

Results of Utility Function I indicate that the SN attribute is likely to have no statistically significant contribution to the respondents' choice of the stove. However, the lack of statistical significance of SN does not mean that social norms have no effect on households' choices. Since TPB constructs are interconnected, SN influences may be influencing ATB or PBC or both. This finding is in line with field observations. Because the data are 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 after the baseline survey. In terms of the influence of ATB attribute in predicting choices, Utility Function I suggests that considering firewood conservation as less important is likely to influence the overall choice of the stove significantly toward not choosing the ICS. One potential reason for the inconsistency in the direction of influence of different categories of ATB in predicting the choice could be due to the lack of significant representation of each category of this variable. The PBC attribute has a significant negative correlation with the choice of ICS when households perceive less independence in deciding what stove to use. The value of coefficients suggests 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 the majority of main cooks in the target community are women, they are exposed to the problems associated with traditional methods more than male heads of families. Therefore, it is 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 are to use ICS for cooking their main meals. The interconnectedness between ATB and PBC based on the structure of TPB theory is tested for multicollinearity effects in the regression analysis. A pairwise correlation of the two variables is 0.09 with the significance level of 0.22, suggesting that the two variables are not likely to cause multicollinearity.

Table 4 Likelihood ratio test for Hypotheses 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 utility function (LL_U)	−174.31	−174.31
Log-likelihood of restricted utility function (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

Utility Function II estimates the choices of customers based on conventional attributes for describing the utility of each alternative that does not include user behavior attributes in the utility functions. Similar to all other utility function models, in this model the fuel type and income have a 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 the 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 the 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 Utility Function II. Therefore, a comparison of the 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 a major influence on the choices of households. One potential explanation for the small contribution of the 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 from locally available material without any financial cost. In addition, the ICS for participants in this study was considerably subsidized from its original market price. As a result, households' decisions magnify the importance of other attributes in decision-making related to price.

Utility Function III includes only one category of TPB instead of all TPB constructs in addition to the conventional attributes of utility function. This utility function model presents a 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 (Utility Function I), this model suggests that the likelihood of choosing ICS is significantly correlated with higher levels of perceived independence in decision-making.

To compare how each model of Utility Functions I, II, and III is in performing a more robust estimate, results of AIC, Bayesian information criterion (BIC), and Hit Rate are presented at the bottom of Table 3. Koppleman and Bhat suggest three methods for evaluating models including an informal judgment test (if results simply make sense or not), goodness of fit, and likelihood ratio (LR) test [69]. Based on the discussion in explaining Utility Function I and Utility Function III, the inclusion of user behavior attributes to predict choices is justifiable. Although goodness of fit values suggest Utility Function I is performing a better estimate, this could simply be due to more predictive variables and should be interpreted along with other tests such as LR.

The results of the LR test are presented in Table 4. Hypothesis I compares the utility function without any TPB variables (Utility Function II in Table 3) with the base model (Utility Function I in Table 3). Similarly, Hypothesis II evaluates the utility function with one TPB construct (Utility Function III in Table 3) with the base model (Utility Function I in Table 3). Results of the LR test suggest that both hypotheses could be rejected at 90% confidence level. Therefore, TPB attributes are likely to have a statistically significant contribution in predicting users' choices of the stove.

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 a higher market share in a sustainable way. This proposed framework that integrates UCBD with TPB in a DCA framework reveals that conducting a survey from a sample of the target population could help improve the compatibility of designed products or services with user needs. The main contribution of the presented framework is the systematic integration of theories and models that have been independently validated in the literature to describe behaviors that could be aggregated to explain clean technology adoption in low-resource and developed settings, including environmentally responsible behaviors, health-related behavior, and rational decision-making. However, the application of including quantitative behavioral methods in decision-based design is not limited to designing clean technologies or design for low-resource settings.

The framework presented in this 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, usage context, and 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 efficiently gathering only relevant key input data that leads to insightful results is reflective of the high costs and the level of efforts associated with collecting data in 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 the stove. Such findings suggest that in the target community of the case study, ICS should be designed to prioritize firewood savings over other attributes such as smoke reduction to improve user's intentions to replace traditional stoves. Similarly, findings suggest that main cooks do not necessarily have enough authority to make decisions regarding the choice of the stove independently. Therefore, appropriate information campaigns should be utilized to increase the awareness for the necessity of such behavior changes throughout the community for both husbands (generally the main decision-makers in the households) and 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 into the design phases for large-scale international development interventions. In addition, this framework provides insight for the design of appropriate macroscale information campaigns and behavior change communications that target the main hindrances against increased intentions to use clean technologies. Policymakers may utilize this method and models 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 additional 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. The preliminary model developed in this study provides an illustration of how practitioners may 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 or other clean tech interventions. In addition, such a decision-making model can represent the decision criteria in adoption studies that investigate community scale emerging adoption patterns using agent-based modeling [70].

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