An Agent-Based Model for Adoption of Clean Technology Using the Theory of Planned Behavior

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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 a 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 technology adoption through lenses of social networks, individual and society scale beliefs, and rational decision-making behavior. Based on the 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 the potential changes in technology or intervention strategy. These scenarios include influence of stove malfunctions, price elasticity, information campaigns, and strength of a social network. Results suggest that higher adoption rates are achievable if designed technologies are more durable, information campaigns provide realistic expectations for users, policymakers, and education programs work toward women's empowerment, and communal social ties are recognized for influence maximization. The application of this study provides insight for technology designers, project implementers, and policymakers to update their practices for achieving sustainable and to the scale clean technology adoption rates. [DOI: 10.1115/1.4047901]

Keywords: agent-based design, decision theory, design for humans

1 Introduction

Technologies created to address needs in low-income regions play a crucial role in community development and empowerment. Ten out of the 17 sustainable development goals can be met through successful adoption of appropriate technologies such as clean cookstoves, water filtration systems, renewable energy technologies, and waste management processes [1]. Predicting and monitoring 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 the 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 a 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.

2 Background

Community-scale technology adoption is a phenomenon that emerges from individual households' decision-making behavior. There are two main attributes that define technology adoption in groups of people and hence should be considered in the models. First, households independently make a volitional decision on 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 and behavior are influenced by social contexts [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].

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Models for the behavior of agents to reflect the process of technology adoption within ABMs can be described in various ways. The diffusion of innovation theory developed by Everett Rogers is among the well-known theories, which capture multiple aspects of adoption from the 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 the diffusion of innovation 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 form the society based on when they may adopt a technology, including early adopters, early majority, late majority, and laggards [5]. The diffusion of innovation is among the widely used models across several branches of science since its introduction in 1962 [6]. Although diffusion of innovation 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 that would enhance their performance. 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 the robustness of TAM led to an extended version of TAM called TAM2. In this version, two general categories are added to the original TAM to capture social influence processes such as social norms (SN) and cognitive instrumental processes such as results demonstrability [11]. A comparison between TAM2 and TPB suggests that TAM2's attributes are captured by TPB which is more parsimonious than TAM2 [12].

Inspired by categories of attributes that are utilized in the diffusion of innovation, 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 the 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 is a barrier for many case studies [14]. The 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 TPB. Developed by Ajzen [15], TPB explores the belief-based factors that formulate the intentions of individuals to make a choice. According to TPB, there are three categories of attributes, or constructs, that determine intention which is the main factor that leads to behavior. These three constructs are a user's attitude toward the behavior (ATB) based on behavioral beliefs, 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 the successful application of TPB to explain user behavior with respect to improved cookstoves (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 diffusion of innovation, TPB, and UTAUT. Rogers presents the role of social networks in the diffusion of innovation 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 at an exponential rate [5]. In addition to the 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 an 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 such as 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 the 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 a small-world network [20,21].

In addition to making decisions based on the influence of society, the idea that individuals choose alternatives that maximize their utility is widely regarded in neo-classical economic theories. In this study, discrete choice analysis is used to model choice behavior from a set of mutually exclusive alternative technologies using the principle of utility maximization [27]. The integration of discrete choice analysis with ABM is a common practice throughout literature to capture rational decision-making, e.g., Ref. [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 an efficient methodology that integrates rational decision-making with behavioral models to simulate the process of technology adoption through a social network in low resource settings. While there are studies that have developed integrated approaches to investigate technology adoption, the current study's approach is novel in terms of integrating small-world networks with TPB and utility maximization theory in an agent-based model. The main contribution of this work using survey data collected in a low-income region is to demonstrate that technology adoption for consumers at the bottom of the pyramid is not solely derived based on cost. 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 lead 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. All research with human subjects was overseen by the Oregon State University Institutional Review Board under study number 7257. The model investigates the proliferation of ICS adoption in households through a theoretical community. Diffusion and the decision to adopt are based on a combination of the social influences of peers and the individual decision-making behavior based on the utility maximization theory. The discrete choice analysis representing utility maximization theory is integrated with TPB to improve the 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 Refs. [22,23]. The development of utility functions based on these is presented in Ref. [22].

In the ABM developed here, households in the community are represented by agents that individually make decisions to maximize their utility regarding their choices of the 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.

The village-level progression of ICS adoption is represented as a flowchart in Fig. 1. This model is developed in Mesa, a platform for ABM analysis using PYTHON [31]. 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. The variables used in the analysis are presented in Table 1.

3.1 Model Initialization.

The developed model extends characteristics of households that were surveyed in a representative rural community in Apac, Uganda. While the relevant survey data are presented in Table 1, the detailed information on data collection and survey results is presented in another work of authors [22]. The stated stove preferences of these 175 randomly selected households informed the utility function of the model [22]. Results of regressions on the collected data determined weights of influences of attributes presented in the utility function. The 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 the 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.

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 the

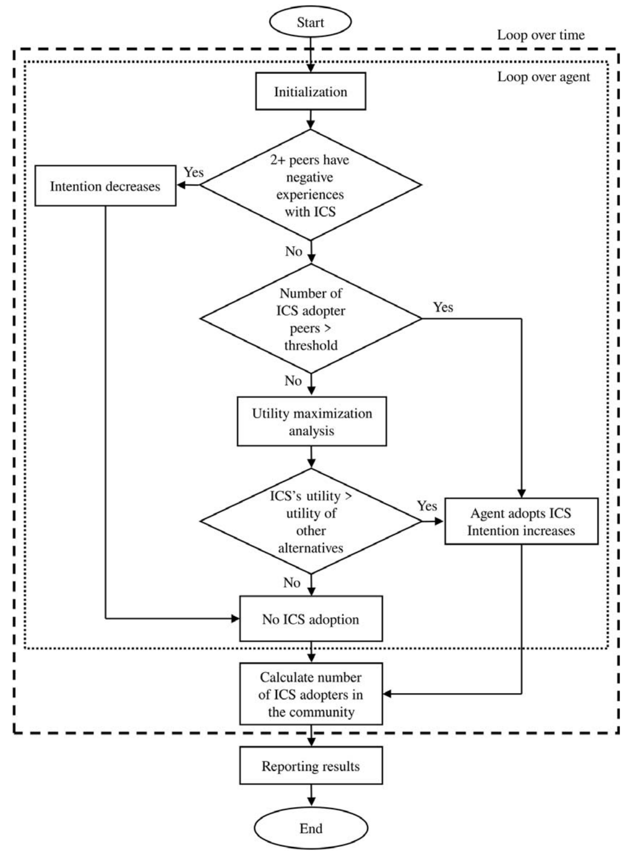

Fig. 1 Flowchart of the model

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 exhibits 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 represent the fact that people change their preferences, social ties, 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].

This study captures choices that are made based on the strong influence of peers through word-of-mouth or social need motivation by incorporating an imitation process of decision-making based on the Consumat approach [32]. 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, an agent copies the choice that the majority of their peers successfully make. In this model, the threshold that determines the majority of peers follows the recommendations of Kempe et al. [24]. In their work, the maximum influence from the spread of information through social networks occurs when 63% of the links are activated [33]. Therefore, we assume imitation leads the agents to copy their peers' choice of the stove if more than 63% of them have adopted an ICS, bypassing utility analysis.

3.3 Decision-Making Based on Discrete Choice Analysis.

In addition to the direct social influence, the decision to adopt also includes the utility maximization theory and TPB. Equation (1) illustrates the integration of TPB attributes along with technological attributes that predict choices of the agent (i) for technology

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]Ref. [23].
[b]Ref. [20].

alternative (n) as the deterministic part of the 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) [22].

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

TPB analysis of data collected from the sample suggests that the most important representative of the ATB attribute is an individual's evaluation of the importance of firewood consumption. Similarly, the evaluation of individuals regarding the importance of the opinion of friends and family about the 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. These post-adoption experiences were modeled with two general cases. The first case assumes that the agent's needs are satisfied and they have a pleasant experience with the new technology. As a result, the TPB attributes improve in favor of the new technology, leading to higher intentions for continued use. The second case assumes that the new technology is not fulfilling the agent's expectations. This is often the case in projects due to stove break down and malfunction. In response, the model decreases behavioral attributes indicating that the person is less likely to keep using the new technology. The ultimate choice of each agent is then communicated with their social ties to capture social influences.

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

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 unit less time-step, the choices of the stove are updated either through a social influence or utility maximization process, and each household's opinion about cookstoves is updated based on their satisfying or dissatisfying experiences. The updated choice of stove, as well as the agent's dynamic attributes, informs the next time-step updating the social network set up according to the network update probability. Since the stove choice of agents has changed from the previous time-step, agents' decisions are updated again to inform the next run, as illustrated with the dashed box in Fig. 1.

4 Results and Discussion

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

4.1 Scenario I: Price Elasticity.

One of the key factors in decision-making is the price of available alternatives [34]. The influence of price fluctuation on technology adoption patterns was simulated in the model using the *ceteris paribus* effect of positive and negative price elasticity (or the rate at which demand changes due to price changes) for ICS. Negative elasticity assumes that as the price of an ICS increases its demand decreases (ICS is normal good as defined in microeconomics). Positive elasticity assumes that as the price of an ICS increases, demand for it increases by some ratio. It should be noted that the ICS owners in this study received their cookstoves fully subsidized. As a result, their decisions on ICS adoption were not significantly influenced by the price of the technology.

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 Fig. 2 suggests that if households consider ICS as a normal good, the 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 positive price elasticity value from Table 1 of 0.019), simulation results suggest that changes in the sign of price elasticity significantly reduces the adoption rate in the community from the status quo. The negative sign of beta implies that households consider ICS a normal good. Therefore, increasing its price leads to a 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. This means that as the price of the ICS increases, the utility of the ICS assigned by the household also 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 may not be representative. A potential explanation for assigning higher utility to ICSs as their price increases is the social status that ownership of the technology provides for the household, referred to as Giffen goods in economics [35]. Although the discussion regarding causes of positive price elasticity of demand is 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. Additionally, if further investigations suggest that ICS are a normal good (i.e., they have a negative price elasticity), then adoption is not likely to reach the desired scale based on the results presented in Fig. 2.

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 Fig. 3, the influence of changes in each of these categories on overall adoption behavior is 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 the baseline. Information campaigns and behavior change communications are two examples of the methods that could influence such attributes consistently throughout the community.

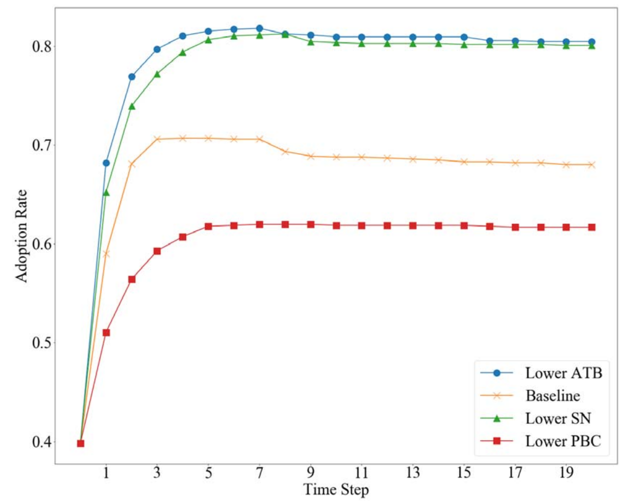

Fig. 3 Influences of changes in TPB attributes on community scale ICS adoption

Results of the analysis suggest that a uniform decrease by one unit on a scale of one to five in households' perception of their independence in making decisions, or PBC, regarding the choice of stove reduces ICS adoption rate in the community. This finding matches with the results of Ref. [36], which found that women who are more exposed to risks associated with inefficient cooking are more likely to adopt ICS. However, in many contexts, they may lack the authority to purchase such stoves.

Lowering households' ATB regarding the importance of firewood consumption by one unit on a scale of one to five increases the adoption rates over time. This counterintuitive finding suggests that the current technology's performance may not be 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 the technology does not reduce their firewood consumption as expected, despite the efforts to change their behavior and the cost of acquiring an ICS. Therefore, information campaigns should reflect the actual performance of the technology instead of exaggerating their performance.

Assigning less value to the importance of opinions of friends and family by reducing one unit on 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 on 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 [37]. Another study in western Honduras applies social network analysis to describe how the spread of information solely through word-of-mouth by active community members led to a successful ICS intervention [38].

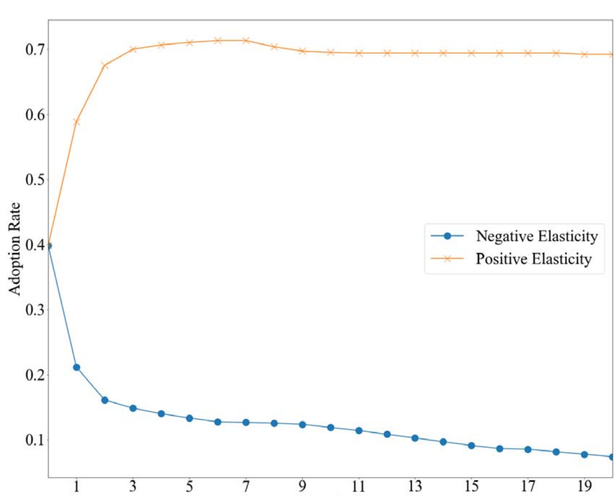

Fig. 2 Price elasticity's impact in community scale ICS adoption

4.3 Scenario III: Degree Centrality of Households. This scenario studies the influence of social networks on adoption based on degree centrality. Degree centrality is the number of households in which each agent is connected, essentially representing the number of peers with which information is exchanged. The degree centrality of this network represents the overall social capital of the community in which social capital is a measure for intra-communal link strength [37]. Social capital provides the capacity within a social network for collective actions [39]. Thus, the strength of social capital impacts on adoption patterns can be

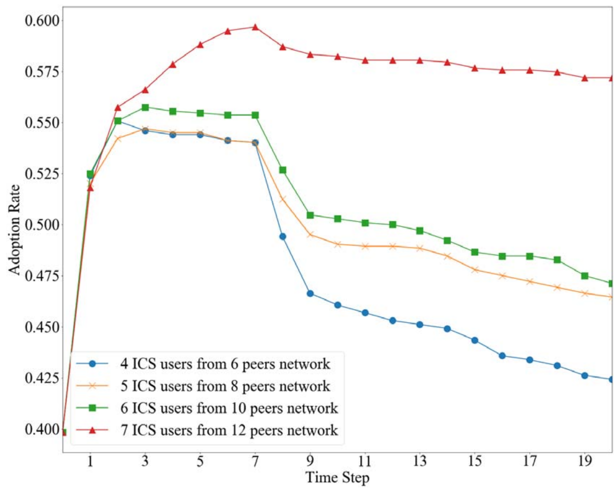

Fig. 4 Influences of degree centrality on community scale ICS adoption

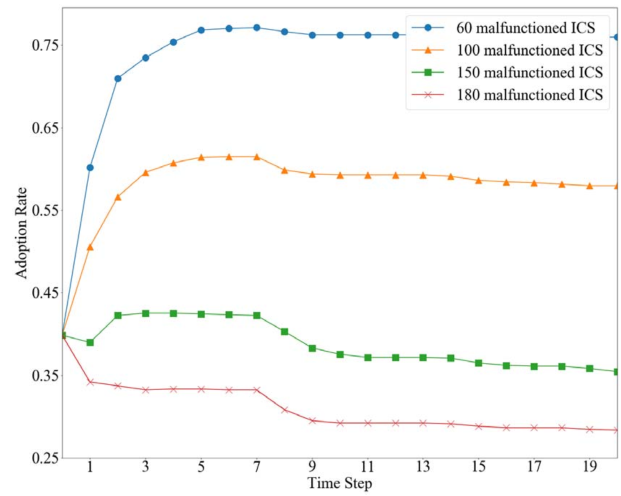

Fig. 5 Influences of stove malfunction on community scale ICS adoption

simulated in the model by varying the degree centrality modeled as the number of peers connected to each agent varies from 6–12 households (Fig. 4).

Results suggest that stronger social capital improves adoption rates *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 the spread of positive influence, negative feedback caused by stove malfunctioning leads to decreasing long-term adoption behavior for a network with less degree centrality. This finding is in line with an independent study in a Peruvian Andes community [37]. 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 their peers. While a household that is connected to 11 other households, only two of which have negative experiences with their ICSs, is affected by the negative feedback of only one-sixth of their peers. Such a change in weight of influence of peers leads to decreasing adoption rates 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 [40]. While these cookstoves optimize combustion to reduce firewood consumption and smoke emissions, high temperatures, corrosive environments, material limitations, and cost constraints are some challenges that could lead to early stove failure from continuous use. Therefore, it is important to capture the effect of stove failure on community-scale adoption patterns.

Figure 5 illustrates the adoption rates in the community for four scenarios based on the number of ICSs that fail to work properly due to durability issues. This is modeled by randomly assigning 60 (14%), 100 (24%), 150 (36%), and 180 (43%) malfunctioning stoves among all ICS owners in time-step zero. 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. The impact of the spread of negative feedback as the result of stove malfunctioning reflects independent findings in the literature [41]. Throughout time such negative influences are likely to lower the intention of households who are not experiencing any issues with their ICSs to cook fewer meals with it. Therefore, stove designers and project implementers need 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 a model's performance against the intended designed study while validation evaluates to what extend the model explains the real-world system. Following recommendations of North and Macal [42], the model in this study was verified to implement the designed study illustrated in Fig. 1. Given the data collected from a randomly selected sample from a community, this study assumed that the sample's choices and attributes are likely to be representative of a community with 1000 households. The technology adoption behavior of this hypothetical community is predicted based on the theory of planned behavior, utility maximization theory, social network analysis, and agent-based modeling. The key assumptions in this study include the following: (1) applicability of the theory of planned behavior in the surveyed context, (2) extendibility of sample size to the hypothetical population of the agent-based model, and (3) significant external factors that may drive the decision-making behavior of households. Other work by authors suggested that the correct application of TPB could quantify attributes that formulate intentions for technology adoption in the surveyed context [22]. While investigating the last two key assumptions could be the subject of future research,

North and Macal 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. A full discussion on the survey procedure is presented in Ref. [23].
(2) *Theory validation*: The theories implemented in this study are among the well-established theories in the literature. The discrete choice analysis, TPB, Social Networks, and diffusion of innovation methods have been reviewed extensively and applied in different domains of technology adoption using ABM through literature as discussed in the

background. While there is a consensus on the validity of the theories that form the foundation of this work based on their numerous applications, the integrated model developed here should be investigated independently from the underlying theories and as a novel approach for theoretical validity. Such investigation is suggested for future work.

(3) *Model output validation*: The output of the model in scenarios II, III, and IV agrees with independent analytical work discussed at the end of each scenario. Therefore, the 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 diffusion of innovation 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. The 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 the influence of social networks. Households' decisions and their peers' choice of stove affect their TPB-based behavioral attributes through time. The dynamic ABM platform provides the opportunity to study the 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. Technology designers can benefit from the results discussed in this paper that shed light on how technology performance coupled with user preferences alters the impact assumed in the design phase.

The methodology in this study captures the 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 widespread community beliefs and recognize the power and level of autonomy 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 a lack of autonomy to make such decisions.

The role of societal 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 the diffusion of innovation theory for investigating how identifying households with a higher social reputation could influence the 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.

The results of this study could be improved by incorporating community member social status and level of influence into the model. Therefore, designing the social network of the target community by reflecting the weight of influences for households that are naturally more influential in the community could improve the robustness of the model.

Applying this model to different types of technologies that aim to address the challenges of the bottom of the pyramid based on appropriate user heterogeneity attributes could improve overall project success. Validation of the model could be investigated through a planned independent study that records actual behavior for comparing model prediction with behavior. Additionally, investigating the technology adoption through lenses of bounded rationality or validity of the underlying assumption of rational decision-making could be another topic for similar future work in the domain of low-income regions. On a larger scale, integrating adoption behavior models to extended village-scale models, developing policy level toolkits for international development, and developing macro-scale energy policy systems could improve the overall approach to relieve energy poverty for international development.

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Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request. Data provided by a third party are listed in Acknowledgment. The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

References

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

[2] He, L., Wang, M., Chen, W., and Conzelmann, G., 2014, "Incorporating Social Impact on New Product Adoption in Choice Modeling: A Case Study in Green Vehicles," Transp. Res. Part D Transp. Environ., **32**, pp. 421–434.

[3] Macal, C. M., and North, M. J., 2009, "Agent-Based Modeling and Simulation," Proceedings of the 2009 Winter Simulation Conference (WSC), Austin, TX, Dec. 13–16, pp. 86–98.

[4] An, L., 2012, "Modeling Human Decisions in Coupled Human and Natural Systems: Review of Agent-Based Models," Ecol. Modell., **229**, pp. 25–36.

[5] Rogers, E. M., 2010, *Diffusion of Innovations*, 4th ed., Free Press, New York.

[6] Sahin, I., 2006, "Detailed Review of Rogers' Diffusion of Innovations Theory and Educational Technology-Related Studies Based on Rogers' Theory," Turkish Online J. Educ. Technol., **5**(2), pp. 14–23.

[7] Weigel, F. K., Hazen, B. T., Cegielski, C. G., and Hall, D. J., 2014, "Diffusion of Innovations and the Theory of Planned Behavior in Information Systems Research: A Metaanalysis," Commun. Assoc. Inf. Syst., **34**(31), pp. 619–636.

[8] Davis, F. D., 1989, “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology,” MIS Q., **13**(3), p. 319.
[9] King, W. R., and He, J., 2006, “A Meta-Analysis of the Technology Acceptance Model,” Inf. Manag., **43**(6), pp. 740–755.
[10] Hwang, Y., Al-Arabiat, M., and Shin, D.-H., 2016, “Understanding Technology Acceptance in a Mandatory Environment: A Literature Review,” Inf. Dev., **32**(4).
[11] Venkatesh, V., and Davis, F. D., 2000, “A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies,” Manage. Sci., **46**(2), pp. 186–204.
[12] Benbasat, I., and Barki, H., 2007, “Quo Vadis, TAM?,” J. Assoc. Inf. Syst., **8**(4), pp. 211–218.
[13] Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D., 2003, “User Acceptance of Information Technology: Toward a Unified View,” MIS Q., **27**(3), p. 425.
[14] Williams, M. D., Rana, N. P., and Dwivedi, Y. K., 2015, “The Unified Theory of Acceptance and use of Technology (UTAUT): A Literature Review,” J. Enterp. Inf. Manag., **28**(3), pp. 443–488.
[15] Ajzen, I., 1991, “The Theory of Planned Behavior,” Orgnizational Behav. Hum. Decis. Process., **50**(2), pp. 179–211.
[16] Ajzen, I., 2013, “Theory of Planned Behaviour Questionnaire. Measurement Instrument Database for the Social Science”.
[17] Lai, P. C., 2017, “The Literature Review of Technology Adoption Models and Theories for the Novelty Technology,” J. Inf. Syst. Technol. Manag., **14**(1), pp. 21–38.
[18] Kaufmann, P., Stagl, S., and Franks, D. W., 2009, “Simulating the Diffusion of Organic Farming Practices in Two New EU Member States,” Ecol. Econ., **68**(10), pp. 2580–2593.
[19] Schwarz, N., and Ernst, A., 2009, “Agent-based Modeling of the Diffusion of Environmental Innovations—An Empirical Approach,” Technol. Forecast. Soc. Change, **76**(4), pp. 497–511.
[20] Sopha, B. M., Klöckner, C. A., and Febrianti, D., 2017, “Using Agent-Based Modeling to Explore Policy Options Supporting Adoption of Natural gas Vehicles in Indonesia,” J. Environ. Psychol., **52**, pp. 149–165.
[21] Zhang, T., and Nuttall, W. J., 2012, “An Agent-Based Simulation of Smart Metering Technology Adoption,” Int. J. Agent Technol. Syst., **4**(1), pp. 17–38.
[22] Pakravan, M. H., and MacCarty, N., 2020, “Design for Clean Technology Adoption: Integration of Usage Context, User Behavior, and Technology Performance in Design,” ASME J. Mech. Des., **142**(9), p. 091402.
[23] Pakravan, M. H., and MacCarty, N. A., 2020, “What Motivates Behavior Change? Analyzing User Intentions to Adopt Clean Technologies in Low-Resource Settings Using the Theory of Planned Behavior,” Energies., **13**(11), p. 3021.
[24] Kempe, D., Kleinberg, J., and Tardos, É., 2005, *Influential Nodes in a Diffusion Model for Social Networks*, Springer, Berlin Heidelberg, 1127–1138.
[25] Kiesling, E., Günther, M., Stummer, C., and Wakolbinger, L. M., 2012, “Agent-based Simulation of Innovation Diffusion: a Review,” Cent. Eur. J. Oper. Res., **20**(2), pp. 183–230.
[26] Watts, D. J., and Strogatz, S. H., 1998, “Watts−1998-Collective Dynamics of ‘Small-World,” Nature, **393**(6684), pp. 440–442.
[27] Ben-Akiva, M. E., and Lerman, S. R., 1985, *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Boston, MA.
[28] Rai, V., and Robinson, S. A., 2015, “Agent-based Modeling of Energy Technology Adoption: Empirical Integration of Social, Behavioral, Economic, and Environmental Factors,” Environ. Model. Softw., **70**, pp. 163–177.
[29] Sopha, B. M., Klöckner, C. A., and Hertwich, E. G., 2011, “Exploring Policy Options for a Transition to Sustainable Heating System Diffusion Using an Agent-Based Simulation,” Energy Policy, **39**(5), pp. 2722–2729.
[30] Shafiei, E., Thorkelsson, H., Ásgeirsson, E. I., Davidsdottir, B., Raberto, M., and Stefansson, H., 2012, “An Agent-Based Modeling Approach to Predict the Evolution of Market Share of Electric Vehicles: A Case Study From Iceland,” Technol. Forecast. Soc. Change, **79**(9), pp. 1638–1653.
[31] Masad, D., and Kazil, J., 2015, “Mesa: An Agent-Based Modeling Framework,” 14th Python in Science Conference (SCIPY 2015), p. 51.
[32] Jager, W., and Janssen, M., 2012, “An Updated Conceptual Framework for Integrated Modeling of Human Decision Making: The Consumat II”.
[33] Kempe, D., Kleinberg, J., and Tardos, É., 2003, “Maximizing the Spread of Influence Through a Social Network,” Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining —KDD ‘03, p. 137.
[34] Levine, D., Cotterman, C., Levine, D., and Cotterman, C., 2003, *Maximizing the Spread of Influence through a Social Network*, SIGKDD, Washington DC.
[35] Masuda, E., and Newman, P., 1981, “Gray and Giffen Goods,” Econ. J., **91**(364), pp. 1011–1014.
[36] Miller, G., and Mushfiq Mobarak, A., 2013, “Intra-Household Externalities and Low Demand for a New Technology: Experimental Evidence on Improved Cookstoves,” *NBER Work Paper Series*, pp. 1–58.
[37] Adrianzén, M. A., 2014, “Social Capital and Improved Stoves Usage Decisions in the Northern Peruvian Andes,” World Dev., **54**, pp. 1–17.
[38] Ramirez, S., Dwivedi, P., Ghilardi, A., and Bailis, R., 2014, “Diffusion of non-Traditional Cookstoves Across Western Honduras: A Social Network Analysis,” Energy Policy, **66**, pp. 379–389.
[39] Robins, G., 2015, *Doing Social Network Research: Network-Based Research Design for Social Scientists*, SAGE, Los Angeles.
[40] Hanna, R., Duflo, E., and Greenstone, M., 2016, “Up in Smoke: The Influence of Household Behavior on the Long-run Impact of Improved Cooking Stoves,” Am. Econ. J. Econ. Policy, **8**(1), pp. 80–114.
[41] Chen, W., Collins, A, Cummings, R, Ke, T., Liu, Z., Rincon, D., Sun, X., Wei, W., Wang, Y., and Yuan, W., 2011, “Influence Maximization in Social Networks When Negative Opinions May Emerge and Propagate,” Proceedings of the Sixth Conference on Uncertainty in Artificial Intelligence, Boston, MA, April, pp. 379–390.
[42] North, M. J., and Macal, C. M., 2007, “ABMS Verification and Validation,” *Managing Business Complexity*, Oxford University Press, pp. 221–234.