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AN AGENT-BASED MODELING APPROACH FOR CLEAN TECHNOLOGIES ADOPTION USING THEORY OF PLANNED BEHAVIOR BASED DECISION-MAKING

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ABSTRACT

Technology adoption in low-income 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.

1. INTRODUCTION

Technologies created to address needs in low-income 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 [1]. 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.

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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 [2]. 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 [3]. 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 [4].

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 [5]. 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 [5]. DoI is among the widely used models across several branches of science since its introduction in 1962 [6]. Although DoI is among robust theories for technology adoption, its focus is more toward technology (innovation) rather than decision-maker's intentions [7].

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 [8]. 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 [9]. One of the main limitations of TAM is capturing social effects on

decision-making for technology adoption [10]. 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 [11]. A comparison between TAM2 and TPB suggest that TAM2's attributes are captured by TPB which is more parsimonious than TAM2 [12].

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 [13]. 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 [14]. 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 [15], 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 [16]. 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 [17].

TPB has been integrated with ABM for studying technology adoption in domains such as organic farming practices [18], environmental innovations [19], natural gas vehicles [20], and smart residential electricity meters [21]. A review of the literature suggests that TPB is among the most robust models for analyzing adoption behavior from the user acceptance perspective [10]. In addition, previous works of authors present successful application of TPB to explain user behavior with respect to ICS adoption in low-income contexts [22], [23].

It is conventional wisdom that society plays an important role in shaping individuals' behaviors. Many technology adoption theories reflect the role of society in their models such as DoI, TPB, and UTAUT. 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 [5]. 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 [15].

Researchers have emphasized using social networks to describe the role of society in technology adoption [24]. 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 [25]. 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 [26]. 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 [20], [21].

In addition to making decisions 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 [27]. The integration of DCA with ABM is a common practice throughout literature to capture rational decision making, e.g. [28]. The rational process of utility maximization is analyzed based on different attributes incorporated from multiple disciplines. Psychological approaches in calculating utility often fall short in terms of providing quantitative insights in terms of technology related attributes [29], while engineering approaches lack systematic incorporation of users' behavioral elements for robust choice modeling [30].

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.

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 [22], [23]. The development of utility functions based on these are presented in [31].

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 [32]. 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.

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 [31]. 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 from 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.

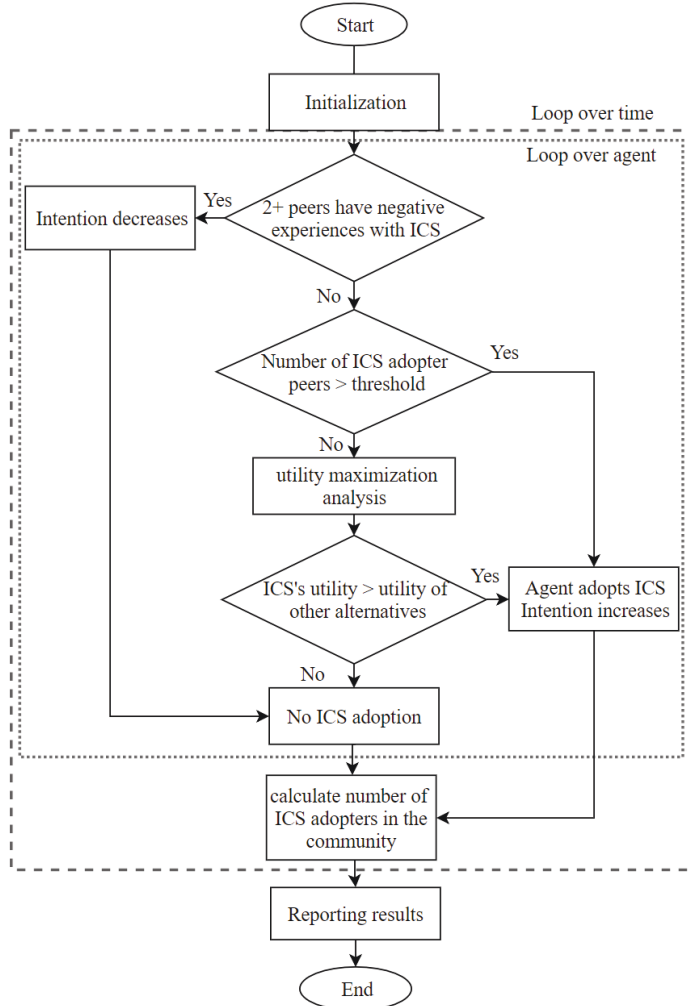


FIGURE 1. FLOWCHART OF THE MODEL

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 [26]. 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. The 20% update probability is chosen based on assumptions of previous work in low-income countries [20].

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 [33]. 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. [24]. In their work, the maximum influence from spread of information through social network occurs when (63%) of the links are activated [34]. 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.

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 (W_{in}). The three TPB constructs included in the utility function are attitude toward behavior (ATB), social norms (SN), and perceived behavior control (PBC) [31].

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

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 [23].

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. The ultimate choice of each agent then is communicated with social ties to capture social influences.

TABLE 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 - < 25,000 UGX, - 25,000 - 50,000 - > 50,000 UGX
Fuel type	Tech.	Static	Field observation (0 for firewood, 1 for charcoal)
Stove price	Tech.	Static	Field staff's experience 5: open fire, 25: mud stove, 75: charcoal stoves, 100: ICS, normalized)
Stove type	Tech.	Static	Field observation (open fire, mud stove, charcoal stove, ICS)
Number of peers	Model	Static	Assumption based on literature ^b – from 6 to 12
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 (open fire: 18%, mud-stove: 42% ICS: 40%)
β^{ATB}	Agent	Static	1: -16.686 , 2: 31.523 3: -2.834 , 4: -1.783 ^a
β^{SN}	Agent	Static	1: 1.204 , 2: -0.556 3: -0.551 ^a
β^{PBC}	Agent	Static	1: -45.382 , 2: -11.706 3: 4.105 , 4: 2.730 ^a
β^{Income}	Agent	Static	0.071 ^a
β^{Fuel}	Agent	Static	-1.049 ^a
β^{Price}	Agent	Static	0.019 ^a

^a [23]^b [20]

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.

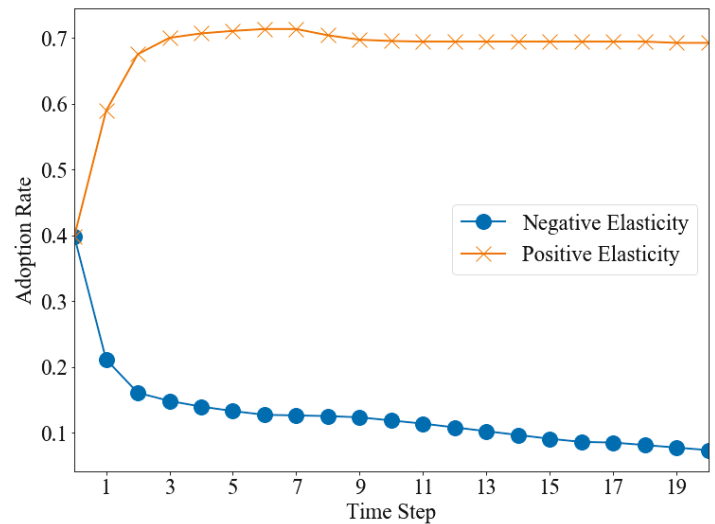
TABLE 2. TPB ATTRIBUTE DISTRIBUTION IN SAMPLE AND PROJECTED POPULATION [22]

	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. 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.

4.1 Scenario I: Price elasticity

**FIGURE 2:** PRICE ELASTICITY'S IMPACT IN COMMUNITY SCALE ICS ADOPTION

One of the key factors in decision-making is the price of available alternatives [35]. The ICS owners in this study received

their cookstoves fully subsidized. As a result, 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 2 suggests that if households consider ICS as a normal good, adoption of cookstoves is not likely to approach satisfactory scales through time. Despite the value of negative elasticity in the model, which is set to (-0.001) compared to the value from Table 1 (0.019) for positive price elasticity, results of simulations suggest that changes in the sign of price elasticity significantly reduces the adoption rate in the community from status quo. Negative sign of beta implies that households consider ICS a normal good. Therefore, increasing its price leads to decrease in its demand. However, 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 [36]. 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. In addition, if further investigations suggest that ICS is a normal good, one can conclude based on the results presented in Figure 2 that ICS adoption is likely to not reach to the scale.

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

As discussed above, according to TPB, three categories of attributes formulate intention. In Figure 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.

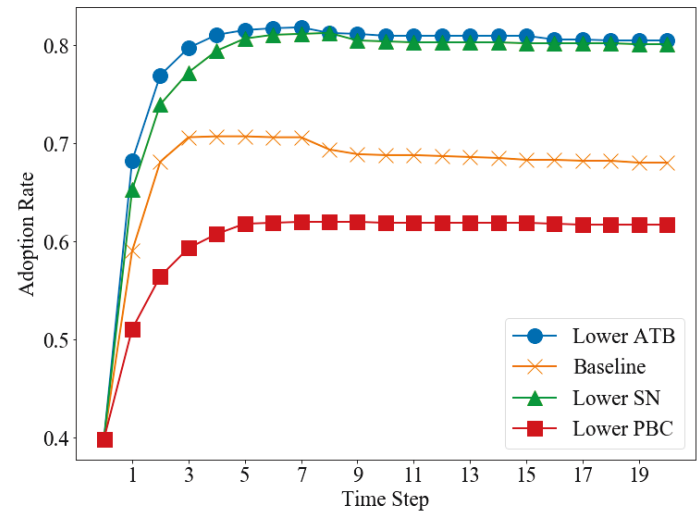


FIGURE 3: INFLUENCES OF CHANGES IN TPB ATTRIBUTES ON COMMUNITY SCALE ICS ADOPTION

Results of the analysis suggest that a uniform decrease by one unit in a scale of one to five 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 [37], 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 by one unit in a scale of one to five 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 by reducing one unit in a scale of one to five 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 [38]. 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 [39].

4.3 Scenario III: Degree centrality of households

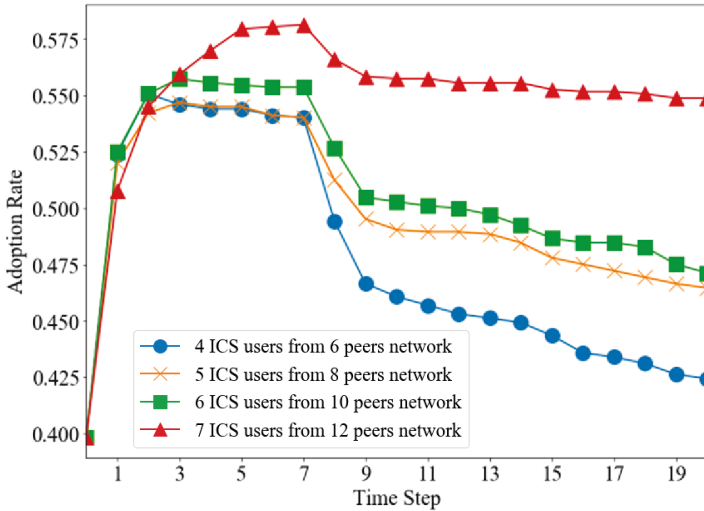


FIGURE 4: INFLUENCES OF DEGREE CENTRALITY ON COMMUNITY SCALE ICS ADOPTION

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 [38]. Social capital provides the capacity within a social network for collective actions [40]. 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.

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 improve initially likely due to spread of positive influence, negative feedback caused by stove malfunction 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 Scenario IV: Rate of ICS malfunction

The durability of ICS is among the major challenges that impact adoption rates [41]. While these cookstoves optimize combustion to reduce firewood consumption and smoke

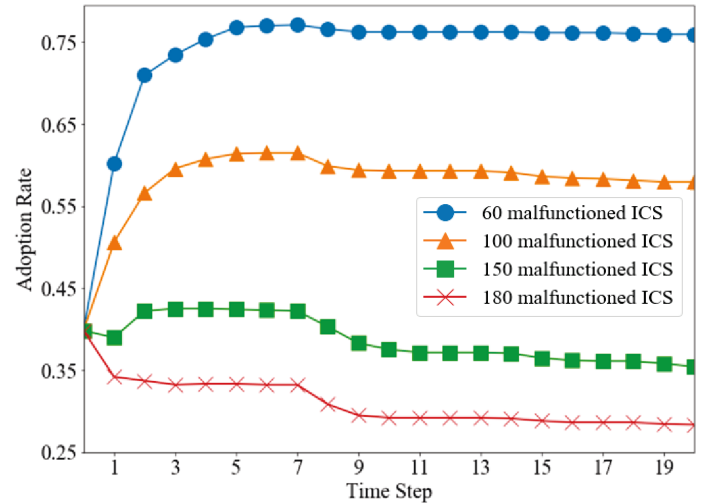


FIGURE 5: INFLUENCES OF STOVE MALFUNCTION ON COMMUNITY SCALE ICS ADOPTION

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 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 more than one peer 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.

5. VERIFICATION AND VALIDATION

Verification refers to the process that examines models performance against intended designed study while, validation evaluates to what extent the model explains the real-world system. Following recommendations of Macal and North [42] the model in this study has been verified to implement the designed study illustrated in Figure 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 [23].

(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.

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. The technology designers can benefit from the results discussed in this paper that sheds light on how technology performance coupled with user preferences alters the impact assumed in the design phase.

The methodology in this study captures dependency of technology adoption throughout time based on technology performance and user preferences. 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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