How Modeling the Adoption of Household Clean Energy Technologies can Inform Stakeholder Decisions

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Abstract—**Increasing the adoption of household clean energy technologies is important to achieving sustainable development and to improving the environmental, economic, and social impacts of these technology interventions. While much work has been done to understand the many factors driving successful interventions, little research has been done to quantify and then model the adoption of these technologies. Current optimization models to maximize impact rely on the effective prediction of adoption, yet this piece remains the least understood component. The purpose of this paper is to outline the various ways in which being able to model the adoption of household clean energy technologies would be beneficial for designers, implementation organizations, and policymakers to aid in their design and decision-making processes. We provide a brief review of the literature and current challenges to adoption, examples of current methods and modeling tools that can be used to optimize sustainable impacts, and how these tools could be improved through adoption modeling. We discuss the benefits of being able to model adoption for various stakeholders in the clean energy sector along with proposing some methodologies that can be used to accomplish this goal.**

Keywords—cookstoves, sustainable development, engineering for global development

I. Introduction

The Sustainable Development Goals ratified by the United Nations establish a unifying agenda to achieve sustainable development by 2030 via 17 goals. Goal number 7 aims to "ensure access to affordable, reliable, sustainable, and modern energy for all" by 2030 [1]. Today, around 1 billion people do not have access to electricity, and nearly 3 billion people globally rely on biomass to cook and heat their homes due to unstable electric grids, high electricity prices, or lack of access to affordable clean cooking facilities [2]. While countries work to increase electrification rates and reduce costs, many are left to use inefficient practices to provide for their families. These traditional methods, often represented by the ubiquitous three-stone fire, result in around 2 million premature deaths each year from exposure to smoke [3].

In response to this global health problem and environmental concerns, development practitioners and academics have been collaborating to design improved cookstoves and other clean energy technologies to meet global energy needs such as cooking, heating, and lighting. Household clean energy technologies include products such as liquid petroleum gas (LPG) or improved cookstoves; and solar PV, water heating, and lighting. After decades of work in the energy sector, one thing is clear: the displacement of traditional cooking practices with cleaner technologies is a complex problem. Improved cookstoves often require a change in cooking behavior, disrupting practices that are deeply ingrained in most communities and cultures. For example, improved cookstoves could require new methods of fuel preparation or result in meals that taste different and thus may be less desirable. Additionally, stoves are often used to accomplish other ends such as warmth, light, and pest control, all of which could be largely hindered by improved cookstove designs, thus requiring additional energy technologies to meet these needs.

This challenge is especially important as achieving environmental, economic, and societal impact, referred to as the triple bottom line of sustainability [4], hinges on both high technical performance and large-scale dissemination and consistent use of these clean technologies [5]. For this paper, environmental impact includes decreases in greenhouse gas emissions and deforestation through reductions in fuel consumption and increased efficiencies; economic impact includes any cost to purchase and maintain the technology, fuel savings, and the creation of new opportunities; societal impact includes any reduction in health problems or related injuries, increases in time savings from cooking and/or fuel collection, and advancement of gender equity.

Historically, household clean energy technologies have faced problems achieving scale due to low rates of adoption. For improved cookstoves, they may end up being used in tandem with traditional cookstoves, referred to as stove stacking, or going completely unused [6]–[9]. Low adoption often results from a lack of understanding of end-user needs and unsustainable programmatic approaches to technology dissemination [10], [11]. Other energy technologies such as low-cost solar water heaters face similar adoption challenges largely due to barriers in cost [12].

Over the last ten years, more attention has been given to those factors affecting adoption including ones that influence purchasing the technology and those factors influencing continued use after purchase [13]–[18]. Puzzolo et al. carried out an extensive review of cookstove literature assessing the many factors impacting cookstove adoption [13]. Their list of factors spans technology and fuel characteristics, community characteristics, market, regulation, and policy decisions, all of which are necessary but not sufficient considerations to ensure full adoption. Figure 1, informed by the work of Puzzolo et al. [13] and Kshirsagar and Kalamkar [21], illustrates how these factors affect adoption and the dependence of impact upon sustained technology use. Design related factors include technical performance (e.g. fuel consumption, time to cook, smoke/emissions, durability, etc.), affordability, and usability. Community characteristics encompass demographics, cultural norms, values, and gender roles, among others. Lastly, market, regulations, and policies include variables such as marking approaches, user training, subsidies, and supply chain.

Jürisoo et al. incorporated the time element into understanding the dynamic interactions between users and their environment that shape their decision-making process for buying and using improved cookstoves for case studies in Kenya and Zambia [19]. For these case studies, a user journey map was created to identify critical points in the user journey in which behavior change could be supported or opposed. Chronologically, key points included becoming aware of the new stove technology, purchasing the stove, and then fully adopting the stove, between which are several opportunities to provide support for successful transitions. From this process, they were able to identify user archetypes and opportunities to better support behavior change.

While Puzzolo et al., Jürisoo et al., and others have identified several variables to help understand drivers of adoption, few have tried to quantify it for predictive modeling of impacts, discussed in more detail in the Optimizing Impacts section. Economists and businesses have for years been using market demand forecasts to predict the number of consumers who will purchase their products or services. This is typically done through several steps including defining the market, forecasting drivers of demand, predicting how they will change over time, and conducting a sensitivity analysis on the assumptions made [20]. This process is ideal, but difficult to accomplish in data-scarce sectors, especially within developing contexts.

The purpose of this paper is to illustrate the importance of being able to model and predict the adoption of household clean energy technologies for product designers, implementation organizations, and policymakers. We provide examples of current tools that can be used to optimize sustainable impacts, how these tools could be improved through the use of adoption modeling, and some methodologies that can be used to accomplish this.

II. Design Considerations

Engineers and designers must consider a variety of factors when designing household clean energy technologies. Design related factors specifically addressed in this paper include technical performance, affordability, and usability [21]. These factors, in turn, affect how users interact with their stove or other household energy technologies, rates of adoption, and the environmental, economic, and societal impacts possible. For example, if someone only uses an improved cookstove for 10% of all cooking activities, the benefits of reduced emissions, fuel savings, and time savings may not be realized.

Vast amounts of research have gone into designing cookstoves that meet technical performance metrics which include emissions, fuel usage, materials, durability, and safety. The "Handbook for Biomass Cookstove Research, Design, and Development", developed by the Global Alliance for Clean Cookstoves in partnership with MIT's D-Lab, provides a thorough overview of the technical research on cookstoves over the years and how to practically implement results of this research [22]. More recently, ISO standards for lab and field

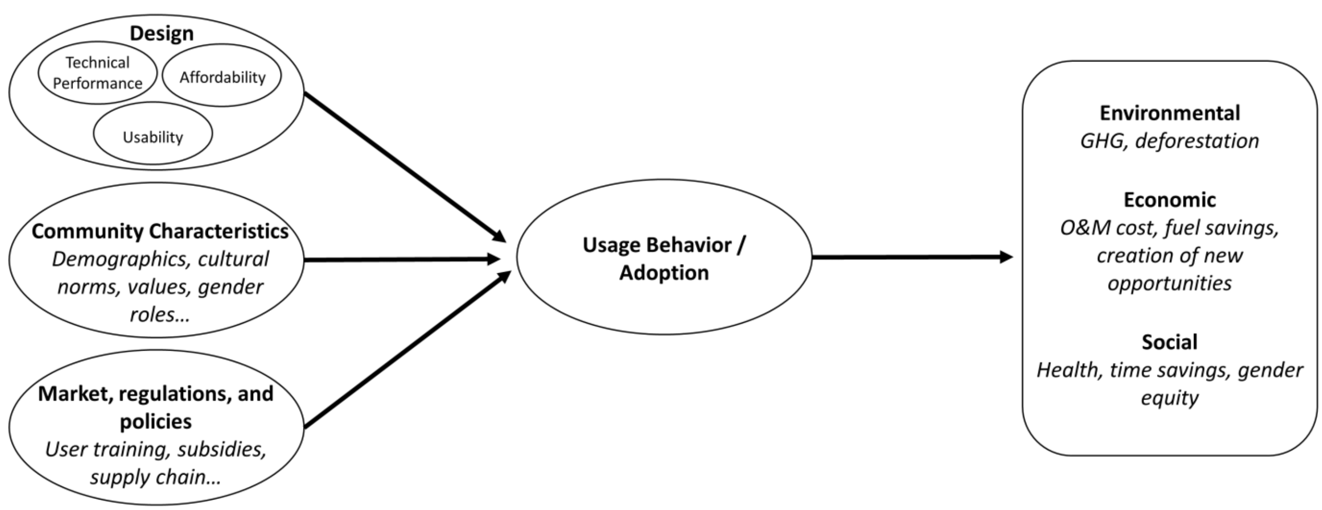

Fig. 1. Many factors impact the adoption of household clean energy technologies thus influencing environmental, economic, and social impacts

testing for emissions, performance, safety, and durability were established to compare across stove models, results of which have been compiled [21], [23]–[25]. Additionally, several computational fluid dynamic models have been developed relating stove geometry, turbulence, and combustion chemistry to heat transfer, combustion, and fluid flow [26]–[28]. These models can be used to optimize technical performance subject to cookstove design features without requiring cost and resource-intensive iterative design.

Despite the many advantages that come with higher-performing stoves, these stoves may face more barriers to adoption. First, higher-performing stoves may increase the overall cost of the stove, with cost identified as one of the biggest barriers for people looking to purchase cookstoves [29], [30]. For example, one review paper [21] comparing cookstove performance across a range of metrics found the Wood Flame Fan Stove to be the top performer at a cost of approximately $229, far outside the budget for most impoverished peoples. Other top models were "rocket" ($9-75) and gasifier type stoves ($89-99). In contrast, stove models under $5 performed on par and, at times, worse than the traditional three-stone fire [21].

Second, increasing technical performance often increases the behavior change required to operate the stove, which can reduce the usability of the stove and its ability to meet local needs. For example, many gasifier stoves require wood to be chopped into small pieces before being used while rocket stoves may increase the amount of tending required due to narrow combustion chambers, majorly impacting the many daily tasks cooks often have to complete while also cooking [31], [32]. In Peru, households with improved cookstoves with chimneys were required to climb onto their roof to clean the chimney of ash to maintain stove performance [33]. Due to this difficulty, only one-third of participants in the study reported cleaning their chimney at least once a month. In 2018, Moses and MacCarty [34] developed a usability testing protocol acknowledging the role that usability plays in achieving sustainable impact. The protocol utilizes a mixed-methods approach with qualitative and quantitative tools to help designers understand the end user's needs and to validate and/or improve current stove designs. This protocol has since been incorporated into new ISO standards to assess stove usability in the field [23]. Future research identified by the authors includes more explicitly connecting usability results from this protocol to long-term usage patterns and adoption.

III. Optimizing Impacts

Turning to the broader design literature, complex design decisions of this kind can be addressed using optimization algorithms to assess design tradeoffs. Recently, Mattson et al. [35] proposed a method for assessing design tradeoffs within the three-pillar sustainability space using existing multi-objective optimization methodologies (e.g. Pareto optimality) [36], [37]. This approach aims to maximize the environmental, economic, and social impacts by improving or redesigning an existing product subject to various design parameters and constraints. This is done by explicitly linking design parameters to each sustainable outcome. The authors then applied this to the Village Drill, a human-powered drill to create boreholes where modern technologies are not available, showcasing the applicability of this approach for products for the developing world. Included in this multi-objective optimization are aggregated economic, social, and environmental impact metrics using the weighted sum approach. Although novel and useful for design optimization, this method does not consider the effect technology adoption would have on the sustainability impacts nor the parameters outside design affecting adoption.

The Village Energy Model, developed by MacCarty and Bryden [38], expands beyond design parameters to include energy needs, socio-economic factors, technology characteristics, and available fuels to compare multiple energy technologies and their anticipated impact subject to these localized constraints. These different parameters are incorporated into the model through various sub-models that can be modified independently of each other. Attributes relating to various energy technologies and local constraints are fed into the systems model. At this point, different technology designs and applications are considered, and their rates of adoption assigned. From this model, the various sustainable impacts of interest can be predicted.

The model allows for cost-benefit analysis, optimization, forecasting, and trade-off analysis, all of which can be beneficial for various stakeholders earlier in their decision-making processes. For example, implementation organizations can assess the effectiveness of their dissemination approaches monetarily through cost-benefit analysis while policymakers could utilize forecasting to assess the impacts of policy alternatives. While this model considers outside factors, in addition to technical performance, affordability, and usability, it does not provide design alternatives for a specific technology to optimize sustainable impacts. In this way, Mattson et al.'s multi-objective sustainability optimization could complement the existing Village Energy Model to explore further design alternatives. Additionally, while the Village Energy Model explicitly considers human interaction with the technology including usability, technology stacking, and rebound effect (behavioral responses that negate technological benefits through increased usage), simplistic equations are used. Outputs of this model and their utility to stakeholders in the energy sector are entirely dependent on the rate of adoption and sustained use of the technology, yet prediction of adoption is currently the least understood component. More work is necessary to improve adoption modeling and assessment of forecasted benefits over the long-term.

A. *Economic Impact*

Looking at the three sustainable impact metrics in more detail as they relate to the Village Energy Model, each has its limitations which could be improved through better adoption modeling. The economic term can encompass any anticipated costs to purchase, use, and maintain the product of interest, money saved, and opportunity cost from an intervention. Opportunity cost accounts for the value of time spent collecting firewood and cooking that could be used for other productive means and is context-specific. The anticipated costs to purchase the technology are dependent on design, manufacturing, policies, and financing available. Focusing just on design related economic terms, the cost (or cost savings) to use and maintain an energy technology hinges on the frequency of use compared to traditional cooking practices, how the device is being used, materials, durability, and/or the context-specific cost of fuel. Product lifetime and the maintenance required during that time are contingent on usage patterns in which understanding user behavior is key.

B. Social Impact

For the social impact term, Mattson et al. [35] acknowledged the difficulty in identifying universally relevant social metrics like those used for the economic and environmental impact terms (dollars and carbon-equivalent emissions, respectively). Acknowledging this gap, within the last couple of years academics conducting work in engineering for global development have created a universal social impact metric for design optimization referred to as the product impact metric (PIM) [39]. The PIM assesses the social impact a product has on impoverished consumers. Measurements used to determine the PIM include changes in health, education, standard of living, employment quality, and security following the introduction of a new product and could easily be applied to improved cookstove interventions. The PIM can be used to both predict and assess social impacts and could benefit from the inclusion of adoption modeling.

In comparison, the Village Energy Model assesses social impact using the predicted quality of life, health impacts, and opportunity cost. Quality of life is assessed via social desirability, disruption, convenience, and safety and is recommended as a proxy for technology adoption, although identified as just a starting point for future sub-model development. The PIM could be easily incorporated into the Village Energy Model for social impact as it can be used to predict outcomes, although other methods would be necessary to improve the predictive ability for technology adoption.

C. Environmental Impact

Finally, the environmental term encompasses the CO_2-equivalent emissions produced throughout the product's lifetime, referred to commonly as a life cycle analysis or assessment (LCA), and reductions in deforestation. LCAs systematically account for any environmental impacts embodied in a product to identify process and design alternatives that could reduce the negative impacts of a product. While several studies have completed an LCA for biomass fuel sources [40]–[42] to date, only one comprehensive study exists examining the total lifetime emissions for an improved cookstove [43]. This study found that the embodied emissions from the materials, manufacturing, transportation, and end-of-life of the Berkeley-Darfur stove were largely offset by emission savings during the use phase of the stove. Although a step towards more rigorous quantification of environmental impacts, many assumptions were made for this study and were identified by the authors as limitations. Included in these assumptions were a conservative 35% fuel reduction from lab testing of the stove, extrapolated emissions from lab testing, a five-year lifetime, the assumption of full adoption, and no rebound effects. Many of these assumptions are dependent on adoption levels. LCA for other household energy technologies would also require information related to the level of displacement of traditional cooking methods and any rebound effects.

IV. Methods to Quantify Adoption

A. Sensor-Based Data

In years past, surveys were used to assess cookstove adoption. More recently, studies have found surveys to be unreliable for quantifying actual adoption rates as bias (recall, social desirability, etc.) is common in the results [44], [45]. Since then, several household sensor-based tools have been developed of which can be used to quantify adoption and stove stacking [46]–[49]. Types of sensors include stove temperature sensors (e.g. Stove Usage Monitors, EXACT), fuel consumption sensors (e.g. Fuel Use Electronic Logger), and emissions sensors which can be used to quantify stove usage and performance. While these sensors can be used to quantify outcomes, they have not yet been used to increase the robustness of cookstove LCA through actual fuel use and emission data and quantification of adoption rates in the field.

One drawback of sensor-based data is the upfront cost of the sensors, which may make it difficult to collect statistically representative data from the population of interest within limited monitoring and evaluation budgets [50], [51]. Additionally, sensor-based data on its own cannot provide insight into *why* cookstoves are or are not being used. Other behavioral science models and methods may provide lower-cost options to circumvent this problem in some situations.

B. Behavioral Models

Polizzi di Sorrentino [52] discusses the importance of incorporating behavioral science into LCA, especially for products whose lifetime emissions depend on the use phase of that product (e.g. washing machines, cars, stoves, etc.). Behavioral science could also improve predictions of economic and social impacts based on technology use. Several psychological models exist to predict behavior change using surveys. One popular model that has been used in both health and environmental behavior change interventions is the Theory of Planned Behavior (TPB) [53]–[57]. The TPB was developed to assess a person's intention to change their behavior based on three psychological attributes: attitudes, social norms, and the perceived control one has over executing the behavior [53]. This model uses a person's stated intention as the best predictor of actual behavior.

Previous work by Pakravan and MacCarty [58] has used the TPB to better understand these attributes as they pertain to a person's intention to adopt cleaner cooking practices. Example survey questions assessed participant attitudes on smoke and fuel consumption, strength of peer influence on decision making around cookstoves, and feasibility of replacing their traditional cookstove with an improved one using the Likert scale. Here, the attitudes towards the behavior, the social pressure felt, and the perceived control one feels they have over using an improved cookstove are assessed as they relate to one's stated intention of using an improved cookstove to cook their meals. Intention is then used as the best predictor of actual behavior. Logistic regressions were then used to identify variables most important in explaining intention to use a specific stove.

Through field studies carried out in Honduras and Uganda, they found TPB surveys helpful in identifying priorities in cookstove design. For example, the community in Honduras on average valued reductions in smoke more than fuel reductions while the opposite was true in the community in Uganda. This information could be used to inform new cookstove designs and marketing strategies. They also found that perceived barriers to using improved cookstoves decreased over time as users became more familiar with using the new stove. This finding highlights the importance of ensuring initial positive experiences with cookstoves to facilitate longer-term behavior changes and reinforces past research findings [19]. Although initial results from using this theory as a tool for the clean cooking sector have been promising, more work is required to validate and improve the model.

In comparison to TPB, other psychological models exist that incorporate the role that habits play in decreasing conscious decision making [59], [60], and others have had success adding habits into the TPB model [61], [62]. As traditional cookstove use is an ingrained habit, incorporating habits into the TPB framework may provide more predictive validity and should be explored for this context.

Despite the advantages provided by behavioral models to identify variables influencing the adoption of household clean energy technologies, several drawbacks exist. One major drawback of behavioral science surveys is that they measure proxies of behavior such as intention, habits, and perceived control, but not actual behavior. Additionally, as mentioned earlier, surveys can introduce bias into the results through social desirability, recall, and wording bias. One necessary step to reduce this bias and validate survey data is to triangulate user responses with sensor-based usage data, a practice that has been successfully implemented in many cookstove projects [6], [34], [48], [63]. Lastly, as this method utilizes logistic regressions, the data collected must adhere to strict guidelines which may add complexity and cost for study implementation, as detailed in Table 1 below.

C. Ethnographic Decision Models

Another method that has been used to predict behavior based on parsimonious factors is Ethnographic Decision Models (EDM). EDMs use questions and logical rules about the ordering of these questions to create decision trees [64]. Building an EDM requires four steps: 1.) for a specific behavior, in this case, purchasing/using a household clean energy technology, interview a convenience sample for their decision criteria, 2.) interview a heterogeneous sample to expand and verify decision criteria, 3.) build a hierarchical decision model in which the questions are logically ordered, and 4.) validate the model on a new representative sample of people. This method has been used to accurately predict a range of behaviors.

For example, one study using a survey of 34 questions was able to predict whether an individual recycled their last aluminum can for a national sample with almost 85% accuracy when only three questions from the survey were considered: whether or not the participant was at home; if yes, do they recycle other products besides cans; if no, was there a recycling

TABLE I. ADVANTAGES AND DRAWBACKS TO USING SENSORS, BEHAVIORAL MODELS, AND ETHNOGRAPHIC DECISION MODELS TO PREDICT ADOPTION OF HOUSEHOLD CLEAN ENERGY TECHNOLOGIES

Method	**Advantages**	**Drawbacks**
Sensors	Objective (reduced bias compared to survey methods) Quantitative	On their own, do not provide insight into *why* certain technologies are or are not being used Upfront cost
Behavioral Models	Provide insight into variables most important to predict adoption of technologies	Uses behavioral intention as a proxy for real behavior Surveys can introduce bias (social desirability, recall, wording) Require theoretical understanding of model and experience with survey design that may be barrier for use by those outside of academia Statistical modeling using these methods requires strict data adherence (extensive choice set, errors must be independent, accounting for multicollinearity of variables, typically 200+ data points)
Ethnographic Decision Models	Provide insight into variables most important to predict adoption of technologies Does not require experience with survey design Results can provide parsimonious factors Can be paired with machine learning for simpler identification of most important variables influencing adoption with fewer data points	Require recall of behavior which can introduce bias

bin nearby [65]. EDMs have yet to be used for this context but show great potential in identifying the most relevant factors for predicting adoption using prompts such as "Think of the last time you cooked/heated/warmed something. What devices did you use and why?". As EDMs also rely on recall of past behaviors, sensor-based data to validate this behavior would be necessary. Table 1 highlights the advantages and drawbacks of each of the three methods discussed here.

V. Conclusion

This paper identified how new methods of modeling adoption could improve existing methods and modeling tools, such as the Village Energy Model, to make more informed decisions that maximize economic, social, and environmental impact. Outputs of this model are entirely dependent on being able to quantify adoption, yet the prediction of adoption is not well understood. Assessing the underlying motivations behind cookstove purchases and user experiences throughout the entire process through qualitative methods, in addition to quantitative predictive models such as the Theory of Planned Behavior or Ethnographic Decision Models, could lead to more accurate predictions of usage and more targeted interventions. Future research should validate these proposed methods in heterogeneous contexts. To ensure access to affordable and clean energy for all, effective policies, design, and dissemination strategies of energy technologies will be necessary. Both understanding and then modeling the adoption of energy technologies can aid in the pursuit of these best practices for various stakeholders.

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