Diffusion of clean cooking practices in refugee settings

An agent-based exploratory modelling study of market-based interventions

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TUDelft

Diffusion of clean cooking practices in refugee settings: An agent-based exploratory modelling study of market-based interventions

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Master thesis submitted to Delft University of Technology
in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

in

Engineering and Policy Analysis
Faculty of Technology, Policy, and Management

by

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To be defended on August 27th, 2020

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An electronic version of this thesis is available at
`http://repository.tudelft.nl/`.

The associated code and model are available at
`https://github.com/AnjaWer`.

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Preface

This thesis marks the end of my two years at the Delft University of Technology. I must admit it has been the most challenging project for me during the Engineering and Policy Analysis (EPA) master's program. I started this thesis during my internship at the UNEP DTU Partnership in Copenhagen, where I got introduced to the topic of clean cooking in refugee settings. Having lived in rural Ghana and Tanzania, and visited other low-income countries, I am convinced of the societal relevance of this topic, which motivated me to fully engage in this research. Focusing on the humanitarian context added another dimension of relevance, and allowed me to gain insight into refugee camps, which are increasingly becoming home to a vast number of people around the world. As no field research was possible, and as I wanted to exemplify the value of the skills attained as an EPA student, I decided to take a modelling approach. Yet, being in touch with humanitarian policy makers challenged my approach and nurtured my doubts about modelling and simulation. Though, the exploratory modelling approach offered a valuable means to reduce the pitfalls of modelling, to a certain degree. Ultimately, being faced with the divide between modelling and policy making inspired me to continuously focus on the practical relevance of my research. I would like to express my gratitude to the following people, who supported me substantially in completing this thesis.

First, I would like to thank my supervisors, Tina and Martijn, for your valuable guidance during this thesis, despite the physical distance. You helped me to narrow down my research focus, you encouraged me to take decisions, and to trust in my research abilities. Your critical feedback and suggestions throughout this thesis greatly improved its quality.

A special word of thanks goes to Gerardo for your support during my internship, and to James for introducing me to the topic and connecting me to the right people. I am also profoundly grateful to my interviewees for sharing your experiences and insights into a unique case, which builds the empirical grounding of this study.

Finally, I want to thank Georgios for supporting me, personally and academically, throughout the past months, for distracting me when I found it hard to get my mind out of my thesis, and for sharing our peaceful, small home. I would also like to say thank you to my fellow EPA friends for the many great memories I will keep from the past two years. Lastly, I am very grateful to my family for your caring words and messages, and for your continuous support and encouragement throughout my years of study.

Anja Werntges
Den Haag, August 2020

Executive summary

Access to clean energy (SDG7) has long been neglected within the humanitarian agenda. Currently, refugees are often locked into unsustainable and risky energy practices, especially in low-income countries. Cooking with traditional fuels such as firewood and charcoal makes up the main component of energy consumption by refugee households, but involves severe health risks, contributes to global carbon emissions, and puts pressure on already scarce resources.

The focus of this study is on emerging market-based interventions to deliver clean cooking fuels in refugee camps in protracted crises. Market-based interventions aim to meet the needs of the affected population by providing financial assistance to the people in need while supporting local market actors to supply goods and services directly to the affected population. The outcomes of market-based interventions are highly dependent on whether beneficiaries decide to adopt and continuously use the products. However, clean cooking practices often face various adoption barriers.

This study analyses the adoption of clean cooking fuels in refugee camps through the lens of innovation diffusion theory. The adoption of clean cooking fuels by refugee households is viewed as *innovation* since it is an "idea, practice, or object that is perceived as new" (Rogers, 1983). The aim of this study is to gain insights into the mechanisms and path-dependencies driving the adoption and, by taking a modelling approach, to develop a method to analyse the effects of market-based clean cooking interventions under various scenarios. Interventions addressed by this study include different types of financial assistance for fuel purchase (cash transfers or vouchers), information campaigns, and maintenance activities. Supply-side interventions are not considered. The research question addressed in this study is formulated as follows:

How can Agent-Based Modelling and Exploratory Modelling be combined to analyse the effect of market-based clean cooking interventions in refugee camps?

To address this research question, this study begins with a case study of a Rwandan refugee camp, where the first fully market-based clean cooking intervention in a refugee camp has been implemented. Taking an exploratory approach, semi-structured interviews with humanitarian experts and private sector stakeholders involved in the case are conducted. The case study identified main drivers and barriers for the adoption and sustained use of clean cooking fuels in a refugee camp.

By synthesizing the findings from the case study with innovation diffusion theory, an agent-based model is developed that captures human decision-making behaviour, adopter heterogeneity, and social interactions within social networks, in-

cluding social conformity and the spread of information via word-of-mouth, driving or hindering adoption. Subsequently, this study combines agent-based modelling with exploratory modelling techniques to account for deep uncertainties regarding external factors, model parameters, and the model structure. The effects of cash- and voucher-based interventions are simulated under a wide range of scenarios, and the performance of interventions is evaluated in terms of long-term impact, timeliness, and robustness. Whether diffusion happens and the scale of diffusion is found to be highly path-dependent. A main finding is that cash-based interventions do not lead to significant adoption levels in most scenarios. Voucher-based interventions succeed more often, though the spread of outcomes is wide for most interventions. Information campaigns are found to improve the timeliness of interventions, and increased maintenance capacity is found to enable high and stable adoption levels.

Based on the model outcomes, this study conducts an inductive analysis, by applying scenario discovery, which maps the outcomes of interest to sub-spaces in the uncertainty space. Subsequently, the parameter ranges corresponding to the sub-spaces are translated into circumstances for success or failure of interventions. Thereby, this study offers comprehensive insights into the path-dependencies driving adoption. The success or failure of interventions depends on the nature of the refugee setting and on the specific design of the intervention. Main findings include that integrated cash-based interventions with supporting information campaigns and maintenance activities fail to achieve high and sustained adoption in refugee settings characterized by (1) low percentage of refugee households working and receiving their own income, and (2) unstable prices of clean fuels where positive price shocks are likely to happen; and if (3) the design of the intervention or the business model of the fuel company involves large minimum purchase amounts of clean fuels compared to traditional fuels. On the other hand, integrated voucher-based interventions are successful under most circumstances, but their failure remains possible if (1) the fuel supply is unstable, and if (2) the performance of fuel and stove does not satisfy the users.

Based on the findings, implications for market-based clean cooking interventions are discussed. Given the variety of adoption barriers for clean cooking practices and strong competition from traditional fuels, there is a need for an integrated intervention. Regardless of the type of financial assistance (cash transfers or vouchers), supporting information campaigns and maintenance activities are critical to create robust, timely and long-term impact. Despite limited financial resources, humanitarian policy makers are encouraged to allocate sufficient budget for supporting interventions, especially for long-term technical support and maintenance capacity. Additional prerequisites for successful interventions include facilitating a stable local supply, accessible for all beneficiaries, and selecting a clean cooking system that matches well with local cooking preferences, which is key to avoid that spread of negative information becomes a major adoption barrier. Lastly, this study derives guidelines for the selection of either cash transfers or vouchers to assist clean fuel purchase based on the findings from the scenario discovery. Given the aforementioned supporting interventions and prerequisites, cash transfers can be advised if (1) the host country has relaxed work policies for refugees, (2) minimum purchase amounts for clean fuels are comparable to traditional fuels, or for LPG cylinders, the payment is split into smaller amounts to avoid the barrier created by having to save money for monthly fuel purchases, and if (3) a mechanism for cash transfers is already in place, regular and predictable for beneficiaries; or can be easily introduced. If one of the three circumstances is not fulfilled in a refugee setting, voucher-based interventions are the recommended approach to introduce clean cooking practices into refugee communities. Finally, if cash transfers rather than vouchers are selected, policy makers should be aware of the trade-off that exists between potential benefits from cash transfers, such as reduced logistics or empowerment of beneficiaries, and robustness of the intervention in terms of creating high and sustained adoption levels.

Several suggestions are made for further research. The most important ones are to analyse the role of early adopters and how to integrate them in interventions, to expand the model to include social interactions with the host communities, and to increase the evidence base the model is built upon by consulting refugees themselves.

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Chapter 1

Introduction

1.1 Research problem

More than 70 million people have been forced to flee their home by the end of 2019, which is the highest ever-recorded level of displacement (UNHCR, 2019). Due to complex global challenges such as violent conflicts, natural disasters and climate change, the number of people in need of humanitarian assistance is likely to increase over the next decades. The majority of them are hosted in low- or middle-income countries, often living in refugee camps, where they depend on aid provided by humanitarian organizations or local governments. Typically, humanitarian response focuses on providing shelter, food, water, sanitation, healthcare and education. Access to clean energy (SDG7) has long been neglected within the humanitarian agenda due to limited funding and the hesitation to implement long-term solutions in "temporary" camps. However, as the causes of displacement often become protracted, there is a growing need to provide refugees with access to clean energy. If energy planning is not taken into account since the initial humanitarian response, refugees and humanitarian organizations can become locked into inadequate energy practices.

Currently, about 80 % of people living in refugee camps have no access to clean, safe and secure energy services, and thus depend on firewood and charcoal as their main energy resources (Grafham, Lahn, & Lehne, 2016). This study focuses on cooking fuels as they make up the largest component of energy demand by refugee households. Cooking fuels are especially of concern due to their various implications including for the environment, relations with host communities, financial costs, food security and health. For instance, refugees – especially women and children – are exposed to severe health risks due to indoor-air pollution. According to WHO, more than four million people die each year as a consequence of inhaling smoke from open fires (WHO, 2016). Moreover, the collection of firewood puts pressure on already scarce natural resources and raises the risk of conflicts between refugees and host communities. Local governments have started to urge humanitarian organizations to find alternative solutions to replace the collection and distribution of firewood (Patel & Gross, 2019).

On the policy level, the issue of energy access for refugees has recently gained momentum. In 2018, the Global Plan of Action for Sustainable Energy Solutions in Situations of Displacement (GPA) was launched by a number of UN agencies and NGOs, stating the vision of "safe access to affordable, reliable, sustainable and modern energy services for all displaced people by 2030" (UNITAR, 2018). Technically, a number of promising "clean" cooking solutions exist such as fuel-efficient cookstoves, solar cookers, or combinations of improved stoves and clean fuels such as liquid petroleum gas (LPG) or wood pellets. Moreover, well-designed clean cooking interventions do not only have the potential to reduce the burden on the environment and health, but also offer opportunities to improve livelihoods, create jobs for refugees and host communities, and to become self-sustaining, if local markets are carefully considered in the response.

Market-based interventions have gained particular attention to address the issue of energy access for refugees in protracted crises. Market-based humanitarian response aims to meet the needs of the affected population by providing cash transfers or vouchers to the people in need while supporting local market actors to supply goods and services directly to the affected population. One implication of giving people the choice on how to meet their own needs is that the outcomes of market-based interventions are highly dependent on whether or not beneficiaries adopt and continuously use the new solutions.

However, all too often the implementation of clean cooking programs around the world has failed. Their outcomes in terms of environmental and health benefits are rarely significant, as the adoption and sustained use of clean cooking solutions remain low, e.g. Hanna, Duflo, and Greenstone (2016); Puzzolo, Pope, Stanistreet, Rehfuess, and Bruce (2016); Stanistreet et al. (2019). Introducing clean cooking fuels in a complex humanitarian environment, subject to a wide range of uncertainties and characterized by aid dependency, longstanding cooking traditions, and competition from traditional fuels proves to be particularly challenging. Considering the significant amounts of financial resources that have been spent on clean cooking programs over the years, and that will be spent on emerging market-based clean cooking interventions, this has implications for the limited budget of humanitarian organizations as well as for the local fuel suppliers who invest their own resources in refugee camp markets and depend on the uptake of their products. Finally, if clean cooking fuels are not used, refugees will continue to contribute to deforestation around the camps and remain exposed to severe health risks.

1.2 Research objective

As will be elaborated in the following chapters, this study views the adoption of clean cooking fuels in refugee camps through the lens of innovation diffusion theory. The objective of this study is to gain insights into the mechanisms and path-dependencies driving the adoption and, by taking a modelling approach, to develop a method to analyse the effects of market-based clean cooking interventions under various scenarios. To this end, this study combines agent-based modelling with exploratory modelling techniques, grounded in a case study of a Rwandan refugee camp. Thereby, this study aims to contribute to informing market-based clean cooking interventions in refugee camps.

1.3 Research scope

The focus of this study is on market-based interventions to deliver clean cooking fuels in refugee camps in protracted crises. Interventions addressed by this study include different types of financial assistance for fuel purchase (cash transfers or vouchers), information campaigns, and maintenance activities. Supply-side interventions are not addressed, it is assumed that a local fuel supplier is in charge of the supply.

Following innovation diffusion research, this study focuses on social influences including the spread of information within social networks and social conformity that drive or hinder the adoption. The adoption of clean cooking fuels by refugee households is viewed as *innovation* as it is an "idea, practice, or object that is perceived as new" (Rogers, 1983). Since choosing cooking fuels is not a discrete decision between one or the other, rather people use multiple stoves and fuels for different types of food ("stove stacking"), the term *adoption* in this study refers to using clean cooking fuels as main fuel type within a household.

Furthermore, this study only focuses on cooking fuels and does not consider the adoption of new cookstoves. It is assumed that refugees receive stoves for free or for lease to direct the focus of the analysis towards the sustained adoption of clean cooking fuels instead of the one-off decision to adopt stoves.

This study does not aim to answer questions related to the coordination of interventions, logistics, or cost-efficiency of interventions. Neither does this study seek to design a business model for private fuel suppliers engaged in refugee camp markets. The scoping of the research will be elaborated on in the subsequent chapter.

1.4 Structure of this study

This first chapter provides an introduction to the research problem of this study. Chapter 2 reviews relevant literature and formulates the research gaps addressed by this study. Chapter 3 elaborates on the research objectives and the research methodology used to answer the research question. Chapters 4 to 9 provide answers to the sub-research questions. In chapter 10 the limitations to this study and implications of the findings are discussed. Chapter 11 concludes the study by summarizing the answers to the sub- and main research questions, reflecting on the scientific and societal contribution, and formulates suggestions for further research.

Chapter 2

Literature Review

Despite the rising policy awareness on the issue of energy access for refugees highlighted by the previous chapter, there has been little research on the issue of clean cooking in the humanitarian context up until now. This chapter discusses relevant existing literature, introduces core theoretical concepts, and defines the research gaps, that will be addressed in this study.

First, the search strategy including criteria for the selection of grey and scientific literature is outlined. Second, the relevant literature is reviewed in three sections. Each of these sections leads to the definition of one research gap. All three research gaps will be summarized at the end of this chapter.

2.1 Search strategy

Different types of sources were considered for this literature review, reaching from peer-reviewed scientific articles to *grey literature*. The latter includes reports by governments, international organizations, NGOs and the likes. Schöpfel (2011) defines *grey literature* as not being published by "primary publishers". It can be peer-reviewed or not.

2.1.1 Criteria for grey literature

For this literature review, reports and studies by humanitarian organizations and international partnerships engaged in energy access for refugees were taken into account. In particular, members of the GPA and the Moving Energy Initiative (MEI), a partnership inaugurated in 2015 between Energy 4 Impact, Practical Action, UNHCR, the Norwegian Refugee Council and Chatham House, have produced relevant literature on market-based energy interventions in refugee settings.

2.1.2 Criteria for scientific literature

Peer-reviewed scientific articles were searched for in the research database Scopus. In addition, a range of references have been identified through *snowballing* search (Jalali & Wohlin, 2012), which means starting from available literature reviews and key references, relevant other authors and documents have been pinpointed. Table 2.1 lists the search terms used to search throughout titles, abstracts and key words ("TITLE-ABS-KEY") in the research database, with no other search limits in place:

Section	Search terms
2.2	("energy access" OR "clean cooking") AND ("refugee camp" OR "displacement setting" OR "humanitarian context"); "market-based interventions" AND ("refugee camp" OR "displacement setting" OR "humanitarian context"); ("clean cooking" OR "cooking technologies" OR "cookstoves" OR "clean fuels") AND "adoption barriers"
2.3	"agent-based modelling" AND ("innovation diffusion" OR "technology adoption") AND "household"; "agent-based modelling" AND "clean cooking"; ("clean cooking" OR "cooking technologies" OR "cookstoves" OR "clean fuels") AND "innovation diffusion"; ("refugee camp" OR "displacement setting" OR "humanitarian context") AND "innovation diffusion"
2.4	"agent-based modelling" AND ("innovation diffusion" OR "technology adoption") AND "deep uncertainties"; "agent-based modelling" AND "exploratory modelling";

Table 2.1: Search terms used for literature review

2.2 Clean cooking in refugee settings

Literature on energy access in refugee settings is scattered and most of it comes in the form of grey literature. The research focus has been on identifying and analysing current energy practices in refugee camps and their financial, environmental, safety and health impacts, mainly based on case studies and qualitative analyses (Gunning, 2014). Very few comprehensive research studies exist that emphasize on the lack of knowledge on energy use in refugee settings (Caniato, Carliez, & Thulstrup, 2017; Lahn, Grafham, & Annan, 2015). According to Lahn et al. (2015), the design of energy interventions is "technical, complex and highly dependent on context". However, there is very limited scientific research that aims to inform energy interventions in humanitarian contexts, thus their effects remain poorly understood (Barbieri, Riva, & Colombo, 2017).

2.2.1 Market-based humanitarian response

There is an emerging body of literature on humanitarian energy interventions which stresses the need to implement market-based approaches rather than free distributions by aid organizations (Haselip & Rivoal, 2017; Huber & Mach, 2019; Landeghem, 2016; Patel & Gross, 2019; Whitehouse, 2019). As opposed to in-kind distributions, a *market-based approach* refers to giving the affected population "cash or vouchers to procure (...) commodities/services they need in local markets, whilst providing direct support to local market actors to meet supply and demand" (Martin-Simpson, Parkinson, & Katsou, 2018). Market-based approaches are aligned with the growing push among humanitarian organizations to strengthening refugees' self-reliance (UNHCR, 2017).

With regard to energy interventions, Whitehouse (2019) and other authors argue that engaging the private sector offers adaptive and long-term mechanisms to meet energy needs of refugees and host communities in a cost-efficient manner, while giving refugees the option to choose for themselves. Initial research shows that refugees are willing to pay for access to energy, including for cooking fuels (Corbyn & Vianello, 2018; Patel & Gross, 2019). Munoz (2016) investigates energy interventions in several refugee settings and suggests possibilities for linking short-term relief to long-term development where market-based approaches are taking a prominent role. According to this literature, market-based approaches are especially relevant for *protracted crises*, which UNHCR defines as refugee situations with "25,000 persons or more who have been in exile for five or more years in developing countries" (UNHCR, 2008).

Rouse (2019) describes market-based humanitarian response in the energy sector in terms of demand-side and supply-side interventions. Demand-side interventions aim to encourage the adoption of products offered to refugees, by providing cash transfers or vouchers, running information campaigns, or offering technical support and maintenance, to encourage the adoption of products offered to refugees. On the supply-side, humanitarian organizations support local energy suppliers in entering refugee camps as a new market, by offering grants to reduce upfront risks, capacity-building or logistical support (Bellanca, 2014; Rouse, 2019).

Market-based clean cooking interventions addressed by this study comprise financial assistance for fuel purchase (cash transfers or vouchers), information campaigns and maintenance activities. Thus, this study focuses on market-based interventions on the demand-side to encourage the adoption of clean cooking fuels in refugee camps. Supply-side interventions are not addressed, it is assumed that a private fuel company is in charge of the supply.

2.2.2 Barriers to the adoption of clean cooking practices

Clean fuels refer to cooking fuels such as LPG or pellets, which produce relatively low indoor-air pollution and carbon emissions when being burned in modern cookstoves. The term "clean" should be understood relative to *traditional fuels*, which refer to firewood, charcoal and other primary biomass which are burned in traditional stoves such as mud stoves or three-stone stoves. Clean fuels can be renewable such as pellets or non-renewable such as LPG (Malla & Timilsina, 2014). *Clean cooking systems* describe the combination of clean fuels and modern cookstoves, such as LPG cookstoves or pellet-based cooking systems. Most of the research in the clean cooking field revolves around *improved cookstoves*, which refer to fuel-efficient cookstoves to reduce the consumption of traditional fuels (Dagnachew, Hof, Lucas, & van Vuuren, 2020).

D. Wilson et al. (2016) study the adoption of improved cookstoves in refugee settings and point out that the outcomes of clean cooking interventions depend on whether or not beneficiaries decide to adopt and use the new technologies. Patel and

Gross (2019) draw first lessons based on case studies of market-based clean cooking interventions in different refugee settings including in Niger, Ethiopia, Kenya, Tanzania and Rwanda. In most cases, the attempts to create a sustained demand for clean cooking fuels did not succeed, especially after the cash assistance ended (Patel & Gross, 2019).

In their ethnographic study, Miller and Ulfstjerne (2020) denounce the ineffectiveness of clean cooking interventions and argue that the perspectives of the people affected by these innovative solutions, refugees and host communities, are often overlooked in research and program implementation. According to them, energy use is embedded in a broader sociocultural context and effective energy interventions must consider the social aspects including interactions with host communities. Corbyn and Vianello (2018) highlight the need to integrate refugees' preferences and priorities in the design of energy interventions. Munoz (2016) mentions the lack of information on refugees' energy preferences as a challenge for using market-based approaches. Although the ongoing research on market-based energy interventions offers more inclusive and holistic approaches, little is known about the barriers to the adoption and sustained use of clean cooking fuels from the perspective of refugees.

Besides the humanitarian context, literature on clean cooking interventions around the world shows that their outcomes are rarely significant or sustained (Hanna et al., 2016; Puzzolo et al., 2016; Stanistreet et al., 2019). Various researchers have studied factors influencing cooking fuel choice and the barriers for the adoption of improved cookstoves and/or clean fuels in developing countries (Malla & Timilsina, 2014; Ruiz-Mercado, Masera, Zamora, & Smith, 2011; Seguin, Flax, & Jagger, 2018). However, none of them focuses on the barriers for the adoption of clean cooking fuels in refugee camps.

2.2.3 Summarizing the first research gap

The understanding of how people living in refugee camps make decisions about choosing their cooking fuels remains limited, which makes it difficult to tailor market-based clean cooking interventions to the refugees' needs, which, in turn, can lead to low adoption and use rates and impede the achievement of health and environmental benefits. Thus, there is a need to research the decision-making behaviour and the barriers to the adoption and sustained use of clean cooking fuels in refugee camps.

2.3 Innovation diffusion

Adopters' decision-making behaviour has received significant attention in innovation diffusion research. *Diffusion* is defined as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 1983). An *innovation* is generally associated with a new technology, but the term can be used more widely to describe an "idea, practice, or object that is perceived as new" (Rogers, 1983).

2.3.1 Adoption of clean cooking practices as innovation

This study defines the adoption of clean cooking practices by refugee households as *innovation*. Since choosing cooking fuels and stoves is not a discrete decision between using one or the other, but instead people use multiple stoves and fuels for different types of food ("stove stacking"), there is a need to clearly define what is meant by *adopting* a new fuel. In this study, *adoption* refers to using clean fuels as main cooking fuel. This implies that traditional fuels (i.e. charcoal and firewood) can still be in use to some extent. It further implies that people who are using clean cooking fuels as part of their fuel mix, but not as their main fuel, are not considered adopters. This specific definition of adoption allows to focus not only on the initial adoption decision, but on the sustained use of clean fuels, which is key to achieve the health and environmental benefits of clean cooking interventions.

Moreover, this study only focuses on clean cooking fuels and does not consider the adoption of new cookstoves. It is assumed that refugees receive stoves for free or can lease them, otherwise in the absence of purchasing power the upfront cost of stoves are likely to hinder any significant adoption. Although this is a strong assumption, it is considered a realistic one for the context of refugee camps. This is in contrast to typical innovation diffusion cases, where there is often a financial risk associated with adopting the innovation. Buying new fuels, while disregarding the upfront cost for a new stove, does not involve a major financial risk, nevertheless, switching the main cooking fuel is likely to involve inertia. The focus on clean fuels implies that adopters can simply reverse their adoption decision by ceasing to buy them, revert back to traditional fuels, and decide to adopt again in the future. This is considered a more realistic representation of the decision to buy and keep using clean cooking fuels.

2.3.2 Theoretical foundations

The Diffusion of Innovation (DoI) theory developed by Rogers (1983) provides the theoretical foundation in diffusion research. DoI captures several aspects contributing to diffusion, from the innovation attributes to communication between adopters, heterogeneity of adopters, and the decision-making process. For this study, the following two concepts are most relevant.

Innovation-decision process

According to DoI, the innovation-decision process describes human decision-making about adoption of an innovation as a five-stage process involving: knowledge, persuasion, decision, implementation and confirmation. First, in the knowledge phase, individuals learn about the existence and the functions of the innovation. Second, in the persuasion stage, individuals seek information about the innovation with the objective to reduce uncertainty about the expected consequences, and form an attitude towards the innovation, either favorable or unfavorable. Third, in the decision stage, individuals choose between adopting or rejecting the innovation. Fourth, in the implementation stage, individuals put their decision into practice. Up until the decision stage, the process has been a "strictly mental exercise", only in the implementation stage it is translated into behaviour change. Fifth, in the confirmation stage, individuals seek to reinforce their decision, or else to reconsider it. (Rogers, 1983)

Adopter heterogeneity

Potential adopters play different roles in the diffusion process according to their attitudes towards risk and uncertainty, and which communications channels they use and rely on. Rogers (1983) defines *innovativeness* as ”the degree to which an individual is relatively earlier in adopting new ideas then the other members of a system”. He classifies the members of a social system into five categories: innovators, early adopters, early majority, late majority, and laggards. Innovators are the first to adopt an innovation, they are least averse to risk and uncertainty as they cannot rely on evaluations of the innovation from their peers. Early adopters are opinion leaders, they are particularly respected by their peers and closely looked at for advice and information about the innovation. In order to maintain their opinion leadership, they aim to provide sensitive judgements about the innovations. The early majority takes more time before adopting than the early adopters, lets other try and test first, but they are not the least to adopt. The late majority is more sceptical about new ideas and requires changing social norms before being convinced to adopt. Finally, the laggards are particularly averse to risk and uncertainty, and thus the last to adopt an innovation.

DoI critique

Critical voices point out that innovations are not adopted simply through communication and the spread of favorable attitudes, and that DoI does not sufficiently consider situational barriers to adoption, such as the lack of access or lack of financial resources (C. Wilson & Dowlatabadi, 2007).

2.3.3 Modelling innovation diffusion

To capture the complex process of innovation adoption and diffusion through social systems, researchers have proposed various models. The most influential one is an aggregate model introduced by Bass (1969), which is based on differential equations that specify the flow from non-adopters to adopters. The model is structurally similar to a basic epidemic model, where the diffusion is represented as a contagious process with two main drivers: internal influences (e.g. word-of-mouth) and external influences (e.g. advertising). Thus, an individual's probability of adopting a new product is described as a function of the number of adopters and an external influence (Kiesling, Günther, Stummer, & Wakolbinger, 2012).

However, aggregate models have several limitations. For instance, aggregate models assume homogeneity of potential adopters, which is in contrast to diffusion theory, they do not allow for distinguishing different kinds of social influences in the diffusion process, and they only differentiate between adopters and non-adopters, which heavily simplifies the complex human decision-making process.

To address these limitations, there is growing literature within diffusion research that propose agent-based modelling (ABM) to capture the complex patterns of social interactions, adopter heterogeneity, and individual decision-making. ABM is an individual-based modelling approach, which allows to model heterogeneous agents that interact with one another according to a set of behavioural rules and can modify their behaviour over time. These interactions may lead to the emergence of macro-level phenomena (Van Dam, Nikolic, & Lukszo, 2013). For instance, agents make individual decisions on whether or not to adopt a new technology based on heterogeneous properties, and spread information about it to other agents, which then leads to an emerging increase in the level of adoption. Due to its flexibility to describe behavioural aspects in great detail, ABM is among widely-used approaches to analyse technology adoption by households (Hansen, Liu, & Morrison, 2019; Rai & Robinson, 2015). For example, ABM studies have addressed the diffusion of residential solar PV (Palmer, Sorda, & Madlener, 2015), sustainable heating systems (Sopha, Klöckner, & Hertwich, 2011), electric cars (Wolf, Schröder, Neumann, & de Haan, 2015), or natural gas vehicles (Hidayatno, Jafino, Setiawan, & Purwanto, 2020).

2.3.4 Social influences and path-dependency

Social influences and flows of information driving innovation diffusion processes are evolving and path-dependent. Decisions are being shaped by social influences, and the consequences of decisions, in turn, shape social influences, contributing to emergent diffusion patterns.

ABM studies on innovation diffusion differ in the level of detail how social influences are incorporated. Many ABMs only consider one type of social influence, conformity, where agents consider adoption once a critical threshold of adopters among peers is met, e.g. Hidayatno et al. (2020). Yi and Ahn (2017) propose an ABM approach for new product diffusion that considers the impact of word-of-mouth (WoM) communications. In their model, an initial expectation is assigned to the agents, which is updated based on the satisfaction of adopters in their neighbourhood. Depending on the value of the product, the impact of WoM can both drive or hinder diffusion. The authors focus on the interplay of initial expectations, post-purchase satisfaction and sales, considering different product values and heterogeneous consumers. Wang, Zhang, Li, and Li (2018) propose a more nuanced approach to model anecdotal information exchange in the diffusion of residential PV in China. Similar to other ABMs, they use a social network-based model and include the social effect consisting of the attitude of peer adopters as a factor in the utility function. Additionally, Wang et al. (2018) consider the influence of information from peer adopters in other factors in the utility function, such as in the expected risk probability and the expected revenue.

2.3.5 Existing applications in the clean cooking field

Evidence from various studies suggests that peer influence is a significant driver for the (non-)adoption of improved cookstoves and clean fuels (Seguin et al., 2018; Srinivasan & Carattini, 2020). However, the majority of quantitative studies in the clean cooking field are based on descriptive statistical analysis or econometric estimation approaches (e.g. discrete choice models or fuel preference models) to predict fuel choices by households (Alem, Beyene, Köhlin, & Mekonnen, 2016; Kowsari & Zerriffi, 2011; Poblete-Cazenave & Pachauri, 2018). Nevertheless, these approaches are correlational and do not capture the complexity of adoption decisions, social interactions, or emergent patterns over time.

Few studies have applied diffusion concepts in the context of clean cooking. Ramirez, Dwivedi, Ghilardi, and Bailis (2014) study the diffusion of cookstoves in Honduras and use social network analysis to reveal patterns driving the success of cooking stove interventions.

One recent ABM study was found that analyses the emergent adoption rate of improved cookstoves in a community in Uganda (MacCarty & Pakravan, 2019). MacCarty and Pakravan (2019) use the Theory of Planned Behavior (TPB) and utility maximization theory to formalize individual decision-making within social networks to gain a better understanding of cookstove adoption patterns. TPB is a popular theory used in ABMs to model household decision-making on technology adoption. It was developed by Ajzen (1991) and defines an individual's behaviour by the his or her intention to engage in the behaviour, which, in turn, is determined by three attributes: attitude, subjective norms and perceived behavioural control. TPB requires survey data to derive the relative contribution of each of the three attributes to the decision (Zhang & Vorobeychik, 2019). MacCarty and Pakravan (2019) propose the first method that allows for analysing the process of technology adoption and diffusion in the field of clean cooking. However, there are several aspects that distinguish their research from this study, and several limitations to their approach that call for further research. First, MacCarty and Pakravan (2019) focus on the adoption of fuel-efficient stoves, whereas sustained use of the stoves or adoption of clean fuels is not addressed. Their aim is in fact to better integrate consumers' intentions in the design of cookstoves from an engineering point of view, which is in line with TPB. They use survey data gathered in a community in Uganda to specify consumer attitudes, perceived behavioural control and personal norms. Moreover, their model is limited in terms of adopter heterogeneity and social interactions. Lastly, the context of their study differs from the one of this study, being a refugee camp.

2.3.6 Summarizing the second research gap

Although ABM grounded in innovation diffusion theory is widely used as a method to analyse path-dependent social influences and explore emerging diffusion dynamics in innovation diffusion research, there is very limited research applying diffusion concepts in the clean cooking field, and specifically, no similar research in the context of refugee camps.

Thus, to analyse the impact of market-based interventions on the adoption of clean cooking fuels in refugee camps, there is a need for a method that integrates individual decision-making, adopter heterogeneity and diffusion through social networks, based on concepts from DoI theory.

2.4 Deep uncertainties in diffusion models

Several studies highlight that innovation diffusion processes and the simulation models used to support informing policies are subject to *deep uncertainties* regarding the context, future scenarios or the structure of the models themselves (Hidayatno et al., 2020; Moallemi, de Haan, Kwakkel, & Aye, 2017; Moallemi & Malekpour, 2018). Lempert, Popper, and Bankes (2003) define *deep uncertainties* as conditions in decision-making "where analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes".

2.4.1 Diffusion of clean cooking practices as a deeply uncertain process

Following this line of research, this study views the diffusion of clean cooking practices in a refugee camp as a deeply uncertain process. In the context of this study, deep uncertainties arise from various sources. First, there are deeply uncertain external factors such as volatility in fuel prices or refugee population numbers. Second, there is only limited data available for such a context, and additional data gathered in interviews or surveys may not adequately represent household characteristics. Third, there are several competing theories which can be used to define the individual decision-making behaviour of agents. In the case of this study, where no previous research has attempted to describe adoption decision-making behaviour of refugees and where there is limited availability of primary data, this implies that the structure of the model itself remains deeply uncertain.

2.4.2 Exploratory Modelling and Analysis

Exploratory modelling and analysis (EMA) is an approach which allows to incorporate deep uncertainties in modelling studies. This approach involves using the model for exploratory purposes by conducting experiments under a wide range of scenarios rather than for prediction. Thereby, the impact of deep uncertainties on the outcomes of model-based studies can be analysed, which, for instance, allows to identify vulnerabilities of policies to changes in future scenarios or model assumptions (J. Kwakkel & Haasnoot, 2018; Marchau, Walker, Bloemen, & Popper, 2019). EMA is a generic approach that has been combined with various ABMs, e.g. Greeven et al. (2016); Moallemi and Köhler (2019). Among the ABM studies on innovation diffusion, one recent study proposes a tailored exploratory model-based diffusion analysis approach by integrating DoI theory with agent-based modelling and exploratory modelling to analyse the diffusion of natural gas vehicles in Jakarta, Indonesia (Hidayatno et al., 2020). Other ABM studies on innovation diffusion often only explore a small number of pre-defined scenarios and test the results by conducting limited sensitivity analyses (MacCarty & Pakravan, 2019; Palmer et al., 2015; Rai & Robinson, 2015; Sopha et al., 2011; Wolf et al., 2015). Hence, deep uncertainties are oftentimes ignored, and the resulting policy recommendations are likely to fail if uncertainties unfold differently than anticipated.

2.4.3 Summarizing the third research gap

This study views the diffusion of clean cooking practices in refugee camps as a deeply uncertain process. There is a need to account for deep uncertainties in model-based analyses of the complex processes of innovation diffusion, but the number of studies adopting the exploratory modelling and analysis approach remains limited. Specifically, no study was found that uses exploratory modelling techniques for model-based diffusion analysis neither in the context of refugee camps nor in the clean cooking field. Thus, there is a need to expand the research integrating exploratory modelling techniques in the model-based study of innovation diffusion in refugee camps.

2.5 Conclusion

The literature review revealed that (1) there is insufficient knowledge on the barriers for the adoption and sustained use of clean cooking fuels in refugee camps, (2) there is currently no method that integrates individual decision-making and social interactions to analyse the effect of market-based clean cooking interventions, (3) there is insufficient consideration of deep uncertainties in model-based diffusion studies.

Chapter 3

Research Formulation

This chapter discusses the research formulation to address the three research gaps identified in the previous chapter. The identified research gaps include the insufficient knowledge on the adoption barriers for clean cooking fuels in refugee camps, the lack of method to analyse the effect of market-based clean cooking interventions, and the insufficient consideration of deep uncertainties in model-based diffusion studies.

First, this chapter formulates the research objectives and the main research question. Subsequently, the research methodology as well as the sub-research questions and the research methods are described.

3.1 Research objectives

This study analyses the adoption of clean cooking fuels in refugee camps through the lens of innovation diffusion theory. Following the line of diffusion research, the adoption of clean fuels as main cooking fuel by refugee households is viewed as *innovation* since it is an "idea, practice, or object that is perceived as new" (Rogers, 1983). The focus is on refugee camps in protracted crises, by considering a Rwandan refugee camp as a case study. The impact of different market-based interventions on the adoption of clean cooking fuels by refugee households is analysed. Interventions addressed by this study include different types of financial assistance for fuel purchase (cash transfers or vouchers), information campaigns and maintenance activities. Supply-side interventions are not addressed, it is assumed that a private fuel company is in charge of the supply.

The objective is to gain insights into the into the mechanisms and the path-dependencies driving the adoption and, by taking a modelling approach, to develop a method to integrate individual decision-making behaviour, social interactions, and deep uncertainties, to analyse the effect of market-based clean cooking interventions under various scenarios. Thereby, this study aims to contribute to informing market-based clean cooking interventions in refugee settings. This research goal is summarized in the main research question as follows:

How can Agent-Based Modelling and Exploratory Modelling be combined to analyse the effect of market-based clean cooking interventions in refugee camps?

3.2 Research methodology

The research methodology adopted by this study to answer the main research question comprises several research methods. Based on a case study and in combination with existing diffusion theory, an agent-based model is developed that allows to explore the effects of alternative interventions under various scenarios by using exploratory modelling techniques. The main research question is answered in six steps, with six sub-questions guiding through the process. Figure 3.1 illustrates the research flow diagram, summarizing the research phases, the sub-research questions, and the research methods, which will be described in the next section.

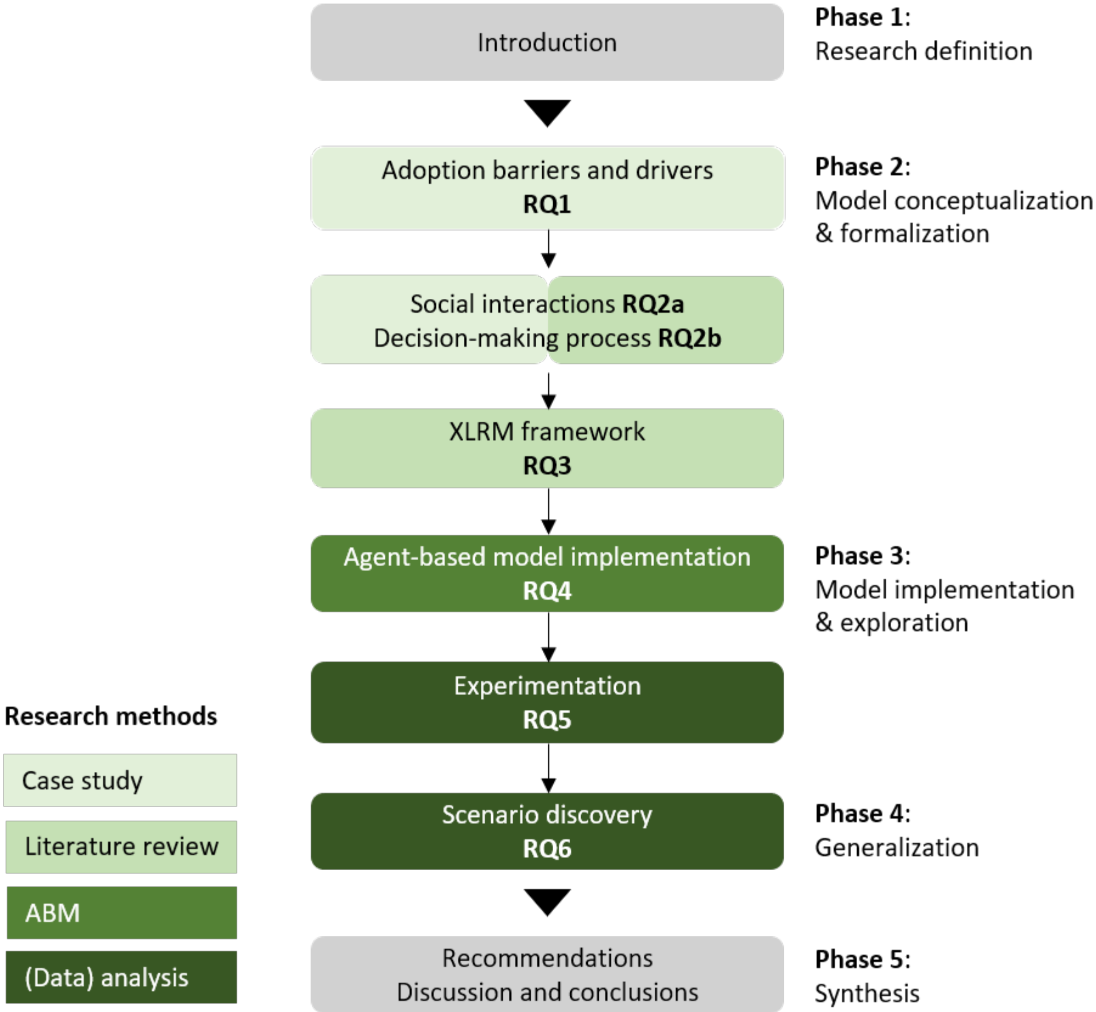


Figure 3.1: Research flow diagram

3.3 Sub-research questions

The first sub-question seeks to identify relevant barriers and drivers for refugees to adopt and use clean fuels in a Rwandan refugee camp. The second sub-question aims to conceptualize and formalize the decision-making process of refugees and the social interactions that influence the diffusion process. The third sub-question seeks to identify interventions, uncertainties and key performance metrics. Subsequently, the fourth sub-question guides the implementation of an ABM that captures the social interactions and individual decision-making behaviours. By exploring and analysing the model outcomes, the fifth sub-question aims to gain insights into the effects of market-based clean cooking interventions under various scenarios. Finally, the sixth sub-question aims to generalize the outcomes of this study to inform future interventions. The different research methods used to answer each of the sub-research questions will be elaborated on in this section.

Sub-question 1: What are the barriers and drivers to the adoption and sustained use of clean cooking fuels for people in Kigeme refugee camp in Rwanda?

The first sub-question aims to identify the barriers and drivers to the adoption and sustained use of clean cooking fuels in a specific case. The case study provides a specific context to be able to examine an existing market-based intervention. A case study is an appropriate research method for a field of research characterized by little empirical evidence and the lack of theories (Eisenhardt, 1989; Yin, 2003). The case was selected based on the following three criteria, to ensure it is in line with the scope of this research.

(i) The refugee context classifies as protracted crisis.

(ii) Market-based clean cooking interventions have been implemented (or are being implemented).

(iii) Contacts to humanitarian organizations in the field and data are available.

Based on the three-criterion selection process, the Kigeme camp in Rwanda was chosen for the case study. Rwanda is among the first low-income refugee hosting countries where humanitarian organizations have been implementing market-based clean cooking interventions. The intervention in Kigeme camp is considered an important case to learn from.

To answer the first sub-question an exploratory approach is chosen. First, desk research is carried out to gather and review grey literature in the form of published and unpublished reports by implementing organizations operating in the Kigeme camp in Rwanda. Second, semi-structured interviews are designed to interview humanitarian experts and private sector stakeholders involved in the Rwanda case. Semi-structured interviews are chosen as research method, as opposed to structured interviews or questionnaires, due to their exploratory nature and flexibility to account for new contents brought up by the interviewees. Open-ended questions allow interviewees to raise new issues, while a pre-planned interview guide also allows to gather comparable qualitative data (Moen & Middelthon, 2015).

Sub-question 2: How can a conceptual model of the diffusion of clean cooking practices in refugee camps be formulated?

(a) How can a conceptual model of the social interactions be formulated?

(b) How can a conceptual model of the adoption decision-making process be formulated?

Having identified the main barriers and drivers to the adoption of clean cooking practices in the case of the Kigeme camp in Rwanda, the next step is to conceptualize and formalize the diffusion process. This step involves conceptualizing and formalizing (a) the social interactions that influence the diffusion, and (b) the adoption decision-making process. Therefore, the second sub-question is split in two parts.

Two research methods are used to answer the second sub-question. First, the case study serves as a base for the conceptual model and provides reference points of a real case. Second, the literature review including DoI theory and state-of-the-art literature using ABM to analyse the innovation diffusion provides theoretical foundations for conceptualization and formalization of the diffusion process. Drawing from concepts from DoI, this step requires to combine existing theory with the empirically identified barriers and drivers.

Sub-question 3: How can the diffusion of clean cooking practices be conceptualized in terms of interventions, uncertainties, and key performance indicators (KPIs)?

The third sub-question aims to structure the diffusion of clean cooking practices in terms of interventions, uncertainties, and KPIs. Answering the third sub-question involves adopting the XLRM framework (Lempert et al., 2003), whereby uncertain factors ('X'), intervention levers ('L'), and key performance metrics ('M') will be defined, after having determined relationships ('R') between system variables in the second sub-question. Interventions, uncertainties and KPIs are specified based on a reflection of the case study and the literature review.

Sub-question 4: How can the diffusion of clean cooking practices be implemented in an agent-based model?

To provide an answer to the fourth sub-question, the outcome of the conceptualization and formalization phase is implemented in an agent-based model, using Mesa, a platform for ABM analysis available in Python.

Following the growing line of diffusion research using ABM, the agent-based modelling approach is adopted in this study as it allows to account for social interactions, agent heterogeneity, self-defined decision rules, and emergent system behaviour. Agents are interacting with one another according to a set of behavioural rules and can modify their behaviour over time. These interactions may lead to the emergence of macro-level phenomena (Van Dam et al., 2013). In this study, the result of social interactions and individual decision-making is the emergent diffusion of clean cooking practices within a refugee camp.

The implementation phase also includes the parametrisation of model variables, which is based on data from the Rwanda case study, where possible, and on diffusion literature. During and after the implementation, various verification methods are used to check whether the model behaves as intended.

Sub-question 5: Based on the model, what are the effects of different market-based clean cooking interventions under various scenarios?

Subsequently, the model is used to systematically explore the effects of different market-based interventions and the impacts of deeply uncertain factors on the outcomes based on the exploratory modelling and analysis approach (EMA). EMA involves sampling scenarios from the uncertainty space and simulating the effects of interventions under a wide range of scenarios. The experimentation and data analysis are performed by using the EMA workbench, an open source tool for exploratory modelling in the Python library (J. H. Kwakkel, 2017).

Sub-question 6: How can the outcomes of this study be used to inform market-based clean cooking interventions in other refugee settings?

The final step is to generalize the outcomes of this study to inform market-based clean cooking interventions in other refugee settings. Answering the sixth sub-question involves three steps. First, before generalizing the outcomes, the model results are validated to test whether the model produces plausible effects with respect to reality. The validation includes cross-validation based on literature and empirical validation based on the case study. Second, the performance of interventions is further analysed in terms of the KPIs and reflected on. Third, this study adopts the EMA approach, by applying scenario discovery, to provide insights into the path-dependencies driving the adoption of clean cooking fuels in refugee camps. By mapping the outcomes of interest to combinations of uncertain parameters, circumstances for success or failure for a subset of interventions can be identified. Based on the findings, recommendations to inform market-based clean cooking interventions are made.

3.4 Conclusion

This chapter describes the research objectives and the research methodology used in this study. The process of answering the main research questions involves six sub-research questions. Based on a case study of a Rwandan refugee camp using semi-structured interviews, combined with DoI theory, this study develops an agent-based model to capture social interactions, adopter heterogeneity and human decision-making behaviour. Exploratory modelling techniques are used to incorporate deep uncertainties in the model-based study by simulating the effects of interventions under a wide range of scenarios, and by applying scenario discovery to identify circumstances that lead to success or failure of interventions. Thereby, the objective is to address the identified research gaps and to provide an answer to the main research question. The next chapter begins by addressing the first two sub-research questions.

Chapter 4

Case Study

This chapter aims to analyse the adoption of clean cooking fuels in a Rwandan refugee camp. This case provides a specific context where a market-based clean cooking intervention has been implemented and provides insights into what barriers and drivers to the adoption and sustained use of clean cooking fuels could be observed in this context. The observations from this case will serve as a base to conceptualize the diffusion of clean cooking practices including the social interactions and the decision-making of refugees. First, the background situation in Rwanda is described. Second, the background situation in Kigeme camp is explained. Third, the set-up of the semi-structured interviews is described. Lastly, the findings from the interviews are presented.

This chapter addresses the first sub-question and provides reference points of a real case to answer the second sub-question, which will be fully addressed in the subsequent chapter.

What are the barriers and drivers to the adoption and sustained use of clean cooking fuels for people in Kigeme refugee camp in Rwanda?

How can a conceptual model of the diffusion of clean cooking practices in refugee camps be formulated?

4.1 Background

Rwanda is hosting about 145,000 refugees, mostly coming from its neighbouring countries, the Democratic Republic of the Congo (DRC) and Burundi. Burundian refugees arrived in 2015, while some of the Congolese refugees have been living in the country since the 1990s. Most of them live in the six camps spread across the country, with a little more than 10 % living in urban areas (UNHCR, 2020).

Refugees in the camps mainly depend on firewood and charcoal as their cooking energy resource. UNHCR used to provide firewood rations that covered between half and three-quarter of monthly household needs, the remaining needs were covered by purchasing charcoal, or collecting firewood. However, due to the increasing damage to the environment in the surroundings of the camps, the government has banned the use of firewood in the camps by the end of 2018. Thus, humanitarian organizations had to find alternative solutions for providing cooking fuels in the camps. Ongoing operations include the in-kind distribution of briquettes and LPG cylinders, as well as cash transfers to purchase fuel in Kigeme camp. (UNHCR, 2020)

4.2 Cash for fuel in Kigeme camp

Kigeme camp was opened in 2005, closed in 2009, and reopened in 2012. It is home to about 20,000 people from the DRC. Figure 4.1 shows an image of the Kigeme camp, located in southwestern Rwanda.

Figure 4.1: This image shows the Kigeme refugee camp in Rwanda in 2012. Eldon (2012). Kigeme refugee camp [Online image]. Oxfam. Retrieved from `https://www.flickr.com/photos/46434833@N05/8073663190`.

In Kigeme, UNHCR has facilitated two cooking fuel companies to enter the camp market and sell their products directly to the refugee households. Households receive cash transfers to be able to purchase fuel. In 2016, a Rwandan company, Inyenyeri, opened a business in Kigeme camp, which has been the first fully market-based attempt to introduce clean cooking fuels in a refugee setting. Inyenyeri offered biomass pellets in combination with improved cooking stoves. The wood equivalent required to produce pellets is relatively low and the stoves adhere to high performance standards (tier-4), thus the combination is considered as clean cooking system. The company's business model involves costumers leasing a stove in exchange for committing to purchase a minimum amount of pellets each month. Refugee households pay for the pellets through cash transfers they receive or other sources of income from informal economic activities. It started as a pilot project with 100 households, followed by another phase with 300 households, and Inyenyeri's objective was to reach all households in Kigeme at the end of the scale-up process.

In 2018, following the government's policy, the distribution of in-kind firewood ceased, and the cash transfers were expanded to all households in Kigeme. While initial interest for pellets could be observed, the sustained demand for pellets remained low. A survey by UNHCR from the end of 2019 shows that only 35 % of refugees had already used pellets and 15-20 % were using pellets as their main fuel. Instead, refugees continued to collect firewood and purchase charcoal. By early

2020, Inyenyeri announced that it had to cease all operations due to bankruptcy, including the closure of their shop in Kigeme.

At the time of writing, according to UNHCR field staff, the cash transfers for fuel in Kigeme are ongoing but camp residents mainly buy charcoal or use firewood for cooking. Figure 4.2 shows a selection of cooking fuels and stoves used in Rwandan refugee camps, including firewood being burned in a fuel-efficient stove, the sale of charcoal in Migombwe camp, the pellet-based cooking system offered by Inyenyeri, and Inyenyeri's office in Kigeme camp.

(a) (b) (c) (d)

Figure 4.2: These images show different types of cooking fuels and stoves used in Rwandan refugee camps: (a) firewood with fuel-efficient stove, (b) charcoal for sale, (c) pellet-based cooking system, and (d) shows Inyenyeri's office in Kigeme. Haselip, J. (December, 2019). Kigeme camp and Mugombwe camp, Rwanda.

The second cooking fuel company in Kigeme camp offered briquettes. In the absence of improved cooking stoves, briquettes are not considered a "clean" fuel. The wood equivalent required to produce them is significantly higher than what is needed for pellets. Moreover, their uptake remained even lower due to widespread dissatisfaction with their quality, e.g. the smoke production. Since this study revolves around the adoption of clean cooking practices, the focus in this case study is on the pellets-based cooking option. A comparative analysis of both pellets and briquettes options would potentially be useful to identify more product-specific barriers, however, could not be done as part of this study.

4.3 Semi-structured interviews

To better understand the barriers and drivers to the adoption and sustained use of pellets by refugee households in Kigeme camp, semi-structured interviews with humanitarian experts and private sector stakeholders involved in the case are conducted. Semi-structured interviews were chosen as research method due to their exploratory nature. The open-ended questions allowed interviewees to raise new issues during the interviews, while the interview guide also provided some comparable qualitative data. The interview guide can be found in the Appendix A. The first interview helped to reassess the initial interview guide and to tailor the questions for the subsequent interviews. In each interview, a few additional questions were added during the interview to better understand certain points raised.

Three of the interviews were carried out through phone or video calls. Subsequently, the contents have been summarized and grouped under the original questions, while keeping the wording and contents as close as possible to the original transcript. One interview was received in written form due to unstable internet connection. Table 4.1 lists the interview partners.

Organization	Position	Location
UNHCR	Energy Advisor	Switzerland
UNHCR	Energy and Environment Officer	Rwanda
Inyenyeri	Former VP Operations	Rwanda
Inyenyeri	Camp Field Manager	Rwanda

Table 4.1: Interview partners for semi-structured interviews

4.4 Analysis

"Refugees are human beings, what drives them to buy/accept a given product is nowhere different to what drives other categories of society to adopt."

The main purpose of the interviews was to identify barriers and drivers to the adoption and sustained use of clean cooking fuels by refugee households and to identify main factors relevant to the adoption decision-making process.

The interviews were targeted at stakeholders who all had different roles in the intervention. Each interviewee offered a different perspective on what are the most relevant barriers and drivers in his or her opinion. Thus, the results are highly observer-dependent. This section aims to synthesize the issues raised in the interviews by structuring the contents along barriers and drivers, independent on who mentioned which aspect and the relative importance assigned to them. Where possible, citations from the interviews are added as a reference.

It should be noted that such an analysis involves selecting certain aspects out of all the aspects mentioned in the interviews due to limited research time. Therefore, the analysis is likely to contain biases or miss some aspects. However, the purpose is not to provide a detailed analysis of the particular case of Kigeme, but rather to gain a general understanding of the decision-making and potential barriers for the adoption of clean cooking fuels by refugees. Although the interview contents are specific to the particular case of clean cooking interventions in Kigeme camp in Rwanda, this section aims to reflect on them and provide broader insights that are relevant for other refugee settings.

4.4.1 Drivers

There are several factors that drive the adoption of clean cooking fuels. The following drivers could be identified based on the interviews.

Performance

"Pellets are clean, and they could be used inside small houses in the camp without fear of smoking or burning the entire house."

"The initial interest was certainly there. My understanding was that the tier-4-cookstove and pellet combination was the preferred way of cooking compared to charcoal, to LPG and to firewood."

All interviewees mentioned the performance factors of the pellets and the corresponding stove as main driver for the adoption. Performance factors mentioned include the ease of use, convenience, time savings during cooking and preparation, reliability of the stove, fuel-savings, health benefits and cleanliness of the stove and fuel. Cooking solutions that do not produce much smoke and can be used indoors are especially attractive for people with small houses and little indoor ventilation, such as in temporary refugee shelters.

Free stoves

"You don't pay for the stove, you only pay for the fuel. It is like pay-as-you-go cooking, so there is no upfront cost barrier to join. That's the way to go for cooking."

The fuel company offered a tier-4 cookstove to costumers without any additional cost if they committed to purchase a minimum amount of pellets each month. The minimum amount required was 10 kilogram per household. Therefore, there was no upfront cost barrier for the stove. This aspect seemed to have attracted many refugee costumers initially. Several interviewees pointed out that, for refugee contexts, a solution which involves providing free stove is needed. Otherwise the upfront cost for the stove would hinder any significant uptake.

Peer influence

"Peer influence is very important to influence the adoption and rejection of a solution. People convince each other. Those who have the stove convince the others why it's good to have. And likewise, they campaign anything simply because they don't like it."

Peer influence appeared to be both a diver and a barrier to the adoption. Positive information about the pellets and stoves was communicated among peers. As shown by the citation above, adopters talked to their peers about the benefits of the new stove and fuel, and thus contributed to higher adoption rates (and the opposite). According to one interviewee, positive information that was mentioned includes the cleanliness of the pellet-based cooking system and the fact that stoves were provided for free. This suggests that communications among refugee households strongly supported the spread of information about the first and second driver described in this section, performance and free stoves.

Moreover, social conformity was mentioned as a factor driving the adoption of clean fuels. Not only information exchange, but also seeing well-respected community members using clean fuels can label the use of clean fuels as something desirable. This suggests that programs targeting well-respected community members could be beneficial. In Kigeme camp, there was no specific targeting of costumers.

4.4.2 Barriers

There are various factors that contribute to low adoption and use of clean cooking fuels. The following barriers have been pointed out by the interviewees.

Economic barrier and strong competition

"The reason why refugees did not buy pellets or briquettes was the availability of firewood and charcoal on the market. They are slightly cheaper than briquettes and pellets."

"If you're getting extra financial assistance, even though it's supposed to be for a specific product, your first priority is to pay for essentials, which is food, clothing, your children's material for school or health care."

According to the interviewees, charcoal remains the "default" fuel among the refugee households in Kigeme, and firewood, despite being banned by the government, is still being used as a cheaper alternative. Due to different energy densities it is difficult to compare the exact quantities and cost of the different cooking fuel options. However, it appears that charcoal and firewood are perceived by refugees as lower cost options. Moreover, as the income of most households is limited, other items and services such as food, clothing, school material and health care are considered more important than buying clean fuels. Thus, people prefer to reduce spending on fuel as much as possible.

Peanut effect

"That's really a big, big factor. People tend to go for a market model that works with their income. For example, I went on a trip [to another refugee setting], where they use gas, and it was clear that if you buy firewood you spend almost double the amount you spend for LPG, but with LPG you have to buy a whole cylinder. So, you end up spending more money on firewood, but since you cannot save enough money at once to fill up your cylinder, they choose to buy firewood with the little money they get on a daily or weekly basis. Because you simply cannot raise the amount of money needed to buy a full cylinder at once."

People prefer to spend small amounts of money for charcoal or wood, frequently, instead of raising money for a bigger purchase of pellets or LPG. Charcoal is sold in bags that allow for exchanging any amount of money to charcoal, whereas pellets are sold per kilogram and LPG is sold per cylinder. In this specific case study, households had to buy at least 10 kilogram per month in order to use the stove for free. Therefore, although there were no upfront cost for the stove, people had to raise money to pay for the 10 kilogram per month. Another interviewee added to this that it is sometimes possible to buy charcoal on credit and pay for it later. This financial flexibility was not given for the pellet option and seems to have contributed to it being seen as less suitable for this context.

The phenomenon that people fail to add up small cost over time is commonly observed in other areas, it is known in behavioural economics as the peanut effect and was introduced by Markowitz (1952).

Unpredictability of cash transfers

"The refugee market is a unique one because it's not only about the supply of stoves and fuel, but also about the supply of cash transfers."

A major part of the refugees' income comes from cash transfers from humanitarian organizations, namely UNHCR and the World Food Program (WFP). There are three different kinds of cash transfers, one for food items, one for non-food items, and one for cooking fuels. According to one interviewee, the cash transfers were little coordinated and did not always come as frequently as expected. This seems to have led to a financial uncertainty and in some cases refugees taking credits at high interest rates, which then had to be paid back once the cash transfer arrived before any money could be spent on clean fuels.

Peer influence

"They said that it was expensive, it was too hot and could damage saucepans, it was a propaganda to take over their kitchen by giving women more free time, it was too novel and too hard to use,..."

Similar to the positive information, the spread of negative information appears to be a barrier to the widespread adoption. Some people who adopted the pellet-based cooking systems had negative experiences with them and communicated their experiences to peers, as shown by the citation above. Additionally, the negative information communicated among peers included the perceived mismatch of the cooking system with local cooking preferences, as explained by one interviewee. The stoves have solar-powered batteries and in some cases the batteries would run out of power while cooking hard, long-boiling food such as beans, which is a staple food in this particular context.

Inertia and lack of familiarity

"People stick to what they know. Unless something is a lot cheaper or a lot easier to use, there's a strong inertia to keep using traditional fuels, charcoal and wood, because it's much more familiar and readily available."

Several interviewees pointed out that people are used to cooking with charcoal and firewood for generations. It is ingrained in cultural and social practices. Thus, people are likely to stick to traditional cooking practices and there is an inertia regarding changes. Incentivizing the adoption of clean fuels involves changing human behaviour.

Communication between implementing parties

The communication between the implementing parties of the market-based clean cooking intervention - humanitarian actors and private sector company - appeared to be a limiting factor for the success of this particular intervention. As mentioned by one interviewee, a refugee camp is a difficult market for a private sector company. The responsibilities for the implementation of a market-based approach are divided between humanitarian actors and private sector stakeholders, such as the supply of products, information campaigns, technical support, cash transfers. None of the interviewees commented on this aspect in detail, however, the initial agreement and responsibilities seemed to be differently understood by different parties involved in the Kigeme case.

It should be noted that this is not an adoption barrier at the household level in contrast to the previous barriers, but it explains at the implementation level why the intervention faced difficulties. Effective communication is thus an important aspect to consider for future market-based interventions.

4.4.3 Main decision factors

In addition to identifying the drivers and barriers, it is important to understand which of the mentioned factors are the most relevant ones to the decisions made by refugees when choosing cooking fuels. This understanding is needed to build the conceptual model of the decision-making process, which follows in the next chapter.

Therefore, the interviewees were asked to name the three main decision factors for refugee households when choosing which fuels to use for cooking. The answers are summarized in table 4.2. From the table it can be concluded that the decision factors proposed by the interviewees are relatively similar. All interviewees mentioned cost or affordability as one of the main decision factors. Performance factors, more specifically convenience of use, cleanliness of the stove and fuel appear to be important. Lastly, familiarity with the cooking practice and the availability of the fuel in or near the camp were brought forward as main decision factors.

Interview	**Decision factors**
A	Cost, performance, familiarity
B	Cost, convenience of use, cleanliness of the stove and fuel
C	Affordability, meeting cooking needs/preferences, availability
D	Cost, convenience of use, availability

Table 4.2: Main decision factors identified by interviewees

4.5 Conclusion

This chapter presents the findings from the case study of the Kigeme camp in Rwanda, where the first fully market-based clean cooking intervention in a refugee camp has been implemented. Semi-structured interviews with humanitarian experts and private sector stakeholders involved in the case were conducted, which allowed to identify drivers and barriers for the adoption and sustained use of clean cooking fuels, as well as main decision factors. The main drivers are: (1) attractive performance factors of clean cooking systems, such as ease of use, time savings, health benefits, cleanliness and the possibility to cook indoors, (2) the free distribution of high-quality stoves by committing to buy a minimum amount of pellets per month, (3) positive peer influence including the spread of information about the benefits of clean cooking and the availability of free stoves, and conforming to the behaviour of others. The main barriers are: (1) limited financial resources and strong competition from charcoal and firewood, (2) the peanut effect, which describes that people tend to prefer spending small amounts of money on charcoal or wood frequently, instead of raising money for a bigger monthly purchase of clean fuels, (3) unpredictability of cash transfers, which led to financial uncertainty among refugees, (4) negative peer influence, in particular the spread of information including negative experiences regarding e.g. difficulties in usage, the risk of damage to cooking materials, limited cooking time due to solar-powered batteries, (5) lack of familiarity compared to traditional cooking practices which are ingrained in cultural and social practices for generations, (6) the lack of effective communication between implementing parties. The case study findings provide the base for the next chapter, the formulation of the model.

Chapter 5

Model Formulation

This chapter constitutes the core of the conceptualization and formalization phase of this study. The conceptual model is formulated which represents the diffusion of clean cooking practices in refugee camps. The construction of the conceptual model builds on the findings from the case study interviews and the literature review. First, the model agents will be described. Subsequently, the conceptual model of the social interactions is formulated. Third, the agent decision-making process is formulated. This chapter motivates the assumptions and abstractions made, a full set of model assumptions can be found in the Appendix B.

The sub-questions addressed in this chapter are as follows:

How can a conceptual model of the diffusion of clean cooking practices in refugee camps be formulated?

(a) *How can a conceptual model of the social interactions be formulated?*

(b) *How can a conceptual model of the adoption decision-making process be formulated?*

5.1 Model agents

The agents in the model represent refugee households, the residents of a refugee camp. In fact, one agent represents 10 refugee households. A trade-off had to be made between the number of agents in the model and the number of scenarios to be explored in the experimentation phase. Reducing the number of agents allows to reduce computational time significantly.

The choice to consider the households and not the individual as the model agents was made because decisions on which fuels and stoves are used for cooking are often made at the household level. This level of analysis, however, neglects the internal household decision-making dynamics, such as different gender roles (Schunder & Bagchi-Sen, 2019). In refugee settings in low-income countries men often tend to be the decision-makers regarding how to spend the household's income whereas women are tasked with cooking and collecting fuel. Furthermore, in some contexts, a change in cooking fuel can imply a switch in responsibilities, for instance, if the household member who is in charge of collecting firewood is not the same as the one who is in charge of purchasing goods.

By disregarding the internal household dynamics, this study omits influences on the decision-making process that are certainly relevant for understanding the adoption of alternative fuels and stoves, but are highly context-specific and considered out of scope of this study.

5.2 Social interactions

The main assumption in the model is that social influences exist and have an impact on the diffusion of clean cooking practices in a refugee camp. This assumption is made based the observations from the case study as well as on the literature review. It allows to focus on the mechanisms how these influences occur, and how they act as a driver or a barrier in the diffusion process. Social influences are constantly evolving and path-dependent. They shape the decisions made by the households, and these decisions, in turn, contribute to the evolving social influences.

As found in the case study, social influences include the spread of information through communications between adopters and potential adopters, which appears to have an influence on adoption decisions made by households. This finding is in line with diffusion literature, which identifies the spread of information in a social system as a key mechanism for innovation diffusion (Rogers, 1983). As seen in the case study, the effect of information can be both a driver and a barrier for adoption, depending on whether the information communicated is favorable or defavorable. Furthermore, as mentioned by one interviewee, social influences on decision-making can be exerted through social norms, i.e. familiarity and prevalence of the innovation among peers.

Therefore, in the model, two kinds of social interactions are considered: the micro-level information effect and the meso-level conformity effect.

5.2.1 Information effect

On the micro-level, word-of-mouth (WoM) communications represent direct social influences by households communicating with others. The effect of WoM communications is modelled by an information exchange about the new cooking system. Agents who have adopted clean fuels and those who have stopped using them send out information to potential adopters among their social ties.

The information can be favorable or unfavorable. It represents the level of satisfaction of the sender which is translated in the receiver's expected satisfaction value. Agents who are not yet aware of the availability of clean fuels only receive an awareness message without information regarding the expected satisfaction.

5.2.2 Conformity effect

On the meso-level, the conformity effect entails that people are more likely to adopt clean cooking fuels if they are used by their peers, especially by well-respected community members.

While the WoM communications happen within an agent's social network, the conformity effect applies to agents from the entire agent population. This conceptual choice is made to differentiate between both social influences. For the information effect, it is assumed that only people who know each other and care about the other's opinion exchange information, thus the social tie is of relevance. The conformity effect, on the other hand, is considered as a social-behavioural driver at the community level, where prevalence of clean cooking practices among peers within the entire community represents a shift in social norms. Thus, social ties and communication flows are considered less relevant.

5.3 Social network

Household agents are connected through a social network, which in turn influences their decision-making. In the network, nodes represent households and edges represent the social ties and communication flows between households. Social networks can have different configurations, among the most common structures are random graphs, spatial proximity networks and small-world networks. In this study, the social network is modelled by a small-world network, which was introduced by Watts and Strogatz (1998) and is based on the idea that real social networks include spatial proximity and random components. Thus, small-world networks are highly clustered and at the same time have small path lengths (Watts & Strogatz, 1998). In other words, households are assumed to have social ties to the closest neighbours and to have a few relational contacts (friends or relatives) among the refugee population. Information is assumed to be communicated through social ties only. Due to their characteristics, small-world networks are commonly used in diffusion literature to represent real social networks (Sopha et al., 2011; Palmer et al., 2015; MacCarty & Pakravan, 2019; Xiong, Wang, & Bobashev, 2018).

The small-world network is generated based on the Watts-Strogatz algorithm with the average node degree k, which describes the average number of social ties, and the probability of rewiring p, which describes the randomness of edges. Details on the algorithm can be found in the Appendix C.

5.4 Decision-making process

The decision-making process is illustrated in figure 5.1. Adapted from Rogers (1983)' conceptual model of five distinguished phases in the adoption of an innovation, the household agents go through five decision stages: ignorance, awareness, decision, adoption and rejection. The agents' decision to remain in the same stage, or to transition to the next one depends on several different decision rules, or barriers, which are further explained in the following sections. Social interactions play a major role in the decision-making process.

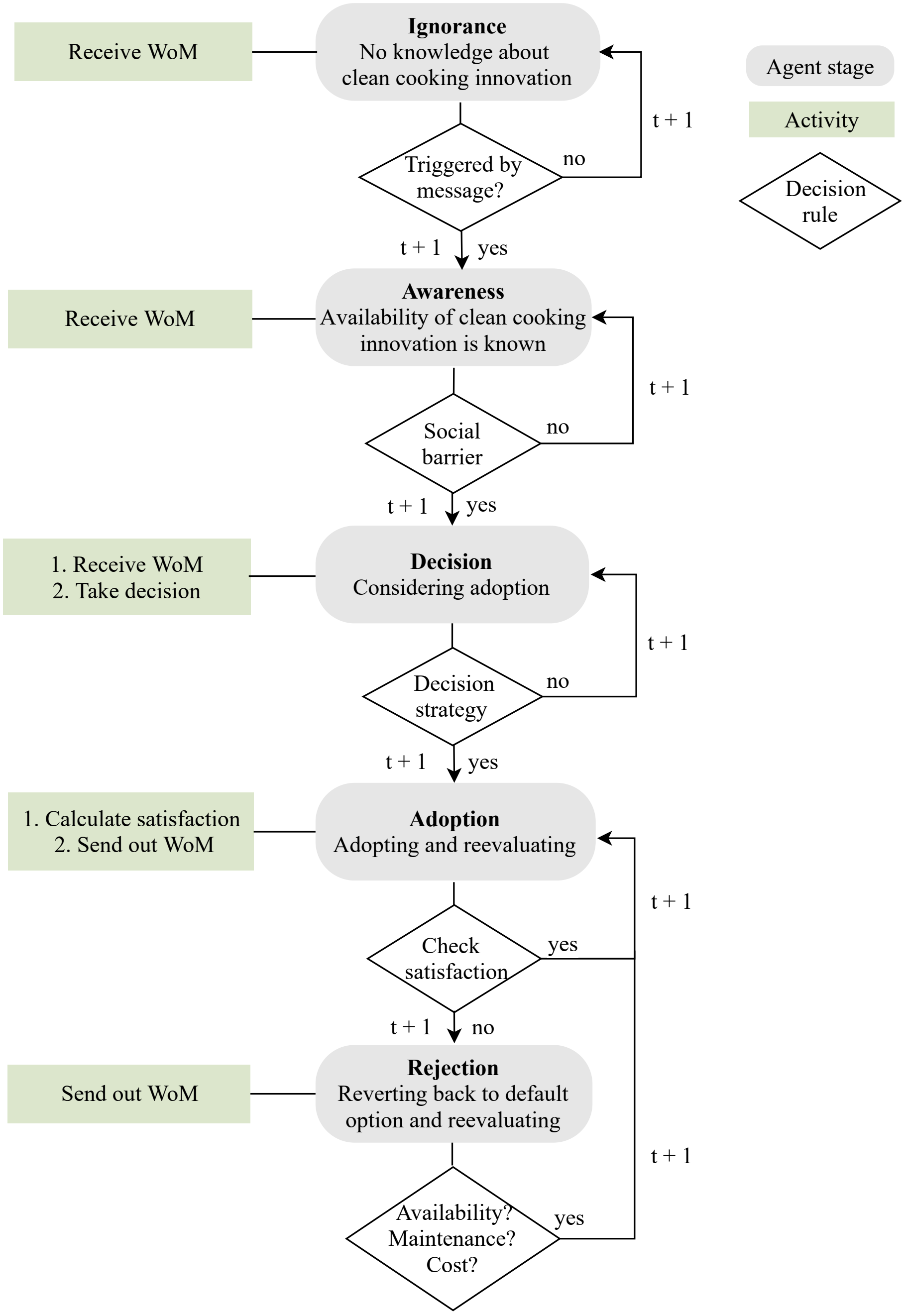


Figure 5.1: Five-stage agent decision-making process

5.4.1 Ignorance barrier

Agents who are not initial adopters start in the ”ignorance” stage. This stage illustrates that agents first are not aware of the availability of clean cooking fuels, thus they stick to their previous fuel choice and do not consider adoption of clean fuels. This relates to the behavioural concept of availability bias, which means that people primarily draw on existing knowledge and information, and thus miss the adoption opportunity due to lack of knowledge (Moglia, Cook, & McGregor, 2017).

In order to overcome the ignorance barrier, agents need to receive an awareness message from adopter or though information campaigns. Subsequently, the agents enter the ”awareness” stage.

5.4.2 Social barrier

The "awareness" stage entails households being aware of the availability of clean cooking fuels. Agents start gathering information about the clean cooking systems from their peers. However, as there are not many adopters among peers, the information remains little persuasive, thus the agents do not yet consider adoption for themselves.

The social barrier symbolizes the conformity effect and the familiarity that is increasing once some people in the community become adopters. Agents only move on to the "decision" stage if the percentage of peers who have adopted, tried and tested the new cooking fuel is above the agent's social threshold. The social threshold, meaning the required percentage of adopters among the agent population, depends on the agent's adopter category, which is defined in section 5.5. Heterogeneous social thresholds among the agent population enable some agents to adopt earlier, which, in turn, increases the likelihood of others to follow. If "early adopter" agents are among the adopters, they count 1.5 times. This conceptualization captures the definition of early adopters as opinion leaders, according to DoI theory, i.e. their behaviour is particularly respected by their peers.

Therefore, the social barrier comprises that agents check whether the ratio of adopters is equal or above their individual social threshold $\theta_{info,i}$, formalized as follows:

$$\frac{N_{adopters}}{N} \geq \theta_{social,i}$$

5.4.3 Adoption decision

In the "decision" stage households are assumed to have gathered enough information and certainty about clean fuels, which allows them to evaluate the received information, while considering the adoption cost, and finally to take a decision on whether to adopt or not. The decision is repeated every four time steps, thus an agent who rejects adoption at this point can decide to adopt at a later point in time.

The initial adoption decision is made based on one of four decision strategies. As suggested by the case study findings, although certain decision factors were agreed upon, it is unclear and disputable what the main adoption barrier is. In light of the lack of data and research on cooking fuel adoption, we simply do not know how people decide on which fuels to use. Therefore, in this model, four stylized decision strategies for the initial adoption decision are considered. Which strategy is used can then be varied in the experimentation to analyse the impact of different assumptions regarding the initial adoption decision.

The definition of decision rules is inspired by the Consumat theory. The Consumat theory offers a social psychological meta-framework to model consumer decision-making (Jager & Janssen, 2012). According to this framework, consumers engage in different behaviour depending on (a) their level of need satisfaction and (b) the level of uncertainty associated with the decision. Jager and Janssen (2012) propose four decision rules: *repetition*, which describes repeating the previous behaviour; *imitation*, which means following the behaviour of peers; *inquiring*, which is to consider the behaviour of all other agents; *optimising*, meaning to examine all possible opportunities, whether they are used by peers or not.

The Consumat framework has been used in agent-based diffusion models to describe agent decision-making. For instance, Sopha et al. (2011) use a psychological model based on the Consumat theory coupled with the Theory of Planned Behavior (TPB). In their model, agents select a decision strategy based on probabilities derived from an empirical survey. The model comprises four decision strategies: repetition, imitation, deliberation, social comparison. While repetition is based on previous behaviour and imitation is based on the prevalence of behaviour among peers, deliberation and social comparison are based on the calculation of intention, which consists of the agent's attitude, personal norms and perceived behavioural control, as defined by TPB.

Moglia, Podkalicka, and McGregor (2018) develop an agent-based model of residential energy efficiency technology adoption. In their model, decision strategies are dynamically assigned to agents based upon evaluations of needs satisfaction and uncertainty.

Drawing from this literature and a reflection on the case study findings, this study defines four decision strategies to describe the initial adoption behaviour of household agents in the case of clean cooking adoption. Figure 5.2 illustrates how the decision strategies are incorporated in the decision-making process. Each agent is assigned to a (static) decision strategy, which determines how the adoption decision is made. The information and economic barriers are defined in next two subsections.

The definition of the strategies is as follows:

1. *Deliberating*: The deliberation strategy characterizes agents who consider both the information received from peers and the cost of the alternatives in their decisions. *Deliberating* agents have to overcome both the economic barrier and the information barrier in order to adopt. This is the default decision rule in the model.

2. *Imitation*: The imitation strategy assumes that agents solely follow the behaviour performed by peers. Once their social threshold is exceeded, *imitating* implies that agents directly move on to the adoption stage.

3. *Advice-seeking*: The advice-seeking strategy implies that agents mainly rely on information received from others. *Advice-seeking* agents only consider the information barrier in the adoption decision.

4. *Cost-optimizing*: The cost-optimizing strategy assumes that agents prioritize cost over all other factors. *Cost-optimizing* agents choose the cheapest fuel, taking into consideration the time discounting for traditional fuels, which will be explained in the section on the economic barrier.

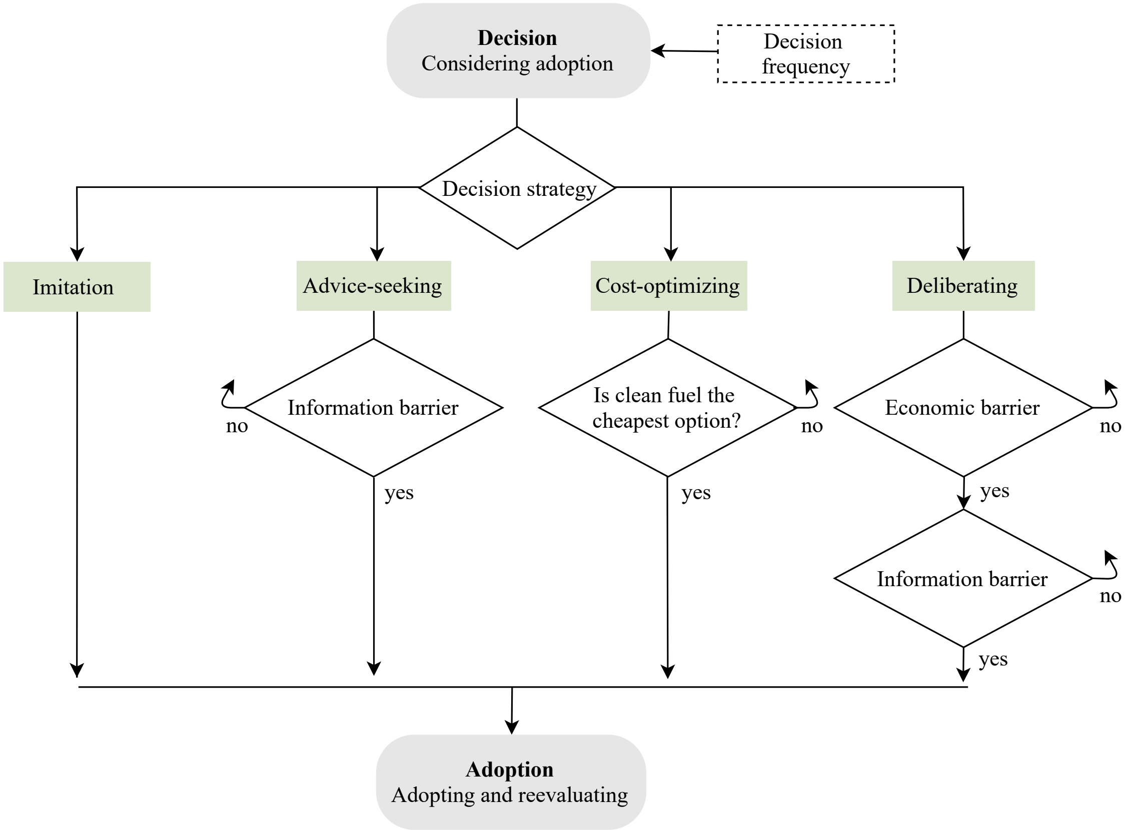


Figure 5.2: Four decision strategies characterizing the initial adoption decision. The decision strategy is part of the decision-making process illustrated in figure 5.1

Information barrier

Households are assumed to gather information by communicating with others within their social network. The information that is communicated builds up the expectations of potential adopters regarding the clean fuel and the new cooking system as a whole. The information exchange contains adopters' satisfaction with the product, which is based on (a) performance, (b) cost, (c) availability. Performance aggregates several factors such as cleanliness of stove and fuel, time spent cooking, or convenience of use. The calculation of the satisfaction level will further be described is the next section.

The information received, thus the expected satisfaction, takes a value between 0 and 1. A high value, close to 1, indicates that the household has received positive information and gains a positive attitude towards adoption, whereas a low value, close to 0, reflects that the household has received mostly unfavorable information. An agent receives information based on direct WoM communications as explained in section 5.2. Every new information received is stored in the agent's information pool and counts double if the new information is less favorable than the agent's current expected satisfaction value. For any agent who has not yet received information, any new information counts only once. Double-counting the new, less favorable information allows to account for cognitive biases in the way humans perceive new information. For instance, unfavorable information is often more likely to be communicated and/or risk aversion among people implies that even a single unfavorable information received can be enough to shadow much positive information.

Before every decision, an agent updates its expected satisfaction value, by setting it to the arithmetic mean of all new, single and double-counted, information, formalized as follows:

$$e_i(t) = \frac{1}{n} * \sum_{k=1}^{n} info_k$$

where $e_i(t)$ is the expected satisfaction of agent i at time t, and n is the number of new information inflows received.

The rule to over overcome the information barrier is again threshold-based, whereby the threshold depends on the agent's adopter category, similarly to the social barrier. An agent is assumed to have received sufficient positive information about the new cooking system if the expected satisfaction value is equal or above its individual threshold $\theta_{info,i}$, formalized as follows:

$$e_i(t) \geq \theta_{info,i}$$

Economic barrier

The economic barrier accounts for limited financial resources of households. Agents check whether the cost difference between the clean fuel and their current fuel is above a certain percentage of their income. The specified percentage of income is called ability-to-pay (ATP), which refers to the percentage of income that the agent is able to spend *more* on clean fuel, as compared to her current spending on traditional fuels. It is important to note that the ATP in this case only refers to the cost difference, not the absolute cost.

Moreover, the ATP is expressed as a percentage of the agent's income to account for income variability between households. To simplify the cost considerations, it is assumed that all households are able to spend the same percentage of their income on cooking fuel. Thus, agents who have a higher income are likely to overcome the economic barrier before their peers who have a lower income.

The rule to overcome the economic barrier is defined as follows:

$$atp * y_i \geq c_{cf} - c'_{tf}$$

where y_i is the income of agent i, atp is the ability-to-pay, c_{cf} is the average monthly cost for clean fuels per household, and c'_{tf} is the time-discounted cost for traditional fuels.

The concept of time discounting is used to formalize the peanut effect, i.e. that people prefer to spend smaller amounts of money on fuel more frequently, instead of bigger amounts less frequently, as found in the case study. Thus, compared to clean fuels which often have to be bought in larger amounts, the cost for a similar amount of traditional fuels are split over a period of time, where the future cost are perceived lower than they actually are. Time discounting is commonly applied in economics to account for future utilities (Frederick et al., 2002).

The time-discounted cost for traditional fuels is calculated as follows:

$$c'_{tf} = \sum_{i=0}^{T-1} \frac{1}{(1+r)^i} * \frac{c_{tf}}{T}$$

where r is the discount rate, T is the number of time steps that are considered in the time discounting (e.g. if $T = 4$, the cost are split over four steps with the cost in the three next time steps being discounted; this can be viewed as charcoal being purchased every week, while clean fuels being purchased every month), and c_{tf} is the average monthly cost for traditional fuels per household. This exponential discounting function is chosen due to the lack of empirical data and since it is a simple and common representation of time preferences.

5.4.4 Post-adoption

Once the agents have decided to adopt the clean fuel, they move on to the "adoption" stage. Here, the *expected* satisfaction value is replaced by the *experienced* satisfaction, and communicated via WoM to peers who are potential adopters.

Satisfaction

As already mentioned, the level of satisfaction with the new fuel and cooking system aggregates multiple factors. The factors are defined based on the findings from the case study. According to the interviewees, the main decision factors for the choice of cooking fuels are cost, performance, availability and familiarity. Therefore, the utility function includes three factors - cost, performance, availability - while the fourth factor, familiarity, is already reflected by the social barrier.

The satisfaction is calculated as sum of the partial utilities of these three factors. Thus, the satisfaction for agent i at time t is defined as follows:

$$u_i(t) = \frac{1}{3} \times u_{cost,i}(t) + \frac{1}{3} \times u_{perfomance,i}(t) + \frac{1}{3} \times u_{availability,i}(t)$$

All three partial utilities take either a value of 1 or 0 to keep the formalization as simple as possible. Adopters receive experience events every time step, which set the performance utility either to 1 or 0, based on the *probability of bad performance*. If this probability is low, most adopters receive a performance utility of 1 which represents the performance benefits of clean cooking systems such as cleanliness, convenience of use, time savings, which can be directly observed by the user. The availability reflects whether the clean fuel is available for purchase. Similar to the performance utility, it is set based on the *probability of supply shock*. If this probability is 0, the availability utility takes value of 1 for all agents, while a *probability of supply shock* above 0 suggests lack of supply which leads to some agents receiving an availability utility value of 0. The cost utility is based on the same rule as the economic barrier suggests, i.e. it is set to 1 if the relative cost difference is below what the agent is able to pay, else it is set to 0. For the purpose of simplification and better traceability, the satisfaction value is normalized and all three utilities contribute in the same way to the level of satisfaction.

Reevaluation

The "adoption" stage is not an absorbing stage. Based on the level of satisfaction, agents decide whether to keep buying clean fuels or stop using them. Agents remain adopters as long as their level of satisfaction is equal or above a certain threshold, which is formalized as follows:

$$u_i(t) \geq \theta_u$$

where θ_u represents the satisfaction threshold, which is the same for all agents.

This formalization suggests that agents are likely to stop using the clean fuel, if there is an increase in cost relative to the alternative, if they experience any issue related to the performance or quality of the cooking fuel or system, or if the fuel becomes unavailable, for instance due to delays in supply.

5.4.5 Rejection

Agents who are dissatisfied stop using the clean fuel and enter the "rejection" stage, where they revert back to their default fuel option. Similar to the adoption stage, agents who rejected are assumed to be senders of information. They send out the (dis)satisfaction value to potential adopters.

This stage is not an absorbing stage either. Agents reevaluate their decision every four time steps and can become adopters again. The rule comprises that agents can only go back to the adoption stage, if all three factors - cost, availability and performance - are set to 1.

This conceptualization is chosen to consider that households can simply decide to adopt clean fuels again, if the circumstances that made them reject have changed. The model accounts for changes in all three factors of the satisfaction function, which can occur, for instance, due to price shocks, increased availability or maintenance activities. If all three conditions - cost, availability, and performance - are fulfilled, agents decide to buy clean fuels again.

5.5 Agent heterogeneity

Heterogeneity within a population of potential adopters is a key factor driving diffusion of innovations. Some people tend to adopt innovations earlier than others which, in turn, increases the likelihood for others to adopt. Sources of heterogeneity between the agents are modelled by (a) adopter categories, and (b) differences in income.

5.5.1 Adopter categories

The definition of the agent categories follows Rogers (1983)' adopter categories, which, in essence, represent different adoption propensities within a population. According to DoI, social influences on someone's adoption decision is dependent on her level of "innovativeness".

Rogers (1983) defines five categories: innovators, early adopters, early majority, late majority, and laggards. Innovators are the least averse to risk and uncertainty and have the highest propensity to adopt innovations, whereas laggards are particularly risk averse and wait to adopt until an innovation is widely tested and used. Assuming adoption propensities are normally distributed, as proposed by Robertson (1967), the innovator group consists of 2.5 % of the population, the early adopters and the early majority consists of 13.5 % and 34 %, respectively. The late majority occupies 34 % and the laggards 16 % of the population.

In the decision-making process developed in section 5.4, there are two main parameters that reflect different adoption propensity among agents: the social threshold and the information threshold. Both parameters represent the "innovativeness" of an agent. Agents who have a low social threshold tend to consider adoption earlier than their peers who have a higher social threshold. Likewise, agents who have a low information threshold require relatively little favorable information from their peers in order to adopt. On the other hand, agents who have a high information threshold wait until they have received mainly positive information about the clean fuels, and thus certainty, before they decide to adopt. Additionally, early adopter agents count 1.5 into the social barrier, which symbolizes their status as opinion leaders whose behaviour is particularly respected by their peers.

This conceptualization is chosen to reflect that the impact of social conformity and the impact of information received from peers are both dependent on the agent's degree of "innovativeness", in line with DoI theory.

5.5.2 Household income

Finally, as found in the case study, refugees receive the same level of cash assistance, but additionally carry out (often informal) economic activities. To consider this fact, the income varies across the agents. This implies that agents overcome the economic barrier at different moments in time, which complements the heterogeneous adoption propensities.

5.6 Model environment

The model environment comprises all parts of the system that are not influenced by other system components. The environment is characterized by the structure in which the agents are embedded, the time which activates sequences of actions and events, and the information inputs agents receive apart from the inter-agent information exchange. As described in section 5.3, the structure takes the form of small-world networks to represent the social network between households, which is a predetermined feature generated in the initialization. Time is modelled by discrete time steps, which lead to the activation of sequences of actions and events. Information inputs that agents receive from the environment during the time of simulation take the form of (a) shocks, and (b) interventions. Shocks either occur globally for all agents at once such as price shocks, or they occur at the agent-level such as negative performance events or delays in fuel supply. Similarly, interventions are part of the model environment, as they cannot be affected by agents, but provide agents with new information. Interventions and external factors are part of the XLRM framework which will be elaborated on in the next chapter.

5.7 Conclusion

This study views the diffusion of clean cooking practices as an emergent behaviour resulting from social interactions and individual decision-making. This chapter formulates a model to represent social interactions that influence the diffusion and the individual decision-making process. The model formulation draws from DoI concepts, synthesized with the empirically identified barriers and drivers from the case study. The model developed in this chapter will be complemented in the next chapter, by conceptualizing the diffusion in terms of interventions, uncertain factors, and performance metrics.

Chapter 6

XLRM Framework

In the previous chapter the conceptualization of the system and the relationships ('R') between system variables have been determined. This chapters aims to complete the XLRM framework (Lempert et al., 2003), by defining interventions ('L'), uncertain factors ('X'), and key performance metrics ('K') to evaluate the performance of interventions. Interventions, uncertainties and KPIs are specified based on a reflection of the case study and the literature review. First, interventions are defined, subsequently, uncertain variables are defined which includes external factors, uncertain parameters, and uncertain model structures. Lastly, the definition of KPIs is discussed.

Thereby, this chapter addresses the third sub-question:

How can the diffusion of clean cooking practices in refugee camps be conceptualized in terms of interventions, uncertainties, and key performance indicators (KPIs)?

6.1 Interventions

This study focuses on market-based clean cooking interventions by humanitarian organizations. Furthermore, the focus is on demand-side interventions, to encourage the adoption of clean fuels by refugee households, as opposed to supply-side interventions which support local fuel companies or facilitate their entry in the camp market. This distinction is made based on Rouse (2019). In this study, four levers are considered: unconditional cash transfers, vouchers, information campaign, maintenance capacity. Interventions consist of one or several levers. Interventions are based on one type of financial assistance (cash transfers or vouchers), and optionally complemented by information campaigns and/or increased maintenance capacity.

6.1.1 Unconditional cash transfers

Cash transfers are at the core of market-based interventions to enable refugees to meet their needs by purchasing products on the market. As found in the Rwanda case study, cash transfers can consist of multiple parts, e.g. one for food, one for non-food items, and a separate one for cooking fuel. In this model, cash transfers for food and non-food items (other than cooking fuel) are assumed to be exogenous.

The lever *cash transfer* in this model only includes the part of cash transfers that is intended to cover cooking fuel needs, at least partially. Unconditional means that the beneficiaries can use the money for any purpose. This lever attempts to address the economic barrier by increasing refugees' income. In the model, it is assumed that all household agents receive the same monthly amount of cash for fuel.

6.1.2 Vouchers

Instead of providing cash transfers, the money can be directed towards price subsidies for clean cooking fuels. In refugee settings, price subsidies often take the form of vouchers (or conditional cash transfers), which cover all or up to a certain amount of the cost of clean cooking fuels. This lever attempts to reduce the economic barrier by directly reducing the cost of clean cooking fuels. In the model, the lever *voucher* involves subtracting a specified amount from the clean fuel cost. This amount equals the amount of unconditional cash transfers, so both levers can be compared.

6.1.3 Information campaign

Information campaigns are used to address the ignorance and the information barriers. For instance, information campaigns in refugee camps can take the form of group gatherings, where the use of clean cooking systems is demonstrated. Moreover, individual visits to households can help support the spread of information on the benefits of clean cooking practices.

In this model, applying the *info campaign* lever means to (a) transition agents from the ignorance stage to the awareness stage, and (b) inform potential adopters in the awareness and decision stages, i.e. every time step a specified number of agents receive an awareness message and the value 1 is added to their information pool. The agents are chosen randomly. The reach of the information campaigns per time step is limited to represent limited campaigning capacity in terms of financial resources and personnel. Information campaigns are only activated in the first 50 time steps, which is considered a sufficient time period to reach all households at least once.

6.1.4 Maintenance capacity

When adopters experience performance issues with the new cooking system, they are likely to reject clean cooking fuels and spread negative information about them. Performance issues can appear due to (a) bad quality of stoves and fuels, or (b) mismatch with cooking preferences, which leads to the performance being perceived as negative by the user. Increasing maintenance capacity can support the sustained use of clean cooking fuels and reduce the spread of negative information. For instance, bad quality stoves can be repaired or replaced, the stove model and fuel can be adjusted to better match local preferences, and technical support can help the users to better reap the benefits of clean cooking.

In the model, the *maintenance capacity* lever involves setting the performance utility value of a specified number of agents in the rejection stage every time step to 1. The agents are chosen randomly.

6.2 Uncertainties

Refugee settings are highly dynamic and uncertain environments. The expected outcomes of interventions, however, rely on assumptions about the current status and future conditions. Moreover, the development of a novel model involves numerous uncertain parameters and structural uncertainties. Therefore, it is important to identify uncertainties regarding external factors and within the model structure, to analyse the impact of changes in uncertainties on the outcomes. In this section, first, the process of identifying the uncertainties considered in this study is described, subsequently, the three types of uncertain variables incorporated in the model, shocks, uncertain parameters and uncertain model structure, are elaborated on.

6.2.1 Identification of uncertainties

The identification of uncertainties in this model-based study is done based on W. Walker and Rotmans (2003), who propose an uncertainty matrix to support modellers in identifying, structuring and prioritising uncertainties in policy analysis. W. Walker and Rotmans (2003) define three dimensions of uncertainty: location, level and nature. The *location* of the uncertainty refers to where the uncertainty occurs within the model itself; the *level* describes the scale of uncertainty from total ignorance, scenario uncertainty, recognised uncertainty, to deterministic knowledge; the *nature* refers to the whether it is epistemic uncertainty, i.e. due to the lack of knowledge, or variability uncertainty, i.e. inherent randomness or non-rational human behaviour.

In the XLRM framework of this study, only a limited number of uncertainties can be considered. Structuring the uncertainties in terms of the uncertainty matrix allowed to identify which of them are most relevant to include in the experimentation as they are expected to have the highest impact on the results. Note that other uncertain factors may have a higher impact on the model results in absolute terms, however, for this study changes in the *relative* differences between the outcomes for different interventions are most important.

The uncertain variables considered in this study are listed in table 6.1, along with their location within the model, the nature, level, and their range. The table only contains uncertainties at the *scenario* uncertainty level. Additionally, there are a number of *statistically* uncertain variables in the model, which are expressed in terms of triangular distributions based on literature, such as the income of agents and the social thresholds of the adopter categories.

Uncertainty	**Location**	**Nature**	**Level**	**Range**
Ability-to-pay	Parameters	Epistemic	Scenario	[0, 0.05]
Time discount factor	Parameters	Epistemic	Scenario	[0, 0.1]
Probability of bad performance	Parameters	Variability	Scenario	[0, 0.02]
Average node degree	Parameters	Epistemic	Scenario	[4, 12]
Probability of rewiring	Parameters	Epistemic	Scenario	[0.1, 0.9]
Price shock magnitude	Inputs (scenarios)	Variability	Scenario	[-0.2, 0.2]
Price shock frequency	Inputs (scenarios)	Variability	Scenario	[0, 6]
Probability of supply shock	Inputs (scenarios)	Variability	Scenario	[0, 0.02]
Ratio of *imitating*	Model structure	Epistemic / variability	Scenario	[0, 0.25]
Ratio of *advice-seeking*	Model structure	Epistemic / variability	Scenario	[0, 0.25]
Ratio of *cost-optimizing*	Model structure	Epistemic / variability	Scenario	[0, 0.25]

Table 6.1: Uncertainties considered in the XLRM framework of this study

6.2.2 Shocks

Shocks are incorporated in the model to represent potential future changes in external factors. First, price shocks represent price variability which is likely to be relevant to the planning of market-based humanitarian response. For instance, in the case of LPG, the gas price depends on volatile global market prices, if it is not subject to government regulations such as price caps to stabilise fuel prices. In the Rwanda case study, the pellet price did not change throughout the implementation period, nevertheless, prices for traditional fuels are often not stable either. As mentioned by one interviewee, charcoal prices are highly sensitive to demand and supply dynamics, and fluctuate throughout the year, depending on whether it is wet or dry season. Thus, the price difference between clean fuels and traditional fuels is likely to be subject to future changes. In the model, price shocks represent sudden changes in the cost of clean fuels. Price shocks are characterized by two variables: (a) *price shock magnitude*, which specifies the increase or decrease in the percentage of the monthly cost of clean fuel, and (b) *price shock frequency*, which specifies the number of shocks that happen equidistantly distributed during one simulation run. After each shock, the cost remain at the new value for a period of 12 time steps, before it is set again to its initial value, to account for the temporary nature of most price shocks and fluctuations. The upper range is six shocks per run. In this study, shocks in the price of traditional fuels are not explicitly considered, as a decrease in clean fuel cost could also be understood as an increase in traditional fuel cost (although not of the same magnitude due to the time discount factor).

In contrast to price shocks which occur globally for all agents at the same time triggered by the discrete time step, the model includes supply shocks which occur at the agent-level based on probabilities. Supply shocks represent delays in supply or insufficiency in supply to cover the fuel demand. Before, every (re-)adoption decision, agents in the decision, adoption and rejection stages check whether the clean fuel is available. The *probability of supply shock* specifies the likelihood for agents to encounter supply delays, and thus having to postpone their adoption decision. Moreover, supply shocks have an impact on the availability utility value of adopters, where the value is updated every time step based on the *probability of supply shock*. Note that supply shocks could also be modelled as global shocks triggered for all agents at once, however, the choice to model them probability-based at the agent-level is made because supply shocks do not necessarily affect all agents at once, for instance, if the fuel company has some fuel reserves and can still serve a part of its clients.

6.2.3 Uncertain parameters

Next to changes in future conditions, there are several parameters that are unknown due to the lack of data and previous research. First, deeply uncertain parameters include the *ability-to-pay* and the *time discount factor* for traditional fuel cost, since no economic study on time preferences for fuel cost or on how much money refugee households in Kigeme camp are able to pay on fuel is available.

Second, the *probability of bad performance* is unknown. This variable specifies the likelihood of performance issues experienced by adopters due to bad quality of stoves and fuels, or mismatch with cooking preferences. As described in section 5.4, every time step, adopters receive an experience event, which updates the performance utility value by setting it either to 1 or 0, based on the *probability of bad performance*.

Deeply uncertain parameters further include the social network parameters, *average node degree* and *probability of rewiring*, as no study has analysed the social network structure in a refugee camp similar to the one of this study.

By including these variables as deep uncertainties in the XLRM framework, a range of possible values and their impacts on the results can be explored in the experimentation phase. Note that the minimum and maximum values of the ranges are similarly subject to uncertainties, nevertheless, one has to take decisions on how to define the range to be able to explore impacts of uncertainties. The parameter settings will further be discussed and motivated in section 7.3.

6.2.4 Uncertain model structure

As described in section 5.4, the conceptual model contains structural uncertainties regarding the initial adoption decision. Deep uncertainties in the model structure are incorporated as uncertain variables by defining ratios for three of the four stylized decision strategies, *imitating*, *cost-optimizing*, *advice-seeking*, while *deliberating* is the default decision strategy, which takes as a value the remaining percentage of agents. For instance, if the ratios for *imitating*, *cost-optimizing*, *advice-seeking* are all set to zero, all agents use the *deliberating* strategy.

6.3 Key performance indicators

The performance of interventions is evaluated based on three KPIs: long-term impact, timeliness, and robustness. The definition of the KPIs is explained in the following and illustrated in figure 6.1, which shows a number of adopters evolving over time.

First, the *long-term impact* of interventions is defined by the final number of adopters at the end of the simulation. This metric serves as a measure of the sustained adoption and continuous use of clean cooking fuels by refugee households. The long-term impact is considered of primary interest for humanitarian organizations, whose objective is to minimize health risks and environmental impact due to the use of traditional cooking fuels over the long-term. Thus, the final number of adopters serves as a proxy for the long-term health and environmental outcomes of clean cooking interventions. This first KPI is also considered important for the fuel company whose objective is to sustain their business in the camp over the long-term. It should be noted that in this study the simulation time is limited to 150 time steps, or three years, which serves as a reference point to compare the impact of different interventions. In figure 6.1, the long-term impact is depicted by N_{final}.

Second, the *timeliness* of interventions is defined by the time to reach the maximum number of adopters, which serves as a measure of how fast interventions achieve impact. Any delay in achieving high adoption levels also implies a delay in achieving health and environmental benefits. Moreover, the longer the adoption curve needs to reach the maximum, the longer the fuel supplier needs to sustain while its supply capacity is under utilized. In figure 6.1, the timeliness metric is depicted by T_{max}.

Third, the robustness of interventions is defined based on literature and context considerations. McPhail et al. (2018) propose a framework for robustness metrics and point out that in some cases the choice of the metric itself leads to different outcomes in decision analysis under deep uncertainty. In this study, robustness is defined by two metrics, which allows to better capture robustness of interventions, and to reflect on the implications of different definitions.

The first *robustness* metric is defined as the percentage of scenarios, in which the final number of adopters lies above a certain threshold. This is a type of satisficing metric, which evaluates the acceptability of system performance relative to a threshold. According to McPhail et al. (2018), the level of risk aversion for this metric can be defined by setting the threshold accordingly. In this study, the threshold is set to 228, which represents 60 % of the targeted households, and is considered an acceptable level of adoption on the longer term. In figure 6.1, the first robustness metric is depicted by R'_{θ}.

The second *robustness* metric builds on the first robustness metric. It is defined as the gradient of the adoption curves at the end of the simulation throughout the subset of scenarios, where the final number of adopters lies above 60 %. More specifically, it is the gradient of the mean of this subset of adoption curves. Taking the mean before calculating the gradient is intended to aggregate all relevant scenarios, and to smooth the curves to reduce the influence from small fluctuations on the gradient. This second robustness metric reflects whether the number of adopters tends towards a stable level or is decreasing over time. It is an important measure as the final number of adopters is highly dependent on the simulation length, but the gradient-based metric allows to gain insights on the future tendency of the adoption level. In figure 6.1, the second robustness metric is depicted by R'_{∇}.

In the following, the first robustness metric is referred to as *threshold-based* robustness metric, called R_{θ}, and the second one as *gradient-based* robustness metric, called R_{∇}. Note that in figure 6.1 the single quotation mark added to both robustness metrics indicates that they are based on aggregated performance across scenarios, in contrast to N_{final} and T_{max}, which are determined for each scenario separately. This implies that for R_{θ} and R_{∇} a single value will be obtained per experiment, whereas for N_{final} and T_{max} distributions across scenarios will be analysed.

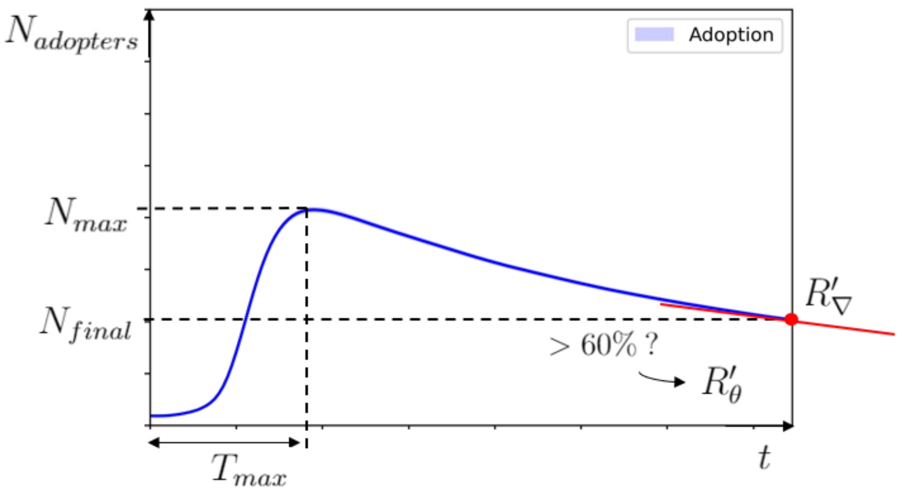


Figure 6.1: Visualization of KPIs. Long-term impact is defined by N_{final}, timeliness is defined by T_{max}, and robustness is defined by R'_{θ} and R'_{∇}. The single quotation mark indicates that the robustness metrics aggregate performance across scenarios, while the long-term impact and timeliness are calculated based on individual scenarios.

6.4 Conclusion

This chapter completes the XLRM framework (Lempert et al., 2003), by defining interventions, deep uncertainties, and KPIs. Interventions in this study are based on one type of financial assistance, cash transfers or vouchers, and complementary levers, information campaigns and increased maintenance capacity. Deep uncertainties include price and supply shocks, as well as uncertain model parameter values and uncertain model structures. KPIs used to evaluate the performance of interventions include the long-term impact, timeliness, and robustness. This concludes the conceptualization and formalization phase in this study.

Chapter 7

Model Implementation

This chapter marks the beginning of the implementation and exploration phase of this study. In this chapter the process of implementing the outcome of the model formulation in an agent-based modelling environment is discussed. First, the choice of the modelling software is motivated. Second, the time sequence of the actions performed by agents and the model activities is specified. Third, the choice of the parametrisation is explained. Subsequently, the development of the user interface for visualization of the model is described. Lastly, the model verification is presented.

The sub-question addressed in this chapter is as follows:

How can the diffusion of clean cooking practices be implemented in an agent-based model?

7.1 Modelling environment

The modelling environment provides the software infrastructure for programming the agents, their behaviour, their interactions and the environment (Van Dam et al., 2013). In this study, the model is implemented using Mesa, an open-source platform for ABM analysis available in Python. It is a Python-based counterpart to NetLogo and Repast, which are other, widely-used, ABM modelling environments. Mesa does not (yet) have an as large user base as NetLogo or Repast, however, its main advantage is that large-scale experimentation can be easily performed, and the model results can immediately be analysed using Python's data analysis tools. Moreover, for users who are familiar with the Python programming language, in particular with object-oriented programming, there is a low barrier to entry. The main disadvantage compared to NetLogo and Repast is the less-advanced user interface including graph plotting and agent display. However, for this study the display of agents is considered less relevant, as the main objective is to conduct experiments with the model, explore and analyse the model results. Nevertheless, the model is visualized for demonstration purposes and the functionality of the Mesa user interface proved to be sufficient for this study.

7.2 Time sequence

The model runs in discrete time steps. Each time step, a specified sequence of actions take place. These involve actions performed by the agents, and model activities. The agents' actions are specified depending on which decision stage they are in. As explained in 5.4, (1) agents in the ignorance stage check whether they have received a message from adopters or information campaigns, (2) agents in the awareness stage check whether their social threshold is exceeded, (3) agents in the decision stage update the information value based on their information pool and check whether the conditions specified in the four decision rules are met, (4) agents in the adoption stage update their satisfaction value, send out WoM information to potential adopters, and check whether the meet the satisfaction threshold, (5) agents in the rejection stage send out WoM information to potential adopters, and check whether the availability, cost and performance values are all set to 1. If the respective decision condition is met, the agents are assigned to the next decision stage (or the previous one in the case of the rejection stage), else they remain in their current stage.

Not all activities occur every time step. The (re-)adoption decisions are made based on a *decision frequency*, which is modelled as a probability. It is set to one in four time steps. The probability-based timing of decisions allows for agents to adopt and re-adopt at different moments in time, instead of all at once. This is considered to better depict the real situation, where households buy new fuel at different times. The frequency is set to one in four steps to represent that clean fuels are bought in bigger amounts, thus with a lower frequency, than traditional fuels. In contrast, the transitions from ignorance to awareness, from awareness to the decision stage, and from the adoption to the rejection stage can happen at any time step. The WoM communications are also send out every time step.

The discrete nature of the simulation model implies that the agents are called one after another to execute their actions. However, the actions of agents depend on other agents' actions. For instance, agents that are early in the iteration order are likely to receive less information input than others that are called later. Therefore, as suggested by Van Dam et al. (2013), the iteration order of agents at each step is randomized to balance the effect of iteration order out. In addition, price shocks are activated, once the model time step reaches the time of the shock defined by the shock frequency. Moreover, information campaigns and maintenance activities are applied every step, if the corresponding levers are activated.

Figure 7.1 illustrates the simulation flow. Each simulation run ends after a fixed number of time steps, which is set to 150. One time step could be thought of as one week. It should be noted that this interpretation of the model time step as a time period in the real world is not determined by data input, but by reflecting on the case study. It is only intended to better embed the simulation in its real-world context and to illustrate its meaning for the reader. Following this interpretation, four time steps represent a period of one month, which is why the adoption decision frequency is set to 1/4 to symbolize that clean fuels are bought on a monthly basis. Thus, 150 time steps represent a period of around 3 years, which is considered a realistic time frame for the planning of humanitarian interventions in protracted crisis. Protracted crises are refugee situations of at least five years, however, as refugee settings are often seen as short-term solutions due to political reasons and the environment often remains dynamic, three years are considered as a reasonable planning period.

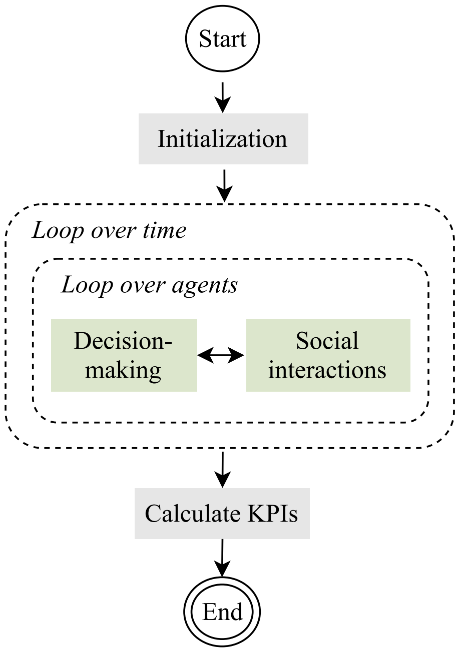


Figure 7.1: Simulation flow

7.3 Parametrisation

Parametrisation involves finding suitable values for the model variables. In this study, where possible, values are based on data from the Rwanda case study, while the more general variables such as the distribution of adopter categories and the social thresholds are based on diffusion literature. Not all parameter values could be based on available data or literature, thus finding suitable parameters was a challenging task as there are many possible parameter settings and not all settings could be explored. Choices and assumptions made to define parameter settings are explained in Appendix D, which also contains a list of the main model variables along with their initial values and sources. The variables considered as uncertain external factors, as explained in section 6.2, are sampled from a continuous range or from a discrete array, as part of the scenarios.

7.4 User interface

For demonstration purposes the model is visualized by developing a user interface in Mesa. This step involved specifying how to visualize the social network underlying the agent interactions, and to specify the model inputs to be set by users and the output chart.

Figure 7.2 illustrates the user interface for the model developed by this study. Visualizing the agents and the propagation of the adoption through the social network involved determining the spatial distribution of the nodes in the small-world network graph. The nodes in figure 7.2 are distributed in an aesthetically pleasing way generated by a force-directed graph drawing algorithm which positions the nodes while minimizing the length of edges and minimizing edge crossing (Kobourov, 2012). This way of spatial distribution allows for socially connected agents to be placed near each other and at the same time keeping some social ties with further away nodes, without providing location input. In figure 7.2, agents in the first three stages are displayed as black nodes. Once agents become adopters, their node color changes to blue. Rejecters are depicted as red nodes. Thereby, the diffusion of clean cooking practices through the social network in a refugee camp is visualized.

The user settable model inputs are displayed as sliders on the left-hand side of the user interface. The input parameters which can be set by users include the four levers, the number of agents and the initial adopters, as well as the uncertain parameters and shock parameters. The output chart displays the number of adopter agents over time.

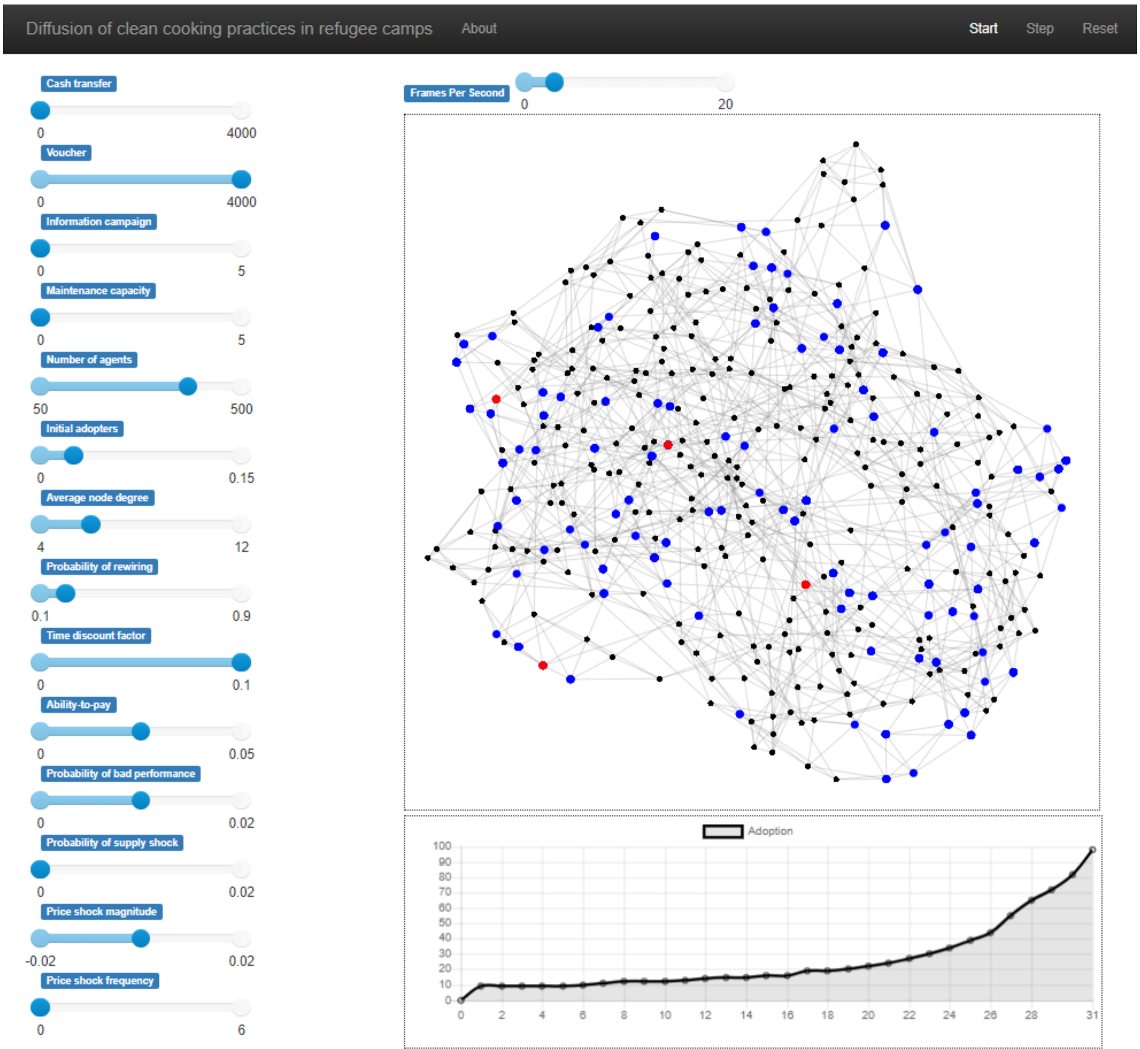


Figure 7.2: Visualization of the model using the Mesa user interface. In the social network graph, nodes represent agents and edges represent social ties. Adopters are displayed as blue nodes, rejecters as red nodes, agents in the first three stages as black nodes. User settable inputs are depicted as sliders. The output chart shows the number of adopters evolving over time.

7.5 Model verification

Model verification means to check whether the formalized concepts and behaviours are implemented correctly and whether the model behaves as intended. It is a very important step before analysing data and drawing conclusions. Various verification methods have been used continuously during and after the implementation, based on Van Dam et al. (2013). The methods include tracking of agent behaviour, running the model with only a few agents, extreme-condition testing and extensive code walk-through. A more detailed explanation of the performed verification steps can be found in the Appendix E.

7.6 Conclusion

This chapter describes the implementation process of the model, using Mesa in Python. The model runs in discrete time steps, where each time step a specified sequence of actions takes place. The agents' actions are specified depending on which decision stage they are in. Model variables are parametrised based on the case study and on diffusion literature. For demonstration purposes, a dynamic visualization of the diffusion of clean cooking practices through the social network is developed. Lastly, the model was verified using several verification methods. The implemented model is used for experimentation purposes in the next chapter.

Chapter 8

Model Results

This chapter discusses the design of experiments and presents the model results. The experimentation is performed in three steps. First, the behaviour of the model is analysed under a large sample of scenarios and different interventions. Second, the impact of shocks on the outcomes of two alternative interventions is analysed. Third, the impact of changes in the decision strategy on the outcomes is evaluated. Lastly, this chapter concludes with a sensitivity analysis.

The sub-question addressed in this chapter is as follows:

Based on the model, what are the effects of different market-based clean cooking interventions under various scenarios?

8.1 Design of experiments

The experimentation aims to analyse the behaviour of the model under different interventions compared to the base model behaviour, which contains no intervention. Since the model comprises numerous uncertain variables, all simulation runs are performed under a large sample of scenarios. Latin hypercube sampling (LHS) is used to sample from the uncertainty space. The experiments are ran using the EMA workbench in Python (J. H. Kwakkel, 2017).

The parameter settings used to specify the experiments are shown in table 8.1. The parameter ranges for the uncertain variables are the same as described in section 6.2. The experiments are divided into three sets. First, 2000 scenarios are sampled from the uncertain variables listed in section 6.2 excluding the shocks, i.e. *price shock magnitude*, *price shock frequency*, and *probability of supply shock*, and the three decision strategy ratios. For all experiments in the first two sub-parts, the decision strategy is set to 100 % *deliberating*. 2000 scenarios appeared to be sufficient in preliminary testing to cover the uncertainty space excluding the shocks and the decision strategy. Second, the shock variables are included in the scenarios, which is why the number of sampled scenarios had to be increased to 5000 to capture the uncertainty space sufficiently. The minimum number of required scenarios was determined by using dimensional stacking. In the third set of experiments, the decision strategy ratios are included in the sampled scenarios.

Note that no base case is defined in this study, instead all interventions are tested under a wide range of scenarios. Since this is a model-based analysis where the external factors and the model structure itself are subject to deep uncertainties, it would be misleading to define an explicit base case. However, by excluding the shocks and the decision strategy as uncertainties in the first set of the experiments, a benchmark is established to be able to compare the effects of different interventions. This should not be understood as a base case, but as a first step, before gradually including the shocks and model structure uncertainties. This three-step experimentation helps to differentiate between the different types of uncertainties.

8.1.1 Base model

Testing the base model behaviour allows to analyse potential diffusion without any intervention in place, all lever variables are set to zero. The base model behaviour is explored with two settings: (A) the percentage of *initial adopters* set to 0, and (B) the *initial adopters* set to 2.5 %. This allows to understand the impact of the percentage of initial adopters. Initial adopters are randomly chosen from the entire population. Throughout the other experiments, the value is set to 2.5 %.

8.1.2 Interventions

The interventions consist of one type of financial assistance (cash transfer or voucher) and complementary information campaigns and/or maintenance activities. The latter two are only considered in addition to the financial assistance, and not in isolation. In the following, the combined interventions consisting of either cash transfers or vouchers and both kinds of supporting interventions are referred to as *integrated cash-based* or *integrated voucher-based interventions*. Interventions involving only financial assistance are referred to as *cash-transfer-only* or *voucher-only interventions*.

The value for *cash transfer* and *voucher* is expressed in the same currency as the fuel price. It is set to 4000 [RWF], which is based on data from an internal report on the Kigeme camp operation. Since only aggregated data on the total amount of monthly cash transfers provided to refugee households was available, the total amount was divided by the number of households. In reality, the amount of cash transfer given out to each household depended on the household size, which varies from 1 to 16 people. Thus, the value of 4000 [RWF] is not an exact representation of the real data, but it should be understood as an indication. Financial assistance covers three third of the monthly clean fuel cost, which reflects the limited budget of humanitarian organizations and inability to cover the full fuel cost.

The *information campaign* and *maintenance capacity* are expressed in terms of the number of agents reached per time step. Both values are not based on data from the case study. However, the reach of 5 agents per time step by information campaign activities, which corresponds to 50 households per week, is considered realistic given the high density of houses in a refugee camp. Note that the *info campaign* is only activated in the first 50 time steps. Similarly, the maintenance capacity of 5 agents per time step, or 50 households per week, suggests that only a limited number of households have access to maintenance activities per week.

Note that the alternative levers that are not listed in the corresponding cell of an intervention are all set to zero.

Set	**Experiment**	**Variables**	**Values**	**Scenarios**
1	Base model A	initial adopters	0	2000 excl. shocks
	Base model B	initial adopters	2.5 %	2000 excl. shocks
	Intervention 1 (I1)	cash transfer	4000	2000 excl. shocks
	Intervention 2 (I2)	cash transfer info campaign	4000 5	2000 excl. shocks
	Intervention 3 (I3)	cash transfer maintenance capacity	4000 5	2000 excl. shocks
	Intervention 4 (I4)	cash transfer info campaign maintenance capacity	4000 5 5	2000 excl. shocks
	Intervention 5 (I5)	voucher	4000	2000 excl. shocks
	Intervention 6 (I6)	voucher info campaign	4000 5	2000 excl. shocks
	Intervention 7 (I7)	voucher maintenance capacity	4000 5	2000 excl. shocks
	Intervention 8 (I8)	voucher info campaign maintenance capacity	4000 5 5	2000 excl. shocks
2	Intervention 4 (I4)	cash transfer info campaign maintenance capacity	4000 5 5	5000 incl. shocks
	Intervention 8 (I8)	voucher info campaign maintenance capacity	4000 5 5	5000 incl. shocks
3	Intervention 4 (I4)	cash transfer info campaign maintenance capacity	4000 5 5	5000 incl. decision strategies
	Intervention 8 (I8)	voucher info campaign maintenance capacity	4000 5 5	5000 incl. decision strategies

Table 8.1: Design of experiments

8.2 Results

First, the results of experiments are presented by showing the number of adopters evolving over time. It should be noted that the figures included in this report only show a sample of 100 runs. This is only for better clarity for the reader, but in the analysis of the KPIs all 2000 or 5000 runs are included. Moreover, the curves are all displayed disaggregated instead of aggregating them e.g. by plotting the mean and confidence intervals, because this would cover up the fact that the outcomes are largely divided, where some scenarios lead to no diffusion, and others lead to different levels of diffusion. The adoption curves over time serve to understand the model dynamics and how the number of adopters evolves over time. The figures for the full sample of scenarios can be found in the Appendix F as a reference.

Second, the results of different interventions are compared in terms of the KPIs by showing box plots. This allows to analyse the distributions of outcomes throughout the scenarios, which are difficult to determine from the adoption curves over time. Box plots summarize the distribution of a set of data by displaying the minimum, the first quartile, the median, the third quartile, and the maximum. The box is drawn from the first to the third quartile, the median is shown by a vertical line through the box. The whiskers reach from each quartile to the minimum or maximum. Outliers are defined as data points that are located 1.5 times the interquartile range above the third quartile or below the first quartile. The interquartile range is the length of the box. Outliers are depicted as black dots outside of the whiskers.

8.2.1 Base model behaviour

Without any interventions and without initial adopters, all agents remain non-adopters and no diffusion takes place.

Figure 8.1 shows the model results in terms of the number of adopters over time if the percentage of initial adopters is set to 2.5 %. Note that this figure only includes 100 sample runs out of the 2000 runs. In the base model with 2.5 % initial adopters, diffusion happens in some of the scenarios. In the cases where the combination of parameter settings leads to diffusion, it can be seen that the adoption curves increase steeply first, before reaching the maximum and decreasing with different slopes. For the following experiments the percentage of initial adopters remains set to 2.5 %.

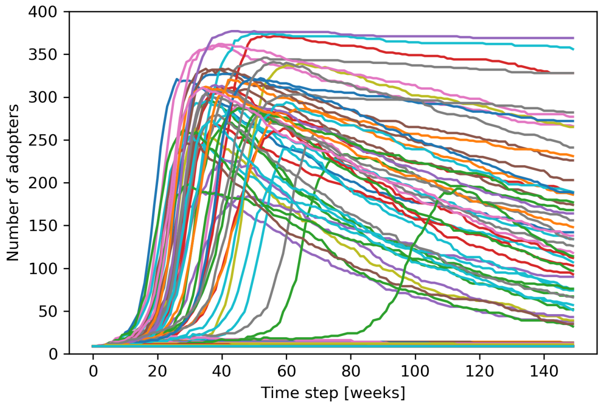


Figure 8.1: Number of adopters over time for the base model with 2.5 % initial adopters. 100 out of 2000 scenarios are displayed, obtained by simulation. In some scenarios, adoption levels increase significantly but are mostly not sustained, in other scenarios, the adoption curves remain at or below 2.5 %.

8.2.2 Effect of cash-based interventions

Figure 8.2 illustrates the adoption curves for cash-based interventions, (a) cash-transfer-only, (b) cash-info, (c) cash-maintenance, (d) integrated cash-based. Going from the cash-transfer-only intervention to the integrated cash-based intervention, it can be observed that the percentage of scenarios which lead to some level of diffusion is increasing, although the curves only represent a limited sample. Similar to the base model behaviour, figures 8.2a and 8.2b show that whenever the number of adopters succeeds to increase, it mostly decreases after reaching its maximum. At the end of the simulation runs, most of the runs are approaching low numbers of adoption. In all four cases there are scenarios in which the numbers of adopters remain close to zero throughout the entire simulation period.

Figures 8.2c and 8.2d display the model behaviour if maintenance capacity is increased. It can be easily observed that this has a stabilising effect on the number of adopters. Once the maximum adoption level is reached, most curves remain close to the maximum. As expected, small fluctuations occur which can be attributed to adopters switching from the adoption to the rejection stage before reevaluating their decision and becoming adopters again after having received maintenance support. Since this study considers the adoption of clean cooking fuels as a repeated purchase decision, this behaviour represents small fluctuations in actual sales. Moreover, in a major part of the scenarios the maximum adoption level remains below the maximum number of agents.

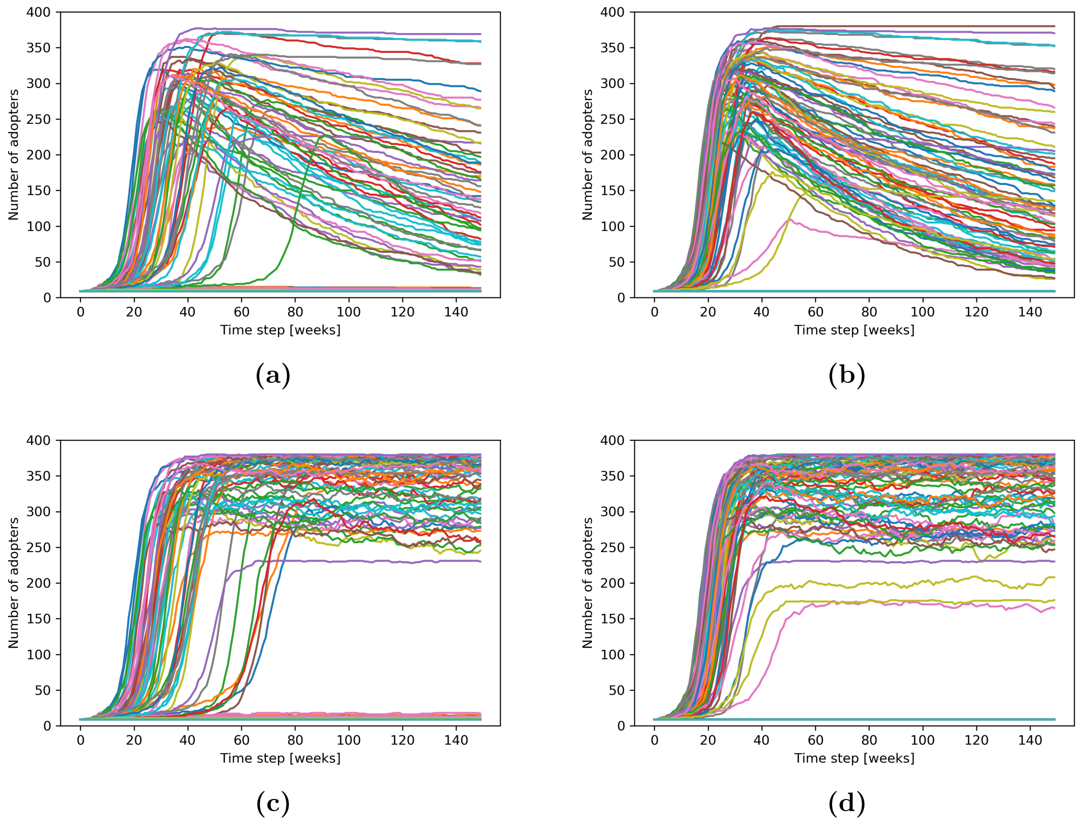
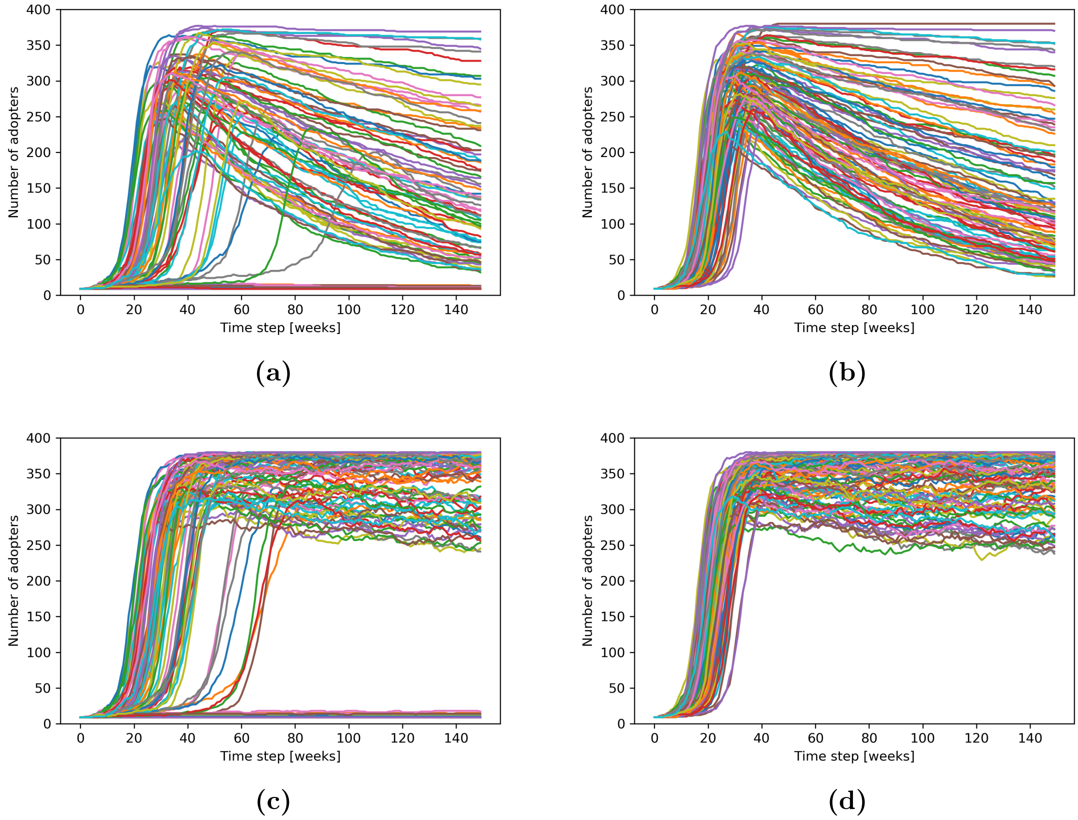


Figure 8.2: The impact of cash-based interventions on the number of adopters over time. (a) Cash-transfer-only, (b) cash-info, (c) cash-maintenance, (d) integrated cash-based intervention. 100 out of 2000 scenarios are displayed per figure, obtained by simulation. The integrated cash-based intervention leads to some diffusion in most scenarios. Increasing the maintenance capacity stabilises the adoption level. None of the four interventions succeeds in raising adoption levels in all scenarios.

8.2.3 Effect of voucher-based interventions

Figure 8.3 depicts the adoption curves for voucher-based interventions. Interestingly, both interventions involving information campaigns, in figures 8.3b and 8.3d, succeed in raising the number of adopters to significant levels in all 100 scenarios displayed. With the voucher-info intervention the number of adopters decreases soon after reaching the minimum in most scenarios. Similar to the previous experiments, increasing the maintenance capacity stabilises the adoption curve while small fluctuations remain. It can further be noticed that increased maintenance capacity appears to increase the maximum adoption level reached for scenarios that lead to diffusion.



(a) **(b)** **(c)** **(d)**

Figure 8.3: The impact of voucher-based interventions on the number of adopters over time. (a) Voucher-only, (b) voucher-info, (c) voucher-maintenance, (d) integrated voucher-based intervention. 100 out of 2000 scenarios are displayed per figure, obtained by simulation. Increasing the maintenance capacity stabilises the adoption level. Both interventions with information campaigns succeed in raising the number of adopters to significant levels in all 100 scenarios displayed.

8.2.4 Comparison of interventions based on KPIs

In this section, to better understand the distribution of the outcomes under different interventions, the results of the base model and the interventions are presented in terms of the KPIs, *final number of adopters*, *time to reach the maximum of adopters*, and *robustness*.

Figure 8.4 shows the box plots of the simulation results for the number of adopters at the end of the simulation run. It can be observed that the integrated voucher-based intervention, I8, results in the highest median of final number of adopters and the smallest spread in outcomes. Note that if boxes do not overlap with each other, this implies that with 95 % confidence the median is above the others. The performance of I8 is closely followed by the voucher-maintenance intervention, I7. The median of cash-based interventions, I3 and I4, also attain a relatively high level, but they both lead to a wide spread in the outcomes. Especially, intervention 3 appears to attain good results in some cases, but very low levels of diffusion in other cases. In fact, for I3 to I8, the maximum number of final adopters convenes with the maximum number of agents, which suggests that under certain conditions all households could be reached. However, in other scenarios, I3, I4, I5, and I6 do not succeed in raising the number of adopters above the initial number. The median for the base model without intervention lies close to zero final adopters, which can only be improved to a limited extend by the cash-transfer-only intervention.

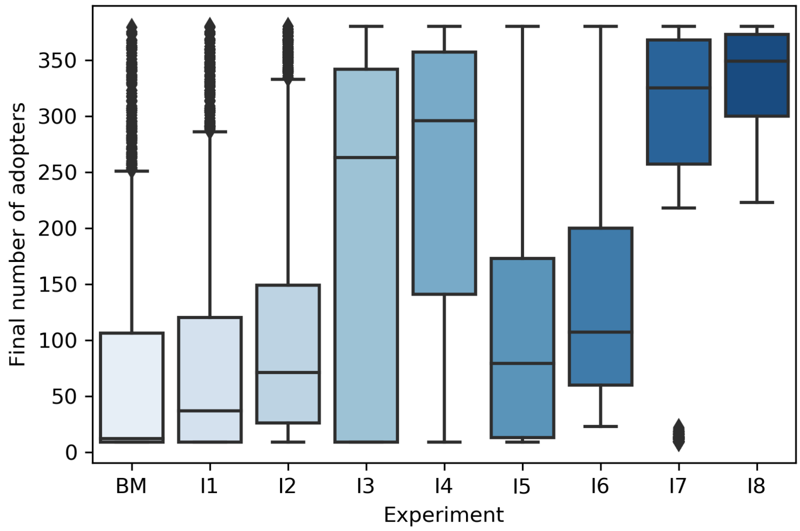


Figure 8.4: The impact of interventions on the final number of adopters (long-term impact). Simulation results for the sample of 2000 scenarios excluding shocks, for the base model (BM), cash-transfer-only (I1), cash-info campaign (I2), cash-maintenance (I3), integrated cash-based (I4), voucher-only (I5), voucher-info campaign (I6), voucher-maintenance (I7), integrated voucher-based (I8) interventions. The integrated voucher-based intervention (I8) results in the highest median of final adopters and the smallest spread in outcomes. Cash-based interventions lead to either little increase in the final number of adopters (I2-I3) or a wide spread in the outcomes (I3-I4).

Figure 8.5 shows the box plots of the simulation results for the *time to reach the maximum adoption level*, per intervention. It should be noted that the data displayed only includes scenarios where the final number of adopters lies above the 75th percentile of the respective intervention to reduce the bias towards zero caused by adoption curves that remain close to zero throughout the simulation period. As expected, it can be observed that the interventions containing information campaigns, I2 and I6, reach the maximum adoption level earlier than other interventions. Cash- and voucher-based interventions combined with maintenance only, I3 and I7, tend to reach the maximum later.

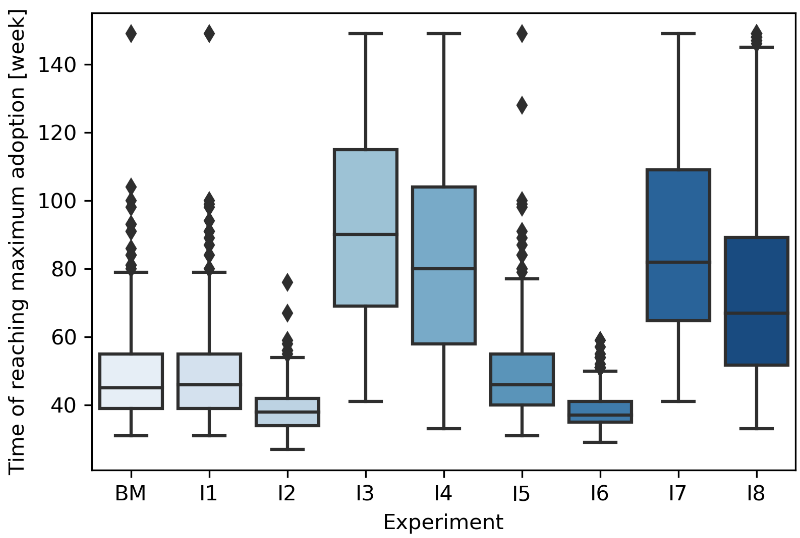


Figure 8.5: The impact of interventions on the time of reaching the maximum adoption (timeliness). Simulation results for the sample of 2000 scenarios excluding shocks, for the base model (BM), cash-transfer-only (I1), cash-info campaign (I2), cash-maintenance (I3), integrated cash-based (I4), voucher-only (I5), voucher-info campaign (I6), voucher-maintenance (I7), integrated voucher-based (I8) interventions. Data displayed only includes scenarios where the final number of adopters lies above the 75th percentile of the respective intervention. The interventions supported by information campaigns (I2 and I6) reach the maximum adoption level earlier than others.

Table 8.2 shows the results of the interventions in terms of the two robustness metrics. To recall, R_θ is the threshold-based metric, defined as the percentage of scenarios, in which the *final number of adopters* lies above 60 % of the agent population. R_∇ is the gradient-based metric, defined as the gradient of the mean of the adoption curves which lie above 60 % at the end of the simulation. The values for both metrics are rounded to two decimal places.

From the results it becomes evident that the integrated interventions, I4 and I8, which combine financial assistance, information campaigns and maintenance, as well as the voucher-based intervention including maintenance, I7, have by a large margin the highest percentage of scenarios which reach more than 60 % adoption ratio. Moreover, the integrated intervention involving vouchers instead of cash transfers succeeds in nearly all scenarios to raise and sustain a high level of adoption ratio. The cash-transfer-only intervention, I1, leads at best to marginal improvement as compared to the base model.

Furthermore, the results for the gradient-based metric suggest that the interventions without increased maintenance capacity, I1, I2, I5 and I6, have a similar tendency towards decreasing adoption levels, as the base model. The all lead to gradients below -0.4. Both financial assistance and maintenance interventions, I3 and I7, significantly reduce the gradient to close to zero. The integrated voucher-based intervention is the only one which results in a small positive gradient; thus it succeeds to create a stable level of adoption.

Experiment	BM	I1	I2	I3	I4	I5	I6	I7	I8
R_θ [%]	8.7	9.85	13.0	55.3	71.4	16.2	20.2	79.0	99.9
$R_\bigtriangledown$	-0.49	-0.41	-0.42	-0.07	-0.01	-0.41	-0.43	-0.06	0.02

Table 8.2: Robustness metrics for the set of scenarios excl. shocks

8.2.5 Effect of shocks

After analysing the effects of different interventions under 2000 sampled scenarios excluding shocks, this section addresses the effect of shocks. Due to the expansion of the uncertainty space, the number of sampled scenarios is increased to 5000. Considering limited computational time, this section only considers two interventions, which appeared to be among the most promising in the previous part. The first one is the integrated intervention consisting of cash transfers, info campaign and maintenance, and the second one takes the alternative financial scheme, vouchers instead of cash transfers.

Figure 8.6 shows five sampled scenarios for the integrated cash-based intervention. Although five scenarios are very far from being representative, the figure displays them only to illustrate the model behavior while keeping clarity. It can be seen, that depending on the parameter setting, the shocks have very different effects. While in some scenarios, the price shocks lead to sudden drops in the number of adopters, even down to zero, in other scenarios price shocks only lead to minor decreases. One hypothesis to explain these different effects is that intervention 4 involves cash transfers which imply high sensitivity to prices depending on the ability-to-pay and the time discount factor. If the ability-to-pay is close to zero, the number of adopters is highly sensitive to prices, as any increase in price above the time-discounted cost for traditional fuels leads to rejection by most adopters. The scale of the decrease may be determined by a combination of factors, where in some cases the income differences among agents lead to only a part of them rejecting if price shocks happen, or by the magnitude of the price shock itself.

The supply shock cannot be as easily observed in figure 8.6 as sudden price shocks, as they occur at the agent-level and at individual times. Further analysis in the scenario discovery phase will show whether supply shocks appear to affect the outcomes of the interventions.

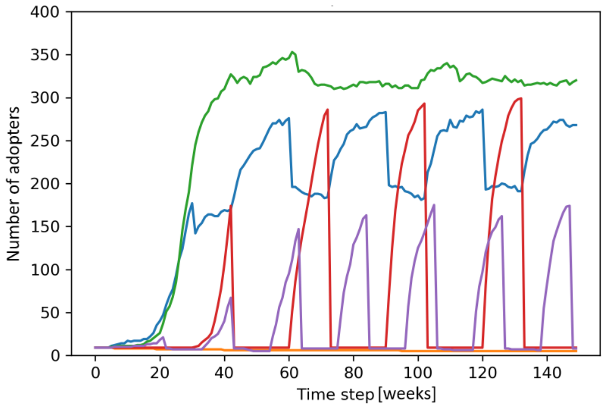


Figure 8.6: The impact of shocks on the number of adopters over time under the integrated cash-based intervention. The figure displays the simulation results for 5 scenarios out of the 5000 sampled scenarios including shocks. Depending on the initial conditions, in some scenarios, the price shocks lead to sudden drops in the number of adopters, even down to zero, in other scenarios price shocks only lead to minor decreases.

Figure 8.7 displays five sampled scenarios for the integrated voucher-based intervention. In some of the scenarios, the adoption curve is limited in magnitude. Small fluctuations in the curve are due to the probabilistic nature of supply shocks or performance issues. No effects of price shocks can be observed. This is expected as the increase in the price of clean fuel is no more than 20 %, thus the monthly cost of 7200 [RWF] minus 4000 [RWF] received by vouchers equals 3200 [RWF], which is still below the time-discounted monthly cost of traditional fuels.

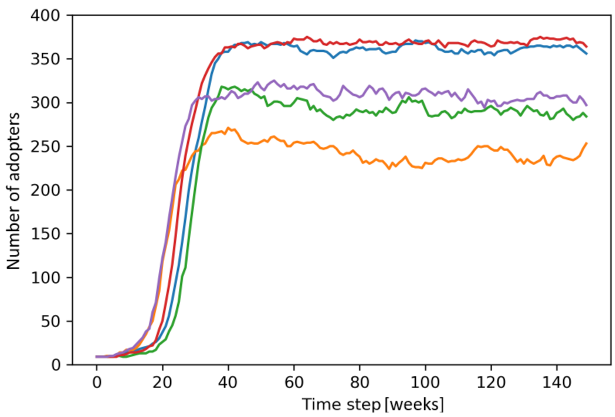


Figure 8.7: The impact of shocks on the number of adopters over time under the integrated voucher-based intervention. The figure displays the simulation results for 5 scenarios out of 5000 sampled scenarios including shocks. Price shocks do not affect the effectiveness of the integrated voucher-based intervention. Supply shocks and performance issues lead to limited adoption magnitudes and small fluctuations in the number of adopters.

8.2.6 Impact of shocks on the KPIs

In addition to observing the model behaviour over time, this section presents potential changes in the three KPIs for the simulation runs including shocks, compared to the scenarios excluding shocks.

Figure 8.8 shows the *final number of adopters* for the cash- and voucher-based interventions, I4 and I8, in the sampled scenarios including the shocks compared to the previous set of scenarios. As expected, there is a slight decrease in the median value, however, as the boxes are largely overlapping, this effect cannot be stated with confidence. For I4, the spread of outcomes becomes much wider due to the shocks. For I8, the width of the outcome spread does not seem to be affected.

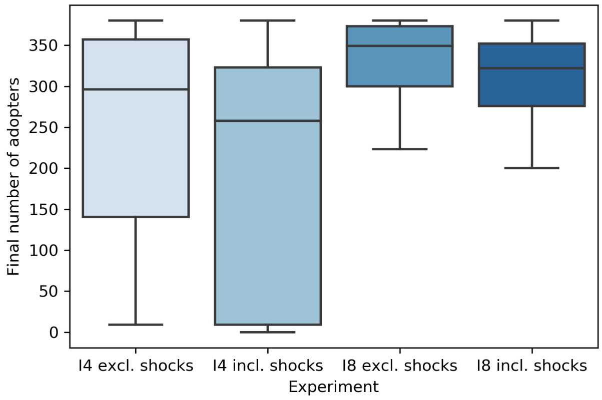


Figure 8.8: The impact of shocks on the final number of adopters (long-term impact). Simulation results for the sample of 2000 scenarios excluding shocks and 5000 scenarios including shocks, for the integrated cash-based (I4) and voucher-based (I8) interventions. I4 is vulnerable to shocks as the outcome spread becomes much wider, while I8 does not seem to be affected significantly.

Figure 8.9 shows the *time to reach the maximum adoption*, which suggests that in the sample of scenarios including shocks the maximum impact of the interventions is slightly delayed, though the boxes are overlapping to a large extend as well. For both financial assistance schemes, integrated interventions appear to reach the maximum impact at similar times under shocks.

Next, the robustness metrics for both integrated interventions under the 5000 scenarios are presented in table 8.3. The threshold-based robustness metric for the integrated cash-based intervention (I4) decreases when shocks are included, from 71.4% to 60.08 %. As expected, for the voucher-based intervention (I8) there is only a relatively small decrease from 99.9 % to 96.94 %, which suggests that despite being faced by shocks, integrated voucher-based intervention succeeds in creating a long-term impact in a large majority of the scenarios.

Similar results are found for the gradient-based metric. Under shocks the gradient-based robustness metric for the integrated cash-based intervention is reduced from -0.01 to -0.23. For the voucher-based intervention the second robustness metric leads to the same result as in the scenario sample excluding shocks, thus stable adoption levels are achieved.

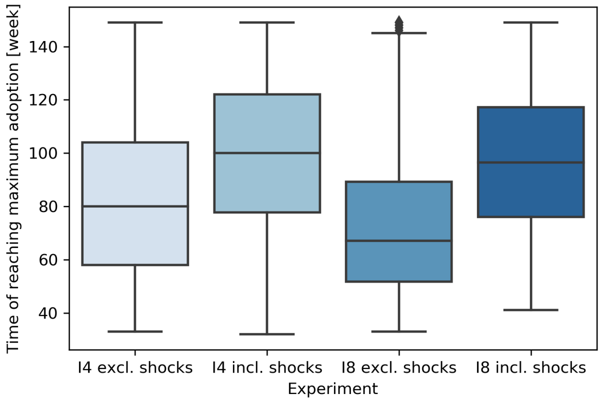


Figure 8.9: The impact of shocks on the time to reach maximum adoption (timeliness). Simulation results for the sample of 2000 scenarios excluding shocks and 5000 scenarios including shocks, for integrated cash-based (I4) and voucher-based (I8) interventions. Under shocks the maximum adoption is reached slightly delayed for both interventions.

Experiment	I4 (shocks)	I8 (shocks)
R_θ [%]	60.08	96.94
R_∇	-0.23	0.02

Table 8.3: Robustness metrics for the set of scenarios incl. shocks

8.2.7 Impact of changes in the decision strategy on the KPIs

After testing the model behaviour in two samples of scenarios, including and excluding shocks, this section analyses the impact of assumptions in the decision strategy on the KPIs. In the two previous sets of experiments, the decision strategy is set to *deliberating*, which is considered the default option, as it includes all adoption barriers: the social, economic and information barrier. In this third set of experiments, scenarios as sampled from the uncertain variables excluding the shocks but including the ratios for the decision strategies, *imitating*, *cost-optimizing*, *advice-seeking*. Shocks are not included in the sampled scenarios, as the main purpose of this set of experiments is to determine whether changes in the main assumption regarding how the initial adoption decision is made lead to changes in the outcomes. Due to limited computational time, similarly to the previous section, only interventions 4 and 8 are tested. 5000 scenarios are sampled to cover the expanded uncertainty space.

Figure 8.10 shows that for the integrated cash-based intervention, I4, changes in the ratios of decision strategies lead to a significantly wider spread in outcomes for the *final number of adopters*. For the integrated voucher-based intervention, I8, the *final number of adopters* is reduced in some scenarios, but the overall performance remains high.

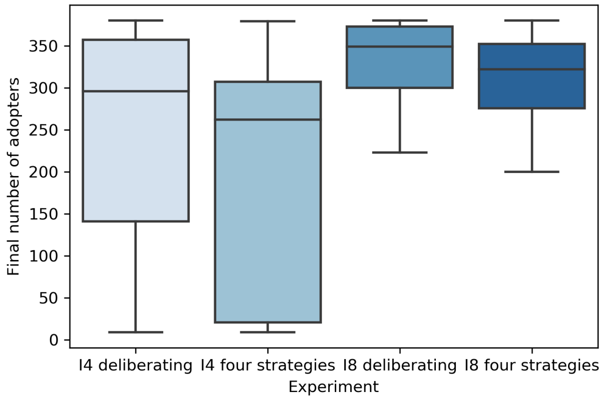


Figure 8.10: The impact of changes in the decision strategy ratios on the final number of adopters (long-term impact). Simulation results for 2000 sampled scenarios with deliberating as default strategy and for 5000 sampled scenarios considering 4 decision strategies, for the integrated cash-based (I4) and voucher-based (I8) interventions. For I4, changes in the decision strategy lead to a significantly wider spread in outcomes; for I8, the performance remains high and the outcome spread small.

Figure 8.11 shows the *time to reach the maximum adoption* for both interventions with different ratios of decision strategies. While for the integrated cash-based intervention, I4, there is no visible difference from the benchmark, the impact under the voucher-based intervention, I8, when considering heterogeneous decision strategies comes into effect later in time. Though the boxes overlap.

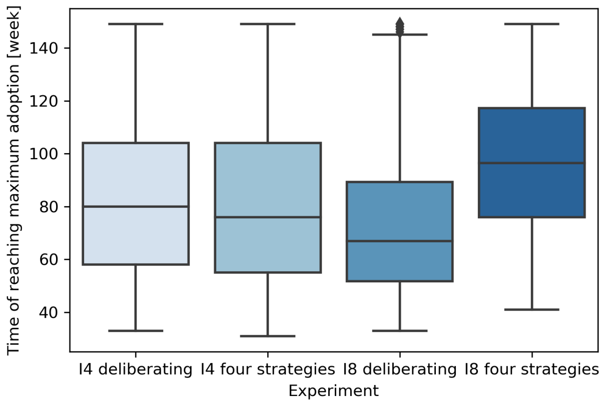


Figure 8.11: The impact of changes in the decision strategy ratios on the time to reach maximum adoption (timeliness). Simulation results for 2000 sampled scenarios with deliberating as default strategy and for 5000 sampled scenarios considering 4 decision strategies, for the integrated cash-based (I4) and voucher-based (I8) interventions. For I4, there is no visible difference from the benchmark; for I8, timeliness is delayed on average.

The robustness metrics are indicated in table 8.4. The threshold-based metric is decreased significantly for intervention 4, from 71.4% to 63.1 %, while intervention 8 still scores high with 98.23 %. For the gradient-based metric different results are found. While the integrated cash-based intervention only leads to a slightly more negative gradient of -0.02, the voucher-based intervention results in a significant decrease in the gradient-based metric, from 0.02 to -0.04. Nevertheless, both results are still close to zero, which indicates that relatively stable adoption levels are attained. Further research is needed to analyse whether increasing the upper range of the ratio of each decision strategy above 0.25 would lead to different outcomes.

Experiment	I4 (strategies)	I8 (strategies)
R_θ [%]	63.1	98.23
R_∇	-0.02	-0.04

Table 8.4: Robustness metrics for the set of scenarios with four decision strategies

8.3 Sensitivity analysis

In this section, the sensitivity of the model behaviour to changes in key parameters that are not part of the uncertainties is analysed. It should be noted that this section does not aim to perform a global sensitivity analysis, although this study involves various parameters which should not be seen in isolation. Rather, the aim of this section is to better understand the path-dependency of the diffusion process, which is demonstrated by varying key parameters, and whether changes in the model behaviour occur due to variations in key parameters incorporated in the base model.

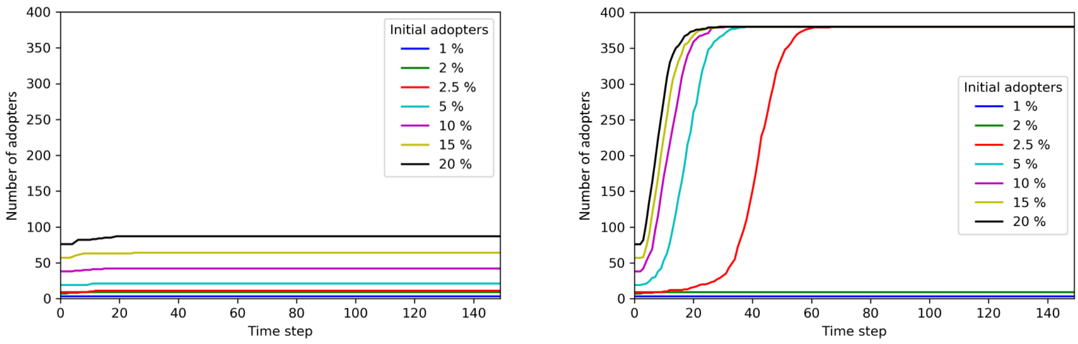
For this purpose, the base model with lever parameters set to zero is employed and all uncertain parameters are fixed. Shock parameters are set to zero and the decision strategy is set to its default *deliberating*. For reproducibility, table 8.5 indicates the values chosen for the remaining uncertain parameters. Table 8.5 further indicates which key parameters are varied. These include the initial adopters, the social thresholds per adopter category, the information thresholds per adopter category, as well as the ability-to-pay which essentially represents the economic threshold. Varying the different threshold values allows to analyse their individual impact on the model behaviour and how they interact with each other.

Parameter	**Value**
Initial adopters	Varying
Ability-to-pay *atp*	Varying
Social thresholds $\theta_{social,i}$	Varying
Info thresholds $\theta_{info,i}$	Varying
Time discount factor	0.1
Probability of bad performance	0 (0.02)
Average node degree	6
Probability of rewiring	0.2

Table 8.5: Set-up for sensitivity analysis

8.3.1 Initial adopters

First, the effect of changes in the percentage of initial adopters is displayed by figure 8.12. Naturally, this is an important parameter determining if and how fast path-dependent diffusion takes into effect. Figure 8.12a shows the base model behaviour for various percentages of initial adopters while the economic barrier, represented by the ability-to-pay set to 2.5 %, hinders most agents from following adoption. Even with 20 % initial adopters, the adoption level only increases marginally. In contrast, in figure 8.12b the base model behaviour is shown, where the ability-to-pay is set to 7.5 % to remove the economic barrier for all agents, i.e. for all agents the available share of income to purchase fuel is above the relative cost difference between clean fuel and traditional fuel. In this case, 2.5 % initial adopters are sufficient to initiate diffusion, although it is delayed compared to higher percentages of initial adopters. On the other hand, for 1 % and 2 % initial adopters, diffusion does not kick off.



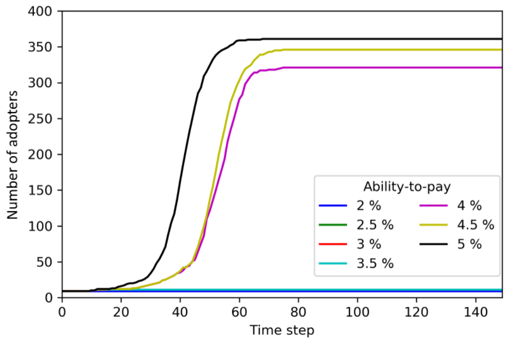
(a) (b)

Figure 8.12: Varying the percentage of initial adopters. (a) Results for the base model including the economic barrier (atp = 2.5 %), (b) results for the base model excluding the economic barrier (atp = 7.5 %). When the economic barrier is in place, even 20 % initial adopters only lead to a marginal increase in the adoption level. Without the economic barrier, 2.5 % initial adopters are sufficient to initiate diffusion.

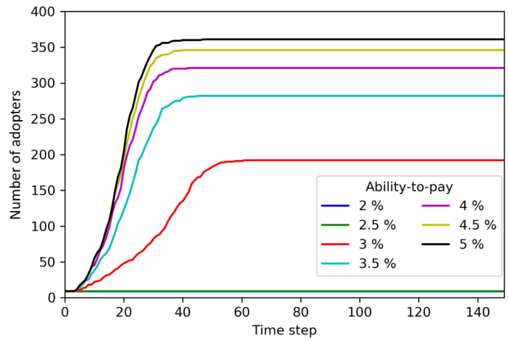
8.3.2 Ability-to-pay

The ability-to-pay is part of the uncertain parameters, thus already included in the scenario samples. Nevertheless, as one main parameter representing the economic barrier it has a strong influence on the impact of changes in other parameter values, as shown by the previous section. Therefore, the ability-to-pay is considered the next key parameter worthwhile to address in this sensitivity analysis.

The analysis of the ability-to-pay parameter involves two parts. First, the behaviour of the base model for various ability-to-pay values is analysed in isolation and displayed by figure 8.13a. Second, the social barrier is removed in the base model by setting all five social thresholds to zero, the results are shown by figure 8.13b. It can be observed that, if the social barrier is in place, diffusion starts to kick off for an ability-to-pay of at least 4 %, while without the social barrier an ability-to-pay of 3 % is sufficient to create significant adoption levels. Interestingly, in the first case, either almost all of the agents or none of them become adopters, while in the latter case, intermediate adoption levels can be attained. Moreover, the existence of the social barrier appears to influence the slope of the increasing adoption curve.



(a)



(b)

Figure 8.13: Varying the ability-to-pay. (a) Results for the base model including the social barrier, (b) results for the base model excluding the social barrier (all social thresholds = 0). When the social barrier is in place, diffusion starts to kick off for an ability-to-pay of at least 4 %, while without the social barrier an ability-to-pay of 3 % is sufficient to create significant adoption levels. With the social barrier, no intermediate adoption levels are attained.

8.3.3 Social thresholds

As implied by the previous section, the social thresholds have an impact on the model behaviour. They are not part of the uncertain parameters but kept constant in the samples of scenarios, as they are not expected to have an impact on the relative model results of different interventions. However, this section aims to improve the understanding of how different social threshold settings affect the base model behaviour. Note that in order to focus on the social barrier, the ability-to-pay value is set to 7.5 % in this part of the analysis.

Figure 8.14 illustrates the model results for various social threshold settings. The base model setting refers to the five social threshold specifications expressed in terms of triangular distributions, one per adopter category, adapted from Hidayatno et al. (2020). The base model settings are described in Appendix D. Varying the social threshold values involves changing five different parameters. First, for all five adopter categories the maximum values of the triangular distribution are used instead of the distributions. This change of setting hinders diffusion. Similarly, the minimum values of the triangular distributions are used, which leads to the fastest increase and highest level of adoption. Third, only one of the five parameters is changed compared to the base model: the social threshold for the laggards is set to 0.85. This leads to a small step in the adoption curve, the increase in new adoption slows down and speeds up again once the threshold for laggards is passed. Lastly, the heterogeneity among the agents is reduced, first by setting the social threshold for the late majority (LM) equal to the one for the laggards, subsequently by setting the social thresholds for the early majority (EM) and the late majority (LM) equal to the one for the laggards. The latter reduction of heterogeneity prevents diffusion from taking into effect.

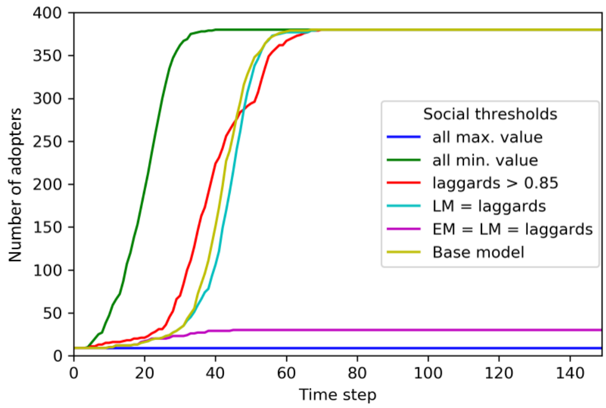


Figure 8.14: Varying the social thresholds. The base model (with atp = 7.5 %) involves five $\theta_{social,i}$ parameters, innovators: 0, early adopters: triangular(0, 3%, 7.5%), early majority: triangular(3%, 7.5%, 15%), late majority: triangular(7.5%, 15%, 25%), laggards: triangular(10%, 25%, 40%). Variations involve using the maximum values of the triangular distribution (blue), using the minimum values of the distributions (green), only the social threshold for laggards is set to 85% (red), reducing the heterogeneity among the agents with late majority (LM) = laggards (turquoise), and early majority (EM) = late majority (LM) = laggards (purple). Increasing social threshold values or reducing heterogeneity can prevent diffusion from taking into effect.

8.3.4 Information thresholds

Lastly, the effect of changes in the information thresholds are analysed. The information thresholds are a concept developed by this study, thus testing the effect of varying parameter values is particularly important. Similar to the social thresholds, this analysis involves varying five different parameters, one per adopter category. Note that similarly to the previous section, the ability-to-pay value is set to 7.5 %. Moreover, the probability of bad performance is set to 0.02

Figure 8.15 shows the model results for various information threshold settings. The base model refers to the following five parameter values: 0 for innovators, 0.9 for early adopters, 0.95 for early majority, 0.99 for late majority, 1 for laggards. The choice of the base model parameter values is explained in Appendix D. As shown by figure 8.15, increasing the information thresholds collectively leads to damping of the maximum adoption level. Furthermore, it can be observed that there is a range of values which do not lead to significant changes in the model behaviour.

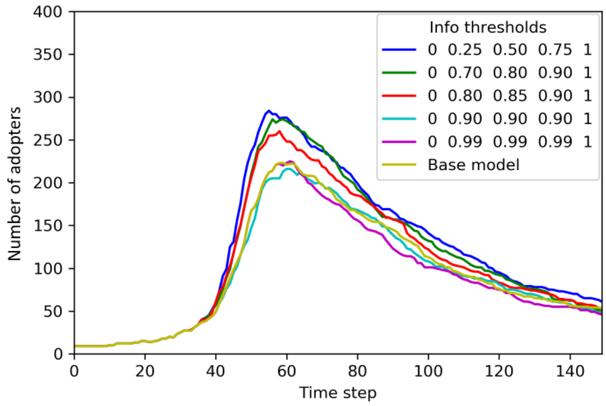


Figure 8.15: Varying the information thresholds. The base model (with atp = 7.5 % and p_bad_performance = 0.2) involves five $\theta_{info,i}$ parameters, innovators: 0, early adopters: 0.9, early majority: 0.95, late majority: 0.99, laggards: 1. Various different settings are tested. Increasing the information thresholds collectively leads to damping of the maximum adoption level, there is a range of values which do not lead to significant changes in the model behaviour.

8.4 Conclusion

This chapter discusses the design of experiments and presents the model results. In the first set of experiments, the behaviour of the model is analysed under a large sample of scenarios and different cash- and voucher-based interventions. In the second set of experiments, the effect of shocks on the performance of the integrated cash-based and voucher-based interventions is analysed. It is found that voucher-based interventions are more robust than cash-based interventions. In the third set of experiments, the impact of changes in the decision strategy is analysed. In the final part of the chapter, key parameters of the base model are varied to analyse sensitivity of the model behaviour. The model results are further discussed in the next chapter.

Chapter 9

Analysis

In this chapter, the validation of the model is discussed, and the results of the experimentation phase are analysed and interpreted. First, the model is validated based on literature and the case study. Second, the performance of interventions is analysed and interpreted. Third, scenario discovery is applied to identify ranges of uncertain parameters that lead to success or failure of a set of interventions. Lastly, the parameter ranges are translated into scenario narratives.

Thereby, this chapter addresses the final sub-research question as follows:

How can the outcomes of this study be used to inform market-based clean cooking interventions in other refugee settings?

9.1 Model validation

Model validation involves checking whether the model succeeds in creating behaviour that is realistic and helps to address the problem of this study. It is evident that the predictive capacity of the model is highly limited, however, the purpose of the model is not to predict the future or reproduce exact past behaviour but rather to gain insights into the mechanisms that drive the adoption of clean cooking practices in refugee camps. Therefore, the focus of this model validation is on the shape of the adoption curve and on the qualitative outcomes rather than on the quantitative model results. First, this section provides a cross-validation of the model behaviour. Second, the model behaviour is compared to the case study.

9.1.1 Cross-validation

There is no directly comparable study in the literature, however, it is possible to compare the model behaviour to other studies within diffusion literature and clean cooking literature.

First, diffusion curves suggested by Rogers (1983)'s DoI theory take an S-shaped form. Figure 9.1 displays the mean for the number of agents in the adoption, rejection and ignorance stages over time for the integrated cash-based intervention. The underlying sample for this figure is the one with 2000 scenarios excluding shocks. It can be observed that the adoption curve increases in an S-shaped manner. As the number of adopters increases slowly at first, the rate of new adopters increases, which leads to an exponential increase of the number of adopters, before the rate of new adopters slows down until the maximum of adopters is reached. This behaviour is considered realistic with respect to the social barrier. The more households use clean cooking fuels, the more households become aware of them, receive information and consider adoption for themselves, which, in turn, leads to more people becoming aware and interested in adoption. In contrast to DoI, most of the diffusion curves do not reach the maximum of all agents in the model. This is expected, since this study includes several adoption barriers, in addition to the social barrier, which hinder many agents to move on to the adoption stage.

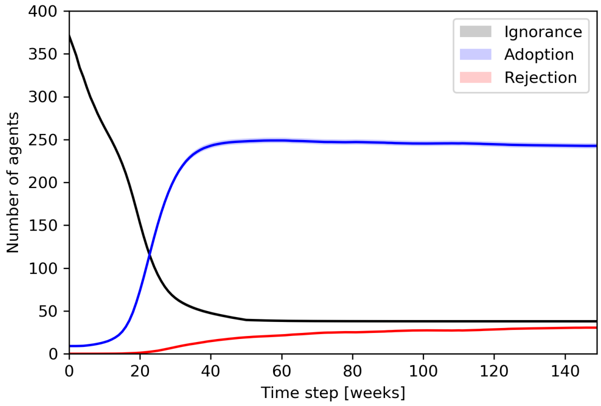


Figure 9.1: Validation curves for the integrated cash-based intervention. Mean number of agents in ignorance, adoption and rejection stages over time. Sample of 2000 scenarios excluding shocks. The adoption curve increases in an S-shape manner.

Figure 9.2 displays the mean for the number of agents in the adoption, rejection and ignorance stages over time for the cash-transfer-only intervention. In the S-shaped DoI curve there is no decrease in the adoption, as people are considered adopters and remain it as soon as they have adopted the innovation. This study considers *repeated* adoption decisions, which implies that people who stop using clean cooking fuels are not considered adopters. Therefore, after reaching the maximum of adopters, if no maintenance activities are in place, there is a decrease in the number of adopters. The decrease in this study is due to negative experiences with the performance of the cooking system, supply shocks or price shocks. It can further be observed in figure 9.2 that a major part of agents remains in the ignorance stage as they are not reached by information from adopters nor by information campaigns.

S-shaped diffusion curves can also be observed in other ABM studies on innovation diffusion, such as Xiong et al. (2018) and Stummer, Kiesling, Günther, and Vetschera (2015). In contrast, in some other ABM studies, such as MacCarty and Pakravan (2019) and Sopha et al. (2011), logarithmic increase of the adoption curves can be observed. Both latter studies use the Theory of Planned Behavior as theoretical underpinning instead of threshold-based decision rules, which may be one explanation for the difference in shape.

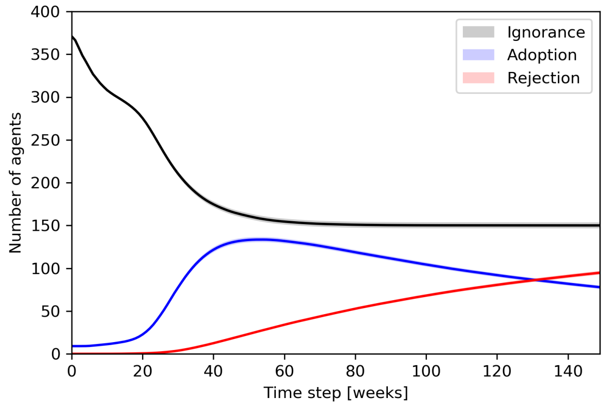


Figure 9.2: Validation curves for the cash-transfer-only intervention. Mean number of agents in ignorance, adoption and rejection stages over time. Sample of 2000 scenarios excluding shocks. Without maintenance activities, the adoption curve decreases after reaching the maximum.

Additionally, the model results have been compared to studies in the clean cooking field, which often show no significant long-term impact of clean cooking interventions. For instance, Hanna et al. (2016) conduct a randomized-controlled trial in India to measure the impact of an improved cookstove program in terms of the health outcomes and greenhouse gas emissions, and find no significant impact four years after the program, as households failed to maintain and continuously use the improved cookstoves. Thus, the behaviour of households appears to be critical for the long-term impact of clean cooking interventions. This fact is confirmed by the model results of this study where the interventions without maintenance activities lead to adoption curves approaching zero on the long-term in most scenarios.

9.1.2 Empirical validation

In this section the model behaviour is compared to the real case in Kigeme camp in Rwanda. Despite the lack of extensive validation data, several observations can be made.

As found in the case study interviews, the initial interest in adopting pellets was high as the apparent benefits of clean cooking seemed to attract people in Kigeme. Though at first, the initial uptake was limited by availability and lack of financial assistance as the initial phase was carried out as a pilot project with only 100, then 300 targeted households. When the supply capacity was increased and the cash transfers expanded to all households, the number of adopters significantly increased, however, due to several barriers including competition from other fuels and spread of negative information it remained largely below the total number of refugee households, and decreased over time. It is evident that the solely cash-based program did not succeed in creating long-term uptake of clean cooking fuels in Kigeme camp. This fact is confirmed by the model results, where cash-transfer-only interventions perform poorly on the long-term in most of the scenarios.

There are two data sources which provide a more quantitative indication of the adoption levels in the Kigeme case. UNHCR conducted a survey at the end of 2019 which suggests that 35 % of the households have used pellets at some point during the program period from 2016 to 2019, and 15-20 % were using pellets as main fuel by the end of 2019. Though, this data was not agreed upon by all interviewees. One interviewee explained that the maximum adoption level reached for pellets in Kigeme camp was two thirds of the total household population. Whether households actually used pellets as their main fuel or rather as a complementary fuel remains unclear.

As this study defines adoption as using clean cooking fuels as main household fuel, the more conservative UNHCR survey data is chosen for the empirical validation of the model results. For this part of the validation, the adoption curves generated by the model under the sample of 2000 scenarios are studied to check whether in certain scenarios the model reproduces realistic adoption levels. Figure 9.3 shows the model results in terms of adoption levels over time for the sample of 2000 scenarios for the cash-transfer-only intervention. The figure containing all 2000 scenarios is used for the validation instead of figure 8.2a because the latter only shows the results for the sample of 100 scenarios which are not representative. It can be observed that the maximum adoption levels vary largely. Among the curves with rising adoption levels but relatively low maximum adoption, several maxima lie around 150 agents, or 1500 households, which is close to the 35 % maximum adoption ratio suggested by the UNHCR survey data.

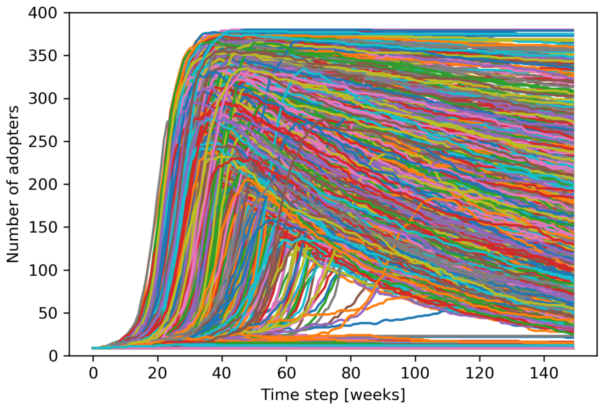


Figure 9.3: Model results for the cash-transfer-only intervention. Number of adopters over time for the sample of 2000 scenarios. Same figure as in Appendix F.1a, displayed for easy reference.

However, it becomes evident that - excluding the scenarios where adoption remains close to zero - a large part of scenarios leads to maximum adoption ratios exceeding 35 %. This is also in line with the sample of 100 scenarios displayed by figure 8.2a. There are several explanations for the overshoot in the maximum adoption ratio generated by the model. The two main input parameters restricting the adoption maximum are the *probability of bad performance* and the *ability-to-pay*. Overshoot suggests, for instance, that the chance for households in Kigeme camp to experience performance issues with the clean cooking system was above the one in most scenarios included in the simulation. The parameter range included in the scenario sample for the *probability of bad performance* is from 0.0 to 0.02, i.e. up to 2 % of households per week are not satisfied with the performance. Moreover, not only the parameter range but also the speed of the information flows through the social network in the model can be an explanation for the overshoot. If households experience performance issues frequently, but the negative information flows too slowly through the network, the maximum adoption level may not be sensitive enough to the chance of negative experience. Furthermore, the chance of negative performance interacts with the *ability-to-pay* in limiting the adoption maximum. Overshoot of the adoption curve can also be an indication that the ability-to-pay of households in Kigeme camp was below the one in most scenarios included in the simulation, reaching from 0 % to 5 % of the income.

Additionally, the model omits several context-specific aspects of the real case, for instance the gradual introduction of clean cooking fuels in a pilot phase before expanding the cash program to all households. A side-effect of this pilot phase can be that many households were already informed about the availability of pellets on the camp market. Thus, when the cash transfers were expanded to all households, they did not begin in the "ignorance" stage as assumed in the model. Finally, the percentage of initial adopters is set to 2.5 % in the model which is the benchmark to compare the effect of interventions but not based on data from the case study. It is known that 300 households were part of the pilot phase, however, there is no data on how many of them used pellets as their main fuel. Thus, the exact percentage of initial adopters in Kigeme camp remains unknown.

Therefore, it can be concluded that empirical validation based on the case study is challenging. In fact, it is not the purpose of this study to replicate the exact adoption curve of the case study in quantitative terms. Nevertheless, it was found that for certain parameter settings the model reproduces realistic adoption levels, with a steep increase in adoption at first, an intermediate maximum adoption ratio, and a failure of the cash-transfer-only intervention on the long-term.

9.2 Analysis of interventions

A main outcome of the experiments is that the diffusion of clean cooking practices in refugee camps is unlikely to attain a high level within the targeted population, if there are no interventions supporting the initial and sustained uptake. The two financial assistance schemes - cash transfers and vouchers - showed significant differences in results in terms of the KPIs. The complementary interventions - information campaign and increased maintenance capacity - appear to improve performance for both financial schemes. More importantly, complementary interventions are often critical to create widespread and long-term adoption.

Moreover, the diffusion process is highly path-dependent. The spread of outcomes is large for most of the interventions. Whether diffusion happens and the scale of diffusion highly depend on the the setting of the initial conditions. If a minority of adopters is attained, who are satisfied and spread favorable information, the adoption curve increases sharply, if the right initial conditions are in place. On the other hand, a minority of adopters who are dissatisfied can prevent the majority of others from following, thus limiting the potential scale of diffusion.

In this section, the model results for the different interventions are analysed further to better understand their relative performance and potential trade-offs.

9.2.1 Robustness

Cash-based interventions without complementary interventions fail to attain and sustain high levels of adoption in most scenarios. This suggest that, although cash-transfer-only interventions could work under certain favorable conditions, in most cases they are unlikely to lead to widespread adoption. Given the lack of data and high level of uncertainty in most refugee settings, driving the adoption of clean cooking fuels simply by providing cash transfers has a low chance of success. Supporting information campaigns to increase the chance of success for cash-transfer interventions can be helpful, but do not succeed in increasing nor in stablising the number of adopters notably throughout the range of scenarios. The implementation of maintenance activities seems to have a bigger role in order to attain high numbers of adopters. The combined cash transfer and maintenance intervention leads to very good results in some cases, but very low levels of diffusion in other cases. Even the integrated cash-based intervention fails in some scenarios to create any increase in adoption levels. More specifically, this study found that the integrated cash-based intervention succeeds in 71.4 % of the scenarios to create long-term adoption levels above 60 % of the refugee household population. Regarding the future tendency of the adoption levels, the results for the gradient-based robustness metric suggest that interventions without increased maintenance capacity fail to stablise adoption levels over time. Only the integrated cash-based intervention achieves stable adoption levels.

Moreover, cash-based interventions were found to be vulnerable to price shocks and supply shocks. The threshold-based robustness metric is reduced to 60.08 % for the scenario sample including shocks, while the results for the gradient-based metric suggest a tendency for the adoption level to decrease over time. Structural changes regarding the initial adoption decision strategy in the model also lead to a reduction in the threshold-based robustness metric to 63.1 %, though to no significant change in the gradient-based metric. Therefore, it can be concluded that the robustness of cash-based interventions, even supported by information campaigns and maintenance activities, is limited.

Voucher-based interventions are found to be significantly more robust than cash-based interventions. However, similarly to cash transfers, only providing financial assistance in form of vouchers is not sufficient in most scenarios. Likewise, supporting information campaigns do not kick-start notably higher adoption levels nor can the adoption be sustained over time. On the other hand, voucher-based interventions supported by maintenance activities throughout the full time period achieve high levels of adoption in most scenarios. Voucher-based interventions in combination with information campaigns and maintenance activities are most robust. This study found that the integrated voucher-based intervention lead to adoption levels above 60 % of the refugee household population in 99.9 % of the scenarios. As confirmed by the positive gradient-based robustness metric, these high adoption levels tend to be stable. Furthermore, integrated voucher-based integrations are less vulnerable to price and supply shocks, although shocks decrease the threshold-based robustness metric to 96.94 %. Structural changes in the initial adoption decision strategy in the model reduce the threshold-based metric to 93.9 % and lead to a slightly negative gradient-based metric. Thus, the integrated voucher-based intervention does not perform as well if the model is structurally changed, but both robustness metrics still suggest high performance across most scenarios with a slightly downward sloping trend in the adoption levels.

9.2.2 Timeliness

Analysing the interventions in terms of robustness shed a clear light on which interventions can be recommended and which ones are unlikely to succeed in most cases. This section addresses the timeliness KPI, as a second dimension to compare the performance of different interventions. Timeliness in achieving impact of interventions can be important in humanitarian response. For instance, if local governments urge humanitarian organizations to provide alternative cooking fuels due to increasing deforestation in the surroundings of refugee settings, a transition in cooking fuels should take into effect soon after the start of the implementation of an intervention. As market-based interventions rely on gradual transition from non-adoption to adoption, delays in achieving high adoption levels can be a significant drawback. As mentioned before, any delay in creating high adoption levels also involves delays in income for private clean fuel suppliers.

This study found that the integrated cash- and voucher-based interventions are significantly slower in reaching the maximum adoption level than if only financial assistance is provided. Cash- and voucher-based interventions combined with maintenance tend to reach the maximum adoption even later. One can argue that this effect can be explained by the higher absolute number of adopters if interventions involving increased maintenance capacity are applied. However, it remains an important observation. To put the model results into perspective, for instance, for the voucher-only intervention the biggest impact in terms of adoption can be expected less than 40 weeks after start of the implementation, while the highest adoption levels for the voucher-maintenance intervention can be expected 80 weeks after start of the implementation.

This study suggests that information campaigns can support cash- and voucher-based interventions by increasing the speed of diffusion within the refugee population. In refugee contexts characterized by (1) pressure from host governments to act fast to halt deforestation, or (2) when private fuel companies rely on the uptake of their products to sustain their business, this can be an important aspect. Thus, solely facilitating clean cooking fuels to become available on the market and providing financial assistance is not sufficient. Especially if the type of fuel is less known among the targeted population, information campaigns can help spread information, attract initial adopters, who then inform and attract others. On the other hand, if the type of fuels is well-known as a high-quality fuel, like LPG, information campaigns could be targeted at specific aspects, such as user safety or ease of use, to reduce potential concerns or misconceptions.

However, it can be concluded that the timeliness of achieving impact by implementing integrated cash- and voucher-based interventions remains relatively low. This is certainly true, if the results are compared to in-kind distributions of clean fuels in refugee settings, where the clean fuels are immediately taken up. Therefore, cash- and voucher-based interventions are less suitable for refugee contexts which rely on immediate taking into effect of the impact created by a transition to clean cooking fuels.

9.2.3 Long-term impact

Aside from the robustness and timeliness of interventions, this study focuses on the long-term impact. Although the long-term nature of interventions is often undesired in refugee settings due to political reasons, long-term impact is highly relevant for clean cooking practices where the environmental and health benefits do not take into effect unless the clean fuels (and clean cooking systems as a whole) are continuously used over years. Likewise, if a market-based approach is chosen, any fuel company involved needs a sustained demand from refugee costumers to be able to sustain their business in or near the camp market.

This study found that increasing the maintenance capacity is crucial to create long-term impact of cash- as well as voucher-based interventions. Maintenance activities do not only stabilise the demand for clean fuels over time, but also help to create higher maximum adoption levels. Without sufficient maintenance activities, depending on the scenario, either diffusion does not kick off at all, the number of adopters decreases fast after reaching the maximum, or the maximum of adoption level is limited. The latter can be explained by the spread of negative information, i.e. if initial adopters are not satisfied as they do not receive technical support, they are likely to share their negative experiences, which, in turn, prevents others from adopting.

Therefore, supporting maintenance activities throughout the implementation period of cash and voucher-based interventions are critical to ensure that high levels of adoption can be achieved and sustained over the long-term.

9.2.4 Trade-offs

The model only considers three KPIs: robustness, timeliness and long-term impact of interventions. The previous sections already addressed the trade-off that exists between the long-term impact or robustness, and the timeliness of interventions. Interventions that perform well in terms of long-term impact and robustness, perform less well when it comes to timeliness, i.e. how soon the positive impact takes into effect.

In addition to the three KPIs, there are other considerations for evaluating interventions which are not included in the model but are equally important to compare different interventions. From the model results only, trade-offs appear to be easily avoided by implementing integrated voucher-based interventions, although this is only true for refugee contexts where a slow transition to clean cooking practices is acceptable. Since this is misleading, this section addresses additional trade-offs humanitarian decision-makers are facing when choosing which kind of approach to use to deliver clean cooking solutions.

The rationale behind unconditional cash transfers is that providing cash is considered as giving refugees the choice on how to meet their own needs. This implies a shift away from aid-dependency in the traditional sense, where humanitarian organisations provide food and non-food items to refugees. In protracted crises, it is argued that shifting towards more independence is critical to enable self-reliance on the long-term. Moreover, if a cash-transfer mechanism is already in place for other items, implementing cash transfers for fuel involves less logistics than implementing a voucher program. Even if there is no cash-transfer mechanism yet in the specific context, depending on the circumstances cash transfers are likely to be more cost-efficient than vouchers by reducing logistics cost (UNHCR, 2015).

Furthermore, the model does not include cost of supporting interventions nor cost-effectiveness considerations. Naturally, maintenance activities are costly. Sustaining high maintenance capacity over many years involves significant cost for personnel and materials, especially if stoves have to be replaced. On the other hand, information campaigns are temporary activities, requiring personnel, but do not require much material cost. Only comparing the performance of both supporting interventions in terms of the three KPIs considered in this study omits the significant cost difference. More insightful comparisons are the ones between financial assistance only and combined with information campaigns and/or maintenance activities. This allows to understand the effect of supporting interventions and whether it is worth to spend financial resources on them, in addition to the money spent on cash transfers or vouchers. As found in this study, in most scenarios, investing in cooking systems with high performance standards and good match with local preferences as well as in maintenance capacity is crucial to avoid failure of market-based interventions.

9.3 Scenario discovery

In the previous section, different interventions are compared in terms of the KPIs, and trade-offs between them are determined. It is evident that the diffusion process is highly path-dependent and the outcomes of interventions depend on the initial settings of uncertain parameters. In this section, the aim is to understand under which circumstances interventions succeed or fail. Improving the understanding on which circumstances lead to which outcome in the wide spread of model results is critical to be able to inform future interventions.

Therefore, the next step in the analysis is scenario discovery. Scenario discovery is a technique which helps to identify combinations of uncertainties which lead to either desired or undesired outcomes. In this study, the Patient Rule Induction Method (PRIM) algorithm is applied to identify scenarios in which interventions are likely to succeed or fail, by determining sub-spaces of the uncertainty space that belong to the outcomes of interest (Bryant & Lempert, 2010). In figure 9.4 the mapping of model outcomes to sub-spaces in the uncertainty space is visualized for a three-dimensional space.

The first step is to classify outcomes by defining which outcomes are of interest. This study uses the main KPI, the *final number of adopters*, to define the outcomes of interest, as it represents the long-term impact of interventions. More specifically, two types of outcomes are of interest in this study: (1) success of an intervention, where desired outcomes are defined as scenarios with a *final number of adopters* above the 75th percentile of this intervention, and (2) failure of an intervention, where undesired outcomes are defined as scenarios with a *final number of adopters* below the 25th percentile. The second step involves mapping the outcomes of interest to multi-dimensional "boxes" in the uncertainty space. The boxes are characterized by one or more parameter ranges, depicted as blue edges in figure 9.4. Parameters not included in the set describing the limits of the boxes remain unconstrained. The last step is to develop scenario narratives by interpreting each box as a scenario. Appendix G contains more details on the PRIM algorithm.

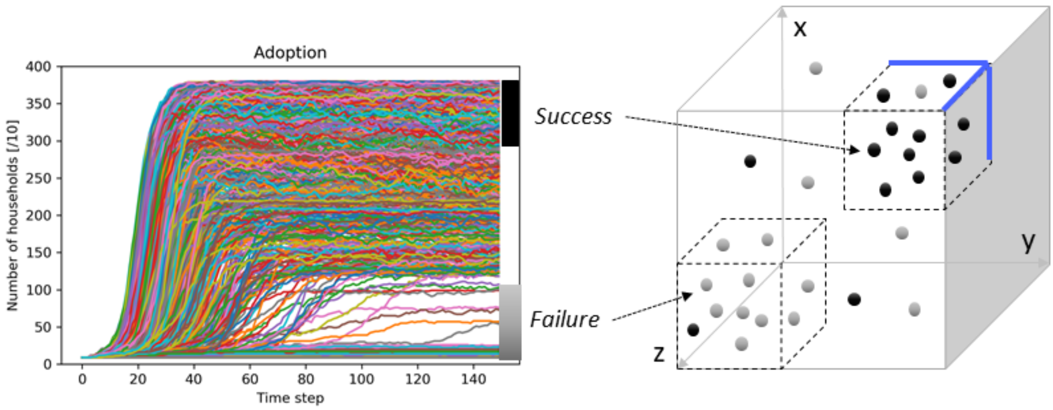


Figure 9.4: Mapping model outcomes to sub-spaces in the uncertainty space using the PRIM algorithm adapted from Greeven et al. (2016)

9.3.1 PRIM set-up

The scenario discovery phase includes the sample of scenarios without shocks, as well as the sample including the shocks. First, scenarios leading to the success of cash-transfer-only interventions are analysed. This allows to understand what are favorable circumstances, under which solely financial assistance can lead to the diffusion of clean cooking practices. Second, circumstances that lead to the success of both integrated intervention under shocks are analysed. Third, the scenarios leading to the failure of the integrated cash- and voucher-based interventions under shocks are analysed.

Table 9.1 shows the set-up used in this study to apply PRIM. The outcome subset describes the outcomes of interest in terms of failure or success, as defined in the previous section. The density threshold is an additional input parameter for the algorithm which determines the required density of a sub-space. For instance, for an uncertainty sub-space to be found by the algorithm at least 80 % of outcomes within the sub-space have to be of interest. Peel alpha is a parameter controlling the peeling stage, which basically determines the size of grid for finding uncertain parameter ranges.

Scenarios	Outcome subset	Density threshold	Peel alpha
I1 excl. shocks	above 75th percentile	0.8	0.1
I4 incl. shocks	above 75th percentile	0.8	0.1
I8 incl. shocks	above 75th percentile	0.8	0.2
I4 incl. shocks	below 25th percentile	0.8	0.1
I8 incl. shocks	below 25th percentile	0.8	0.1

Table 9.1: PRIM set-up

9.3.2 PRIM results

Figures 9.5 and 9.6 present the parameter ranges for the uncertainties identified by the PRIM algorithm. Figure 9.5 indicates the set of parameter ranges describing the sub-space which corresponds to success of the cash-transfer-only intervention. Figures 9.6a and 9.6b show the set of parameter ranges for success and failure of the integrated cash-based intervention. Figures 9.6c and 9.6d display the set of parameter ranges for success and failure of the integrated voucher-based intervention, respectively. Each combination of parameter ranges describes a sub-space in the uncertainty space. The meaning of the parameter ranges is discussed in the next section.

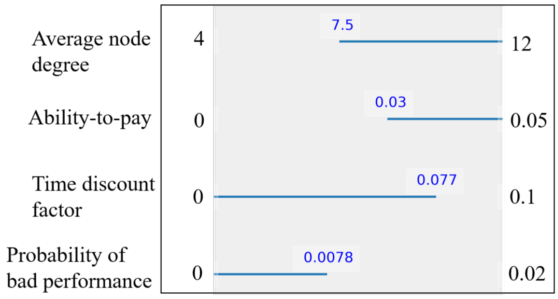


Figure 9.5: Circumstances for success of cash-transfer-only intervention. Success defined as final number of adopters above 75th percentile. Parameter ranges obtained by PRIM algorithm.

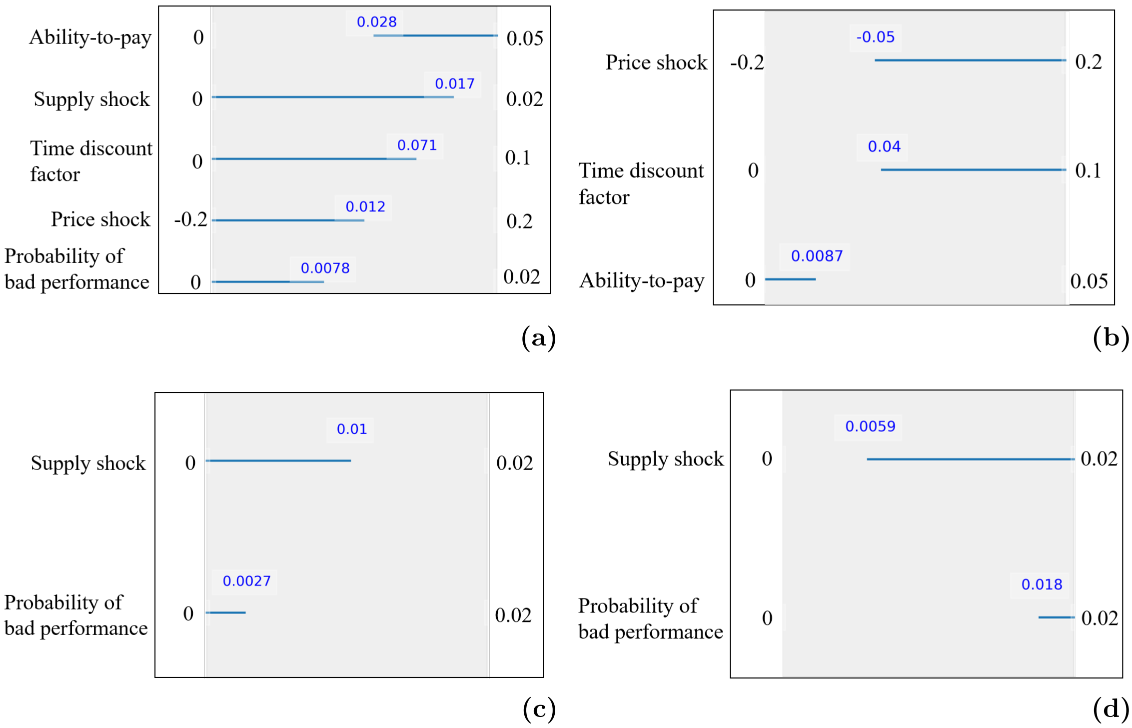


Figure 9.6: Circumstances for success and failure of integrated interventions. Success defined as final number of adopters above 75th percentile, failure defined as final number of adopters below 25th percentile. (a) Success of integrated cash-based, (b) failure of integrated cash-based, (c) success of integrated voucher-based, (d) failure of integrated voucher-based intervention. Parameter ranges obtained by PRIM algorithm.

9.3.3 Scenario narratives

In this section, the parameter ranges indicated by the PRIM results are translated into scenario narratives. First, the circumstances for success of the cash-transfer-only intervention are discussed. Second, the circumstances for success and failure of integrated cash-based and voucher-based interventions are elaborated on.

Circumstances for success of cash-transfer-only intervention

The model results suggest that interventions relying only on cash transfers fail in most of the scenarios to create high levels of adoption, but they do succeed in a small number of scenarios. Thus, the aim of the first part of the scenario discovery is to better understand what are the specific circumstances that lead to success of this intervention.

Figure 9.5 shows that the cash-based intervention is likely to succeed if the average node degree is above 8, the ability-to-pay is above 3 %, the time discount factor for traditional fuel cost is below 0.077 and the probability of performance issues is below 0.07 per week and household. These four conditions suggest the following: Cash-based interventions without any supporting interventions are mostly suitable for refugee settings, which are characterized by (1) a high density of houses, where households are socially connected to many others, and (2) people having the possibility to work and owning at least parts of their income in addition to receiving financial assistance. Moreover, for cash-based interventions to succeed, (3) the minimum purchase amount of clean fuels has to be comparable in size to the rations of traditional fuels being sold in the camp environment, and (4) the type of clean cooking fuels and stoves needs to be high quality and a good match with local cooking preferences. While the first two circumstances are related to the nature of the refugee setting, the latter two circumstances are a matter of how the interventions are designed.

(1) suggests that typical refugee camps where households live in shelters and houses agglomerated in a small area are a favorable environment for the diffusion of clean cooking practices, if the other three circumstances are met as well. One hypothesis to explain this finding is that in highly dense refugee camps information spreads faster and social effects occur sooner. Therefore, if there are little quality concerns about the clean cooking fuels and people have sufficient money to afford them, diffusion is likely to succeed in dense social networks in refugee camps. In contrast, in refugee settings, where households are spread over a large area and barely in touch with each other, cash transfer interventions are likely to fail.

(2) suggests that refugee settings which are subject to relaxed work policies by the host country government are better suited for cash-based interventions. The ability-to-pay parameter in this study refers to the percentage of income that households are able to pay *more* on fuels as compared to their current spending on traditional fuels. Thus, the meaning of this parameter is not necessarily that households need to have a higher income to afford clean fuels, but rather it refers to how people perceive the benefits of clean cooking in monetary terms. For instance, as mentioned by one interviewee, if people carry out income-generating activities, they value time savings from clean cooking more than if they do not use the time to generate income.

If the first two circumstances are given in a particular refugee setting, the design of the intervention is the crucial success factor. In particular, (3) suggests that the minimum purchase amount of the clean fuel needs to be comparable to the fuel alternatives, so that the time preferences do not play a major role in the purchase decisions. This is a drawback for LPG, where new gas is purchased by filling entire cylinders. A possibility would be to adapt the payment mechanism for LPG in a way where the payment is split into weekly amounts instead of monthly. For other clean fuels such as pellets, reducing the minimum purchase amount to smaller rations appears more feasible. Moreover, (4) implies that performance issues should be avoided as much as possible. While clean cooking systems such as the pellet-based system in the case study or LPG stoves often adhere to high quality standards, the match with local preferences remains an important issue. As found in the case study, the battery-powered stove did not match with the local cooking preferences where long-boiling beans are a staple food, which led to the spread of negative information about its performance, and many households not using pellets as their main cooking fuel for this reason. It may be impossible to avoid such performance issues and mismatch completely, but studies testing the fit with local preferences or the willingness to adapt cooking practices to the performance offered by the particular cooking system could support the success of cash-based interventions. Moreover, supporting information campaigns and maintenance activities could make sure to spread understanding on how to use the new cooking system in a way that allows to reap the benefits of clean cooking and offer technical support.

Circumstances for success of integrated interventions

After analysing the circumstances for success of cash-transfer-only interventions, this section addresses the success of the integrated interventions. The scenario sample includes shocks to understand the role of the entire uncertainty space. Especially the outcomes of the integrated cash-based integrated intervention are widely dispersed, which suggests that some scenarios represent more favorable circumstances than others.

Figure 9.6a shows that the integrated cash-based intervention is likely to succeed if the ability-to-pay is above 2.8 %, the time discount rate is below 0.071, the probability for performance issues is below 0.7 % per week and household, the probability for supply shocks is below 1.7 % per week and household, the price shock is negative. This suggests that integrated cash-based interventions are most suitable for refugee settings which are characterized by (1) relaxed work policies by host country governments, (2) minimum purchase amounts of clean fuels which are comparable to rations traditional fuels being sold, and (3) the type of clean cooking fuels and stoves needs to be high quality and a good match with local cooking preferences. These three conditions are similar to the ones found for the cash-transfer-only intervention. Moreover, two additional conditions are as follows, (4) a stable supply which covers the needs of all households, including potential newly arriving refugees, and none or rare supply shocks, and (5) negative price shocks which lead to a decrease in clean fuel prices. The latter condition could also arise through an increase in the price of traditional fuels. For instance, as mentioned by one interviewee, charcoal prices often fluctuate throughout the year as they are responsive to demand and supply dynamics. In the rainy season, charcoal prices often jump significantly due to shortage of supply. In line with conventional logic, the finding (5) of the scenario discovery suggests that sudden increases in charcoal prices (or decreases in clean fuel prices) foster the diffusion of clean cooking practices, thus rainy season could present a suitable time period to enter the refugee camp market for clean fuel suppliers.

As shown by figure 9.6c, for the integrated voucher-based intervention, only two parameter ranges seem to be critical for success. First, supply shocks have to be less probable than 1 % per week and household, and performance issues should occur particularly rarely, less than 0.27 % per week and household. This suggest that if (1) there is sufficient fuel availability for all households with rare supply delays, and (2) the performance standards of the specific clean cooking fuel and stove are high and matching with local preferences, voucher-based interventions with supporting information campaign and maintenance activities are likely to lead to high levels of adoption.

Circumstances for failure of integrated interventions

Although both integrated interventions appear successful in many scenarios, there are certain scenarios in which they are likely to fail, especially the integrated cash-based intervention. Therefore, in this last section of the scenario discovery, the circumstances for failure are discussed. Similar to the previous section, the scenario sample includes shocks.

Figure 9.6b shows that the integrated cash-based intervention is likely to fail if the ability-to-pay is below 0.87 %, if price shocks happen which increase the clean fuel price, and if the time discount rate is above 0.04. Price-related parameters appear more critical in the case of failure than performance issues or supply shocks. These three parameter ranges suggest the following: Integrated cash-based interventions are less suitable for refugee settings, which are characterized by (1) high aid-dependency and low percentage of refugee households working and receiving their own income, and (2) unstable prices of clean fuels where sudden increases are likely to happen. Moreover, if (3) the specific type of fuel is characterized by a large minimum purchase amount compared to traditional fuels, for instance, LPG cylinders being filled and sold on a monthly basis. If these three circumstances occur combined, cash-based interventions, even combined with information campaigns and maintenance activities, are likely to fail in creating and sustaining high levels of adoption.

Figure 9.6d shows the circumstances for the failure of the integrated voucher-based intervention. Similar to the success of this intervention, only two parameters appear to be relevant. The integrated voucher-based intervention is likely to fail, if supply shocks happen with a probability above 0.56 % per week and household, and the probability for performance issues is above 0.18 % per week and household. This suggests that integrated voucher-based interventions are most vulnerable in circumstances, which are characterized by (1) regular supply shocks or delays, which could occur in refugee settings surrounded by conflicts or frequent natural disasters, where sudden increases in refugee numbers are common. In such environments keeping sufficient stock of clean fuels to cover the needs of all long-term and newly arriving refugees is challenging. Moreover, integrated voucher-based interventions are most vulnerable in circumstances characterized by (2) high probability of performance issues, which is to be expected and is in line with the high percentage of failures of clean cooking programs. This finding suggests that voucher-based interventions supported by information campaigns and maintenance activities are less vulnerable to price-related factors as they reduce the economic barrier, but their failure remains possible - if the fuel supply is unstable and if the performance of fuel and stove does not satisfy the users.

9.4 Conclusion

This chapter builds on the experimentation phase of this study, by analysing and interpreting the model results. First, the model is validated based on literature and on empirical findings. Subsequently, the performance of interventions is further analysed in terms of robustness, timeliness, long-term impact, and trade-offs are determined. Finally, scenario discovery is applied to map outcomes of interest to sub-spaces in the uncertainty space. Interpreting the parameter ranges of the sub-spaces allowed to identify circumstances for success of the cash-only intervention and for success and failure of both integrated interventions. Identified circumstances concern the nature of refugee settings and the design of interventions. By improving the understanding on which circumstances lead to which outcome in the wide spread of model results, scenario discovery provided insights for generalization of the outcomes of this study.

Chapter 10

Discussion

This chapter discusses the outcomes of the previous chapters and reflects on the limitations to this study. In the previous chapters a method was developed to capture social interactions within social networks, human decision-making behaviour and deep uncertainties, to analyse the effect of market-based clean cooking interventions in refugee camps and identify circumstances for success and failure of interventions. A conceptual model was formulated based on a case study of a Rwandan refugee camp and innovation diffusion theory and implemented by combining agent-based modelling and exploratory modelling techniques.

This chapter provides a critical perspective on the outcomes of this study. First, the limitations to this study are reflected upon by discussing critical assumptions, addressing the limitations specific to the model and by reflecting on the research approach. Second, the implications of the two robustness metrics defined by this study are discussed. Lastly, this chapter concludes with formulating implications of the findings for policy makers.

10.1 Limitations to this study

Naturally, this study has several limitations due to simplifications that had to be made and due to the research approach chosen. Thus, before reflecting on the implications for policy makers, this section addresses the main limitations of this study. First, critical assumptions are discussed, subsequently the limitations specific to the model are addressed, and finally the research approach is reflected upon.

10.1.1 Critical assumptions

First, the main assumption of this study is to view the diffusion of clean cooking practices as a social process, where social influences have a major impact on people's adoption decisions. Social influences considered in this study are social conformity and information exchange between peers. This assumption is made based the observations from the case study as well as on the literature review. Although there is a number of studies which provide evidence for the social influences in the diffusion of clean cooking practices, there is no data which confirms the social impact on people's adoption decisions in the particular case of Kigeme camp nor in other refugee settings. However, the assumption that social influences exist and act as a driver or barrier in the diffusion process, allows to focus on the mechanisms how the influences occur and how they can be directed towards amplifying the diffusion process instead of hindering it. Moreover, market-based interventions aim to provide refugees with purchasing power to become independent costumers instead of dependent beneficiaries. With this objective in mind, the assumption that clean cooking fuels are simply a new product, a new practice, which as most other new products is diffused in a population by word-of-mouth and social conformity effects appears reasonable. Though in reality, refugee settings often differ significantly from other markets, being subject to additional regulations and policies around humanitarian work.

Second, refugee camps are viewed as a closed social system. Social interactions with host communities are not included in this study, but are certainly of relevance in protracted crises, where both refugee and host populations have lived next to each other for many years. Especially, if one considers the cooking fuel market, there are often strong interdependencies between host communities, who sell charcoal and wood, and refugees who often represent a large customer base for charcoal and wood sellers. Thus, the assumption that refugee camps are a closed social system has two main caveats. First, by making this assumption, the impact of the diffusion of clean cooking practices on local charcoal and wood sellers and on their livelihoods is omitted in this study. In fact, this impact can represent a barrier for the implementation of clean cooking interventions, which rely on the acceptance and cooperation of host communities as well as refugees. Second, by defining the refugee camp as a closed social system, where social ties only exist between people from within the refugee population, the social influences that exist between host community members and refugees regarding cooking fuel and stove decisions are left out. For instance, in refugee settings where people frequently leave the camps, communicate with host community members, and observe local cooking practices, it is likely that similar social influences, information effects and conformity effects arise between people from the host communities and the refugee camp. Moreover, host communities often use the same types of cooking fuels and stoves, thus are exposed to the same health risk and environmental concerns as refugees. Therefore, as pointed out by one interviewee, rather than only focusing on refugee beneficiaries, clean cooking interventions should take a broader perspective and address the entire ecosystem consisting of refugee camps and host communities.

Third, this study assumes that there are only two fuel options: clean fuels and traditional fuels. The fact that most households use multiple fuel types and stoves at the same time, referred to as "stove stacking", is omitted by this assumption. This is an assumption which is often found in clean cooking literature, although other authors emphasize that it is a strong simplification which disregards the complexity of choices regarding cooking fuels and stoves, e.g. Kowsari and Zerriffi (2011). In this study, *adoption* is defined as using clean cooking fuels as main fuel type within a household. This definition of adoption implies that traditional fuels can still be in use to some extent. It further implies that people who are using clean cooking fuels as part of their fuel mix but not as their main fuel, are not considered adopters. This simplification was necessary in this study to analyse the introduction of clean cooking practices through the lens of innovation diffusion theory, by focusing on the social interactions and on the decision-making process rather than on the cooking practices. Further research is advised to analyse the more complex patterns of cooking practices.

Fourth, this study assumes that stoves are provided for free or for lease to refugee households. This assumption is made to direct the focus of the analysis towards the continuous uptake and use of clean fuels instead of the one-off decision to adopt stoves. Therefore, no sunk cost for stoves are considered, households can stop using clean fuels at any moment. One implication of this assumption is that humanitarian organizations or private companies have to invest financial resources in the provision of free stoves. This can either mean a risk for the private company, leading to little interest from the private sector to engage in refugee camp markets, or it can be a barrier for humanitarian organizations, whose budget is often limited. Moreover, especially in light of investments in stoves, sharing of responsibilities between humanitarian organizations and private sector actors can represent a barrier to the success of market-based interventions, such as in the case study. By taking the assumption of free stove provision, this study neglects aspects at the implementation-level which are relevant for humanitarian decision-makers and practitioners, but out of the scope of this study.

10.1.2 Model limitations

Next, the limitations specific to the model are discussed. Generally, it is important to highlight that the model is only a highly stylized representation of social interactions and the human decision-making process. At best, the model outcomes can help to identify the general direction of possible effects, as well as identify critical uncertain factors to consider. ABM research has often been criticized for lack of validation and empirical grounding (Zhang & Vorobeychik, 2019). Likewise, this study is based on innovation diffusion theory, but is limited in terms of empirical data and could only be partially validated in quantitative terms. Furthermore, there are various specific limitations to the model developed by this study, the most important ones are discussed in the following.

First, the structure of the social networks is initialized at the start of the simulation run and is limited to two parameters: the *average node degree* and the *probability of rewiring*. Although small-world networks are often used in literature to represent social networks (Kiesling et al., 2012), they have limited capacity to capture the complexities of real social networks. More importantly, keeping the social network structure constant throughout the simulation time is a drastic simplification in light of constantly evolving social ties. It is also assumed that the number of agents remains constant, which is in fact unrealistic in refugee settings, where sudden inflows and outflows of refugees are common. This assumption had to be made, as the high computational time of creating new social networks after population shocks during the simulation time reduces the number of possible scenarios for exploration significantly. For this reason, a trade-off had to be made which involves keeping the number of agents constant, and only considering population shocks indirectly by accounting for supply shocks and price shocks which could be caused by sudden inflows of refugees. Furthermore, in the social networks no correlations between social ties, adopter category or income are considered. This is also a simplification as real social networks are not only created based on random processes, but often include correlations, e.g. people with the same income level are more likely to be connected to each other.

Second, communication is modelled as a one-way process. The households in the adoption and rejection stages send out information to potential adopters who only act as receivers. This simplified representation of communication is chosen because the information flow from people who have experience with the product to people who are considering its adoption is viewed as most influential. However, in innovation diffusion, not only adopters (and those who used to be adopters) share their experiences with others, but also non-adopters can take a prominent role in spreading information as shown by other studies, e.g. Duflo, Abhijit, Chandrasekhar, and Jackson (2012) on the diffusion of micro-finance.

Third, the utility function representing the satisfaction level of adopters is limited to three partial utilities, which take values between one and zero, and all count equally to the total utility value. In addition, the performance utility is a highly aggregated factor, which combines ease of use, speed of cooking, health benefits, cleanliness, and other performance factors. This model formulation does not allow to compare different types of clean cooking systems, for instance pellet-based systems versus LPG, since technology attributes are not explicitly included in the model.

Fourth, as found in the empirical validation of the model, in the majority of scenarios the adoption curves exceed the maximum adoption level from the case study. The two main input parameters restricting the adoption maximum are the *probability of bad performance* and the *ability-to-pay*. Overshoot suggests that for either one or both parameters, the upper (lower) range was too low (high) in the experiments. Moreover, not only the parameter range but also the speed of the information flows through the social network in the model can be an explanation for the overshoot. If the negative information flows too slowly through the network, the influence on agents' decisions is delayed, thus the maximum adoption level is not sensitive enough to the probability of bad experience. In the model, negative information is double counted in the information pool of agents to increase the influence of negative information. However, if agents receive positive information and are not restrained by other factors, it is likely that they adopt too soon for negative information to reach them. Reducing the decision frequency can increase sensitivity of the maximum to performance issues, though this also delays the overall diffusion dynamics.

Fifth, the economic barrier in the model does only lead to significant differences among agents with different incomes for a small range of parameters. The economic barrier is formulated as a function of the clean fuel cost, the time-discounted traditional fuel cost, the ability-to-pay and the household income. As the ability-to-pay describes the percentage of the income households are able to pay more for fuel compared to their current fuel spending, which takes a value between 0 and 5 %, the marginal difference between households with higher incomes and the ones with lower incomes is small. Thus, in many scenarios, either most agents are able to afford clean fuel cost, or most are not.

Sixth, agent heterogeneity is limited to adopter group and income. Different household sizes are not considered in the model. All agents represent 10 households and each household consists of 5 people, which is the average household size in the case study. Moreover, different decision strategies are formulated to represent structural uncertainties in the model, however, potential correlations between adopter group and decision strategy are not considered.

Furthermore, prices and supply are exogenous in the model. There is no feedback effect from increasing adoption levels to prices nor to supply availability.

Moreover, only a limited number and complexity of interventions are included in the model. The interventions are defined based on fixed lever parameters and are not adaptive to evolving adoption levels over time. Moreover, the model does not include the external effect of interventions. For instance, providing cash transfers or vouchers for fuel can already raise awareness on the availability of clean fuels on the camp market. Thus, agents would initially be in the second stage in the model.

Lastly, the model only captures three KPIs, the long-term impact, timeliness, and robustness. Thus, no cost or cost-effectiveness considerations are included in the model. This makes it difficult to understand trade-offs between interventions from the model results only and to evaluate different interventions in a comprehensive way.

10.1.3 Reflection on the research approach

The research approach used in this study integrates three different research approaches. Based on a case study, an agent-based model is developed and combined with exploratory modelling techniques, to simulate the effect of market-based interventions under a wide range of scenarios, and to apply scenario discovery. In this section, the combined agent-based exploratory modelling approach will be discussed first, followed by a discussion of the exploratory approach used for the case study.

Agent-based exploratory modelling

Whether the approach is considered a suitable for the problem addressed in this study depends on how the purpose of the study is defined. As found in the literature review, agent-based modelling has been widely applied in innovation diffusion studies. While some of these studies are empirically driven and aim at providing future predictions, e.g. Rai and Robinson (2015), others are theoretically-grounded and aim at exploring the general direction of effects, e.g. Sopha et al. (2011). MacCarty and Pakravan (2019) were the first to apply the agent-based modelling approach to the diffusion of clean cooking practices in low-income countries and to prove that it can provide insights. Their model is based on the Theory of Planned Behavior and they use survey data as input. Nevertheless, predictive capacity of their model is limited.

It is clear that the purpose of this study is not to provide accurate quantitative predictions. If that was the case, the agent-based modelling approach would not be suitable given the limited availability of data. Rather, this study aims at improving the understanding of adoption barriers for clean cooking practices and the possible effect of market-based interventions considering both social interactions and human decision-making behaviour. The first step in the modelling process was to conceptualize the social interactions and the decision-making process. Moreover, the conceptualization phase includes the definition of diffusion as an emergent behaviour, the result of numerous micro-level and meso-level social interactions, as well as repeated individual decisions. Additionally, the agent-based modelling approach allowed to incorporate heterogeneous adopter categories and decision strategies.

Therefore, a main outcome of this study is not only to provide an indication of the effect of market-based interventions, but using the agent-based modelling approach allowed to develop a conceptual model of the diffusion as an emergent and path-dependent process, the social mechanisms driving adoption, including information exchange and social conformity, and the role of heterogeneous adopters. Using those concepts proved to add to the understanding of why clean cooking interventions often fail and do not achieve the expected adoption levels.

In this study, ABM is combined with exploratory modelling techniques, which has been done in several studies before. In fact, Hidayatno et al. (2020) propose an integrated agent-based modelling and exploratory modelling approach for model-based innovation diffusion analyses.

Exploratory modelling supports the systematic exploration of uncertainties, which proved to be beneficial in this study, where the diffusion model is highly path-dependent. Nevertheless, the number of scenarios and variables which can be considered in the experimentation was limited by computing power and limited research time. Therefore, choices had to be made about which variables to include as uncertainties and which ones to regard as fixed. Additionally, the ranges of uncertainties had to be defined, which limits the exploration capacity as well. Furthermore, the outcomes of the scenario discovery are used to inform interventions in other refugee settings. This involves interpreting the meaning of the parameter ranges found by the scenario discovery algorithm, which is not always obvious. Finally, including structural uncertainties in the exploration can be highly beneficial to improve the validity of the results, but it also involves making choices on which structural uncertainties to include. Moreover, if all uncertainties are explored simultaneously, it becomes difficult to distinguish their effects, to understand the model behaviour, and to interpret the scenarios that lead to success or failure of interventions.

Therefore, in this study, exploratory modelling helps to embrace deep uncertainties in the path-dependent diffusion process and, in particular, scenario discovery provides a tool for inductive analysis of the path-dependencies. However, the modeller has to find a balance between necessary complexity and required simplicity due to practical constraints.

Case study

The case study provides the evidence base for the model developed in this study. Taking an exploratory approach, semi-structured interviews with humanitarian experts and private sector stakeholders involved in the market-based clean cooking intervention in Kigeme camp in Rwanda were conducted. The exploratory approach proved to be suitable for the case study, since it was largely unclear which topic would be raised by the interviewees and it offered the necessary flexibility to adjust the focus during the interviews. Moreover, the question about the main decision factors also allowed to gather comparable qualitative data. The results from the interviews are highly observer-dependent, as each interviewee offered a different perspective on what are the most relevant barriers and drivers to the adoption and sustained use of clean cooking fuels in this case in his or her opinion. Synthesizing and analysing the issues raised during the interviews involved selecting certain aspects due to limited research time. Moreover, the focus of this study was not on providing a detailed analysis of the particular case of Kigeme, but rather to gain a general understanding of the decision-making process and potential adoption barriers for refugees regarding clean cooking practices. Therefore, the analysis is likely to contain research biases and lack certain aspects or depth. Moreover, findings from one particular case are likely not to be sufficient to draw general conclusions, especially as the context differs notably between different refugee settings. Further research is needed to conduct additional case studies.

Most importantly among all limitations, this study did not consult refugees themselves. The model conceptualization relies on the opinions of humanitarian experts and managers from the pellet company instead of the decision-makers, people living in Kigeme camp, themselves. Several interviewees mentioned that they simply do not know certain answers and that the answers they provided are based on their own opinions or anecdotal information, and not on scientific research. In-depth interviews with cooks and decision-makers within refugee households are needed to further improve the understanding about the barriers to the adoption and sustained use of clean fuels from the perspective of the people who use them. Moreover, survey data is needed to fill in the lack of input data for the model and to add quantitative insights on what people value most when choosing cooking fuels and stoves, and what is needed to bring about sustainable transition.

It can be concluded that the exploratory approach chosen for the case study interviews was suitable for the scope of this study, though it has several limitations including the inability to collect quantitative data. Nevertheless, it supports the conceptualization of the model notably and provides valuable practical insights from a case, which is an important real-world experiment to learn from.

10.2 Measuring robustness

This study proposes two robustness metrics to evaluate the effect of interventions across various scenarios. The threshold-based robustness metric indicates the percentage of scenarios in which adoption levels are above 60 % at the end of the simulation. The gradient-based robustness metrics is defined as the gradient of the mean of the adoption curves with an adoption level above 60 %. Naturally, both metrics lead to different outcomes in quantitative terms. This section discusses whether the choice of robustness metric leads to different implications and how the two metrics interact in measuring robustness.

In order to compare the implications of both robustness metrics, table 10.1 summarizes the outcomes for all three sets of experiments. The first column shows the relative order of the eight interventions in terms of the robustness scores for the threshold-based metric R_θ and for the gradient-based metric R_∇. The second column shows the absolute changes in the robustness scores for set 2 which includes shocks compared to set 1 for interventions 4 and 8. Similarly, the third column shows the absolute changes of the robustness scores in set 3 which includes different structural decision strategies compared to set 1 for interventions 4 and 8. Here, the changes compared to the base sample of scenarios are analysed individually per intervention, as the absolute changes in the robustness metric induced by shocks or structural changes are of interest rather than the relative order.

	Relative order Outcomes set 1	Absolute changes Outcomes set 2	Absolute changes Outcomes set 3
R_θ	$I8 > I7 > I4 > I3$ $> I6 > I5 > I2 > I1$	I4: $\searrow$ 11.13% I8: $\searrow$ 2.96%	I4: $\searrow$ 8.3% I8: $\searrow$ 1.67%
R_∇	$I8 > I4 > I7 > I3$ $> I1 > I2 > I6 > I5$	I4: $\searrow$ 0.22 I8: $\rightarrow$ 0.0	I4: $\searrow$ 0.01 I8: $\searrow$ 0.06

Table 10.1: Comparison of robustness metrics based on outcomes

Several conclusions can be drawn from this table. First, the two robustness metrics lead to different rankings of the eight interventions in terms of robustness. Nevertheless, the integrated voucher-based intervention (I8) scores best irrespective of the metric used. Moreover, the four most robust interventions, being either cash transfers or vouchers combined with increased maintenance capacity, are the same for both metrics. Only the relative order within the group of the first four and last four changes depending on the robustness metric. For instance, both voucher-based interventions without maintenance activities (I5 and I6) score last in terms of the gradient-based robustness metric, even lower than the cash-based interventions.

Second, the impact of shocks on robustness is comparable for both metrics. For the integrated cash-based intervention (I4) a drastic decrease in robustness is found in terms of the percentage of scenarios above 60 % adoption ratio R_θ as well as regarding the tendency for decreasing adoption levels (R_∇). For the integrated voucher-based intervention the threshold-based robustness metric decreases slightly, while the gradient-based metric remains unchanged. Thus, the findings for both metrics are aligned, and suggest that the integrated cash-based intervention is vulnerable to shocks, whereas the integrated voucher-based intervention is less vulnerable.

Third, the impact of structural changes in the decision strategies on robustness *depends* on which robustness metric is used. The threshold-based robustness metric for the integrated cash-based intervention appears to be significantly reduced by changes in the decision strategy. However, the gradient-based metric for the same intervention is only slightly reduced. For the voucher-based intervention, it is even more evident that the threshold-based metric is decreased by less than 2 %, while the gradient-based metric shows a drastic decrease in robustness. As a result, if robustness is measured by the gradient-based metric in this case the voucher-based metric is less robust than the cash-based intervention.

Thus, the choice of robustness metric results in different outcomes regarding the impact of structural changes in the model on the performance of interventions. Nevertheless, for the comparison of all eight interventions and the impact of shocks, both metrics lead to similar qualitative implications, despite small differences in the ranking of interventions.

Is one robustness metric sufficient or are two robustness metrics necessary? It is evident that the threshold-based robustness metric is strongly affected by the choice of the simulation length. In this study, the simulation length is set to 150 time steps which serves as a benchmark for comparison of the performance of different interventions. However, observing the ratio of adoption at the end of the simulation and assessing the robustness based on the threshold of 60 % appears to be a rather arbitrary definition. For any other simulation length, the threshold-based robustness metric is likely to take on different values. It reflects the performance of interventions across various scenarios at a specific moment in time, long after the start of the implementation. Though it does not reflect whether the adoption levels remain stable or decrease over time.

Therefore, the gradient-based robustness metric is proposed to shed light on the future tendency of the adoption levels. The gradient indicates whether adoption levels have stabilised or are decreasing at the moment of measurement. This is an important metric to account for the differences between scenarios which lead to adoption ratios above 60 % but in fact decreasing adoption curves, and those that lead to stable adoption levels. Ultimately, creating stable adoption levels is the main objective when designing and implementing market-based clean cooking interventions. On the other hand, evaluating the robustness of interventions solely by calculating the gradient of the adoption curves is not sufficient either, as it lacks the information about the share of scenarios in which high adoption levels can be created, which is an equally important insight for decision-makers.

Therefore, it can be concluded that both robustness metrics are individually *insufficient* for evaluating robustness of market-based clean cooking interventions in this study. The threshold-based metric and the gradient-based metric are *necessary* to (a) assess the performance of interventions across a large sample of scenarios, and (b) reflect the future tendency of adoption levels to remain stable or to decrease. Robustness is thereby defined by high performance across many scenarios and the ability to sustain the positive impact beyond the specific moment of measuring performance.

10.3 Implications of the findings

The discussion of the critical assumptions, the model limitations and the suitability of the research approach pointed out limitations to this study. Nevertheless, the findings of this study have important implications for future market-based clean cooking interventions, which are formulated in this section. The aim of this section is to provide specific policy recommendations intended for humanitarian policy makers, humanitarian practitioners, and private actors engaged in the supply of clean cooking fuels in refugee settings. First, recommendations concerning both cash-based and voucher-based interventions are made based on the findings. Second, guidelines for the selection of the type of financial assistance for fuel are derived. Third, additional recommendations are made which need further research.

10.3.1 Policy recommendations

This study found that solely focusing on financial assistance is not sufficient to create widespread and sustained adoption of clean cooking practices, which is key to reduce health risks and environmental damage from cooking with traditional fuels significantly and over the long-term. Given the variety of adoption barriers for clean cooking practices and strong competition from traditional fuels, there is a need for an integrated intervention.

First, regardless of the type of financial assistance (cash transfers or vouchers), supporting information campaigns and maintenance activities are critical for market-based clean cooking interventions to enable robust, timely, and long-term impact. Despite limited financial resources, humanitarian policy makers are encouraged to allocate sufficient budget for supporting interventions in the planning of interventions.

Second, social influences are a powerful driver for the adoption of clean cooking practices but can easily become an important barrier. A minority of satisfied early adopters spreading favorable information is likely to induce self-propelling adoption levels. On the other hand, a minority of dissatisfied adopters can prevent others from following and lead to failure of clean cooking interventions. To avoid the spread of negative information, the following is advised: (1) Select a high-quality clean cooking system which is known to match well with local cooking preferences, to be tested by assessments prior to the start of the implementation, (2) offer technical support and maintenance throughout and beyond the program period.

Third, information campaigns are recommended to increase the timeliness of widespread adoption of clean cooking practices, which is especially relevant for refugee settings characterized by pressure from host governments to act fast to halt deforestation, or private actors relying on the demand by refugee costumers for their products. Information campaigns are advised to point out the hidden cost of traditional cooking practices: the environmental impact, the health impact, and the financial cost over time by purchasing small amounts of charcoal and wood. This is indented to challenge current cooking practices, initiate discussions within the refugee community, and create a favorable social environment towards changes in cooking habits.

Furthermore, as suggested by the strong path-dependencies, interventions have to be tailored to the specific context. The success or failure of interventions depends on the nature of the refugee setting and on the specific design of the intervention. One key decision to be made is the selection of the type of financial assistance. Figure 10.1 provides guidelines for the selection of either cash transfers or vouchers to assist clean fuel purchase, derived from the circumstances for the success of integrated interventions identified by this study and complemented by key practical considerations. The first three blocks summarize the prerequisites for successful market-based interventions: (1) Select a high-quality clean cooking system which matches well with local cooking preferences, (2) allocate sufficient budget for long-term technical support and maintenance, and (3) facilitate a stable local supply, accessible for all beneficiaries. If the local context does not allow for the facilitation of a stable local supply of clean fuels on or near the refugee camp market, in-kind distribution of clean fuels is advised.

The latter three question blocks support the selection between cash transfers and vouchers. If cash transfers are selected, special attention must be paid to the following: (1) The minimum purchase amounts for clean fuels should be comparable to traditional fuels, where possible, to avoid the barrier created by having to save money for monthly fuel purchases. For LPG cylinders, the payment should be split into smaller amounts. The calibration of such payments needs careful attention and comparison to other products sold in the specific context. (2) Regular, predictable and coordinated cash transfers are important to provide beneficiaries with the necessary financial certainty. The same advice is valid for vouchers that only cover small parts of the clean fuel cost.

Moreover, if cash transfers rather than vouchers are selected, policy makers should be aware of the trade-off that exists between potential benefits from cash transfers, such as reduced logistics or empowerment of beneficiaries, and robustness of the intervention in terms of creating high and sustained adoption levels. Alternatively, vouchers could be used as a transitional means to introduce clean cooking practices into refugee communities, familiarize people with them, and to enable a gradual transition towards cash transfers.

Lastly, monitoring and evaluation of interventions is recommended in order to increase the knowledge base and to allow for interventions to be adapted to changing circumstances.

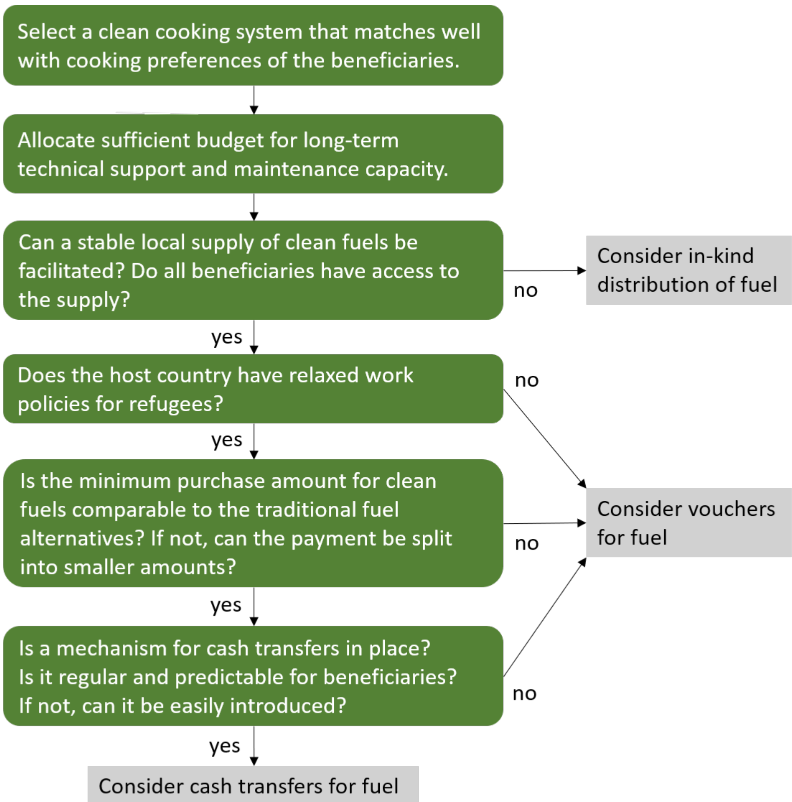


Figure 10.1: Guidelines for the selection of the type of assistance to introduce clean cooking fuels in refugee camps, derived from the findings of this study.

10.3.2 Recommendations which need further research

This section adds several recommendations based on the findings from the case study, which are not sufficiently analysed by this study, but should be considered in the design of market-based clean cooking interventions.

First, this study did not address the role of host communities for clean cooking interventions. Yet, rather than only focusing on refugee beneficiaries, policy makers are encouraged to consider the broader social system including the host communities. Further research is needed to inform inclusive market-based clean cooking interventions for both refugees and host communities.

Second, providing free stoves is a driver for the adoption of clean cooking fuels in refugee settings, as it removes the upfront cost barrier and attracts initial demand. Further research is advised to design a feasible solution for the provision of free stoves which minimizes the risk for private actors engaged in the refugee camp market as well as for humanitarian organizations.

Third, especially in light of financial investments, sharing of responsibilities between humanitarian organizations and private sector actors can represent a barrier for market-based interventions. Hence, effective communication and clear distribution of responsibilities between the implementing parties are critical. Developing an institutional framework could be beneficial to better inform the different roles for the actors involved in market-based clean cooking interventions.

10.4 Conclusion

This chapter discussed the limitations to this study by debating the critical assumptions, the limitations specific to the model, and by reflecting on the suitability of the research approach. Moreover, the implications and interactions of the two robustness metrics proposed by this study were discussed. It was is concluded that the threshold-based metric is necessary to assess the performance of interventions across many scenarios measured at a specific moment in time, and the gradient-based metric is necessary to reflect the future tendency of adoption levels to remain stable or decrease. The chapter further discussed the implications for policy makers based on the findings of this study by formulating recommendations for the design of market-based clean cooking interventions, by providing guidelines for the selection of the type of financial assistance, and by suggesting recommendations which require further research.

Chapter 11

Conclusion

This study began by illustrating the implications of the lack of energy access for refugees, focusing on the environmental impact and health risks due to the use of traditional cooking fuels. The objective of this study was to gain insights into the mechanisms and path-dependencies driving the adoption of clean cooking fuels in refugee camps, and to develop a method to analyse the effects of market-based clean cooking interventions under various scenarios. To this end, the study combined agent-based modelling with exploratory modelling techniques. In chapters 1 to 3 the problem was introduced, and relevant literature was discussed, which led to the research formulation. Chapter 4 to 9 provided answers to the six sub-research questions. Chapter 10 discussed the limitations to this study and the implications of the findings.

This chapter concludes this study by revisiting the sub-research questions, followed by providing the answer to the main research question. Subsequently, the scientific and societal contribution of this study will be discussed. Lastly, various directions for further research are suggested.

11.1 Revisiting the sub-research questions

In the first section of this chapter the sub-research questions guiding this study are revisited one by one. The first sub-question aimed to identify drivers and barriers for refugees to adopt and use clean cooking fuels in a Rwandan refugee camp. The second sub-question guided the conceptualization and formalization of the decision-making process of refugees and the social interactions that influence the diffusion process. The third sub-question aimed to identify interventions, uncertainties and key performance metrics. The fourth sub-question addressed the implementation of the ABM capturing the social interactions and individual behaviours relevant to the diffusion process. The fifth sub-question aimed at analysing the effects of interventions under various scenarios. Lastly, the sixth sub-question addressed the exploratory analysis and generalization of the model results.

Sub-question 1: What are the barriers and drivers for the adoption and sustained use of clean cooking fuels for people in Kigeme refugee camp in Rwanda?

The first sub-question aimed to identify the barriers and drivers to the adoption and sustained use of clean cooking fuels in a refugee camp in Rwanda. The Kigeme camp in Rwanda with around 20,000 Congolese refugees provided a specific context of a protracted crises, where a market-based intervention has been implemented with the aim to introduce clean cooking practices. Refugee households received cash transfers to purchase pellets (or briquettes) instead of wood and charcoal, but the intervention failed to sustain high demand for clean fuels. Semi-structured interviews with humanitarian experts and private sector stakeholders involved in the Rwanda case study were conducted to gain different perspectives on what are the most relevant barriers and drivers in their opinion. Synthesizing the issues raised during the interviews led to answering the first sub-question, as follows.

The main drivers for the adoption and sustained use of clean cooking fuels identified in the Rwanda case study are: (1) attractive performance factors of clean cooking systems, such as ease of use, time savings, health benefits, cleanliness and the possibility to cook indoors, (2) the free distribution of high-quality stoves by committing to buy a minimum amount of pellets per month, (3) positive peer influence including (a) the spread of information about the benefits of clean cooking and the availability of free stoves, and (b) conforming to the behaviour of others.

The main barriers for the adoption and sustained use of clean cooking fuels identified in the Rwanda case study are: (1) limited financial resources and strong competition from charcoal and firewood, (2) the peanut effect, which describes that people tend to prefer spending small amounts of money on charcoal or wood frequently, instead of raising money for a bigger monthly purchase of clean fuels, (3) unpredictability of cash transfers, which led to financial uncertainty among refugees, (4) negative peer influence, in particular the spread of information including negative experiences regarding e.g. difficulties in usage, the risk of damage to cooking materials, limited cooking time due to solar-powered batteries, (5) lack of familiarity compared to traditional cooking practices which are ingrained in cultural and social practices for generations, (6) the lack of effective communication between implementing parties.

Sub-question 2: How can a conceptual model of the diffusion of clean cooking practices in refugee camps be formulated?

(a) How can a conceptual model of the social interactions be formulated?

(b) How can a conceptual model of the adoption decision-making process be formulated?

Having identified the main barriers and drivers to the adoption of clean cooking fuels in the case of Rwanda, the next step was to conceptualize and formalize the diffusion process. This study views the diffusion of clean cooking practices as an emergent behaviour resulting from social interactions and individual decision-making. Therefore, answering the second research question involved conceptualizing and formalizing (a) the social interactions than influence the diffusion, and (b) the individual adoption decision-making process.

The model conceptualization and formalization draw from concepts from Diffusion of Innovation theory, complemented by state-of-the-art literature using ABM to analyse innovation diffusion, and synthesized with the empirically identified barriers and drivers from the case study. The model of the social interactions includes (1) the micro-level information effect, and (2) the meso-level conformity effect. The information effect represents direct word-of-mouth communications between people within social networks, while the conformity effect represents social norms and the likelihood of people to imitate common behaviour in their community.

The decision-making process involves five discrete stages: ignorance, awareness, decision, adoption, and rejection. Depending on their stage, agents perform different actions. Decisions to adopt or stop using clean fuels are taken in the decision stage, the adoption stage, and in the rejection stage to re-adopt. Thus, neither the adoption nor rejection stages are absorbing. Repeated decisions are modelled to capture the fact that every month households can decide again which type of fuel they prefer to use. Agents in the ignorance, awareness and decision stages receive WoM information from agents in the adoption and rejection stages. This information includes the simple notice about availability of clean fuels for agents in the ignorance stage, while agents in the awareness and decision stage receive WoM information about the (dis-)satisfaction level of adopters and rejecters. The satisfaction of adopters is calculated based on a utility function involving three factors - cost, performance, availability - which are based on the findings from the case study interviews. The initial adoption decision is based on one of four decision strategies, deliberating, imitating, cost-optimizing, and advice-seeking. Each one of the strategies puts most emphasis on (or two) of the adoption barriers: the social, economic, or information barrier. Adoption barriers are formalized based on threshold-models. Lastly, the model considers heterogeneity of agents by incorporating five different agent groups with different levels of risk aversion reflected by heterogeneous social and information thresholds, as well as heterogeneous household incomes.

Sub-question 3: How can the diffusion of clean cooking practices be conceptualized in terms of interventions, uncertainties, and KPIs?

The third sub-question aimed to structure the diffusion problem of this study in terms of the XLRM framework proposed by Lempert et al. (2003), whereby intervention levers ('L'), exogenous uncertain factors ('X'), and key performance metrics ('M') have been defined by reflecting on the case study and the literature. The relationships ('R') between system variables have been determined in the second sub-question.

Interventions in this study are based on one of the two types of financial assistance (cash transfers or vouchers) and complementary interventions. The following levers are considered in the model: (1) unconditional cash transfers, (2) vouchers, (3) information campaigns, (4) increased maintenance capacity.

Deep uncertainties relevant to this model-based study have been identified based on W. E. Walker and Bloemen (2019)'s framework. Deeply uncertain external factors include: price shocks in terms of magnitude and frequency, supply shocks, the time discount factor for traditional fuel cost, the ability-to-pay, the probability for adopters to experience bad performance, the average node degree in the social network, and the probability of rewiring. Deep uncertainties within the model structure include the distribution of decision strategies among agents, specified by the ratios of imitation, advice-seeking, and cost-optimizing. The ratio for deliberating is defined by the remaining percentage.

Three KPIs are specified by this study: long-term impact, timeliness, robustness. The long-term impact of interventions is measured by the final number of adopters at the end of the simulation run. The timeliness of interventions is defined by the time when the maximum adoption level is reached. The robustness of interventions is determined based on two metrics, the percentage of scenarios in which interventions succeed to reach adoption levels above 60 % of the population at the end of the simulation time, and the gradient of the mean of the adoption curves above 60 %, which reflects the trend of adoption levels beyond the simulation time.

Sub-question 4: How can the diffusion of clean cooking practices be implemented in an agent-based model?

The conceptualized and formalized model was implemented in an agent-based model, using Mesa in Python. The implementation involved specifying the timing of actions, parametrising the model variables, developing the user interface, and verifying the model.

The model runs in discrete time steps, where each time step a specified sequence of actions takes place. The agents' actions are specified depending on which stage they are in, defined in the second sub-question. The transition between stages is based on conditions, representing the different adoption barriers, which need to be overcome throughout the decision-making process. Price shocks are activated based on the price shock frequency, equidistantly distributed throughout the simulation time. Supply shocks happen probability-based for each agent individually. The total simulation period is set to 150 time steps.

The parametrisation is based on data from the Rwanda case study, on diffusion literature such as the distribution of adopter categories and the social thresholds, while the information thresholds are determined by inspecting model behaviour and modelling constraints. The remaining uncertain parameters are included as ranges in the XLRM framework to be explored in the experimentation. The diffusion through the social network is subsequently visualized by developing the user interface in Mesa. The user interface also includes sliders for the levers and key model parameters.

The verification included tracking of agent behaviour, running the model with only a small number of agents, extreme-condition testing and extensive code walkthrough. It was concluded that the model is implemented correctly and behaves as indented.

Sub-question 5: Based on the model, what are the effects of different market-based clean cooking interventions under various scenarios?

The fifth sub-question aimed at exploring the effects of cash- and voucher-based interventions under a wide range of scenarios. Analysing the performance metrics of the alternative interventions led to the following findings.

First, cash-based interventions without supporting interventions fail to attain and sustain high levels of adoption in most scenarios. Cash-based interventions supported by information campaigns fail in most cases as well. Increasing the maintenance capacity can improve the adoption levels for cash-based interventions significantly, although the spread in outcomes is large. Integrating cash transfers, information campaigns and maintenance activities leads to better results in most scenarios, but this integrated intervention remains vulnerable to price and supply shocks, and to structural changes in the model regarding the decision strategies.

Second, voucher-based interventions are found to be significantly more robust than cash-based interventions. Although without supporting interventions, voucher-based intervention also fail to attain and sustain high levels of adoption in most scenarios. Supporting information campaigns only improve the adoption levels marginally, but increased maintenance capacity leads to a significant improvement in terms of long-term impact and robustness. The integrated voucher-based intervention supported by information campaigns and maintenance activities leads to high adoption levels in almost all scenarios. Moreover, the integrated voucher-based intervention appears to be less vulnerable to shocks and structural changes in the model, though the latter lead to a slightly downward sloping trend in the adoption levels indicated by the gradient-based robustness metric.

Third, integrated cash-based and voucher-based interventions are significantly slower in reaching the maximum adoption level than if only financial assistance is provided. Information campaigns increase the speed of diffusion and lead to better timeliness of interventions.

Sub-question 6: How can the outcomes of this study be used to inform market-based clean cooking interventions in other refugee settings?

The final step was to translate the outcomes of this study into recommendations to inform market-based clean cooking interventions in other refugee settings. The answer to the previous sub-question already suggested which interventions perform well in terms of robustness, timeliness and long-term impact. Analysing and summarizing the model results led to the following recommendations:

In light of the highly dynamic and uncertain environments around refugee settings, voucher-based interventions are the recommended approach in terms of robustness. Cash-based interventions are likely to fail. Information campaigns are advised to increase the timeliness of the impact taking into effect, which is especially relevant for settings characterized by pressure from host governments to act fast to halt deforestation, or private actors relying on the demand for fuel. For both types of financial assistance, supporting information campaigns and maintenance activities are critical to create robust, timely and long-term impact.

To make informed recommendations for future interventions, it was crucial to better understand which specific scenarios lead to success or failure of interventions. Therefore, this study conducted an inductive analysis, by applying scenario discovery, which led to the identification of circumstances for success or failure for a subset of interventions. The identified circumstances are characteristics specific to the nature of the refugee setting, and the design of the intervention. The following findings are the result of the scenario discovery.

Cash-based interventions without any supporting measures have the potential to succeed in refugee settings characterized by (1) a high density of houses, (2) relaxed work policies for refugees by host country governments; and if the design of the intervention specifically considers (3) small minimum purchase amounts for clean fuels or, in the case of gas cylinders, time payments comparable to traditional fuel alternatives, (4) high-quality clean cooking systems and good match with local cooking preferences.

Integrated cash-based interventions supported by information campaigns and maintenance activities are suitable for refugee settings characterized by (1) relaxed work policies by host country governments, (2) stable supply of clean fuels, (3) frequent positive (negative) price shocks for traditional fuels (clean fuels), which implies that it is advised to start the implementation during the rainy season where charcoal and wood prices are high; and if the design of the intervention specifically considers (3) small minimum purchase amounts for clean fuels or time payments comparable to traditional fuel alternatives, (4) high-quality clean cooking systems and good match with local cooking preferences.

Integrated cash-based interventions are *not* recommended for refugee settings characterized by (1) low percentage of refugee households working and receiving their own income, and (2) unstable prices of clean fuels where positive price shocks are likely to happen; and if (3) the design of intervention involves large minimum purchase amounts compared to traditional fuels.

Lastly, integrated voucher-based interventions supported by information campaign and maintenance activities are successful under most circumstances, but their failure remains possible - if (1) the fuel supply is unstable, and if (2) the performance of fuel and stove does not satisfy the users.

11.2 Answering the main research question

Answering the six sub-questions guided this study to provide an answer to the main research question, as follows:

How can Agent-Based Modelling and Exploratory Modelling be combined to analyse the effect of market-based clean cooking interventions in refugee camps?

The focus of this study is on market-based interventions to deliver clean cooking fuels in refugee camps. The outcomes of market-based interventions are highly dependent on whether beneficiaries adopt and continuously use the products. Clean cooking interventions, however, commonly fail to achieve high and sustained adoption levels due to various adoption barriers, a phenomenon studied in innovation diffusion research. Therefore, this study analysed the adoption of clean cooking fuels in refugee camps through the lens of innovation diffusion theory.

Grounded in a case study of a Rwandan refugee camp using semi-structured interviews, this study developed an agent-based model to capture social interactions within social networks, human decision-making behaviour, and adopter heterogeneity. The agent-based model was combined with exploratory modelling, which supports the systematic exploration of deep uncertainties regarding external factors, model parameters and within the model structure. Exploratory modelling proved to be especially beneficial as the diffusion process is highly path-dependent. Combining agent-based modelling and exploratory modelling techniques allowed to simulate the effects of cash- and voucher-based interventions under a wide range of scenarios. Lastly, scenario discovery was applied to identify circumstances that lead to success or failure of interventions. Mapping the outcomes of interest to scenarios was an important step to gain insights into the path-dependencies driving the adoption, and thus to be able to translate the findings into recommendations to contribute to informing market-based clean cooking interventions in refugee settings.

11.3 Scientific contribution

The existing research on the issue of clean cooking in refugee settings is limited, largely empirical, and case-study driven. This study contributes to the current state of knowledge by proposing a method combining agent-based modelling and exploratory modelling techniques to analyse the impact of different interventions on the adoption of clean cooking fuels in refugee camps. Thereby, scientific contributions to three streams of literature are made, including clean cooking literature, agent-based modelling of innovation diffusion, and exploratory modelling literature.

First, by conducting a case study of a Rwandan refugee camp using semi-structured interviews with humanitarian experts and private sector stakeholders, this study adds to the limited scientific knowledge on the drivers and barriers for the adoption and sustained use of clean cooking fuels in the context of refugee camps and provides insights into the decision-making behaviour of refugees when choosing their cooking fuels.

Second, by synthesizing the empirical findings from the case study with existing innovation diffusion theory, this study develops an agent-based model. Using the agent-based modelling approach offers new conceptual insights into the social and behavioural mechanisms driving adoption and diffusion of clean cooking practices within a refugee camp, and into the role of heterogeneous adopters. MacCarty and Pakravan (2019) have been the first and only to apply agent-based modelling in the clean cooking field, to analyse the adoption of fuel-efficient stoves in a community in Uganda, using the Theory of Planned Behavior and utility maximization theory to formalize their model. Hence, this study contributes to the limited application of ABM in the clean cooking field by developing an alternative conceptual model, using an alternative empirical grounding, and focusing on the sustained adoption of clean fuels rather than on stoves. Moreover, this study puts particular emphasis on the social interactions by including micro-level word-of-mouth information flows within social networks and the macro-level social conformity effect. Additionally, instead of modelling adoption as an absorbing stage as found in most literature on innovation diffusion, this study conceptualizes adoption as a transitional stage before rejection which is not definitive either. Agents can reevaluate their decisions and decide to adopt or reject again, which is an important conceptual choice to be able to analyse the long-term impact of interventions.

Third, by combining agent-based modelling with exploratory modelling techniques, this study embraces deep uncertainties regarding external factors and the structure of the model and proposes a method for the systematic exploration of market-based clean cooking interventions. By simulating the effects of cash- and voucher-based interventions under a wide range of scenarios and conducting an inductive analysis of the model outcomes using scenario discovery, circumstances for the success and failure of interventions can be identified. In this way, this study offers comprehensive insights into the mechanisms and path-dependencies driving the adoption of clean cooking fuels in refugee camps.

11.4 Societal contribution

In light of the worsening environmental impact and health risks associated with the use of traditional cooking fuels in refugee settings, humanitarian policy makers are increasingly realizing that cooking fuel should be treated as a basic necessity in humanitarian response. Market-based interventions based on either cash transfers or vouchers are emerging with the aim to deliver clean cooking fuels by engaging local fuel suppliers. Policy initiatives such as the Global Plan of Action for Sustainable Energy Solutions in Situations of Displacement (GPA) launched by a number of UN agencies and NGOs are pushing for the "safe access to affordable, reliable, sustainable and modern energy services for all displaced people by 2030" (UNITAR, 2018). However, over the past decades, attempts to introduce clean cooking practices around the world have often failed due to various adoption barriers, which implies that scarce financial resources have been invested in vain. Against this backdrop, this study contributes to informing market-based clean cooking interventions in refugee settings. The outcomes of this study are intended to inform humanitarian policy makers, humanitarian practitioners, and private sector actors engaged in the supply of clean cooking fuels in refugee camps. Moreover, the outcomes of this study are not only relevant for the energy sector but could potentially also be applied to other sectors within humanitarian response, where products are diffused using market-based approaches, for instance in the WASH sector.

This study highlights the role of social influences for the success or failure of market-based interventions. Only a small number of adopters, if dissatisfied, can prevent widespread adoption and lead to failure of interventions. By conducting a case study of a Rwandan refugee camp, important practical insights could be gained to improve the understanding about the barriers to the adoption and sustained used of clean cooking fuels, and to better tailor interventions to the refugees' needs. Besides peer influence, competition from cheaper, small-bundled and familiar traditional fuels is a major barrier.

This study offers several policy recommendations. A key recommendation includes the need for an integrated intervention. Allocating budget for supporting information campaigns and maintenance activities is critical for cash- and voucher-based interventions to create robust, timely and long-term impact on the adoption of clean cooking fuels in refugee camps. Moreover, despite the efforts from humanitarian policy makers to shift towards cash transfers as they may involve less logistics, be more cost-efficient, or offer a means for empowerment of beneficiaries, this study finds that voucher-based interventions are significantly more robust than cash-based interventions in terms of creating high and sustained adoption levels. Thereby, some of the trade-offs policy makers should be aware of when making decisions on the type of financial assistance are highlighted. Guidelines for the selection of the type of financial assistance for fuel purchase are provided, which offer a practical tool to support decision-making.

11.5 Suggestions for further research

This study developed a method to address the diffusion of clean cooking in refugee settings, a topic which has been poorly covered by research yet. Since the study had to be completed within a limited time frame, many simplifications had to be made in order to focus on the most relevant aspects. Naturally, there are various directions which can be suggested for further research.

First, further research is advised to analyse the role of early adopters, well-respected community members, in the diffusion process and how they can be integrated in market-based interventions. This study considers the role of early adopters by adding weight to their social influence and incorporating lower risk aversion in terms of reduced social and information thresholds, but does not consider higher numbers of connections within social networks for early adopters nor the role they can play in interventions. As well-respected community members, early adopters have a high potential to influence their peers, which can both hinder and accelerate the diffusion of clean cooking practices within refugee communities.

Second, future work is suggested to study the impact of different social network structures on the model behaviour, compared to small-world networks. Furthermore, dynamic agent numbers could be added to the model to incorporate the effect of population shocks. This includes updating the social networks during the simulation time.

Third, additional work is recommended to refine the interventions included in the model. Instead of a fixed amount of financial assistance, different amounts of cash transfers and vouchers could be modelled to analyse, e.g. whether there is a minimum amount required for vouchers to be effective. Moreover, including the cost-effectiveness of interventions in the model would support trade-off considerations.

Fourth, further research is needed to expand the model to include social interactions with host community residents. The conceptual model developed in this study views refugee camps as closed social systems, however, there are often strong interdependencies between host communities and refugees who share the same fuel market. Social and economic interactions between host communities and refugees are likely to have an influence on the choice of cooking practices.

Finally, future work is encouraged to increase the evidence base the model is built upon. This includes gathering survey data to better understand how people make decisions on which cooking fuels and stoves to use, how heterogeneous groups are distributed, gathering data to better define the upper and lower ranges of the uncertainties used in the model exploration, conducting in-depth interviews with refugees, and carrying out additional case studies in other settings to better tailor interventions to the specific context they are embedded in.

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Appendices

Appendix A

Interview guide

This section provides the interview guide used in this study for the case study. Semi-structured interviews with humanitarian experts and private sector stakeholders were conducted. Semi-structured interviews were chosen as research method to include open-ended questions which allow interviewees to raise new issues during the interviews, while simultaneously providing structure to gather comparable qualitative data. In each interview, a few additional questions were added during the interview to better understand certain points raised. After the interviews, the contents have been summarized and grouped under the original questions.

Interview introduction

- *Length*: 30 minutes
- *Primary goal*: Better understand the drivers and barriers for the adoption and sustained use of clean cooking fuels in refugee camps in protracted crises. To this end, a case study of the market-based clean cooking intervention in Kigeme camp in Rwanda is conducted.
- *Broader research purpose*: This interview is part of my MSc thesis research at TU Delft in the Engineering and Policy Analysis Program carried out in collaboration with the UNEP DTU Partnership in Copenhagen. In my research I analyse the impact of market-based interventions on the adoption of clean cooking fuels in refugee camps. The focus is on social influences that drive or hinder the adoption. The outcomes of this interview will be used to support the development of a model to analyse the effect of market-based clean cooking interventions under various scenarios.
- Please feel free to use your own opinions and experiences to answer the questions.

Verbal consent

- Would you let me record the interview?
- Would you like to participate in this interview?

Background information

- Could you briefly describe your role in the Rwandan refugee response?

Drivers and barriers

I'm going to ask you questions about the drivers and barriers for households to adopt and keep using clean cooking fuels. In the case of Kigeme camp, according to a survey by UNHCR from the end of 2019, only about one third of the households have adopted Inyenyeri's pellets at some point, and only 15-20 % kept using them as their main fuel.

- In your opinion, what are the main drivers for refugee households to switch to clean fuels as their main cooking fuel?
  - Would you say, households are more likely to adopt clean cooking fuels if their peers use them?
  - Did people spread positive information about Inyenyeri's pellets? What did they mention?
- In your opinion, what are the main barriers to the adoption, i.e. why did not all households switch to pellets?
- In your opinion, for those households who did adopt pellets as their main cooking fuel but stopped using them, what are the main reasons to stop?
  - Did people spread negative information about Inyenyeri's pellets? What did they mention?
- In your opinion, what are the three main decision factors for refugee households when choosing which fuels to use for cooking?
- Do you think most households are relatively similar in the way they prioritize the different decision factors? What are major sources of heterogeneity among the households?

Way forward

- What are your recommendations to enable a more widespread adoption of clean cooking fuels by refugees? In Kigeme and other refugee settings?

Appendix B

List of model assumptions

1. Main assumption: Social influences exist and have an impact on the diffusion of clean cooking practices in a refugee camp. This assumption is made based the observations from the case study as well as on the literature review. It allows to focus on the mechanisms how these influences occur, and how they act as a driver or a barrier in the diffusion.
2. There are no network externalities, i.e. the utility of a using clean fuels does not increase with the number of households who adopted them.
3. Communication is modelled as a one-way process. Adopters and rejecters send out information to potential adopters, who only act as receivers. This simplified representation of communication is chosen because the information flow from people who have experience with the product to people who are considering its adoption is viewed as most influential.
4. In the social network, no correlations between the number of social ties, adopter group or income are considered.
5. Prices are exogenous.
6. The supply of clean cooking fuels is exogenous. Clean fuels (including the stove) are made available by a local fuel supplier.
7. To simplify, there are only two fuel options: clean fuel or traditional fuel.
8. Decisions are taken at the household level.
9. No sunk cost are considered because the stove is provided for free (for lease). Households can stop using clean fuels at any moment.
10. Households adopt clean fuels by buying and using them as their main fuel.
11. Five discrete decision stages are assumed, following DoI theory.
12. Household update their fuel choice, based on a decision frequency. Households in the ignorance and awareness stages do not take any adoption decision. They do not have (enough) knowledge about availability and expected benefits of clean fuels, thus they always choose the traditional option.

13. Attributes of the technology are not considered explicitly, clean cooking systems are assumed to be better than traditional ones in terms of performance factors.
14. The adoption barriers in the model are limited to the ones that are considered most relevant: ignorance, social, information and economic barriers.
15. It is assumed that a refugee camp is a closed social system with a similar distribution of adopter categories, as proposed by (Robertson, 1967), where the innovators represent 2.5 %, the early adopters 13.5 % , the early majority consists of 34 %, the late majority occupies 34 % and the laggards 16 % of the population.
16. Households have heterogeneous and constant incomes. Households receive the same amount of cash transfers for fuel, if the lever is applied.
17. Different household sizes are not considered. All agents represent 10 households. Each household consists of 5 people, which is the average household size in the case study.
18. The actual fuel consumption per household is not considered in the model. It is assumed to be constant. Based on the adopter ratio, further considerations on fuel consumption and sales could be made, if the required fuel quantity to cover the needs per household is known. Note that the fuel consumption per household is a non-linear function of the household size, where larger households need less fuel per capita than smaller households.

Appendix C

Social network algorithm

This section elaborates on the algorithm used in this study to define the social network within a refugee camp. This study uses a small-world network, where nodes represent refugee households, and edges represent social ties and information flows between households. The social network is generated at the initialization of the model, based on the Watts-Strogatz algorithm, described by algorithm 1. Besides the total number of nodes, the network graph generated by the algorithm is characterized by two parameters: the average node degree k and the probability of rewiring p. For p values above 0 and below 1, the algorithm generates graphs which exhibit the main features of small-world networks, i.e. high degree of clustering and small path lengths (Watts & Strogatz, 1998).

Algorithm 1: Small-world network (Watts & Strogatz, 1998)

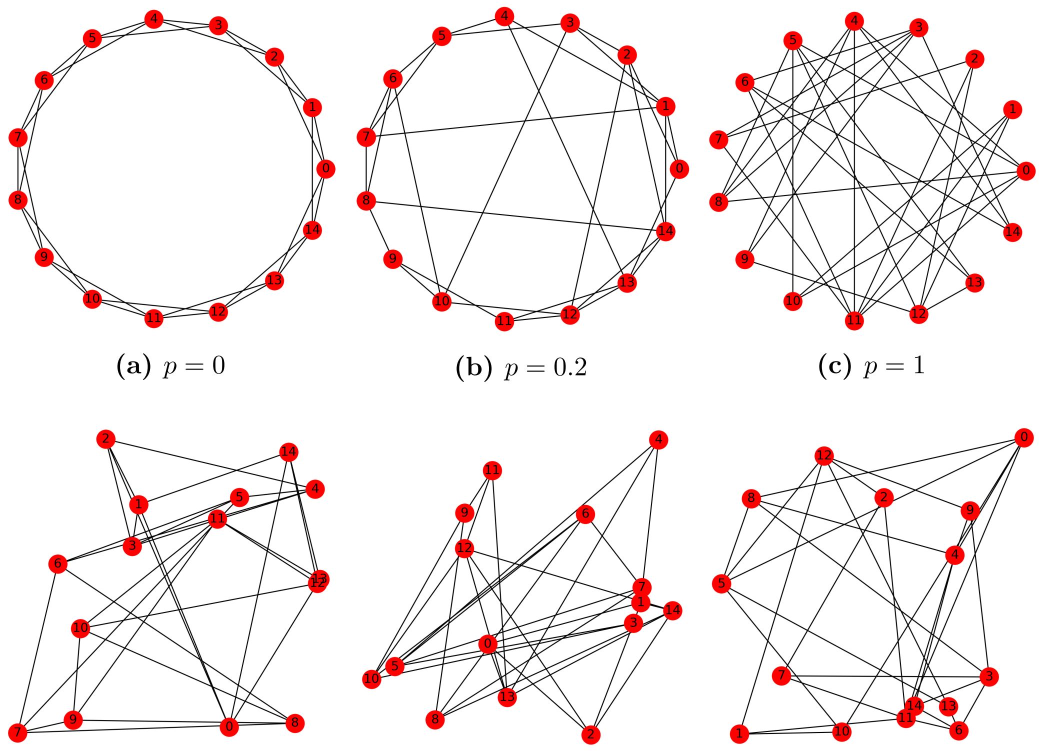
Input:
k Average node degree
p Probability of rewiring
n Total number of nodes
Output: Small-world network graph

---

1. Start with a ring of n nodes, each connected to its k nearest neighbours by undirected edges.
2. Select a node and the edge that connects it to its nearest neighbour in a clockwise sense.
3. With probability p, reconnect this edge to a randomly chosen node, where duplicate edges are not allowed.
4. Move clockwise around the ring and repeat until one round it completed.
5. Lastly, consider the edges that connect the nodes to their second-nearest neighbours. As before, rewire each of these edges based on the probability p, until each edge has been considered once.

To better understand the output of the algorithm, figure C.1 displays a sample of six network graphs with a small number of nodes generated by the Watts-Strogatz algorithm. Graphs (a) to (c) in the first show a circular distribution of nodes in space, as described by algorithm 1. Once the graph is generated, the spatial distribution of nodes does not play a role in this study and is only a matter of visualization. To highlight this fact, graphs (d) to (f) in the second row show a random distribution of nodes in space. The graphs on top of each other, e.g. (a) and (d), are equivalent.

The displayed network graphs are generated with a fixed average node degree and number of nodes (k = 4, n = 15). The probability of rewiring p is varied. For $p = 0$, the graph is a regular ring with each of the 20 nodes connected to four nearest neighbour nodes. As p increases, the randomness of edges increases. For $p = 0.2$, the graph is a small-world network, highly clustered with a small path length. Finally, for $p = 1$, all edges are rewired randomly.



(a) $p = 0$ **(b)** $p = 0.2$ **(c)** $p = 1$

(d) $p = 0$ **(e)** $p = 0.2$ **(f)** $p = 1$

Figure C.1: Network graphs generated by Watts-Strogatz algorithm. Varying the probability of rewiring p, while keeping the average node degree and total number of nodes fixed (k = 4, n = 15). For p = 0, the graph is a ring with each of the 20 nodes connected to four nearest neighbour nodes. For p = 0.2, the graph is a small-world network, highly clustered with a small path length. As p increases, the randomness of edges increases. For p = 1, all edges are rewired randomly. Graphs (a) to (c) show circularly distributed nodes, graphs (d) to (f) show randomly distributed nodes in space. Graphs on top of each other are equivalent in this study.

Appendix D

Parametrisation

This section elaborates on the parametrisation for the implementation of the model. The main model variables along with their initial values and data sources can be found in tables D.1 and D.2. Where possible, values are based on data from the case study, other values are based on literature, but not all parameter values could be based on available data or literature. Thus, finding suitable parameters was a challenging task as there are many possible parameter settings and not all settings could be explored. Choices and assumptions had to be made to define parameter settings, the most important ones are motivated and explained in following paragraphs.

D.1 Thresholds

The information thresholds define the scale of the information barrier that needs to be overcome by agents to move on to the adoption stage. The information thresholds could not be based on literature, as this is a concept developed by this study. Several considerations led to the definition of the values indicated in table D.2. First, the information thresholds depend on the adopter category to represent that the impact of information on an individual's adoption decision differs for different people. Second, the purpose of modelling the information threshold is to create a visible effect of the spread of both negative and positive information on the diffusion process. This is one of the main assumptions of the conceptual model, and implies that the maximum of the adoption curve is damped by this barrier to some degree. This means that, depending on the initial conditions of the variables influencing the information exchange, agents should remain for a shorter or longer time period in the decision stage due to the information barrier. There is a range of values that fulfil this condition. For instance, if in one time step an agent has four adjacent agents that are adopters, among whom three are satisfied with $u_i = 1$ and one is dissatisfied with $u_i = 1$, the agent receives an expected satisfaction $e_i = 3{\times}1{+}1{\times}0.66 = 0.864$. If this value is below the agent's information threshold, in the next time step, e_i is updated again taking into account the previous value of 0.864. As this agent has received unfavorable information, its expected satisfaction will not reach the maximum of 1 anymore. *Laggards* are assumed to remain blocked by the information barrier, once they have received unfavorable information. The *late majority*, *early majority* and *early adopters* have gradually lower thresholds, which allows to meet the thresholds despite some unfavorable information input from their social ties. *Innovators* are assumed not to be constrained in their decisions by any information from peers.

By testing the behaviour of the model under various different parameter settings for the information thresholds and inspecting the expected satisfaction values of agents in the decision stage at the end of the simulation, further understanding about suitable values could be gained. Finally, it was concluded that a range of values would be suitable to fulfill the conditions of damping the maximum of the adoption curve and delaying the adoption decision-making process. In combination with the other parameters affecting the flow of information, e.g. the probability of bad performance, the information threshold values depicted in table D.2 appeared to produce reasonable behaviour of the model in terms of the scale of damping and delay.

Similar considerations apply for the social thresholds. Moreover, the social thresholds are based on literature of an ABM study on innovation diffusion, which uses thresholds to model the social-behavioural barrier in the adoption of natural gas vehicles (Hidayatno et al., 2020).

Note that, although the threshold values are not based on real data, they are not included in the uncertain variables of the XLRM framework of this study. They do have an impact on the model behaviour in absolute terms, however, in this study changes in the *relative* differences between the model results for different interventions are most important. Therefore, the depicted threshold values serve as a benchmark to be able to compare the model behaviour under different initial conditions.

D.2 Adopter categories

The adopter categories are distributed among agents based on Robertson (1967), who proposes a normal distribution for a population, where the innovators represent 2.5 %, the early adopters 13.5 %, the early majority consists of 34 %, the late majority occupies 34 % and the laggards 16 % of the population. In this study, it is assumed that a refugee camp represents a closed social system with a similar distribution of adopter categories.

This is an assumption and not based on data, however, similarly to the thresholds, the actual distribution is less relevant for the purpose of this study. Different distributions lead to different shapes of the diffusion curve, but the values chosen for the distribution parameters serve again as a benchmark to compare the model behaviour under different initial settings. The five adopter categories are simply a conceptual model to incorporate agent heterogeneity in terms of risk aversion. Ultimately, if all agents would belong to the same adopter category, the model behaviour would be drastically different, i.e. diffusion as a sudden jump instead of an S-shaped curve. Nevertheless, it appears sensible to assume that people differ significantly in terms of risk aversion, whether it is a population of a country or a refugee population.

D.3 Uncertain parameter ranges

The parameters that could not be based on real data nor on literature nor set by internal modelling constraints, are part of the uncertain variables in the XLRM framework. For those parameters ranges of values are provided to be explored in the scenarios.

D.3.1 Time discount factor and ability-to-pay

The time discount factor for traditional fuel costs takes a value between 0 and 0.1. For instance, if the factor is 0.1, the time-discounted cost for traditional fuels equal to 5230 [RWF] which is significantly below the monthly clean fuel cost of 6000 [RWF]. Considering the ability-to-pay which lies between 0 and 0.05 and the heterogeneous income, the difference between 6000 and 5230 allows some wealthier agents to afford clean fuels, while others are blocked by the economic barrier.

D.3.2 Probability of bad performance

The *probability of bad performance* can seem surprisingly small, but it determines the chance for each adopter to experience negative performance every time step. Thus, if it is set to 0.01, in 100 time steps, adopters are likely to experience at least one negative performance event, which is then communicated to their peers. In the subsequent time step, adopters can again receive a favorable performance experience. The probability ranges from 0 to 0.02. The upper range was determined by inspecting the behaviour of the model for different settings, where 0.02 can lead to drastic damping of the adoption curve, depending on other initial conditions.

Level	**Variable**	**Initial value/ range**	**Source**
Model	Number of agents N	380 (3800 HH)	UNHCR (Kigeme camp)
	Clean fuel cost c_{cf}	6000 (RWF per month)	UNHCR staff
	Traditional fuel cost c_{tf}	1500 (RWF per week)	Est. charcoal price, based on case study
	Time discount factor r	[0.0, 0.1]	Own specification
	Decision frequency	0.25 (per week)	Based on case study
	Initial adopters	2.5 %	Own specification
	Price shock magnitude	[-0.2, 0.2]	Own specification
	Price shock frequency	[0, 6]	Own specification
	Probability of supply shock	[0, 0.02]	Own specification
	Probability of bad performance	[0, 0.02]	Own specification
	Ratio of imitating	[0, 0.25]	Own specification
	Ratio of advice-seeking	[0, 0.25]	Own specification
	Ratio of cost-optimizing	[0, 0.25]	Own specification
Social network	Avg node degree k	[4, 12]	Own specification
	Probability of rewiring p	[0.1, 0.9]	Adapted from Sopha et al. (2011)
	Social weight of early adopters	1.5	Own specification
Levers	Cash transfers	[0; 4000] (RWF per month)	Based on case study
	Vouchers	[0; 4000] (RWF per month)	Same value as cash transfers
	Info campaign	[0; 5] (50 HH per week)	Own specification
	Maintenance capacity	[0; 5] (50 HH per week)	Own specification

Table D.1: Parametrisation of model variables I. HH signifies households.

Level	Variable	Initial value/ range	Source
Agent	Ability-to-pay *atp*	[0, 0.05]	Own specification
	Income y_i	triangular(12000, 24000, 48000) (RWF per month)	Adapted from Alloush et al. (2017)
	Adopter category	Innovators: 2.5 % Early adopters: 13.5 % Early majority: 34 % Late majority: 34 %, Late majority: 34 % Laggards: 16 %	Based on Robertson (1967)
	Decision stage	1: Ignorance 2: Awareness 3: Decision 4: Adoption 5: Rejection	Adapted from Rogers (1983)
	Social threshold $\theta_{social,i}$	Innovators: 0 Early adopters: T(0, 3%, 7.5%) Early majority: T(3%, 7.5%, 15%) Late majority: T(7.5%, 15%, 25%) Laggards: T(10%, 25%, 40%)	Adapted from Hidayatno et al. (2020)
	Information threshold $\theta_{info,i}$	Innovators: 0.0 Early adopters: 0.9 Early majority: 0.95 Late majority: 0.99 Laggards: 1	Own specification
	Satisfaction threshold θ_u	1	Own specification
	Expected satisfaction e_i	NaN	Own specification
	Satisfaction u_i	Initial adopters: 1 Other agents: NaN	Own specification
	$u_{performance}$	Initial adopters: 1 Other agents: NaN	Own specification
	u_{cost}	1 or 0	Own specification
	$u_{availability}$	1 or 0	Own specification
	Info pool	list()	Own specification

Table D.2: Parametrisation of model variables II. T signifies triangular distribution.

Appendix E

Model verification

This section provides an overview of the steps performed to verify the model, by giving examples. Model verification involves checking whether the model is implemented correctly to ensure that no programming error has been made. Based on Van Dam et al. (2013), who propose methods to verify agent-based models, three main verification methods have been applied in this study: (1) tracking agent behavior, (2) interaction testing in a minimal model, (3) extreme-condition test. In addition, extensive code walk-through helped to identify and eliminate further errors during the implementation. The seed is set to 44 to ensure reproducibility of results despite the stochastic variability within the model itself and Python's random number generator.

E.1 Tracking agent behaviour

First, relevant variables at the model output level as well as at the agent level have been tracked to verify that their values are set correctly. The verification is performed using the debugger extension available in Jupyter Lab. The debugger allows to set break points and to advance through the code line by line. At the same time, model variables and agent variables can be accessed and tracked for each line in the code through the debugger interface. As such, the model and agent variables could be tracked and checked whether their values are set correctly. Advancing though the code line by line further allowed to walk through different functions. As an example, figure E.1 shows the *update_satisfaction* function which calculates the satisfaction value for agents in the adopter stage based on *u_availability*, *u_cost* and *u_performance*. It was found that *u_availability* was not set correctly, in an earlier version during the implementation process. After fixing this error, the well-functioning of the three utility values and the satisfaction update function could be verified. Additionally, printing of variables during the run time has been used to verify some functions.

Figure E.1: Verifying the update_satisfaction function. All three partial utilities are correctly set to 1.

Furthermore, the outputs at the agent level were tracked using the data collector in Mesa. Of particular interest is the stage transition of agents, which is shown for a small number of agents in figure E.2. The agents remain in the same stage for a number of time steps before moving on to the next stage. Some agents enter the second stage relatively late and then move on immediately to stage three, which can be explained by the fact that it is likely that the social threshold is already met by that time. At the end of the run, all agents have moved from the first stage to either the third, fourth or fifth stage. The stage transition appears to be implemented correctly.

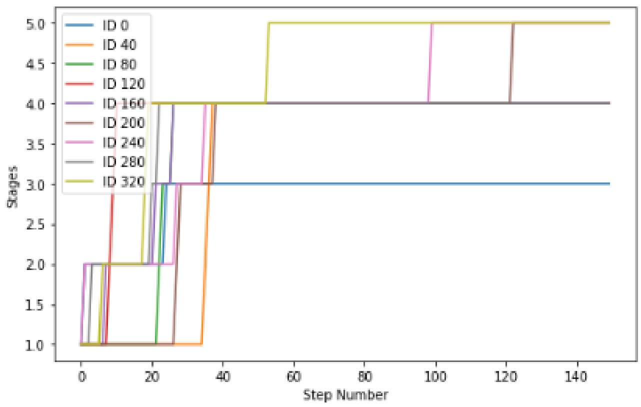


Figure E.2: Verifying the agent stage transition. The stage over time is tracked for a sample of agents.

E.2 Interaction testing in a minimal model

After testing the setting of model outputs and agent variables, the model was run with 15 agents to check whether the interactions work as intended. Based on Van Dam et al. (2013), the model should also be tested with only a single agent, however, in this study extensive debugging with 15 agents is considered sufficient to understand whether the agents behave as intended. 15 agents are considered the minimum to test the interactions and emergent model behaviour.

The connections of agents within the social network structure were verified by testing the generation and integration of the network within the graph module of Mesa. Figure E.3 shows and confirms the correct implementation of the small-world network as structure connecting the 15 agents and defining their social ties.

```
pos = nx.circular_layout(model.G)
plt.figure(figsize = (12, 12))
nx.draw_networkx(model.G, pos)
```

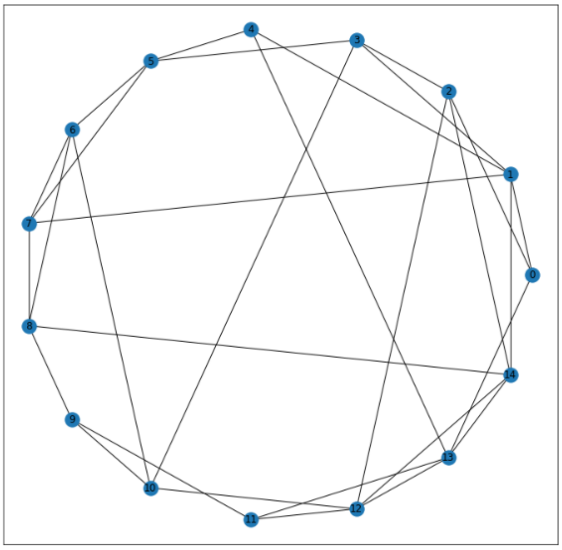


Figure E.3: Verifying the small-world network with 15 agents. Nodes distributed in a circular manner.

The main interactions happen through the flow of information between agents. The *update_info* function was tested, which collects information from the adjacent agents. In an earlier version, it was found that new information added by the *info_campaign* did not have access to updating an agent's expected satisfaction value. This error could be fixed. Lastly, the expected satisfaction information is updated according to the formalization, i.e. it is set to the mean of the *info_pool*, where new, less favorable information is added twice.

E.3 Extreme-condition test

Lastly, the model was tested under extreme conditions. Theoretical predictions about how the model behaves were made and could be confirmed. For instance, the social thresholds were all set to 0, which led to a steep increase in the adoption ratio, as expected. Next, the information thresholds were set to 0, which had a similar effect. Another example is varying of the percentage of initial adopters from 0 to 100 %, which led to the predicted 0 or 100 % diffusion. Moreover, the ability-to-pay was set to 0 or 1 to verify the impact of the economic barrier. All tests confirmed the behaviour that was expected given the design of the model.

Appendix F

Model results

The experiments in this study involve large samples of scenarios. The model results over time are only presented for a limited number of scenarios for better clarity for the reader. In this section of the Appendix the model results for the full set of scenarios are added as a reference. Figure F.1 shows the impact of cash-based interventions on the number of adopters over time for the sample of 2000 scenarios. Figure F.2 illustrates the impact of voucher-based interventions on the number of adopters over time for 2000 scenarios. Figure F.3 displays the effects of shocks and of changes in the decision strategy for the expanded sample of 5000 scenarios.

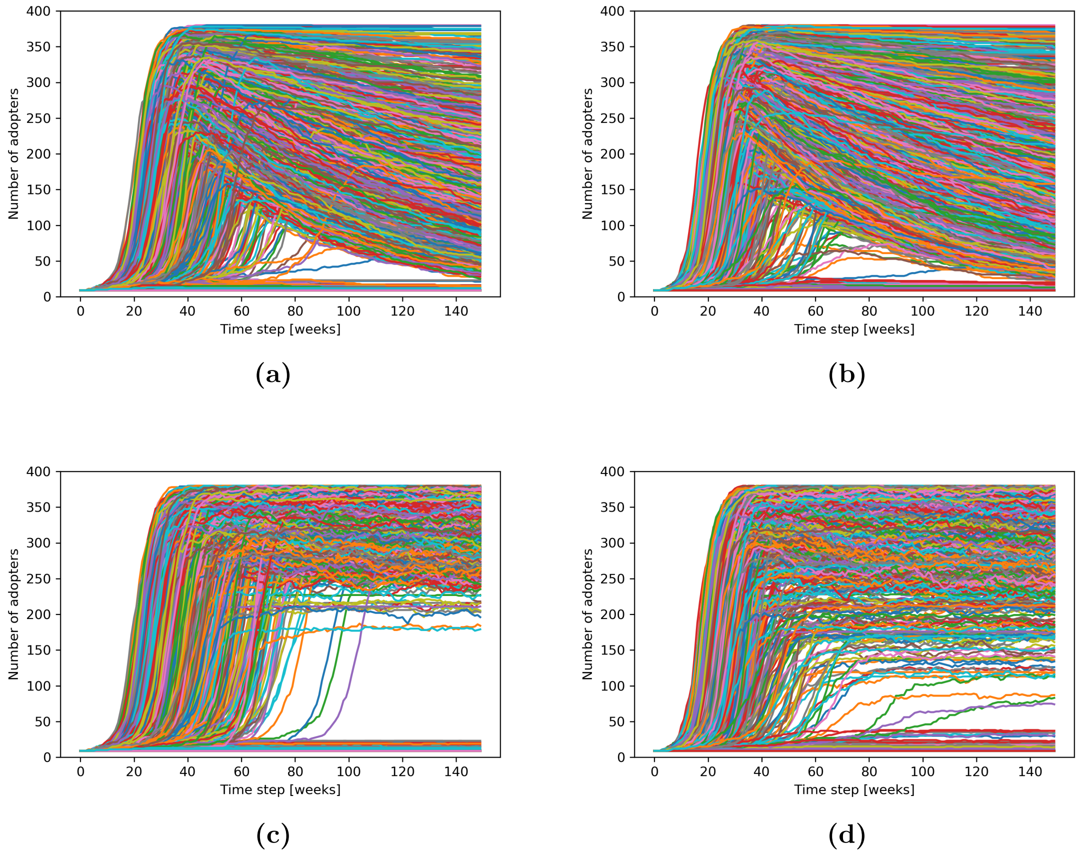
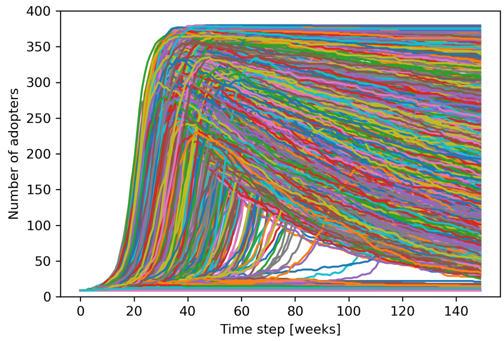
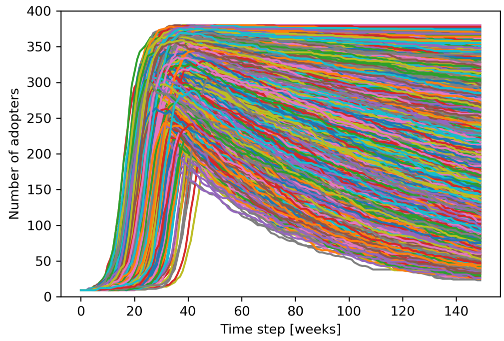


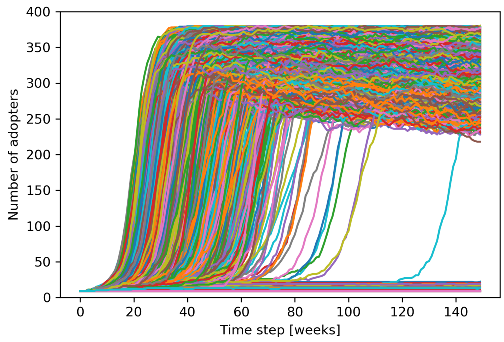
Figure F.1: The impact of cash-based interventions on the number of adopters over time. (a) Cash-transfer-only, (b) cash-info, (c) cash-maintenance, (d) integrated cash-based intervention. 2000 scenarios obtained by simulation.



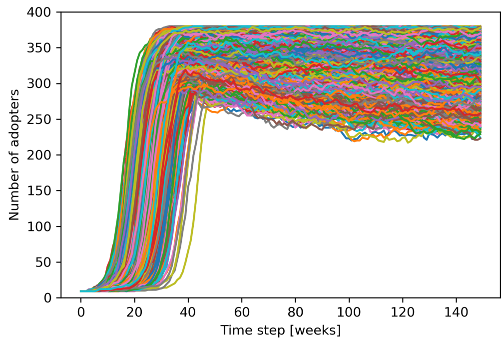
(a)



(b)



(c)



(d)

Figure F.2: The impact of voucher-based interventions on the number of adopters over time. (a) Voucher-only, (b) voucher-info, (c) voucher-maintenance, (d) integrated voucher-based intervention. 2000 scenarios obtained by simulation.

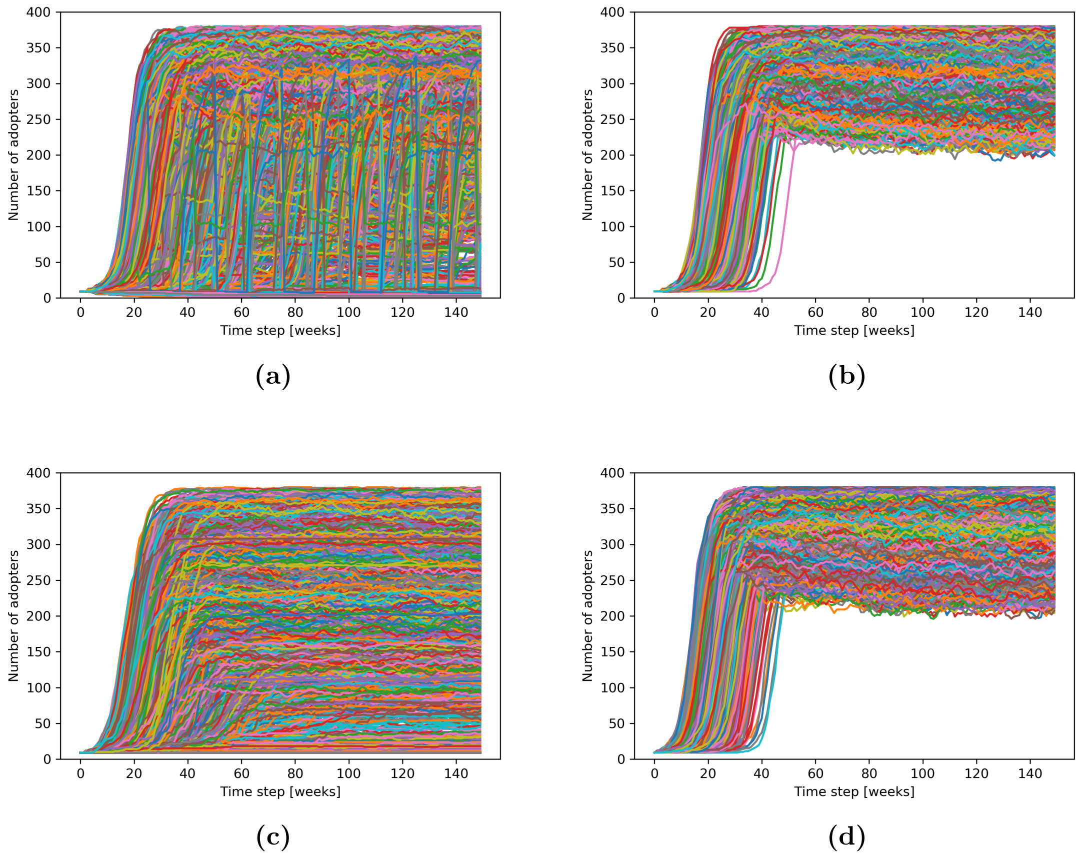


Figure F.3: Number of adopters over time for 5000 scenarios. (a) Effect of shocks under the integrated cash-based intervention, (b) effect of shocks under the integrated voucher-based intervention, (c) effect of changes in decision strategy under the integrated cash-based intervention, (d) effect of changes in decision strategy under the integrated voucher-based intervention. 5000 scenarios obtained by simulation.

Appendix G

PRIM algorithm

This section elaborates on the PRIM algorithm used in this study to carry out the scenario discovery. The Patient Rule Induction Method (PRIM) is applied to identify combinations of uncertain parameters which lead to success or failure of specific interventions. The PRIM algorithm maps the outcomes of interest to "boxes" in the uncertainty space. The boxes are characterized by a set of parameters describing the limits of boxes. Parameters not included in the set remain unconstrained. Algorithm 2 provides a brief overview of how the boxes are determined. The algorithm generates a series of boxes with an increasing density and decreasing coverage.

Bryant and Lempert (2010) define *coverage* as the ratio of the number of outcomes of interest in a sub-space to the total number of outcomes of interest in the entire uncertainty space. *Density* is defined as the ratio of the number of outcomes of interest in a sub-space to the total number of outcomes in that subs-space. In the determination of the final box, there is a trade-off between both measures.

Algorithm 2: PRIM algorithm (Bryant & Lempert, 2010)

Input: Model output data, outcome subset, density threshold, peel alpha
Output: Set of parameter ranges

1. Begin with the entire uncertainty space (here: scenarios sampled from uncertain parameter ranges by using LHS).
2. Gradually "peel" thin slices where the density of outcomes of interest is low. The width of the slices is determined by peel alpha.
3. Repeat until box is found where density threshold is met.

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