Improving access to healthcare in underserved rural areas

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Lisanne van Rijn

Improving Access to Healthcare in Underserved Rural Areas

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Improving Access to Healthcare in Underserved Rural Areas

Verbeteren van de toegang tot gezondheidszorg in achtergestelde rurale gebieden

Thesis

to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
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Prof.dr.ir. A.J. Schuit

and in accordance with the decision of the Doctorate Board.

The public defence shall be held on

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by

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Lisanne van Rijn
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Chapter 1

Introduction

The 2030 Agenda for Sustainable Development, established by the United Nations, encompasses 17 sustainable development goals (SDGs), addressing critical issues including poverty, health, inequality, and climate. Among these, SDG 3 aims to achieve good health and well-being for all. SDG 3 includes targets for reducing the maternal and infant mortality rates, decreasing the burden of communicable and non-communicable diseases, and increasing access to sexual and reproductive healthcare services. SDG 3 is an integral part of the agenda for sustainable development, as it is regarded as a pre-condition for sustainable development (Nunes et al., 2016). For instance, better health is associated with better economic outcomes such as lower healthcare costs and higher productivity, which contribute to SDG 8 (Decent work and economic growth) and SDG 1 (No poverty).

SDG 3.8 emphasizes universal access to essential health services and medicines. Access to healthcare is particularly constrained in rural areas of low- and middle-income countries (LMICs). There is currently no agreed upon definition of rural areas. Rural areas are frequently defined in opposition of urban areas, and the definition of urban areas varies between countries (Mercandalli et al., 2019). In this thesis, we define rural areas according to the "Degree of Urbanization" which classifies rural areas as areas with a population density of less than 300 inhabitants per km^2 or with a population size below 5000 (Food and Agriculture Organization of the United Nations, 2018). The following paragraphs describe the challenges faced in these rural areas using the framework by Levesque et al. (2013), which defines accessibility through five dimensions: 1) Approachability; 2) Acceptability; 3) Availability and accommodation; 4) Affordability; 5) Appropriateness.

Approachability. This dimension assesses whether individuals can identify the availability and need for health services. Disseminating information about healthcare services and their availability poses significant challenges in rural areas. Households in these areas tend to have less access to information channels such as radios, television, and mobile phones and are less likely to have an internet connection. Education levels are also lower in rural areas compared to urban areas. Lower education levels are associated with reduced health literacy, making it more difficult for individuals to perceive the need for care (Kickbusch et al., 2013).

Acceptability. Acceptability concerns whether individuals accept healthcare services based on cultural and social factors. In rural communities, barriers to accessing healthcare can arise due to gender, age, and local community perceptions (Strasser et al., 2016). For example, contraceptive use among female adolescents in Sub-Saharan Africa is lower due to a lack of acceptance of contraceptive use within the community and potential stigma from healthcare workers when trying to access these services (Chola et al., 2023).

Availability and accommodation. This dimension covers several elements. First, it refers to the physical availability of health services. Rural areas often have limited existing healthcare infrastructures. As a result, people in rural areas often face long travel times to health facilities. Limited means of transportation and poor road infrastructure exacerbate these travel times. Second, this dimension encompasses the availability of healthcare personnel and supplies. LMICs in general have a large deficit of healthcare workers, and healthcare workers are often concentrated in urban areas, leaving rural areas underserved (Strasser et al., 2016). Stock-outs of medicines are common in both public and private healthcare facilities (Githinji et al., 2013; Karamshetty et al., 2022). The median availability of essential medicines in low-income countries is below 50% (Bazargani et al., 2014). Reasons for this include insufficient funding, a shortage of trained staff and a inadequate supply chain and inventory management.

Affordability. Affordability refers to the possibility for individuals to spend resources and time to access health services. Health insurance coverage is low in rural areas, making health expenses typically out-of-pocket. Combined with high poverty levels, affordability is a key concern in rural areas. People in rural areas also face high opportunity cost to access health services. Travel times tend to be long and people may need to perform repeated visits to a health facility to obtain the desired health service. As such, people spend a considerable amount of time accessing health services, which is time away from their family, business, or other work responsibilities.

Appropriateness. Appropriateness relates to the quality of the services and whether they meet people's needs. People in rural areas may forego seeking treatment at their 'closest' health facility and instead travel to more distant facilities. The (perceived) quality of services may be higher at the latter. The availability of diagnostic tests, health products, or specialized personnel also influence to what extent the services meet people's needs and thus their unavailability may also lead individuals to select health facilities besides their local health facility (Kahabuka et al., 2011).

There are inherent trade-offs between the five dimensions in the framework. For instance, increasing the availability of health services by constructing new clinics or training personnel requires additional resources, which can increase costs and thus decrease the affordability of the services. Conversely, efforts to increase the affordability of the services, such as reducing production costs, may compromise the quality of the services and hence their appropriateness. These dimensions should therefore not be viewed in isolation, but rather as interdependent dimensions that simultaneously need to be at the appropriate level in order to achieve access (Frost and Reich, 2008).

Healthcare delivery in rural areas in LMICs often makes use of non-traditional delivery models to overcome challenges related to access to healthcare. These include mobile outreach teams and community health workers, which are predominantly used in the public sector, as well as community health entrepreneurs, drones, and telemedicine, which are examples from the private sector. In this thesis, we focus on mobile outreach teams and community health entrepreneurs. We provide a detailed description of the two models in the following sections.

1.1 Mobile outreach teams

Mobile outreach teams are teams of skilled healthcare workers who visit outreach sites in rural areas at regular intervals to bring healthcare closer to populations for whom healthcare was previously inaccessible (Khanna and Narula, 2016). The teams use existing health facilities for their service provision. When such facilities are unavailable, they can use pop-up units like inflatable tents. Mobile outreach teams are frequently deployed by NGOs and can provide a variety of healthcare services. UNICEF uses mobile outreach teams to provide vaccinations, and Médecins Sans Frontières deploys outreach teams to screen for diseases such as tuberculosis.

The empirical context considered in this thesis is that of family planning outreach teams which are deployed by several NGOs, including MSI Reproductive Choices, EngenderHealth, and International Planned Parenthood Federation

Universal access to family planning services is emphasized in SDG 3.7. Increasing access to family planning services is associated with a myriad of health benefits, including reductions in maternal and infant mortality rates (Starbird et al., 2016). Family planning services also present a major lever for reaching several other SDGs including SDGs 1 and 2 (end poverty and hunger), SDG 4 (ensure quality education for all) and SDG 8 (promote sustained economic growth). Access to family planning services enables individuals to obtain higher education levels (Miller, 2010), which lead to higher individual incomes and are a necessary precondition for long-term economic growth (Lutz et al., 2008).

Mobile outreach team contribute to access to healthcare in several ways. First, deploying outreach teams improves the availability of health services. Outreach teams overcome the barrier of (travel) distance to health facilities, as they travel to rural communities to provide services. Second, they consist of trained healthcare providers. The outreach teams are trained to provide high quality healthcare services, while considering the cultural and social norms of the communities they serve. This enhances the acceptability and appropriateness of the services. Third, outreach teams provide free or highly subsidized services, improving affordability.

Humanitarian organizations face various resource allocation problems regarding the deployment of outreach teams. These challenges include how to assign outreach sites to outreach teams, and determine the visit frequencies to sites. Doing this efficiently is growing in importance for humanitarian organizations. Program funding is increasingly constrained. For instance, the UK government reduced its foreign aid budget by 4.5 billion pounds in 2021, heavily impacting global health programs and the humanitarian operations of many NGOs. Donors also increasingly demand greater accountability and transparency in how funding is allocated and the results achieved. NGOs therefore need to demonstrate that they efficiently use the received funding. At the same time, NGOs face the challenge to conduct and adapt their operations in a continuously changing service landscape. Dynamic processes such as population growth, and urban and forced migration, heavily influence the location and magnitude of the demand for health services. The protective measures instated during the COVID-19 pandemic and the supply chain shortages resulting from the pandemic necessitated significant changes in NGOs operations. In this thesis, we address two challenges related to the deployment of outreach teams.

1.2 Community health entrepreneurs.

"Community health entrepreneurship" is a recent healthcare delivery model adopted by several social enterprises. This model has been adopted as response to challenges related to community health worker (CHW) programs in LMICs.

CHWs are individuals in rural communities trained to provide health services in their own community. Their tasks can include distributing health products, promoting healthy behaviours, and referring patients to health facilities. Research has shown that they can successfully increase access to essential medicines for diseases such as malaria, HIV, and tuberculosis (Woldie et al., 2018). The benefit of CHW programs is their potential for scale. CHWs require less time to train compared to traditional health workers and they are less costly. CHW programs in LMICs currently operate 8 million CHWs (Hodgins et al., 2021).

However, CHWs programs face significant challenges. CHWs frequently report stock-outs of the health products they distribute in the community. CHWs resupply at health facilities. Health facilities frequently face stock-outs themselves and may prioritize available stock for themselves due to a lack of formal resupply policies for CHWs (Olaniran et al., 2022). CHW retention is also an issue. The work is often not economically sustainable, as CHWs are often unpaid or underpaid (Pradhan et al., 2020). Many CHWs have other jobs and perform CHW duties on the side, resulting in high work pressure. Job satisfaction is also low due to a lack of training and supervision (de Vries and Pool, 2017).

Community health entrepreneurs (CHEs) sell health products in rural communities. CHEs are typically former CHWs who receive additional training on healthcare services and entrepreneurial skills. CHEs purchase health products from a social enterprise, which manages the supply chain of health products. This model addresses the two aforementioned challenges related to CHW programs. First, CHEs face fewer issues to resupply their products, since the social enterprise has the supply chain expertise to source the products and formal resupply processes exist. Second, the model also provides financial incentives for CHEs to develop their business and ensure the availability of health products. This makes the model more economically sustainable. Social enterprises like Healthy Entrepreneurs, operating 15,000 CHEs in seven countries, and Live Well, employing 430 CHEs in Zambia, exemplify this model.

CHEs help improve access to healthcare. First, they enhance the availability of health products. They improve the physical availability of products, by having the products in stock in their store. They also bring the products closer to the rural communities, since they operate their store in the community they live in. Second, social enterprises are committed to providing the products to rural communities at reasonable prices through low-profit margins. Third, since the CHEs work in the communities they live in, they can build trust with the community more easily. Increased trust makes it simpler to counsel community members on healthy behaviours and product utilization, which helps to improve the dimensions acceptability and appropriateness.

A key challenge for social enterprises using this model is to ensure that the business model is sustainable. Social enterprises are for profit organizations that use their profits for social objectives. CHEs operate in rural areas, with high resupply costs. This means that the distribution network represents a significant cost for the enterprise. At the same time, generating sufficient revenue is a challenge. The social enterprise sells the products to the CHEs with low-profit margins, to keep prices affordable for the community. CHEs also tend to have low sales volumes, because the operate in areas with high poverty levels.

This leads to various questions on how to efficiently organize the distribution network. The sourced health products are typically stored in a warehouse until they are distributed to CHEs. How many warehouses to operate and where to operate them is an important decision. Another decision is how frequently to visit the CHEs to replenish their products. Deciding on the optimal visit frequency is not straightforward. Increasing the replenishment frequency comes with a significant increase in transportation cost, due to the long travel times in rural areas. Visiting more frequently does provide a better service for CHEs, who typically do not have sufficient cash on hand to place large orders to satisfy demand during a long resupply interval. The social enterprises also face supply chain challenges such as maintaining supplier relationships, sourcing the right amount of products, and ensuring timely delivery to the country of operation. In this thesis, we consider the challenge of ensuring health product availability at cash constrained CHEs.

1.3 Thesis outline and contributions

This section gives an overview of the thesis. Chapters 2,3, and 4 can be read independently, as each chapter introduces the necessary concepts and notation. Chapter 5 presents the main findings from each chapter. In the following, we provide a brief description of Chapters 2,3, and 4 and summarize their contributions.

Chapter 2: "Site Reassignment for Mobile Outreach Teams: Investigating the Effectiveness of Decentralized Decision-Making", L. van Rijn, H. de Vries &, L.N. Van Wassenhove. Published in *Manufacturing & Service Operations Management.* In this chapter, we consider the problem of (re)assigning outreach sites to outreach teams. Due to dynamics in demand and supply, once rational site-to-team assignment decisions can become far from optimal over time. Solving this problem through a central planner does not fit the context: outreach teams commonly have a high degree of decision-making autonomy. We study a decentralized approach where subsets of teams collaborate in a series of team meetings to reassign sites. We propose a mixed-integer programming model for centralized site reassignment. We extend this model to represent the decentralized approach and develop a set of simple decision rules for this approach. We use empirical data from six country outreach programs of the non-governmental organization MSI Reproductive Choices. With this research, we contribute to the literature on decentralization in the health and humanitarian sector. Decentralized decision-making approaches are prevalent in this sector, but so far limited literature has focused on the trade-off between centralization and decentralization. In addition, we shed light on what drives the effectiveness of decentralized decision-making by proposing and analyzing a range of potential moderators of the trade-off between centralization and decentralization.

Chapter 3: "Providing Access where it is Needed: Equity and Inclusion through Contraceptive Implant Removals by Mobile Outreach Teams", L. van Rijn, H. de Vries &, D. Gutt. This chapter investigates drivers of the need for outreach teams to provide contraceptive implant removal services and how operational decisions impact this need. Since 2011, the uptake of the contraceptive implant rose significantly in low- and middle-income countries, leading to a corresponding increase in the demand for implant removals. However, the scale-up of implant removal services is lagging, particularly in remote and rural areas. Mobile outreach teams can help improve equity and inclusion, but the extent to which they do so depends on the organization of the teams, e.g., which sites they serve, how frequently they visit them, and how demand for services is generated. We perform a regression analysis to identify drivers of the need for outreach removal services and operational decisions that can help meet this need. These effects are non-trivial, since removal services are provided in tandem with implant insertion services which increase demand for removals. We use service delivery data from NGO MSI Reproductive Choices' outreach teams in Uganda and publicly available datasets on demographics and health facilities. This research extends the literature on equity and inclusion in healthcare. We empirically investigate how operational decisions influence equity and inclusion. We also consider equity in a setting where operational decisions affect needs, whereas previous literature has often considered equity with respect to a fixed need. We also contribute to the growing literature on operations management in family planning, which can help advance the 2030 agenda for sustainable development.

Chapter 4: "Health Product Availability in the Presence of Cash Constraints: A Study of Community Health Entrepreneurs in Rural Kenya", L. van Rijn, H. de Vries &, L.P. Veelenturf. In this chapter, we consider how to address cash constraints at community health entrepreneurs (CHEs). CHEs play a key role in improving access to essential medicines and other health products in rural areas in low-and middle-income countries. We conduct a mixed-methods study. We perform a field experiment that tests two interventions with 458 CHEs in Kenya in collaboration with social enterprise Healthy Entrepreneurs (HE). The first involves setting up stock-hubs. These are small consignment stock locations where CHEs can replenish their inventory on-the-spot, thereby reducing the need for cash-on-hand. The second is a cashflow game designed to help CHEs internalize the importance of reinvesting profits in their business, thereby improving their cashflow resulting from increased sales. We also conduct interviews with CHEs and HE staff members. In this chapter, we study two novel interventions to address cash constraints that fit the operational context of rural areas, where resupply costs are high leading to long resupply intervals. Previous work on cash constrained microentrepreneurs focused on urban areas where suppliers can visit entrepreneurs with a high frequency. We also extend the scarce body of literature on field experiments in operations and supply chain management.

Chapter 2

Site Reassignment for Mobile Outreach Teams: Investigating the Effectiveness of Decentralized Decision-Making

This chapter is based on Van Rijn et al. (2024a).

2.1 Introduction

United Nations Sustainable Development Goal (SDG) 3 emphasizes good health and well-being for all. Access to healthcare remains challenging in rural areas due to healthcare worker shortages, unequal urban-rural distribution of healthcare workers, limited transportation options, and poor road and healthcare infrastructure (Awoonor-Williams et al., 2004; Doerner et al., 2007; Hardee et al., 2017). Non-traditional delivery models, such as mobile outreach teams and community health workers, are key to increase access to healthcare for populations in these areas.

Mobile outreach teams consist of healthcare workers that use vehicles to bring healthcare closer to underserved populations (Khanna and Narula, 2016). Service provision occurs in outreach sites – villages or slums – and uses existing health facilities or pop-up units such as inflatable tents. Mobile outreach teams have been deployed to provide various health services, including family planning (Duvall et al., 2014), vaccinations (Duijzer et al., 2018), and disease screening (De Vries et al., 2021b; Murthy et al., 2012).

Outreach programs are commonly structured as follows. They are managed per country. A country program is divided into regions based on the country's administrative structure. A regional coordinator oversees a region, which typically hosts multiple outreach teams. The country's governments dictates or consults on the set of outreach sites to serve. Outreach teams visit a fixed non-overlapping set of sites. Teams deploy to sites from their team base and generally visit one site per day. The visit frequency to a site depends on the number of sites the team is assigned to and the program's policies or objectives. For example, family planning outreach teams visit sites with more demand more frequently (De Vries et al., 2021a). Outreach teams leverage local knowledge to decide which site to visit when, considering factors like travel times, security, road and weather conditions, village events, cultural differences, and potential local demand (De Vries and Van Wassenhove, 2020; Pedraza-Martinez and Van Wassenhove, 2012).

Outreach programs must determine which site is served by which team. We call this the site-to-team assignment. While site-to-team assignment decisions may once have been optimized, several dynamics can lead to suboptimal assignments over time. First, demand for health services evolves over time, and this evolution varies strongly per outreach site (Alban et al., 2022). Second, outreach sites may be added to or removed from the government's agreed-upon set. Third, volatile funding leads to fluctuations in the number or sizes of teams (i.e., the number of healthcare workers in a team). NGO MSI Reproductive Choices' (MSI) experience in Uganda, where they had to close five outreach teams after the reinstatement of the Global Gag Rule in 2017[1], demonstrates the impact of funding on team assignments (MSI Reproductive Choices, 2018). These dynamics may result in teams being assigned to sites where demand is disproportionate to their size, or teams visiting many sites infrequently, despite high demand. This calls for regular changes to the site-to-team assignment. Such a change in the outreach team serving a given site is called a *site reassignment*.

We define the Outreach Site Assignment Problem (OSAP) as the problem of (re)assigning outreach sites to teams and allocating visit frequencies to maximize effectiveness. A *centralized approach* to solving this problem, where a central planner makes decisions for the country, does not fit the outreach program context. These programs typically grant a high degree of decision-making autonomy to outreach teams. This enables teams to leverage their local knowledge (De Vries and Van Wassenhove, 2020). Top-down approaches also tend to require more complex software and are harder to explain, whereas simplicity and transparency are key for implementing decision-making approaches in practice (Gralla and Goentzel, 2018). Therefore, we must explore better-suited methods to solve OSAP in the outreach context.

Inspired by the common practice in outreach programs of discussing operational matters in regional or national gatherings, we study an approach where small groups of teams whose team bases are close together collaborate to reassign sites they currently serve. We refer to this as the *decentralized approach* or *decentralized decision-making*.

Outreach programs face two fundamental questions about decentralized decision-making. First, it is presently unclear how it influences effectiveness. This leads to the question: *What is the trade-off between decentralization and effectiveness?* Second, this trade-off likely depends on the decentralized decision-making process itself and can thus potentially be moderated by adjusting aspects of the process. Identifying these moderators has important implications for practice. It shows how much can be gained by improving the decision-making process and how much of the trade-off is inherent to decentralized decision-making. This leads to our second question: *What are the potential moderators of this trade-off?*

We study these questions in the context of MSI, one of the largest NGOs aiming to increase access to family planning services. The NGO deploys 500 outreach teams that provide affordable (or free) reproductive healthcare services (most notably family planning services) in 37 countries. We use empirical data from six country outreach

[1]The Global Gag Rule withholds US family planning funding from foreign NGOs that offer abortion-related services with their own funds (MSI Reproductive Choices, 2018).

programs (Madagascar, Malawi, Sierra Leone, Tanzania, Uganda, and Zimbabwe) to develop a case study and a set of test instances. MSI is one of the leading NGOs that collects detailed data on its outreach visits. We follow MSI, and use client volume (i.e. the number of clients served) as a measure to assess effectiveness in this paper. Objectives based on volume, potentially subject to service quality and/or equity constraints, are perceived as appropriate and are frequently used in outreach programs (e.g., Edmond et al., 2020; Schneider et al., 2018).

The contribution of this paper is twofold. First, we study the effect of decentralization, the importance of which has been stressed by several scholars given its prevalence in the health and humanitarian sector (e.g., De Vries and Van Wassenhove, 2020; Gralla and Goentzel, 2018)). Second, we evaluate what drives the effectiveness of decentralized decision-making by proposing and analyzing a range of potential moderators. In addition, we shed light on how the effectiveness of decentralized decision-making is influenced by the specification of the objective function, team participation, and evolving parameters. The insights from this research are relevant to organizations in the health and humanitarian sector deploying outreach teams.

The remainder of this paper is organized as follows. Section 2.2 provides a detailed problem description, and Section 2.3 reviews the relevant literature. In Section 2.4, we mathematically define OSAP, and Section 2.5 outlines the decentralized approach to OSAP. Section 2.6 provides the numerical results. In Section 2.7, we discuss three robustness analyses. Finally, Section 2.8 discusses our findings and concludes.

2.2 Problem description

Our paper considers outreach programs where (1) teams carry out repeated visits to sites, (2) each team has a set of assigned sites, (3) visit frequencies can be chosen from a predefined range (one that is practically, ethically, and medically acceptable and feasible), and (4) visit frequencies and/or team characteristics impact certain outcome/output metrics (cf. Duvall et al., 2014; Edmond et al., 2020; Schneider et al., 2018) for details on outreach programs for family planning, primary healthcare, and infant and maternal care that fit this context).

In a systematic approach to site (re)assignment, three factors have to be taken into account. First, outreach teams can have different characteristics that can influence client volumes. An example is team size. Teams can vary in size to account for differences in client volumes across parts of the country. Sending a large team to a small site means that some staff time is not used. Conversely, a small team may have insufficient time to service all clients at a large site.

Second, the site-to-team assignment determines the travel distance from the base to the assigned sites. A greater distance leads to a longer travel time and thus affects the time teams can start providing services at the site. A later start time can lead to a more crowded schedule, which can cause long wait times and subsequently client dropouts. Teams may also have insufficient time to service all clients at the site.

Third, assignment decisions determine the size and characteristics of the team's set of assigned sites. The number of assigned sites determines how a team allocates its capacity (i.e., the number of days it operates during the year). Reducing the number of sites assigned to a team means that it can increase the visit frequency to some of its remaining sites. For many health services, such an increase will lead to a non-linear increase in the total expected client volume at that site. De Vries et al. (2021a) show for family planning outreach teams that the relationship between client volume and visit frequency is concave non-linear. Increasing the visit frequency to a site reduces the time between consecutive visits and hence the amount of time during which demand for services can build up (e.g., because existing clients need follow-up care or new clients require care). In contrast, increasing the visit frequency to a site might lead to fewer clients switching to alternative providers. Hence, the effect on visit frequencies and subsequent client volumes should be considered when reassigning a site.

In short, OSAP is about assigning sites to teams, considering how client volume is affected by team characteristics, start time, and visit frequency.

2.3 Literature review

We provide an overview of three related streams of literature: mobile outreach planning problems, centralization and decentralization in humanitarian organizations, and related classes of assignment problems.

2.3.1 Mobile outreach planning problems

Studies on mobile outreach planning problems focus on various operational decisions in various healthcare contexts. Doerner et al. (2007) examine a location-routing problem for a mobile healthcare facility. McCoy and Lee (2014) analyze how health clinics can allocate limited motorcycle capacity to outreach sites in Zambia. De Vries et al. (2021b) study the deployment of mobile teams for population screening of infectious diseases. How frequently to visit outreach locations is studied by Thorsen and McGarvey (2018) for a single mobile dentistry clinic and by De Vries et al. (2021a) for a set of outreach teams. This latter paper serves as a foundation for assumptions regarding how visit frequencies affect client volume. Alban et al. (2022) study how to allocate mobile outreach team resources while taking into account the build-up of demand and saturation effects. Yang and Rajgopal (2021) address optimizing mobile clinic location assignments and outreach trips, where one clinic visit can cover several locations. Breugem and Van Wassenhove (2022) analyze the loss of utility resulting from incorporating vertical equity (in the form of asymmetric outcome constraints) in resource-allocation problems, and study an application of outreach teams allocating visits to outreach sites.

All the studies above consider planning problems exclusively from a centralized perspective, except for the study by McCoy and Lee (2014). They consider a decentralized scenario where a central planner allocates capacity to clinics responsible for allocating their allotted capacity. However, coordination between clinics is not considered in this study. In this paper we study various degrees of collaboration between teams.

2.3.2 Decentralization and centralization in humanitarian organizations

Humanitarian operations, especially those in remote locations (Besiou et al., 2014) or resource constrained settings (Jónasson et al., 2022) and involving last-mile logistics (De Vries and Van Wassenhove, 2020), are often characterized by decentralized decision-making structures (Muggy and Heier Stamm, 2014). Unlike planning decisions at a central level, implementing decentralized decisions does not require extensive communication or specialized software (Gralla and Goentzel, 2018). Decentralized planning approaches also safeguard staff autonomy and enable them to incorporate local knowledge (De Vries and Van Wassenhove, 2020). They can also reduce delays in, for instance, procuring vehicles (Besiou et al., 2014), diagnosing HIV in infants (Deo and Sohoni, 2015), and providing relief aid in the aftermath of a disaster (Gatignon et al., 2010). As such, they fit well in established organizational processes in humanitarian organizations (Gralla and Goentzel, 2018).

Centralized decision-making can establish better coordination (Roth et al., 1991). A lack of coordination can lead to duplicated work and inefficient use of resources (Thévenaz and Resodihardjo, 2010). Centralized approaches can also deliver economies of scale (Frennesson et al., 2022), for example, in fleet management when vehicles are procured jointly (Keshvari Fard et al., 2019).

Limited literature has focused on the trade-off between centralization and decentralization. Stauffer et al. (2016) study hub configurations with various degrees of centralization for hubs that support the vehicle supply chain for large humanitarian organizations. They find that a more centralized configuration leads to lower supply chain costs. Muggy and Heier Stamm (2020) compare a centralized and decentralized model where beneficiaries select from which facility to seek post-disaster aid. The authors show that coordination mechanisms exist that lead to centrally optimal solutions even in decentralized settings.

2.3.3 Assignment problems

There is a considerable body of literature on assignment problems with applications in many contexts. Examples include facility location problems (Ross and Soland, 1977), vehicle routing problems (Fisher and Jaikumar, 1981), call-center service network design (Meester et al., 2010), and post-disaster debris processing (Lorca et al., 2017).

OSAP closely resembles the generalized assignment problem (GAP) introduced by Ross and Soland (1975), which entails assigning tasks to a set of agents. A task is associated with a given agent-specific cost and requires certain resources, and each task must be allocated to an agent without exceeding the agent's resource capacity. OSAP differs from GAP in two ways. First, the task (here: site) can be assigned to an agent (here: outreach team) using different "levels" of resources (here: different visit frequencies). Second, the cost (here: expected client volume) depends not only on the agent and the task but also on the chosen level of resources.

OSAP is a special case of the multilevel generalized assignment problem (MGAP), first studied by Glover et al. (1979), where tasks can be assigned to agents with different levels of resources. In contrast with OSAP, MGAP assumes that the resource utilization (number of visits to a site) depends on the resource level (visit frequency), *and* on the task (site) and the agent (team). Previous research, such as that done by Ceselli and Righini (2006), focused on developing centralized solution methods. In contrast, we propose decentralized decision rules.

2.4 The centralized model

In this section, we state OSAP mathematically. The model provides the rationale behind the decentralized approaches presented in Section 2.5. We also use this model in Section 2.6 to quantify the optimality gap for decentralized decision-making.

OSAP considers the assignment of sites to teams and allocation of visit frequencies to sites over a selected planning period (the day-to-day planning of visits in a planning period is not considered). Let $\mathcal{T}$ denote the set of outreach teams and $\mathcal{S}$ the set of outreach sites. Each team has an associated set of sites $\mathcal{S}_t \subseteq \mathcal{S}$, which represent the sites team $t \in \mathcal{T}$ could serve, given the limitations on travel time. A site $s \in \mathcal{S}$ must be assigned to exactly one team, and a visit frequency must be assigned. The latter must lie in a predefined range of possible visit frequencies, denoted by $\mathcal{F}$. Each team has a given capacity, i.e. the maximum number of visits it can undertake in the planning period, denoted by c_t. Each visit involves visiting a single site for a day.

Binary decision variables x_{st}^f take the value 1 if team t visits site s with frequency p^f for $f \in \mathcal{F}$. The expected client volume per visit if team t visits site s with frequency f is represented by μ_{st}^f . Parameter μ_{st}^f captures the effect of visit frequency, start time, and team characteristics on expected client volume. Section 2.6.1 discusses the estimation of these parameters. Given the objective of maximizing client volume, OSAP can be formulated as:

$$\text{maximize} \quad \sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}}\sum_{f\in\mathcal{F}} p^f \; \mu_{st}^f x_{st}^f \tag{2.1}$$

$$\text{subject to} \quad \sum_{s\in\mathcal{S}}\sum_{f\in\mathcal{F}} x_{st}^f \, p^f \; \leq c_t \qquad t \in \mathcal{T} \tag{2.2}$$

$$\sum_{t\in\mathcal{T}}\sum_{f\in\mathcal{F}} x_{st}^f = 1 \qquad s \in \mathcal{S} \tag{2.3}$$

$$x_{st}^f \in \{0,1\} \quad s \in \mathcal{S}, \quad t \in \mathcal{T}, \quad f \in \mathcal{F} \tag{2.4}$$

Constraints (2.2) ensure that the team's capacity is not exceeded. Constraints (2.3) stipulate that exactly one team and one visit frequency must be assigned to each site. Constraints (2.4) define x_{st}^f as binary variables. Finally, objective (2.1) maximizes the total client volume.

If $|\mathcal{F}| = 1$, i.e., there is only one resource level, we can reduce from GAP to OSAP and therefore OSAP is NP-hard like GAP (Fisher et al., 1986). As shown in online supplement D, realistically sized instances can still be solved optimally in reasonable time.

2.5 Decentralized approach

The main aim of the paper is to answer managerial questions about the effectiveness of decentralized decision-making. To do this, we have to make assumptions about how decentralized decision-making takes place. In doing so, our aim is not to propose a definitive method for site reassignment but rather to present a range of potential approaches that can help us answer our research questions.

We propose a decentralized approach where teams participate in team meetings to reassign sites. Before we discuss the details of this approach, we highlight three conditions that need to be in place for such a decentralized approach to work. First, outreach teams must have the opportunity to meet together to discuss site reassignments. MSI's outreach teams in Uganda exemplify how such team meetings can take place in practice. These teams operate independently but occasionally gather with other teams in the same region to discuss operational matters. Such gatherings provide a natural mechanism for teams to discuss site reassignments. Given that outreach programs are commonly managed by region or district, embedding team meetings for site reassignment into regional/district gatherings is considered highly feasible. Alternatively, teams can organize meetings dedicated to site reassignments – online or at a central location. Second, teams need to be *willing* to reassign sites. For MSI Uganda, e.g., this appears to be the case, as evidenced by the numerous reassignments that have occurred in the past years. Third, teams must have a way to identify promising reassignments during a team meeting. In this paper, we propose a range of methods with varying complexity. The simplest one only requires a spreadsheet where information can easily be prefilled and updated. Outreach programs generally employ regional and/or national coordinators who could additionally help facilitate decision-making during the meetings.

The decentralized approach starts with an initial assignment of sites to teams and an initial allocation of visit frequencies to sites. We then perform one or more *iterations* of team meetings. At the start of an iteration, teams are grouped into team meetings. Section 2.5.2 describes several methods for this. Then, for each team meeting, teams in the same meeting reassign sites and reallocate visit frequencies to sites. Section 2.5.1 outlines three approaches for site reassignment and describes the heuristic used to reallocate visit frequencies. Figure 2.1 provides a schematic overview of one iteration.

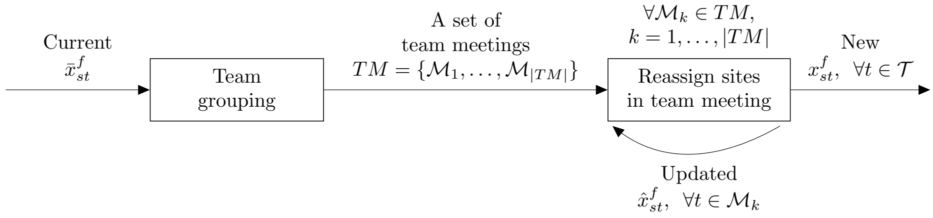


Figure 2.1: Overview of an iteration of the decentralized approach.

2.5.1 Site reassignment approaches in team meetings

In this section, we present three approaches for site reassignment in team meetings. First, we discuss *decentralized optimal reassignment*, which determines the optimal site-to-team assignment within a team meeting. Second, we present two simple decision rules which do not require decision support software. Such software and the expertise to run and interpret it are seldom available in humanitarian organizations (De Vries and Van Wassenhove, 2020). The first rule, *the takeover rule*, makes simplifying assumptions on the type of reassignments considered and the effect of visit frequencies on client volume. The second rule, *the simple takeover rule*, additionally simplifies how the impact of a reassignment is calculated.

2.5.1.1 Decentralized optimal reassignment

We extend the centralized model in Section 2.4 to model the problem of determining the optimal assignment for teams in a team meeting. We refer to this as Decentralized Optimal Reassignment (DOR). Let $\bar{x}_{st}^{f} \in \{0, 1\}$ be the current assignment of sites to teams and visit frequencies to sites. Let $\mathcal{M}_k$ be a team meeting in the set of team meetings in an iteration $TM = \{\mathcal{M}_1, \ldots, \mathcal{M}_{|TM|}\}$. We add constraints $x_{st}^{f} = \bar{x}_{st}^{f}, \ \forall t \notin \mathcal{M}_k$ to the centralized model to ensure that teams not included in the team meeting keep their current assignment. Then we set $\bar{x}_{st}^{f} = x_{st}^{f}$. Then we continue to the next team meeting $\mathcal{M}_{k+1}$ until all $|TM|$ team meetings have taken place.

2.5.1.2 Decentralized decision rules for site reassignment

In this section, we present two decision rules for site reassignment based on two simplifications. First, both decision rules consider only one potential reassignment: *a takeover*, where a team takes over a site from another team. Concurrent exchanges of sites between two or more teams are thus excluded. Takeovers are usually feasible, because the team taking over the site can reduce the visit frequency to one or more of its currently assigned sites to free up capacity for the takeover.

Calculating the impact of a takeover requires visit frequencies to be re-optimized, which is a difficult problem (De Vries et al., 2021a). Both rules therefore make the simplifying assumption that the visit frequency has no impact on client volumes per visit. We denote the client volume per visit that depends solely on s and t by $\hat{\mu}_{st}$, as opposed to the client volume per visit that additionally depends on the visit frequency f, μ^f_{st} (we explain in Section 2.6.1 how we estimate these parameters).

We now outline the process of reassigning sites in team meetings using one of the decision rules. In a team meeting, teams derive a joint list of sites they currently serve in a fixed but pre-determined order (alphabetical in our implementation), which are then consecutively considered for a takeover. The teams use one of the decision rules to determine if a site should be taken over. A takeover takes place if the decision rule identifies it as beneficial and if the team taking over the site has sufficient capacity to do so. Teams continue to consider sites on this list for a takeover. Once teams have considered the complete list, they restart from the beginning and continue until they have gone through this list once without finding any beneficial reassignments.

Takeover rule. The takeover rule (TR) determines whether a takeover should take place using a simplified method to reallocate visit frequencies for any potential takeover to analyze its impact on client volume. Let $\mathcal{R}_t$ denote the set of sites currently assigned to team t and $\mathcal{M}_k$ the team meeting taking place. To consider whether team t_2 takes over a site s_1 from team t_1, we first determine the visit frequencies team t_1 and t_2 would allocate to their new set of assigned sites, $\mathcal{R}_{t_1} \setminus \{s_1\}$ and $\mathcal{R}_{t_2} \cup \{s_1\}$ for team t_1 and t_2, respectively. For the decision rules, the reallocation of visit frequencies is always done using a greedy approach. Though this approach does not guarantee an optimal visit frequency allocation, it is an intuitive and simple way to reallocate visit frequencies.[2] The algorithm is as follows: 1) set all visit frequencies to f^{LB} (the lowest feasible frequency in the set $\mathcal{F}$) for each site; 2) greedily pick the site with the highest $\hat{\mu}_{st}$ and set the visit frequency to the highest feasible frequency in the set $\mathcal{F}$ given the team's remaining capacity; 3) repeat Step 2) until the team's capacity has been allocated. The x^f_{st} resulting from the takeover and visit frequency reallocation is evaluated in objective function (2.1) to determine if the takeover increases client volume. These steps are repeated for all potential teams $t_2 \in \mathcal{M}_k$ for which $s_1 \in \mathcal{S}_{t_2}$. If one or more takeovers that lead to an increase in

[2] The problem of allocating visit frequencies to sites resembles a knapsack problem for each team. A greedy approach would be optimal when: 1) the visit frequency does not affect the client volume per visit, and 2) the set of feasible visit frequencies $\mathcal{F} = \mathbb{R}^+$.

expected client volume are found, then the takeover that leads to the largest increase in expected client volume is performed.

Simple takeover rule. The simple takeover rule (STR) decides whether a takeover should take place using an *estimate* of its impact. In particular, STR estimates the impact of taking over *one outreach visit* to a site instead of the *entire site*. To make this estimate, STR does not need to consider how visit frequencies would be reallocated if the takeover would occur. The estimated gain for team t_2 taking over one outreach visit to site s_1 equals $\hat{\mu}_{s_1 t_2}$. This is an estimate, because the exact increase is non-linear and depends on the visit frequency allocated to site s_1 after the takeover. To allocate one visit to site s_1, team t_2 must drop one outreach visit from a currently assigned site. To estimate the associated loss in client volume, we define the marginal decrease parameter τ_t. This parameter equals the lowest expected client volume across the subset of sites currently assigned to team t where the visit frequency can still be decreased, i.e., $\tau_t = \min_{s \in \mathcal{R}_t}\{\hat{\mu}_{st} \mid x_{st}^{f^{LB}} = 0\}$. Similarly, after the takeover, team t_1 estimates the impact on its client volume of dropping one outreach visit to site s_1 as $\hat{\mu}_{s_1 t_1}$. This is an estimate, because the exact decrease is non-linear and depends on site s_1's allocated visit frequency before the takeover. Team t_1 can then allocate one outreach visit to its remaining sites $s \in \mathcal{R}_{t_1} \backslash \{s_1\}$. To estimate the associated increase in client volume, we define the marginal increase parameter σ_t. This parameter equals the highest expected client volume across the subset of sites currently assigned to team t where the visit frequency can still be increased, i.e., $\sigma_t = \max_{s \in \mathcal{R}_t}\{\hat{\mu}_{st} \mid x_{st}^{f^{UB}} = 0\}$. Team t_2 takes over the *complete* site if the sum of these impacts is positive and greatest among all potential teams $t_2 \in \mathcal{M}_k$ for which $s_1 \in \mathcal{S}_{t_2}$, i.e., if $\max\limits_{\{t_2 \in \mathcal{M}_k \mid s_1 \in \mathcal{S}_{t_2}\}} \hat{\mu}_{s_1 t_2} - \tau_{t_2} + \sigma_{t_1} - \hat{\mu}_{s_1 t_1} \geq 0$. After the takeover, visit frequencies are reallocated using the greedy approach described above.

The advantage of STR is that it requires estimates of only three parameters: $\hat{\mu}_{st}$, σ_t, and τ_t. Parameter $\hat{\mu}_{st}$ can be estimated using historical data and adjusted where necessary by teams. The parameters σ_t, and τ_t can easily be derived from the current assignment and updated in a simple spreadsheet. STR's disadvantage is that it may lead to takeovers which decrease client volume because it implicitly assumes that only three sites are affected by the takeover: the site taken over, the site to which team t_1 reallocates one visit, and the site from which team t_2 drops one visit. In reality, team t_1 may reallocate capacity to *multiple* sites, and t_2 may drop visits from *multiple* sites. In online supplement A, we evaluate the potential estimation error of STR, identify factors that drive this error, and derive a worst-case bound. In theory, the worst case optimality gap of STR is large but in Section 2.6.2, we show that it performs well for realistic instances. DOR and TR will never result in an assignment worse than the initial one. The worst-case optimality gap of these two methods is thus equal to that of the initial solution. Online supplement B elaborates on this.

2.5.2 Grouping teams into team meetings

We propose several rules for grouping teams into team meetings. Our intent is not to propose an optimal way of doing so. Instead, we consider a few simple rules that are easily implemented in practice. Let N denote the number of teams in a team meeting. We consider a potential approach that 1) selects the first one or two teams for a team meeting according to some rule, and 2) adds $N-1$ or $N-2$ teams in ascending order of distance between their base and that of the first team selected in step 1. The latter is to ensure that there is overlap in the set of sites the teams can serve, given restrictions on driving time. Steps 1 and 2 are performed iteratively and repeated until each team is assigned to at least one meeting.[3,4] We now outline briefly four rules for Step 1), i.e. selecting the *first* team(s) for a team meeting. Further details are provided in Appendix 2.A.

- **Baseline.** This rule selects the first team randomly from the list of unassigned teams. It serves as a benchmark for more advanced rules.
- **Maximum sites.** This rule prioritizes the unassigned team that serves the largest number of sites. If this team frees up capacity, it can visit high-expected client volume sites more frequently. Though simple, the rule is myopic: It can be rational for a team to serve many sites, e.g., if many of them attract few clients.
- **Maximum marginal increase.** This rule uses a slightly more informative metric to capture the potential benefit of a team freeing up capacity: marginal increase parameter σ_t. It prioritizes the unassigned team for which σ_t is highest.
- **Complementing teams.** The previous rules do not consider that if a team takes over a site from another team, it must allocate capacity to that site. The complementing team rules pairs a team which would experience a relatively

[3]The number of team meetings until this criterion has been reached may vary depending on the rule.

[4]Teams can participate in more than one team meeting per iteration. This can be beneficial, for instance, if one team can benefit from reassigning sites with several teams with close team bases.

large increase in client volume from having a site taken over with a team that would experience a relatively small decrease in client volume from taking over a site. The rule aims to identify such pairs by selecting the teams t_1 and t_2 for which $\sigma_{t_1} - \tau_{t_2}$ is highest. To ensure that there is overlap in $\mathcal{S}_{t_1}$ and $\mathcal{S}_{t_2}$, only pairs consisting of a team and one of its three closest neighboring teams are considered.

2.6 Numerical results

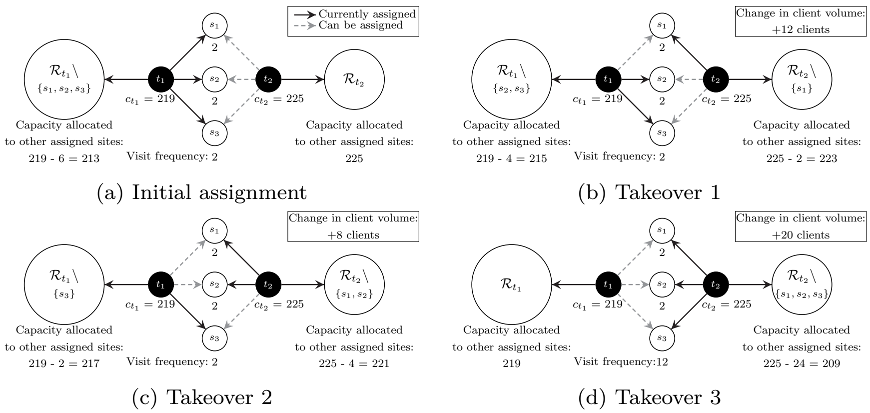
To answer the questions introduced in Section 2.1, we use a case study of MSI's outreach teams in Uganda and a set of randomly generated instances, referred to as random instances. Section 2.6.1 provides details of the case study and the random instance generation. We present the results in Section 2.6.2. Here, our primary aim is to *describe* the impact of decentralization on client volumes and what moderates this impact. However, part of our insights can be used *prescriptively*: they can help humanitarian organizations make design choices for their decentralized approach.

2.6.1 Test instances

2.6.1.1 Case study

MSI's outreach teams provide reproductive healthcare services, including family planning. The WHO defines family planning as the use of contraceptives to allow individuals and couples to plan for and have their desired number of children and to determine the timing and spacing between their births. SDGs 3.7 and 5.6 target increasing access to family planning services.

We set up the case study using data from MSI's outreach services in Uganda from July 2015 to November 2019. The choice for Uganda was based on that: 1) it was one of the first countries where MSI started collecting detailed client data (in 2015), 2) the teams in Uganda have put considerable effort into enhancing the accuracy of their data and were keen to collaborate, and 3) the teams are familiar with the practice of site reassignment in team meetings, but there seems to be room for improvement. For instance, most of the teams have participated in site reassignments but these tended to occur between a team and its closest neighboring team (based on the distance between team bases). Our initial analysis indicates that teams may also benefit from reassigning sites with teams further away. Several teams also serve a disproportionate number of sites. Figure 2.2 illustrates the potential benefit of reassigning sites for a subset of sites and teams in Uganda. In online supplement C, we describe the data cleaning process. Our final dataset comprises 24 outreach teams ($\mathcal{T}$) and 1,919 sites ($\mathcal{S}$).



(a) Initial assignment (b) Takeover 1

(c) Takeover 2 (d) Takeover 3

Figure 2.2: The impact of takeovers of sites s_1, s_2, and s_3 from team t_1 by team t_2 on total client volume and visit frequencies (denoted per year) based on CLIC data from the outreach teams in Uganda. Team t_1 is currently assigned to many sites (indicated by the size of node $\mathcal{R}_{t_1} \backslash \{s_1, s_2, s_3\}$). Takeovers of site s_1, s_2, and s_3 by team t_2 allow team t_1 to increase the visit frequency to its remaining sites with high client volume. Also, site s_3 has high client volume for team t_2 relative to its other currently assigned sites $\mathcal{R}_{t_2} \backslash \{s_3\}$. Team t_2 thus allocates a high frequency to site s_3 and to do so reduces the visit frequency to other sites with lower client volume.

The expected client volume per visit μ^f_{st} depends on the visit frequency, travel times, and team size. Let ST_{st} be the start time if team t visits site s and TS_t team $t's$ size. In online supplement C, we explain the regression analysis that estimates μ^f_{st} as:

$$\mu^f_{st} = \begin{cases} \left[\hat{\lambda}_s \left(\hat{\alpha} + \hat{\beta}\sqrt{\frac{12}{p^f}} - \hat{\gamma}\sqrt{ST_{st}} + \hat{\delta} TS_t\right)\right] & s \in \mathcal{S}_t \\ 0 \quad \text{otherwise} \end{cases} \tag{2.5}$$

The estimated coefficients are $\hat{\alpha} = 1.45, \hat{\beta} = 0.14, \hat{\gamma} = 0.28$, and $\hat{\delta} = 0.06$. The parameter $\hat{\lambda}_s$ represents the baseline client volume per visit. The part between the brackets in (2.5) represents a multiplication factor for the baseline client volume. This factor equals one for the baseline visit frequency (12 visits per year), start time (9.00 AM), and team size (four providers). Decreasing the visit frequency to three would increase this factor to 1.14, meaning expected client volume increases by 14%.

Note that (2.5) includes a non-linear effect of start time on client volume, with a larger negative impact of a later start time early in the morning compared to later in the day. The functional form of the effect of start time on client volume is further discussed in online supplement C and F.

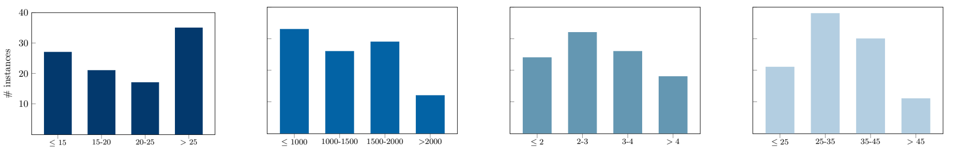
We calculate $\hat{\mu}_{st}$ by setting $p^f = 1$ in (2.5). To derive the initial site-to-team assignment and visit frequencies to sites, we assign each site to the team that last visited it and we allocate initial visit frequencies using the greedy approach described in Section 2.5.1.2. The planning period is set to one year. Table 2.1 describes how we obtain the values of the remaining parameters.

Table 2.1: Parameter values used in the case study.

Parameter	Description
TS_t	Apart from minor variations, teams in MSI Uganda are the same size across visits. We set the team size of team t as the size most frequently recorded across its visits.
ST_{st}	The start time at site s for team t equals the time team t leaves the base, plus the time taken to travel to site s. The base departure time is set at 7.00 AM for all teams. The travel time equals the kilometer distance between the base and the site (see online supplement C for details), divided by the traveling speed per hour. The speed is set at 50 kilometers per hour, which is based on the average driving speed for a subset of 24 routes using OpenStreetMap.
$\mathcal{S}_t$	We set $\mathcal{S}_t$ as all sites within a two-hour drive from team t's base, which is MSI's recommended maximum driving time.
c_t	Team t's capacity of outreach visits over the planning period, calculated as $c_t = \frac{v_t}{m_t} \times 12$, where v_t is the number of visits by team t over m_t months of operation. We increased capacity for one team so that the lower bound frequency could be allocated to all its initially assigned sites. This team served an exceptionally high number of sites (in practice, the visit frequency may be lower than the organization's lower bound). Also, we calculate capacity using four years of service delivery data, but capacity can slightly vary from year to year.
$\mathcal{F}$	MSI currently advises having intervals of between one and six months between visits, often expressed as an integer number of months. Accordingly, over a planning period of one year, the feasible set of visit frequencies equals $\mathcal{F} = \{2, 2.4, 3, 4, 6, 12\}$.

2.6.1.2 Random instances

To generalize our findings, we randomly generate additional realistic test instances. Using data from MSI's outreach teams in Uganda, Madagascar, Malawi, Sierra Leone, Tanzania, and Zimbabwe, we derive realistic distributions for the case study parameters. See Appendix 2.B for details. We use these to randomly generate (in the following order): 1) the number of teams and their locations and sizes, 2) the distribution of the number of sites initially assigned per team, 3) the site locations and corresponding travel times, and 4) the distribution of λ_s per team and the value of λ_s for each site. Given the set of initially assigned sites, initial visit frequencies are allocated using the greedy approach. We generate 100 random instances (see Figure 2.3).



(a) Number of teams (b) Number of sites (c) Average team size (d) Average value of λ_s

Figure 2.3: Characteristics of the 100 random instances.

2.6.2 The trade-off between decentralization and client volume

Here we assess the trade-off between decentralization and client volume and the individual and joint effects of its potential moderators. We do so by calculating the optimality gap: i.e., the gap between the solution of DOR, TR, or STR with specific values of each moderator and the solution of the centralized model. We use MATLAB R2020b for all computations (see online supplement D for the computation times). As a baseline setting for the decentralized approach, we consider one iteration ($i = 1$) of team meetings with two teams ($N = 2$), that are grouped using the baseline rule ($bLine$), and who use STR as a decision-making approach.

Figure 2.4 demonstrates the effectiveness of the baseline decentralized approach, which results in significant improvement compared to the scenario where teams do not collaborate ($N = 1$). In the latter case, teams cannot reassign sites and can only reallocate visit frequencies for their currently assigned sites. The baseline decentralized approach reduces the optimality gap by 3.3 and 4.3 percentage points for the Uganda case and random instances, respectively. Nevertheless, there is a trade-off between decentralization and client volume. For the baseline setting, the gap with centralized decision-making equals 3.2% and 2.3% for the Uganda case and random instances, respectively. We now assess the following potential moderators:

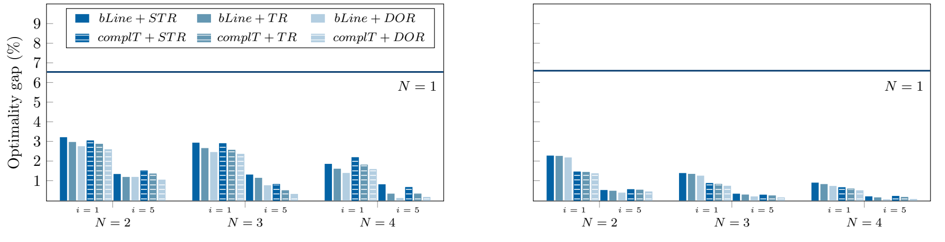
M_1. The number of teams in a team meeting

M_2. The number of iterations of team meetings

M_3. The site reassignment approach in team meetings

M_4. The grouping of teams in team meetings

M_5. The accuracy of central planner parameter estimates



(a) Uganda case (b) Random instances

Figure 2.4: Optimality gaps of all numerical experiments using moderators $M_1 - M_5$ for the Uganda case and the random instances.

The number of teams in a team meeting (M_1). Increasing the number of teams in a team meeting, thereby decreasing the degree of decentralization, moderates the trade-off. Individually, M_1 reduces the optimality gap by 1.4 percentage points for both the Uganda case and the random instances ($bLine + STR$, $N = 4$, and $i = 1$ in Figure 2.4). This moderation effect occurs because an increase in N leads to an increasing number of sites that can be reassigned among teams.

The number of iterations of team meetings (M_2). The number of team meetings is also a moderator. After five iterations of team meetings ($i = 5$), the optimality gaps are 1.3% and 0.5% for the Uganda case and random instances, respectively ($bLine + STR$, $N = 2$, and $i = 5$ in Figure 2.4). Figure 2.5 shows how the optimality gap develops across iterations. The benefit of continued iterations is especially evident for the second and third iteration, after which the improvement is minimal. It is important to note that a reassignment may be feasible or beneficial in one iteration, while it was not in previous iterations. This is because the grouping of teams varies across iterations, and the benefit of reassignments in the current iteration depends on the current site-to-team assignment which evolved based on reassignments in past iterations.

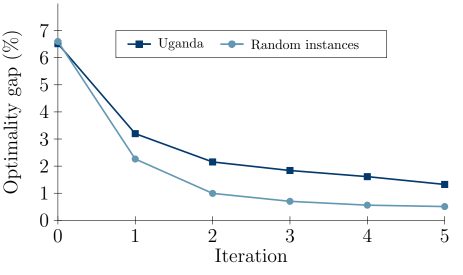


Figure 2.5: The optimality gap per iteration for $bLine + STR$ and $N = 2$. Iteration 0 shows the optimality gap for $N = 1$. The optimality gap for the random instances is the average across all instances.

The site reassignment approach in team meetings (M_3). For this moderator, we compare STR with TR and DOR. Figure 2.4 shows that more complicated decision-making within team meetings leads to a minor improvement in the optimality gap. The relatively small reduction in optimality gap from STR to TR suggests that the marginal increase/decrease parameters can estimate the change in expected client volume due to a takeover reasonably accurately. The minor improvement of DOR over TR first shows that other types of reassignments, for example, an exchange of two sites between two teams, can be achieved by a series of takeovers. This has important practical implications. Takeovers are easier to implement than exchanges. Assessing a potential takeover only requires a calculation for each *team*, whereas assessing a potential exchange requires a calculation for each *site* that might be exchanged until a beneficial exchange is found. Second, the estimated non-linear effect of visit frequencies on client volume is moderate and therefore the bias induced by this assumption and its impact on the optimality gap tend to be small. Overall, although the decision-making within team meetings is a moderator, the effect is small. This shows that:

Insight 1. Simple decentralized decision rules can be used to make reassignment decisions with only a small loss in effectiveness compared to optimal decentralized decision-making.

The grouping of teams in team meetings (M_4). In online supplement E, we show that the complementing teams rule is the best performing grouping rule and that the maximum sites and maximum marginal increase rule do not outperform the baseline rule. This leads to the following insight:

INSIGHT 2. To group teams, it is beneficial to first select a pair of teams in which one team would see a relatively large increase in expected client volume if allocated one more outreach visit and the other team would see a relatively small decrease in client volume if allocated one visit less.

To assess the moderation effect of grouping the teams in meetings, we consider the baseline rule (*bLine*) - the simplest rule - and the complementing teams rule (*complT*) - the best performing rule. The grouping of teams into team meetings is a moderator, but the effect is relatively small compared to moderators M_1 and M_2. Using *complT* instead of *bLine* in the baseline setting reduces the optimality gap by 0.2 and 0.8 percentage points for the Uganda case and random instances, respectively (*complT* + STR, $N = 2$, and $i = 1$ in Figure 2.4). The difference between the two rules is more pronounced for the random instances. The *complT* rule more strongly outperforms *bLine* if the optimality gap of the initial solution is smaller. This indicates that when there is limited room for improvement, it is imperative to carefully choose the right pairs of teams for a team meeting.

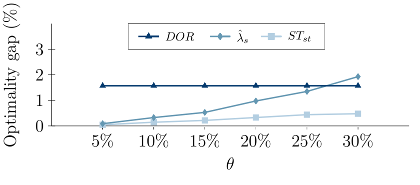
Joint effect of moderators ($M_1 - M_4$). Figure 2.4 shows that for most moderators the direction of the moderation effect is independent of the value of the other moderators. Adding moderator M_1, M_2, or M_3 to any other combination of moderators always leads to a non-negative improvement in the optimality gap. Interestingly, the grouping of teams (M_4) is an exception. For example, the complementing teams rule no longer outperforms the baseline rule when combined with five iterations of team meetings. This may be because the baseline rule leads to more diversified team meetings than the complementing teams rule. As a result, the lowest optimality gap is obtained by jointly exploiting M_1, M_2, and M_3. The magnitude of the effect is also largely independent of the value of other moderators. For example, for the Uganda case, combining M_1 with any combination of other moderators leads to a reduction in the optimality gap of between 0.5 and 1.4 percentage points.

The accuracy of central planner parameter estimates (M_5). Decentralized decision-making may be preferable to centralized decision-making because teams can draw on local knowledge, which suggests that central planner parameter estimates may be biased. The accuracy of central planner estimates also heavily depends on data quality. Though MSI collects detailed data, this is not universally the case for humanitarian organizations. We analyze the moderation effect of the accuracy of central planner parameter estimates.

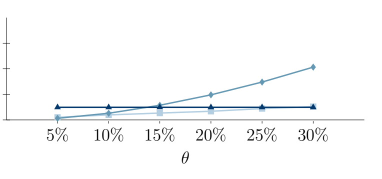
To do so, we incorporate an estimation error in μ^f_{st} for the centralized model. We focus on two areas: baseline client volumes ($\hat{\lambda}_s$) and travel times that determine the start times (ST_{st}). The central planner has a bias of $\bar{\theta}_s$ generated from a uniform distribution on $[-\theta, \theta]$, with $\theta \in \{5\%, 10\%, \ldots, 30\%\}$. We assume that the central planner cannot assign a team to a site for which the actual travel time is longer than two hours to avoid infeasible site-to-team assignments.

Figure 2.6 confirms that the accuracy of baseline client volume estimates moderates the trade-off. Increasingly larger errors in baseline client volume estimates decrease the optimality gap between the centralized and decentralized solution. Decentralized decision-making outperforms centralized decision-making when $\theta \geq 25\%$ and $\theta \geq 15\%$ for the Uganda case and the random instances, respectively. This is because a bias in $\hat{\lambda}_s$ leads to a large bias in the estimated expected client volumes, leading the central planner to incorrectly allocate visit frequencies.

In contrast, incorrectly estimating the start time has a limited effect on the optimality gap and is therefore not a strong moderator of the trade-off. Even estimation errors of up to 30% lead to an optimality gap of at most 0.5%. This is because travel times have a minor effect on expected client volume in this case.



(a) Uganda case



(b) Random instances

Figure 2.6: Optimality gaps of the centralized model with parameter estimation errors in $\hat{\lambda}_s$ and ST_{st} for different values of θ and the optimality gap of DOR for $i = 1$, $N = 4$, and using the complementing teams rule to group teams.

In short, the results from this section show that:

Insight 3. There is a significant trade-off between decentralization and client volume, but this can be moderated by (1) the number of teams in a team meeting, (2) the number of iterations of team meetings, (3) the site reassignment approach in team meetings, (4) the grouping of teams in team meetings and (5) the accuracy of central planner estimates of baseline client volume.

The insights above are based on the Uganda case and the *average* optimality gaps of the random instances. Figure 2.7 shows that decentralized decision-making also performs well in the worst case. The largest optimality gap among the random instances decreases from 16% to 7.5% after one iteration and to 3.1% after five iterations (for $N = 2$ and STR). Importantly, there are no random instances where the optimality gap after one iteration is larger than the *initial* optimality gap for STR. This shows that although STR can, in theory, significantly over- or underestimate the change in client volume, it does not lead to many reassignments that decrease overall client volume.

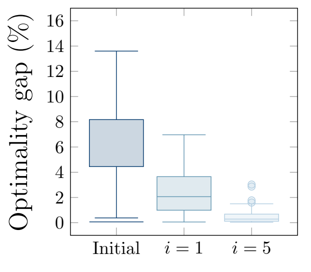


Figure 2.7: Box plots of the optimality gap of the initial solution, after one iteration, and after five iterations for the random instances. The latter two are obtained using STR, $N = 2$, and the baseline rule to group teams.

2.7 Robustness analysis

2.7.1 Alternative objective functions

We now assess how optimizing client volume aligns with frequent objectives in family planning service provision: weighted client volume and couple years of protection (CYP). The former allocates a higher weight $\omega > 0.5$ to specific types of clients, and a weight $1 - \omega$ to other clients. We focus on two types of clients: young clients and adopters (clients who adopted a contraceptive method during an outreach visit and were not using a contraceptive method in the three months preceding the visit). CYP refers to the number of years the contraceptive method protects a couple against pregnancy. Online supplement G provides further details on the input parameters for this analysis.

We use the centralized model to calculate the optimal solution for weighted client volume and CYP. Figure 2.8 shows STR's optimality gap when maximizing client volume and the optimality gap when this solution is evaluated in terms of weighted client volume for different weights ω and CYPs for the Uganda case. The results show that maximizing client volume aligns well with maximizing weighted client volume, especially for $\omega \leq 0.7$. Weights $\omega \geq 0.8$ represent almost a complete focus on young or adopter clients. The solution value obtained by the decision rule is then at most three percentage points further away from the optimal solution's value. The decision rule solution also performs well in terms of CYPs, with not even a percentage point increase in the optimality gap.

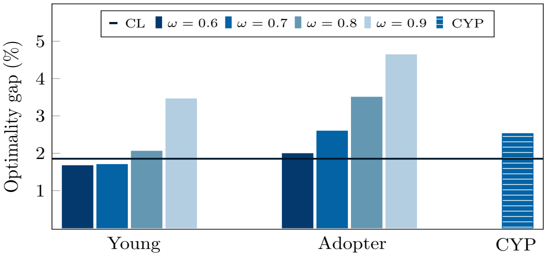


Figure 2.8: Optimality gaps of STR's solution evaluated in terms of weighted client volume and CYPs for $N = 4$ and the Uganda case. The optimality gap of STR when maximizing client volume (CL) is also shown.

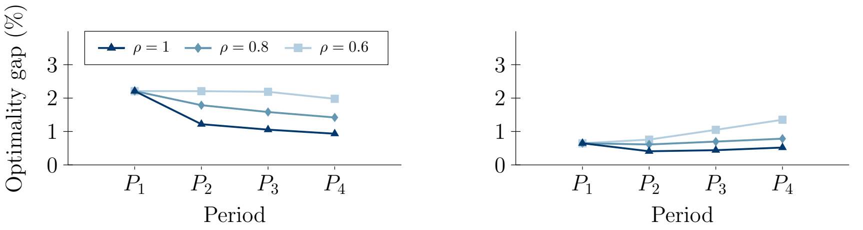
Insight 4. Simple decentralized decision rules that maximize client volume remain close to optimal even when the "true" objective is to maximize weighted client volume or CYPs.

2.7.2 Multi-period analysis

So far, we have assumed that parameters remain constant over time, but they may vary in reality. This section evaluates how two dynamic elements impact the quality of the decentralized approach.

First, we vary the baseline client volume at the site ($\hat{\lambda}_s$) to reflect evolving demand for health services over time. We use estimates from Alban et al. (2022) to randomly draw a realistic growth profile for each site. See online supplement H for details. Second, we introduce a probability ρ that a team participates in a team meeting in a given period, to reflect that teams can opt out of team meetings. We consider four periods and one iteration per period, where starting from period two, $\hat{\lambda}_s$ changes and teams participate in team meetings with probability $\rho \in \{1, 0.8, 0.6\}$.

Figure 2.9 presents the optimality gap across all periods for different values of ρ using STR. The results suggest that the decentralized approach is close to optimal, despite the optimal team-to-site assignment changing over time. The gap still decreases over time when team participation exceeds 80%. For $\rho = 0.6$, the optimality gap increases across periods, but remains small compared to the initial optimality gap (6.5% for the Uganda case and 6.6% for the random instances on average). This shows that organizations should consider ways to incentivize team participation to reap maximum benefits from the decentralized approach.



(a) Uganda case (b) Random instances

Figure 2.9: Optimality gaps of STR with dynamic $\hat{\lambda}_s$ and for different values of ρ, for four consecutive periods, $i = 1$, $N = 4$, and using the complementing teams rule to group teams. The optimality gap represents the average across 15 repetitions for the Uganda case and the average across 15 repetitions across all instances for the random instances.

Insight 5. Simple decentralized decision rules remain close to optimal when client volumes evolve over time and when teams opt-out of team meetings with a low probability.

2.7.3 The effect of visit frequency on visit effectiveness

The parameter estimates used to compute the results above are based on the family planning context. An important factor where outreach programs for different health services may vary, is how visit frequencies affect outcomes (in our case client volume). The build-up of the number of clients requiring the service and/or the outcome loss associated with delay may be stronger or weaker depending on the health service considered (e.g., screening for noncommunicable diseases vs. providing HIV or primary care). This relationship is captured by the parameter β (as shown in (2.5)). Variations in this parameter may especially influence the effectiveness of the simple decentralized decision rules, since they assume that visit frequencies do not affect outcomes (i.e. that $\beta = 0$). In this section, we analyze to what extent the decentralized approach remains effective for different values of β. Specifically, we recalculate μ_{st}^{f} for $\beta \in \{0.05, 0.10, ..., 0.30\}$, and compute the optimality gap between STR and the centralized solution for these new values.

Our results, shown in Figure 2.10, indicate that the decentralized approach remains highly effective regardless of the value of β: after one iteration, the (average) optimality gap remains about 1% for the random instances and 2.2% to 2.6% for the Uganda case. For higher values of β, we observe that the *initial solution* yields a lower optimality gap, indicating less potential gain from site reassignments. As β increases, the effect of team characteristics (e.g., start time and team size) on client volume reduces relative to the impact of visit frequency. The team meetings then serve as a means to reassign sites so that some teams can increase their visit frequency to high-performing sites. Our results demonstrate that the decentralized approach effectively captures this benefit.

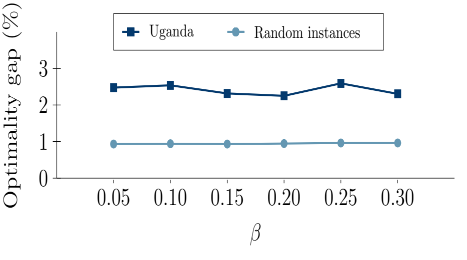


Figure 2.10: Optimality gaps for different values of β, for STR, $i = 1$, $N = 4$, and using the complementing teams rule to group teams. The optimality gap for the random instances represents the average across all instances.

Insight 6. Simple decentralized decision rules remain close to optimal irrespective of how strongly visit frequency impacts a visit's effectiveness.

2.8 Conclusion and discussion

Mobile outreach teams are key for scaling up access to healthcare services in rural areas. Outreach sites are assigned to outreach teams, but dynamics in demand and supply can make once optimal site-to-team assignments far from optimal over time. We develop a decentralized approach for site reassignment where teams collaborate in team meetings. We analyze the effectiveness of this approach and evaluate what drives the effectiveness. We study this approach in the context of the NGO MSI Reproductive Choices, using a case study of its outreach teams in Uganda and a set of randomly generated realistic test instances. Our results provide several important insights.

There is a significant benefit of going from a fully decentralized setting where no teams collaborate to a decentralized approach where two teams collaborate. Our results show that this decreases the optimality gap by 50% after one iteration of team meetings. Nevertheless, there is a trade-off between decentralization and effectiveness, but this trade-off can be moderated.

First, adding a third and fourth team to a team meeting has a positive effect, but the effect is much smaller compared to the effect of going from no collaboration to collaboration between two teams. This suggests that it is more important to introduce collaboration between teams rather than optimize the number of teams involved.

Increasing the number of iterations of team meetings also moderates the trade-off. Our results show that the first iteration of team meetings has the largest impact. Roughly 60% of the decrease in the optimality gap attained in the first five iterations is reached after one iteration. This indicates that team reassignment may not be time-consuming. This is an important finding, as a time-intensive methodology may be a barrier to adopting systematic site reassignment practices.

The site reassignment approach used in the team meetings has a minor moderation effect on the trade-off. We show that simple decentralized decision rules, which require only a spreadsheet, only lead to a slight loss of effectiveness compared to optimal decentralized decision-making. Even a decision rule where teams can only take over sites from other teams and which uses simple calculations to estimate the corresponding impact performs well. Our results suggest that this is even the case when the objective is misspecified (e.g., when the "true objective" assigns different weights to different types of clients), when expected client volumes per site evolve over time, when teams sometimes opt out of participating in meetings, and when the effect of visit frequency on outcomes changes. This finding has important implications for practice, as simple decision rules are commonly used in health and humanitarian organizations (De Vries and Van Wassenhove, 2020) and are less likely to encounter resistance when implemented (Gralla and Goentzel, 2018).

A fourth moderator is the grouping of teams into team meetings. We show that effective collaboration between teams depends on identifying the correct pairs of teams. Organizations should particularly encourage team meetings for pairs that are 1) geographically close, and where 2) one team serves sites with a high expected volume of clients that are visited relatively infrequently (due to limitations on capacity), and 3) the other team serves sites with a lower expected volume of clients that are visited often.

A fifth moderator is the accuracy of client volume estimates made centrally. Our analysis shows that centralized decision-making outperforms decentralized approaches by 0.2-1.5 percentage points after one iteration if a central planner makes estimation errors below 10%. Decision makers should then consider whether the gain in effectiveness due to centralization outweighs the loss of autonomy and flexibility. They could also consider hybrid approaches, e.g., using optimization centrally to suggest site reassignments but allowing teams to retain their decision autonomy. The trade-off disappears for estimation errors above 20% and decentralized outperforms centralized decision-making by roughly 0.5-1.5 percentage points. This confirms that decentralized decision-making is appropriate when accurate client volume estimates highly depend on local information.

A limitation of our work is the lack of empirical data to validate our proposed decentralized decision-making approaches. Field testing decentralized decision-making approaches is required to strengthen evidence of their effectiveness. This would also allow to further establish how the decentralized approach would work best in practice, e.g., how many teams should participate in one meeting and where these meetings should occur, and if it is possible to perform such meetings online. In addition, repeating our analysis for outreach programs of other health services, such as primary care, would help to further develop a comprehensive decentralized decision-making approach for outreach programs. Our results and insights provide a starting point for organizations to reevaluate their current planning practices and to develop and implement a systematic approach for decentralized site reassignment.

A second limitation is that our proposed decentralized approach relies on teams collaborating to improve the *total* number of clients served, even if some teams *individually* serve fewer clients. This raises the question for organizations like MSI of how to design an appropriate incentive structure where teams are motivated to participate in team meetings and operate based on a common objective instead of on their own objectives. Future research on this is much needed.

Our insights on decentralized decision-making can help organizations better understand the effect of decentralization. Health and humanitarian organizations have limited resources. Optimizing the use of available resources is important. We show that current site-to-team assignment decisions are far from optimal and that a decentralized decision-making approach provides a feasible and effective alternative to centralized decision-making when adequately designed.

Appendix

2.A Team grouping rules

Let the set $\bar{\mathcal{T}}$ represent the teams that have not yet participated in team meetings. For reference, the marginal increase and decrease parameters are defined as follows: $\sigma_t = \max_{s\in\mathcal{R}_t}\{\hat{\mu}_{st} \mid x_{st}^{f^{UB}} = 0\}$ and $\tau_t = \min_{s\in\mathcal{R}_t}\{\hat{\mu}_{st} \mid x_{st}^{f^{LB}} = 0\}$, where f^{UB} and f^{LB} denote the upper and lower bound frequency. All grouping rules continue until all teams have been assigned to at least one team meeting.

Baseline. Team t_1 randomly selected from $\bar{\mathcal{T}}$ is the first team to participate in meeting $\mathcal{M}_k$. We then add $N-1$ teams for which $\arg\min_{t_2\in\mathcal{T}\backslash t_1} d_{t_1t_2}$, where $d_{t_1t_2}$ is the distance in kilometers between the team bases of team t_1 and team t_2. Note that this step selects teams solely based on their distances – irrespective of whether they have already been grouped in a previous team meeting. We update $\bar{\mathcal{T}} = \bar{\mathcal{T}} - \{t \in \mathcal{M}_k\}$.

Maximum sites. The rule assigns as first team t_1 the team for which $\arg\max_{t\in\bar{\mathcal{T}}} \sum_{s\in\mathcal{R}_t}\sum_{f\in\mathcal{F}} x_{st}^f$. We then add the $N-1$ teams from $\mathcal{T}\backslash t_1$ with bases closest to team t_1's base and update $\bar{\mathcal{T}}$.

Maximum marginal increase. The first team for the next meeting t_1 is chosen as $\arg\max_{t\in\bar{\mathcal{T}}} \sigma_t$. We then add the $N-1$ teams from $\mathcal{T}\backslash t_1$ with bases closest to team t_1's base and update $\bar{\mathcal{T}}$.

Complementing teams. Let set $\mathcal{T}_t^*$ denote the three closest teams to team t. For all t, we calculate $\sigma_t - \tau_{t^*}$, $\forall t^* \in \mathcal{T}_t^*$. The first pair of teams added to the meeting is the pair for which $\max \sigma_t - \tau_{t^*}$, with $t \in \bar{\mathcal{T}}$ and/or $t^* \in \bar{\mathcal{T}}$. For $N > 2$, we add the $N-2$ teams from the set $\mathcal{T}\backslash\{t, t^*\}$ with bases closest to team t's base to the meeting. Lastly, we update $\bar{\mathcal{T}}$.

For all grouping rules, it holds that if the yielded team meeting is the same as a team meeting in the previous iteration, the last team added to the team meeting is replaced by the next closest team to the first team in the meeting if possible. This does not hold for the complementing teams rule when $N = 2$ as the rule selects a *pair* of teams.

2.B Generation of test instances

In this appendix, we describe the steps in the instance generation process. We use the parameter bounds shown in Table 2.2, based on data from outreach programs in six countries whose characteristics are shown in Table 2.3.

Table 2.2: Input parameters to generate the random instances

	Bounds
Number of teams	[9,33]
Number of sites per team in initial assignment	[37,90]
Average client volume per visit	[23,62]
Average team size	[2,4]
Maximum travel time	{1 hour, 1.5 hours, 2 hours}

The random instances are generated on an (X, Y) plane using equally spaced grid cells. The instance generation consists of the following steps:

1. Generate a number of teams using a discrete uniform distribution with the bounds specified in Table 2.2. Each team is assigned to the center of a randomly selected unoccupied grid cell.

2. For each instance, an expected team size is drawn from a discrete uniform distribution with the bounds specified in Table 2.2, denoted by $\mathbb{E}[TS_t]$. We then draw the size of each team. Specifically, the team size equals $\mathbb{E}[TS_t]$ with probability $\frac{3}{5}$ and $\mathbb{E}[TS_t] + 1$ or $\mathbb{E}[TS_t] - 1$ with probability $\frac{1}{5}$. These probabilities are obtained from the data for the six countries. The capacity of each team is set to $20 \times 12 = 240$ days, as teams can work a maximum of 20 days per month.

3. A continuous uniform distribution is used to draw the expected number of sites per team $\mathbb{E}[|\mathcal{R}_t|]$. For each team, a discrete uniform distribution is used to draw the number of sites initially assigned. The distribution bounds are set such that the lower bound is always above 20 (each site can be visited with the upper bound frequency) and the upper bound never exceeds 120 (each site can be visited with the lower bound frequency) and such that the mean of the discrete distribution is equal to $\mathbb{E}[|\mathcal{R}_t|]$ and the standard deviation is equal to $\frac{1}{3}\mathbb{E}[|\mathcal{R}_t|]$. The setting for the standard deviation is based on that the standard deviation of the number of sites per team is about one third of the average for four out of six countries (Table 2.3).

4. The location of each site assigned to a team is randomly generated within the team base's grid cell. To represent the fact that some countries are more sparsely populated and the travel times are therefore longer, the maximum distance allowed between a team's base and the edges of their assigned grid

cell is varied by generating a maximum travel time which is chosen randomly from the set presented in Table 2.2. The travel time is calculated using the Manhattan distance between the site and the team base and a travel speed of 50 kilometers per hour.

5. The value of λ_s is drawn in three steps. First, to reflect the differences in client volume between countries, the country expected value $\mathbb{E}_{s\in\mathcal{S}}[\lambda_s]$ is drawn from a discrete uniform distribution using the bounds presented in Table 2.2. This is multiplied by 0.8 to capture the difference between client volume and lambda (the ratio of lambda to client volume is 0.8 for the Uganda case). Second, to reflect differences between teams, an expected lambda per team is drawn, $\mathbb{E}_{s\in\mathcal{R}_t}[\lambda_s]$, from a Weibull distribution. The shape parameter is determined by fitting a Weibull distribution to the average client volume per visit per team from the Uganda case and the scale parameter is set such that the mean is equal to $\mathbb{E}_{s\in\mathcal{S}}[\lambda_s]$. Finally, λ_s is drawn from a Weibull distribution. The shape parameter is determined by fitting a Weibull distribution to the λ_s for each team for the Uganda case and taking the average shape parameter across teams. The scale parameter is set such that the mean is equal to $\mathbb{E}_{s\in\mathcal{R}_t}[\lambda_s]$.

6. To calculate μ^f_{st}, the estimated regression coefficients for the Uganda case are used.

Table 2.3: Characteristics of the six country outreach programs

	Madagascar	Malawi	Sierra Leone	Tanzania	Zimbabwe	Uganda
Number of teams	22	27	14	33	9	24
Avg. number of sites per team	152.7	36.5	140.8	84.8	102.0	95.2
Std. dev. of sites per team	53.8	23.3	48.7	29.2	23.5	27.0
Avg. client volume per visit	22.9	35.6	54.3	61.6	40.5	31.1
Team size	[1–3]	[1–6]	[1–5]	[3–6]	[1–4]	[2–4]
Area of country (in 100s km^2)	600	100	75	950	400	250

Chapter 3

Providing Access where it is Needed: Equity and Inclusion through Contraceptive Implant Removals by Mobile Outreach Teams

This chapter is based on Van Rijn et al. (2023).

3.1 Introduction

Improving access to family planning services plays a key role in achieving the United Nations Sustainable Development Goals (SDGs). Expanding access to family planning services helps achieve SDG 3 (good health and well-being) and SDG 5 (gender equality). SDGs 3.7 and 5.6 target universal access to sexual and reproductive healthcare and rights, including access to family planning services. People's ability to make decisions regarding their reproductive lives, e.g., an individual being able to choose the family planning method most suited to their preferences and negotiate its use, strongly supports gender equality and empowerment (Starbird et al., 2016).

In recent years, method choice has expanded with the wider availability of the contraceptive implant because of price reductions and the launch of the Implant Access Program (Bayer Healthcare, 2012; FP2020, 2018; Merck, 2013). A contraceptive implant is a long-term reversible method effective for 3 to 5 years depending on the type. A trained healthcare worker inserts the implant into the arm to start its use and removes it from the arm to discontinue use. Reasons for discontinuing the implant include a desire to become pregnant, side effects, or reaching the maximum duration of use.

The wider availability of implants has led to their increased use, which will naturally lead to a greater need for their removal (Jacobstein and Stanley, 2013). In 2018, estimates for the number of expected removals ranged from 4.9 to 5.8 million in 69 FP2020 focus countries to 2.5 million in just the top five implant-procuring countries (Tanzania, Ethiopia, Kenya, Nigeria, and Zambia) (Christofield and Lacoste, 2016; Sergison et al., 2017).

Recent evidence highlights that the scale-up of removal services is not keeping pace with insertion services. For example, the Expand Family Planning Project recorded 137,000 implant insertions but only 4,092 implant removals from 2014-2016 (EngenderHealth, 2016). A study in Ghana found that 41% of women seeking an implant removal were unsuccessful in their first attempt at doing so, citing reasons such as unavailable providers and costs (Callahan et al., 2020). Limited access to removal services violates client's rights and choice (Christofield and Lacoste, 2016). It also endangers the adoption and long-term success of the method, as evidenced by the low uptake of the Norplant implant, which was partly attributed to inadequate access to removal services (Harrison and Rosenfield, 1998). This underscores that increasing access to removal services is necessary.

Access to removal services is particularly low in remote and rural areas – i.e., there is a significant inequity of access to removal services (Costenbader et al., 2020).

Mobile outreach teams can play a vital role in increasing access to removal services in these areas. Such teams consist of healthcare workers who visit sites in remote and rural areas at regular intervals – generally ranging from 1-6 months to provide a range of affordable (or free) reproductive healthcare services, including implant insertions and removals. An important purpose of outreach teams is extending access to healthcare to people for whom healthcare was previously out of reach (Doerner et al., 2007; Khanna and Narula, 2016). Outreach teams focus on providing services to people who face the highest barriers in using health services, including the poor and young women (Duvall et al., 2014). This makes outreach teams a key tool for improving equity and inclusion.

However, the extent to which outreach teams help attain better equity and inclusion depends on the organization of the outreach teams. A key allocation decision is selecting sites to visit. To align this decision with the aim of enhancing equity and inclusion, organizations must assess where the need for outreach teams to provide removal services is highest. Note that the need for outreach removal services in this case does not refer to a binary decision of whether teams should provide removal services or not, but rather to an assessment of where outreach removal services are most needed to address a gap in existing removal service availability. To obtain such an assessment, organizations could survey all potential sites to gather detailed data on population characteristics and demand, but this would be expensive and time-consuming. Instead, we explore the drivers of the need for outreach removal services, which reveal general characteristics of sites or regions that influence this need. Two specific sets of drivers we explore are related to the availability of other providers of removal services (e.g., the density of different types of health facilities) and demographics (poverty levels).

Given a set of selected sites to visit, organizations must consider how to deploy outreach teams to meet the need for removal services. This is not straightforward. Outreach teams both *generate* demand for removals by providing implant insertions and *fulfill* demand for removals by providing implant removals. They may worsen equity if they create demand they do not fulfill. It is therefore key to understand how the demand generated and fulfilled depends on the way the team is deployed. We study operational decisions that outreach teams can vary to better meet the need for outreach removal services. Here “better meeting the need” does not refer to the quality of the services provided; it denotes to what extent outreach teams are addressing the gap in removal service availability. We specifically study two operational decisions highlighted as important demand drivers in previous research:

the frequency of visits to a site and the way that demand is generated (e.g., marketing messages and referrals) (Alban et al., 2022; De Vries et al., 2021a).

We perform a regression analysis using service delivery data from NGO MSI Reproductive Choices' (MSI) outreach teams in Uganda and several public data sources. MSI is one of the largest NGOs aiming to scale up access to family planning services; it currently deploys more than 500 outreach teams worldwide. Our results yield several important insights. First, the need for outreach removal services is relatively low at sites located in areas with a high density of mid-level health facilities, compared to sites located in areas with a high density of high-level facilities. This suggests that the availability of mid-level health facilities leads to increased access to removal services, but there are still barriers to accessing removal services at high-level facilities. Second, higher poverty levels lead to a higher need for outreach removal services. Clients in high-poverty areas face additional barriers in accessing removal services and outreach teams are a key tool to alleviate this. Third, the extent to which a team meets the need depends strongly on the visit frequency to a site. Each additional visit increases the removal demand fulfilled more strongly than the removal demand generated (the removal demand generated is based on the number of implant insertions performed during outreach visits). As we discuss in Section 3.5, this has important implications for resource allocation. Finally, demand generation efforts can help to better meet the need for removals in high-poverty areas by increasing the awareness of outreach removal service availability.

The contribution of this paper is threefold. First, we generate insights that can help organizations balance the sustained demand for implant insertions with the increasing demand for implant removals. These insights can also be used as inputs for evidence-based objective functions for future modelling and optimization studies on this topic. Second, our insights have important implications for equity and inclusion. Equity is a key concern in many health delivery settings and including equity considerations has important implications for operations (Breugem and Van Wassenhove, 2022; Gallien et al., 2021). Our study is one of the few to empirically investigate how operational decisions influence equity and inclusion. Moreover, much of the literature has focused on equity with respect to a fixed need (e.g., Marsh and Schilling (1994) propose various equity measures that represent need as a parameter). We extend the literature by studying a setting in which operational decisions also influence the need. Third, we contribute to the growing literature on operations management in family planning (for examples see Alban et al. (2022), De Vries et al. (2021a), Karimi et al. (2021) and Van Rijn et al. (2024a)). Increasing access to family planning services is seen as a development "best buy" and is crucial for advancing the 2030 agenda for sustainable development (Starbird et al., 2016).

3.2 Hypothesis development

In this section, we develop two sets of hypotheses. We first consider potential drivers of the need for outreach removal services and then potential operational decisions which can help meet this need.

3.2.1 Drivers

There are several options available to clients when it comes to accessing health services. Besides mobile outreach teams, clients may also access services at private or public health facilities. The choice of which option to use can depend on various factors.

Levesque et al. (2013) conceptualize access to healthcare using five dimensions. One dimension is availability, which refers to the physical accessibility of health services. However, physical accessibility can be challenging in rural areas, as there are often not enough public health facilities to ensure access (Doerner et al., 2007). Availability also encompasses the availability of qualified healthcare personnel and supplies to provide services (Levesque et al., 2013). This is particularly problematic in low- and middle-income countries. Health facilities in both the public and private sector frequently report stock-outs of medicines and supplies (Karamshetty et al., 2022). There is also a significant shortage of trained healthcare workers, particularly in rural areas (Hardee et al., 2017). Additionally, the level of specialization can differ across health facilities, resulting in varying health services being provided. In Uganda, health facilities are classified as private clinics, level II, level III, level IV, or hospital. While low-level facilities are mostly staffed by nurses, mid- and high-level facilities tend to have physician assistants (level III and IV) and doctors (level IV) who can provide more specialized healthcare services (Ministry of Health Republic of Uganda, 2014). Level III or higher facilities are more likely to offer implant insertion and removal services compared to lower-level facilities (Performance Monitoring and Accountability 2020, 2018). The target population varies from 5,000 people for level II facilities to 100,000 people for level IV facilities (Ministry of Health Republic of Uganda, 2011). For ease of exposition, we refer to level II or lower facilities as level II facilities and level IV or higher facilities as level IV facilities. Given these complexities, it is currently unclear how the presence of health facilities at or near the outreach site affects the need for outreach removal services.

During an outreach visit, teams install themselves in an existing healthcare facility at a site. We refer to this facility as the *host facility.* We construct two conflicting hypotheses regarding how the level of the host facility influences the need for outreach removal services. A higher-level host facility is more likely to provide implant insertions and removals. The availability of removal services potentially reduces the need for outreach removal services, as clients can have their implants removed at the host facility. The implants being inserted at the host facility generate demand for removals but the host facility may have insufficient resources to additionally fulfill the demand for removals generated by the outreach teams. This increases the need for outreach teams to provide removal services.

HYPOTHESIS 1a. Sites with higher level host facilities are associated with a lower need for outreach removal services.

HYPOTHESIS 1b. Sites with higher level host facilities are associated with a higher need for outreach removal services.

More generally, clients may access implant services at facilities close to the outreach site. We refer to this as *nearby facilities.* We measure the availability of nearby facilities as the facility density in the county of the site. Facility density has been shown to influence modern contraceptive use (Ettarh and Kyobutungi, 2012). A higher density of higher-level facilities (level III or higher) in the county of the site suggests an increased access to removal services and hence a lower need for outreach removal services. A higher density of higher-level facilities also suggests increased access to insertions leading to higher demand for removal services, which may increase the need for outreach removal services.

HYPOTHESIS 2a. A higher density of higher level facilities in the county of the site is associated with a lower need for outreach removal services.

HYPOTHESIS 2b. A higher density of higher level facilities in the county of the site is associated with a higher need for outreach removal services.

Another dimension of access to healthcare is affordability. Fees in the public or private sector, as well as opportunity costs corresponding to the travel and visit time and the direct costs of travel, have prevented clients from seeking a removal despite desiring one (Callahan et al., 2020). These barriers in accessing removal services for implant users in low-income areas may lead to a dependence on outreach teams for removals, as outreach teams provide free or highly subsidized services. We measure the poverty level per site as the average percentage of people living on less than \$1.25 per day in a 5-kilometer radius around the outreach site.

Hypothesis 3. A higher poverty level at the site is associated with a higher need for outreach removal services.

3.2.2 Operational decisions

An important operational decision is the visit frequency to a site (the number of visits to a site over a given period). Guidelines for selecting visit frequencies exist, such as visiting sites with high client demand more frequently, but they are often loosely specified and adherence is low (De Vries et al., 2021a). McCoy and Lee (2014) show that increasing outreach transport capacity, thereby allowing for more frequent and consistent outreach visits, leads to significant gains in equity. De Vries et al. (2021a) show that the visit frequency is an important determinant of client volume during outreach visits. How visit frequency influences access to removal services has not been studied before. We hypothesize that a higher visit frequency provides greater opportunity for clients to use the outreach services leading to increased access to removal services.

Hypothesis 4. Outreach teams can increase the visit frequency to a site to better meet the need for outreach removal services.

A second key operational decision for the outreach teams is how to generate demand for their services. Outreach teams collaborate with community mobilizers who use demand generation methods to increase awareness of and promote access to family planning services. The aim is to reach clients who are interested in accessing these services and communicate the location and timing of outreach visits. clients desiring a removal may learn of available outreach removal services through these methods. We consider three demand generation methods: marketing messages, word-of-mouth referral, and other provider referral. Exposure to family planning messages, such as megaphone announcements and radio messages, has been shown to increase modern contraceptive use (Babazadeh et al., 2020; Ettarh and Kyobutungi, 2012). Word-of-mouth referral, which involves referrals from existing MSI clients, friends or family members, is also an important factor in the information diffusion for mobile family planning services (Alban et al., 2022).

Hypothesis 5. Outreach teams better meet the need for removal services when clients are exposed to marketing messages more often.

Hypothesis 6. Outreach teams better meet the need for removal services when clients experience word-of-mouth referral more often.

Hypothesis 7. Outreach teams better meet the need for removal services when clients experience referrals by other providers more often.

3.3 Methodology

3.3.1 Data

Our primary data source consists of service delivery data from NGO MSI Reproductive Choices (MSI). We use data from MSI's outreach channel in Uganda over the period July 2015 to November 2019. The teams record details of each visit in a software system called Client Information Centre (CLIC). Details include the site, the date of the visit, the number of clients, and the demand generation methods reported by clients. Each family planning method provided is registered, including all implant insertions and removals. Upon removal, the insertion date of the implant is also recorded.

We use the service delivery data from Uganda because it was one of the first countries in which CLIC was introduced (in 2015). We also use several publicly available datasets, e.g., on poverty levels and health facilities in Uganda. Table 3.1 includes a detailed description of all the independent variables and their sources.

3.3.2 Regression analysis

We use linear regression to determine the effect of the potential drivers and operational decisions. In order to conduct this analysis, we require a variable that indicates the need for outreach removal services. We define this variable as the removal demand ratio, represented by Δ. During outreach visits, teams *generate* demand for removals by performing implant insertions, and they *fulfill* demand for removals by performing implant removals[1]. The removal demand ratio is a measure that compares the demand fulfilled to the demand generated at a given site, by dividing the removal demand fulfilled by the removal demand generated (a precise definition follows below).

We consider the removal demand ratio on the site level, which allows for specification of drivers on the site level. If a site has a high ratio, this means the team

[1]Note that a client can have an implant removed and inserted during the same outreach visit. This counts as both a removal demand fulfilled and generated.

performs many removals compared to the removal demand generated in that site. Consider two sites in which the team operates in the same way. If the ratio is higher in one site, it suggests that the need for outreach removal services is higher in that site. Similarly, consider two sites that are identical in every respect, except for the way the team operates. If one site has a larger ratio, it suggests that the outreach team operates in a way that better fulfills the need for removals.

The removal demand fulfilled is equal to all removals performed between the second visit and the last visit to the site.[2] Calculating the removal demand generated is more complicated, because an implant insertion generates a demand for a removal to be *fulfilled in the future*. For each inserted implant we calculate an expected discontinuation date using a discontinuation curve.

We calculate this discontinuation curve based on CLIC data. Since January 2019, outreach teams record the month and year the implant was inserted upon removal of the implant. We calculate the discontinuation time as the difference between the date of insertion and the date of removal. Aggregating all discontinuation times then provides an estimated percentage of clients that will discontinue their implant x months after insertion. We assume that all implants are removed within 5.5 years, leading to $x \in [1, 66]$. Figure 3.1 shows the estimated cumulative discontinuation curve.

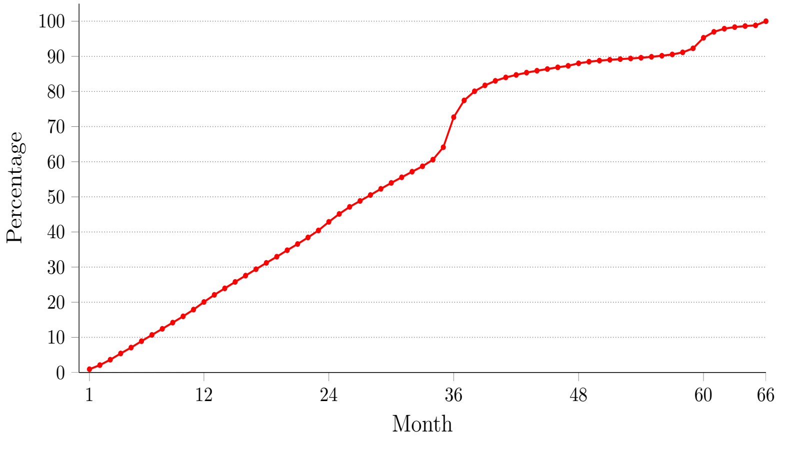


Figure 3.1: Cumulative discontinuation curve based on CLIC data from January 2019 to November 2019 (29,462 observations).

[2]Removals during the first visit are not counted in the fulfilled demand because the removed implants were inserted prior to the first visit and are therefore not included in the removal demand generated.

We then calculate the removal demand generated by counting all implant insertions that have an expected discontinuation date between the first and second to last visit to the site[3]. The removal demand ratio can then be expressed as follows:

$$\Delta_s = \frac{\text{Removal demand fulfilled}}{\text{Removal demand generated}} = \frac{\sum_{\mathcal{V}_s \setminus v_{first}} R_{vs}}{\sum_{\mathcal{V}_s \setminus v_{last}} d_{vs} I_{vs}} \tag{3.1}$$

Here $\mathcal{V}_s$ denotes the set of outreach visits to site $s \in \mathcal{S}$, v_{first} and v_{last} denote the first and last visit to a site, R_{vs} and I_{vs} are the number of removals and insertions during visit v to site s, and d_{vs} is the proportion of insertions expected to result in a removal between visit v and v_{last} for site s.

In the regression analysis, we control for the percentage of clients referred through channels other than word-of-mouth or other providers, age at insertion and removal (grouped into 10–19, 20–29, 30–39, and 39+ years), parity at insertion and removal (grouped into 0, 1–2, 3–4, and 4+ children), and the reason for removal (device expired or other reason). For sites that were operational prior to the start of CLIC data collection in 2015, the removal demand ratio may be skewed due to the inclusion of removals for implants that were inserted before the start of the data collection. To address this issue, we include the year of the site's first visit as a control variable. Finally, because the operational periods of sites can vary (sites may be added or discontinued) , and because we do not have data on implant insertions and removals by other providers, the removal demand ratio may be further skewed. To account for this, we include the number of months a site has been operational as a control variable.

We also implement region fixed effects to safeguard against biases stemming from time-constant unobservable regional differences that might bias our estimates. Uganda is divided into four regions: Central, Northern, Eastern, and Western. Each region has distinct characteristics. They vary in terms of population density, poverty levels, educational attainment, and modern contraceptive use (Uganda Bureau of Statistics - UBOS and ICF, 2018). We do not include team fixed effects because discussions with the outreach team lead in Uganda revealed that differences in removal demand ratio between teams are more likely the cause of regional differences rather than team characteristics. Both regressions use robust standard errors. We perform the regression analysis in STATA.

[3]The implants inserted during the last visit are not included in the removal demand generated because the implant will be discontinued after this visit and the removal can therefore only be fulfilled after the last visit.

3.3.3 Sample

The original CLIC dataset consisted of 2,417 sites and 24 teams. The teams generally consists of three to four healthcare providers. We include only sites that have at least five outreach visits. We exclude sites that have fewer visits because it improves the reliability in the calculation of 1) the site-level variables, such as the visit frequency and the percentage of clients experiencing marketing or referral methods, and 2) the removal demand ratio. Because our analysis requires site locations and geo-coordinates are not readily available for all sites, we further include only sites that have geo-coordinates available. The resulting sample includes 1,545 sites and 24 teams. Table 3.2 presents summary statistics of the variables for the sites in the sample.

3.4 Results

Table 3.3 provides the results of the regression analysis. To help explain the results, we use Figure 3.2, which visualizes different paths clients may take to obtain an implant insertion and removal. For example, clients that access both insertion and removal at other providers than the outreach teams do not influence the removal demand ratio, but clients that switch from an insertion at another provider to a removal at the outreach team lead to an increase in the removal demand ratio.

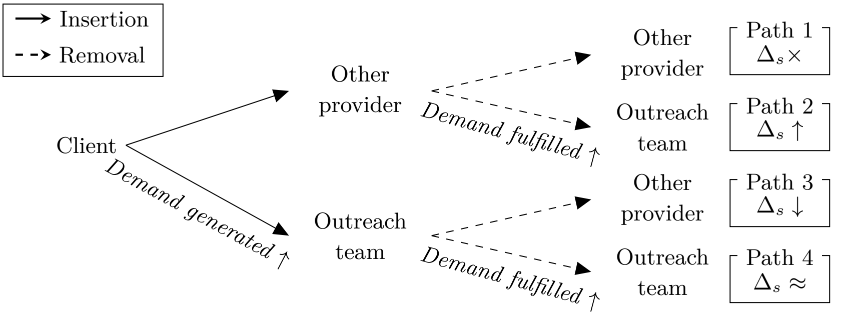


Figure 3.2: Implant insertion and removal process for (potential) implant users and the influence on the removal demand ratio (Δ_s).

Host provider. Table 3.3 shows that the removal demand ratio is significantly higher at level III and IV host facilities compared to level II host facilities. For example, if we consider three sites with host facilities of each level and each with removal demand generated equal to 100, the team at the site with a level III (IV) host facility fulfills an estimated 15 (22) additional removals compared to the site with the level II host facility. One explanation is that at sites with level II host facilities, clients switch from an insertion at the outreach team to a removal at the host facility (Path 3 in Figure 3.2). Another explanation is that at sites with higher level host facilities, clients switch from an insertion at the host facility to a removal at the outreach team (Path 2 in Figure 3.2). The latter appears more likely due to the low availability of implant services at level II facilities. CLIC data on the place of insertion upon removal also points in this direction. Of the implants removed by outreach services, 42% and 47% were reported as inserted by other providers at level III facilities and level IV facilities, respectively. For level II, this percentage is 37%. These statistics show that a considerable proportion of implants removed by outreach teams have been inserted by other providers (Path 2 in Figure 3.2).

Facility density. The density of level III facilities in the site's county has a significant negative effect (Table 3.3). For each additional facility per 10,000 people, the demand fulfilled by the outreach team decreases by an estimated 18% of the removal demand generated. This suggests that clients in counties with a high level III facility density switch from the outreach team to nearby level III facilities for a removal (Path 3 in Figure 3.2). The level IV density does not show a significant effect on the removal demand ratio, despite removal services likely being available. The coefficient is positive, but not significant. This suggests that the number of clients that switch from an insertion at a nearby level IV facility to a removal at the outreach team (Path 2 in Figure 3.2) is about equal to the number of clients that switch from an insertion at the outreach team to a removal at a nearby level IV facility (Path 3 in Figure 3.2). Alternatively, neither path occurs indicating that there is little service overlap between the outreach team and the level IV facility.

The results of the analysis regarding level III facilities seem conflicting. Outreach teams fulfill more demand for removals at level III host facilities, yet less demand in counties with a high level III facility density. A potential explanation for this is that level III facilities in general have resources to provide removal services, but the outreach teams visit level III facilities where this is not the case. Another explanation is that outreach teams incidentally capture part of the removal demand generated by other providers, such as a client desiring a removal who happens to visit the level III host facility on an outreach day. Both explanations indicate that level III facilities in general contribute strongly to access to removal services.

Our results show that the availability of level IV facilities does not necessarily decrease the need for outreach removal services, despite removal services likely being available. Given the available removal services, there is little reason for a client to switch from an insertion at a level IV facility to a removal at the outreach team. This points towards there being little interaction between the services of the outreach team and nearby level IV facilities. Since there are fewer level IV facilities compared to level III facilities, it may still represent a significant travel time for an outreach client to travel to a level IV facility. Alternatively, providers at level IV facilities may not have sufficient capacity to fulfill demand for removals generated by outreach teams. Providers at level IV facilities provide many health services and insertions in particular. Both CLIC data and PMA2020 data show that level IV facilities perform a larger number of implant insertions than do other levels (Performance Monitoring and Accountability 2020, 2018). Providers at level IV facilities might also prioritize different health services because some lower-level facilities can also offer removal services. Qualitative evidence from providers in Ethiopia shows that a work overload can delay removals (McDowell et al., 2017).

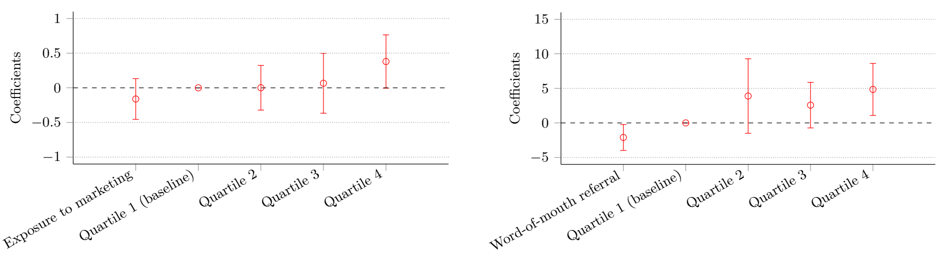
Poverty level. Sites with higher poverty levels have a significantly higher removal demand ratio. Outreach teams provide free or subsidized services. Clients in higher poverty areas appear to utilize these to obtain a removal (Path 4 in Figure 3.2) rather than switching to another provider (Path 3 in Figure 3.2). If we compare two sites with 100 expected removals, with one poverty level equal to the 25^{th} percentile and the other to the 75^{th} percentile, the latter site sees an estimated additional 13 removals.

Visit frequency. Table 3.3 indicates that the visit frequency has a significant positive effect on the removal demand ratio. For each additional visit per year, the removal demand fulfilled increases by an estimated 8% of the removal demand generated. For an average site with removal demand generated equal to 100, this represents eight additional removals for each additional visit per year. The visit frequency variable is also significant in the fixed effects regression.

Demand generation. None of the demand generation variables in Table 3.3 show a significant effect. Additional robustness analyses where we consider separate linear regressions for each region and alternative dependent variables reveal inconsistent results for the exposure to marketing and word-of-mouth referral variables (details provided in Appendix 3.A). To further investigate this, we perform an analysis using one of the distinct regional characteristics: poverty levels. We create a categorical variable that contains poverty level quartiles. To analyze how the effect of our variables of interest - exposure to marketing and word-of-mouth referral - varies across poverty quartiles, we perform a linear regression with the poverty quartiles, the variable of interest, the cross product between the poverty quartiles and the variable of interest, and the control variables as dependent variables.

Figure 3.3 shows the estimated coefficients and corresponding 95% confidence intervals for each cross product. Figure 3.3a shows that the impact of exposure to marketing is significantly larger in the highest poverty quartile compared to the lowest quartile. CLIC data shows that this difference is not due to clients reporting different marketing methods across poverty quartiles. Potentially the marketing methods serve a different purpose. clients desiring a removal are already using family planning services; therefore, the information most relevant to them is the timing of the outreach visits. This information is especially important when clients depend on the outreach teams to use family planning services, which is more likely the case in higher poverty areas.

Figure 3.3b shows that the impact of word-of-mouth referral is also significantly larger in the highest poverty quartile compared to the lowest poverty quartile. This suggests that word-of-mouth networks are important to spread information about removal services and generate demand for removal services in areas with high poverty levels. Households in those areas tend to have lower access to other information channels such as radios, television, and mobile phones (Uganda Bureau of Statistics - UBOS and ICF, 2018).



(a) Exposure to marketing (b) Word of mouth referrals

Figure 3.3: Estimated coefficients for the poverty quartile analysis for exposure to marketing and word of mouth referral variables.

3.5 Conclusion and discussion

Contraceptive implant use has increased significantly over the past few years, which increases the demand for implant removals. However, access to removal services lags insertions, particularly in remote and rural areas, leading to inequitable access to removal services. Outreach teams can improve equity and inclusion, but the extent to which they do so depends on appropriate site selection and team deployment. This paper identifies drivers of the need for outreach teams to provide removal services and operational decisions that outreach teams can make to better align with this need.

Our results reveal that the availability of other providers of implant services (besides the outreach teams) drives the need for outreach teams to provide removal services. The influence of this availability depends on the level of specialization of the other providers. An increased availability of mid-level health facilities increases access to removal services and thus decreases the need for outreach removal services. Our results indicate that the availability of high-level facilities does not necessarily decrease the need for outreach removal services, despite skilled providers likely being present. This suggests that there are barriers to accessing removal services at higher level facilities. The density of high-level facilities is lower than the density of mid-level facilities. Travel times may therefore present a more significant barrier to accessing removal services at high-level facilities compared to mid-level facilities. Insufficient capacity at high-level facilities is another potential barrier, as high-level facilities provide a wider range of health services compared to mid-level facilities. This can lead to long waiting times for clients. Task shifting, specialization, and enhanced utilization of outreach services can alleviate these problems.

We further show that the poverty level around the site is a driver of the need for outreach removal services. Sites with higher poverty levels have a higher need for outreach removal services. Clients at sites in high poverty areas face higher barriers in switching to other providers for a removal because of the costs of doing so. This highlights that outreach teams can strongly contribute to inclusive provision of removal services in poor areas.

Our results further indicate that outreach teams can vary two operational decisions to better meet the need for removal services. First, we demonstrate that a higher visit frequency leads to a stronger increase in removal demand fulfilled compared to removal demand generated and thus helps to meet the need for removal services. This has three important implications. First, it shows that a low visit frequency can form a significant barrier for clients to access removals at an outreach team. This increases the likelihood that clients keep the implant for longer than the recommended duration, leaving them at risk for unintended pregnancies, or that clients search for other providers, which may involve a considerable time and monetary investment. Second, visit frequency is not only an important determinant of client volume (De Vries et al., 2021a), but also of access to removal services. There is a need for further studies on visit frequency optimization for mobile outreach teams that include this aspect. Finally, besides *selecting* sites with a high need for removal services, equity can also be enhanced by *visiting sites with a high need more frequently.* Such prioritization is an example of enhancing vertical equity where *"persons with greater needs should be treated more favourably than those with lesser needs"* (Culyer and Wagstaff, 1993, p.443). This concerns differentiating visit frequencies given a fixed capacity. In a related study, McCoy and Lee (2014) show that increasing outreach transport capacity, thereby allowing for more frequent and consistent outreach visits, leads to significant gains in equity.

Second, efforts to generate demand, by enhancing exposure to marketing and exploiting word-of-mouth effects, can help to better meet the need for outreach removal services in high-poverty areas. Outreach teams fulfill more demand for removals at sites in high-poverty areas where clients report exposure to marketing or referral through word-of-mouth more frequently. Demand generation efforts can increase awareness of when removal services are available and consequently can increase their utilization. This has two implications for outreach operations. First, outreach teams currently collaborate with community mobilizers to generate demand for the outreach services and can increasingly do so to meet the higher need for outreach removal services in high-poverty areas. The community mobilizers can organize marketing campaigns ahead of outreach visits in higher poverty areas to increase awareness of when removal services will be available. In addition, the teams and mobilizers can actively stimulate clients to share information on the services within their community. Second, besides site selection and visit frequency, demand generation efforts are a key tool to improve equity and inclusion. This tool is particularly promising in high poverty areas, where access to other providers may be low and/or where a high visit frequency may be infeasible.

Since 2019, MSI has been collecting data on the insertion location of implants removed by their outreach teams. This data shows that a significant proportion of the implants removed at mid- and high-level facilities were originally inserted by other providers. This suggests that a considerable portion of outreach resources is allocated to removal of implants inserted by other providers. These findings contrast with prior research, which found that a large majority of clients seeking removal attempt to do so at the place where they had the implant inserted (Callahan et al., 2020). Now that more data is available, an interesting direction for future research is to investigate if and to what extent the historical proportion of removals of other provider inserted implants drives the need for outreach removal services.

To sum up, we identified drivers of the need for outreach removal services and potential approaches that organizations and outreach teams can take to help meet this need. Removal services are a fundamental component of comprehensive implant services. Sustained focus on this topic is necessary to ensure equitable and inclusive service provision and to continue progress toward the Sustainable Development Goals.

Table 3.1: Description of the variables used for the analysis and their sources.

Variable	**Description**	**Source**
Level of facility	Health system level of the host facility at the site. The level is expressed as level II or lower, level III and level IV or higher.	CLIC
Facility density	Facility density in the county of the site, calculated as the number of facilities in the county divided by the total population in the county (expressed per 10,000 people).	2018 National Health Facility Master List (Ministry of Health Republic of Uganda, 2018) & Parish Level Profiles from the 2014 National Population and Housing Census (Uganda Bureau of Statistics, 2014)
Poverty level	The average poverty level across all poverty grids in a 5-kilometer radius around the site.	WorldPop Poverty Grid Map (Tatem et al., 2013)
Visit frequency	The number of visits per site per year, calculated as $\frac{v_s}{m_s} \times 12$, where v_s is the total number of visits over m_s months of operation.	CLIC
Exposure to marketing	The percentage of removal clients who reported exposure to marketing messages before the site visit.	CLIC
Word-of-mouth referral	The percentage of removal clients who reported word-of-mouth referral at the site.	CLIC
Other provider referral	The percentage of removal clients who reported other provider referral at the site.	CLIC

Table 3.2: Summary statistics for the variables for the included sites ($n = 1,545$).

	Mean	**Std. dev.**	**Min**	**Max**	**Count**
DRIVERS					
Level of facility					
Level II or lower	-	-	-	-	658
Level III	-	-	-	-	706
Level IV or higher	-	-	-	-	181
Facility density					
Level III	0.47	0.27	0	2.96	-
Level IV or higher	0.11	0.15	0	2.54	-
Poverty level	48%	15%	8%	96%	-
OPERATIONAL DECISIONS					
Visit frequency	3.77	1.47	1.15	12.45	-
Exposure to marketing	79%	25%	0%	100%	-
Word of mouth referral	6%	8%	0%	67%	-
Other provider referral	3%	5%	0%	50%	-
CONTROL VARIABLES					
Other referral channel	89%	11%	0%	100%	-
Age at insertion					
10–19	14%	7%	0%	48%	-
20–29	51%	8%	0%	77%	-
30–39	30%	9%	1%	100%	-
39+	5%	3%	0%	30%	-
Age at removal					
10–19	5%	6%	0%	50%	-
20–29	41%	14%	0%	100%	-
30–39	40%	13%	0%	100%	-
39+	13%	10%	0%	100%	-
Parity at insertion					
0	2%	2%	0%	20%	-
1–2	38%	9%	0%	71%	-
3–4	32%	6%	0%	57%	-
4+	29%	9%	0%	100%	-
Parity at removal					
0	1%	3%	0%	29%	-
1–2	32%	13%	0%	100%	-
3–4	31%	11%	0%	100%	-
4+	35%	15%	0%	100%	-
Removal reason					
Device expired	39%	21%	0%	100%	-
Other reason	61%	21%	0%	100%	-
Year of first visit					
2015	-	-	-	-	1,139
2016	-	-	-	-	260
2017	-	-	-	-	101
2018	-	-	-	-	45
Months of operation	42.91	10.96	8	53	-

Table 3.3: Output from the regression analysis. Column (1) contains the results of the regression without region fixed effects and column (2) with region fixed effects.

	(1) Without region fixed effects		(2) With region fixed effects	
	Coefficient	SE	Coefficient	SE
DRIVERS				
Level of facility				
Level III	0.148***	0.037	0.146*	0.048
Level IV or higher	0.190**	0.091	0.194*	0.062
Facility density in county				
Level III	-0.183**	0.092	-0.124	0.104
Level IV or higher	0.488	0.412	0.484	0.349
Poverty level	0.638***	0.149	0.442	0.307
OPERATIONAL DECISIONS				
Visit frequency	0.082***	0.016	0.090**	0.027
Exposure to marketing	-0.080	0.089	-0.096	0.189
Word of mouth referral	1.582	1.194	1.570	0.911
Other provider referral	0.754	1.348	0.701	1.288
CONTROL VARIABLES				
Other referral channels	-0.276	1.248	-0.406	1.168
Age at insertion				
20–29	0.438	0.554	0.267	0.533
30–39	1.787**	0.737	1.209	0.562
39+	0.409	1.736	-0.201	2.582
Age at removal				
20–29	0.438	0.554	0.267	0.533
30–39	1.787**	0.737	1.209	0.562
39+	0.409	1.736	-0.201	2.582
Parity at insertion				
1–2	-0.303	1.748	-0.711	-1.591
3–4	-1.120	1.578	1.209	1.526
4+	-0.602	2.083	-0.435	0.569
Parity at removal				
1–2	1.793**	0.750	1.638*	0.535
3–4	1.723**	0.737	1.620*	0.672
4+	1.412**	0.708	1.351	0.953
Removal reason				
Other reason	0.289*	0.158	0.219	0.114
Year of first visit				
2016	-0.429***	0.063	-0.436***	0.066
2017	-0.981***	0.119	-1.020***	0.094
2018	-0.877***	0.218	-0.910**	0.202
Months of operation	-0.050***	0.005	-0.051***	0.004
Constant	1.072	2.193	1.903*	0.742
Observations	1,545		1,545	

* p <0.10, ** p <0.05, *** p <0.01

Appendix

3.A Robustness analysis

3.A.1 Regional effects

Because the analysis with region fixed effects showed few significant results, we performed a regression analysis for each region separately. In addition to the country analysis, such an analysis is useful because it reveals region-specific effects that can further inform the detailed planning of the outreach teams. Table 3.4 shows the results. The first column denotes the results from the regression analysis for the complete sample, and the remaining columns show whether the results for each region correspond with the results from the complete sample.

The results indicate that the identified significant drivers are indeed associated with different regions. For most variables where significant effects in several regions are observed, the effect corresponds across regions and with the complete sample. However, for the exposure to marketing variable, we observe a contrasting significant effect in the western region compared to the northern region. We also observe different effects compared to the analysis for the complete sample. Word-of-mouth referral shows a significant effect in the western region, contrary to the complete sample where no significant effect was observed.

Table 3.4: Output from the regression analysis for different dependent variables.

	Δ	Central	West	East	North
DRIVERS					
Level of facility					
Level III	+	○ (contrasting)	○ (contrasting)	+ (corresponding)	○ (contrasting)
Level IV or higher	+	○ (contrasting)	○ (contrasting)	○ (contrasting)	○ (contrasting)
Facility density in county					
Level III	–	○ (contrasting)	○ (contrasting)	– (corresponding)	○ (contrasting)
Level IV or higher	○	○ (corresponding)	– (contrasting)	+ (contrasting)	○ (corresponding)
Poverty level	+	○ (contrasting)	○ (contrasting)	+ (corresponding)	○ (contrasting)
OPERATIONAL DECISIONS					
Visit frequency	+	+ (corresponding)	○ (contrasting)	+ (corresponding)	○ (contrasting)
Exposure to marketing	○	○ (corresponding)	– (contrasting)	○ (corresponding)	+ (contrasting)
Word of mouth referral	○	○ (corresponding)	– (contrasting)	○ (corresponding)	○ (corresponding)
Other provider referral	○	○ (corresponding)	○ (corresponding)	○ (corresponding)	○ (corresponding)

+ Positive significant – Negative significant ○ Not significant

Corresponding effects Contrasting effects

3.A.2 Alternative dependent variables

To assess the robustness of our findings to our choice of dependent variable, we investigate two alternative dependent variables. We consider the following variables:

$$\Delta_s^{bin} = \begin{cases} 1, & \text{if } \Delta_s > 1 \\ 0, & \text{otherwise} \end{cases} \tag{3.2}$$

$$\Delta_s^{diff} = \frac{\text{Removal demand fulfilled} - \text{Removal demand generated}}{\text{Removal demand fulfilled} + \text{Removal demand generated}} \tag{3.3}$$

The variable Δ_s^{bin} distinguishes sites where the removal demand fulfilled exceeds the removal demand generated from sites where the removal demand fulfilled is less than the removal demand generated. The variable Δ_s^{diff} considers the difference between removal demand fulfilled and generated. We scale the difference to account for variations in client volume across sites that influence the magnitude of the difference.

Table 3.5 shows the results. Note that for results to be consistent for Δ_s and Δ_s^{diff}, the effect for Δ_s should be positive and the effect for Δ_s^{diff} should be negative or vice versa. For a majority of the variables, the effects for either one or both of the alternative dependent variables correspond with the primary outcome variable. However, we observe some notable differences. The initial regression analysis showed no significant effects for any of the demand generation variables. The additional analyses show a significant effect for exposure to marketing.

Table 3.5: Output from the regression analysis for different dependent variables.

	Δ	Δ_s^{bin}	Δ_s^{diff}
DRIVERS			
Level of facility			
Level III	+	+	−
Level IV or higher	+	+	−
Facility density in county			
Level III	−	−	+
Level IV or higher	∘	∘	∘
Poverty level	+	+	−
OPERATIONAL DECISIONS			
Visit frequency	+	∘	−
Exposure to marketing	∘	−	+
Word of mouth referral	∘	∘	∘
Other provider referral	∘	∘	∘

+ Positive significant − Negative significant ∘ Not significant
Corresponding effects Contrasting effects

Chapter 4

Health Product Availability in the Presence of Cash Constraints: A Study of Community Health Entrepreneurs in Rural Kenya

This chapter is based on Van Rijn et al. (2024b).

4.1 Introduction

Worldwide, nearly two billion people lack access to essential medicines (World Health Organization, 2017). Access to essential medicines is particularly constrained in low- and middle-income countries, especially in rural areas. The number of public health facilities is often low in these areas and private medicine retailers tend to operate in urban areas (Doerner et al., 2007; Wafula et al., 2012). Additionally, health facilities in both the public and private sector frequently report stock-outs of medicines (Githinji et al., 2013; Karamshetty et al., 2022). Stock-outs of medicines lead to treatment interruptions, reduced confidence in health systems, and adverse effects on disease epidemiology, all of which pose a major challenge to public health (Gallien et al., 2017).

To address this challenge, there is a growing trend of deploying community health workers (CHWs) in low- and middle-income countries (LMICs), especially in remote areas (World Health Organization, 2018). CHWs are lay individuals who receive training to provide health services in the communities they are based in (Woldie et al., 2018). They typically obtain selected health products (e.g., anti-malarial, antiretroviral, and tuberculosis drugs) from nearby health facilities and deliver them directly to their patients doorsteps. CHW programs in LMICs operate at least 8 million CHWs (Hodgins et al., 2021).

However, CHW programs face two significant challenges. First, CHWs frequently experience stock-outs of medicines (Olaniran et al., 2022). Chandani et al. (2014) report that between 50 and 75% of CHWs do not have key health products on stock. Weak supply chain systems and a lack of formal policies make replenishment at health facilities challenging (Olaniran et al., 2022; Pradhan et al., 2020). Second, CHW retention is low with attrition rates varying from 9% to 50% (de Vries and Pool, 2017). CHWs are often either inadequately paid or unpaid, undertrained, and insufficiently supervised (de Vries and Pool, 2017; Pradhan et al., 2020).

Several recent innovative business models show a potentially more effective way to enhance community provision of health products. NGOs such as Living Goods (12,000 CHWs in 2022; global), and social enterprises like Healthy Entrepreneurs (15,000 CHWs in 2023; seven countries) and Live Well (430 CHWs in 2023; Zambia) provide CHWs access to a supply chain of health products which the CHWs can sell within their communities. They also train the CHWs on healthcare services and entrepreneurial skills, such as cashflow and stock management. This approach reduces supply-chain barriers for availability and provides financial incentives to improve access and retention. It turns CHWs into community health entrepreneurs

(CHEs).

Though this approach improves access to health products, recent evidence highlights that it only partially addresses availability issues. A challenge that remains is that CHEs are often severely cash constrained (Aarssen, 2022; Hermus, 2021). CHEs' sales volumes are low due to the low population density and high poverty levels typical in rural areas and profits generated from sales are often allocated to personal expenses (Aarssen, 2022). The substantial travel times to and between CHEs make frequent resupply difficult, resulting in long lead times. This exacerbates the negative effect of cash constraints on availability of health products, because CHEs need more cash on hand to purchase sufficient stock to meet the demand during the resupply interval. A study in Kenya estimates that CHEs miss half of their potential sales due to these constraints (Hermus, 2021).

The negative impact of cash constraints on availability can be addressed in two ways. The first is reducing the need for cash. Interventions that target this include increasing the resupply frequency (Villa et al., 2024), implementing a pay-as-you-sell model (vendor managed inventory), and setting up local hubs where CHEs can resupply their inventory. The second is increasing the cash availability, for instance by extending credit to CHEs (Boulaksil and van Wijk, 2018), or improving their entrepreneurial skills. It is currently unclear which interventions are effective in addressing cash constraints and under which conditions they are effective in the context of rural areas in LMICs. Our research aims to address this gap.

We adopt a mixed-methods approach, where we combine quantitative data from a large-scale field experiment with 467 CHEs with qualitative data from interviews. This study occurs in collaboration with Dutch social enterprise Healthy Entrepreneurs (HE). The field experiment tests two interventions aimed at addressing cash constraints. The first intervention is to set up "stock-hubs" in a cluster (a cluster is a group of on average 15 CHEs that operate in the same area). Stock-hubs are small consignment stocks close to the CHEs, where they can replenish their stocks on-the-spot. A stock-hub coordinator (an existing CHE) manages the stock-hub. Compared to the current replenishment model, CHEs can replenish their stocks more frequently and in smaller quantities, which requires less cash on hand. The second intervention is a cashflow game. The aim of the game is to help CHEs internalize the value of retaining money in their business, thereby improving the cashflow resulting from increased sales. We also conduct interviews with CHEs and HE staff members to gain a deeper understanding of the empirical reality during and after the field experiment.

The contribution of this paper is twofold. First, we study how to address cash constraints at CHEs under high resupply costs. Cash constraints are not only an issue for CHEs, but also for microentrepreneurs in general which represent a significant part of the labor force in developing countries (De Mel et al., 2008; Hipple, 2010; Villa et al., 2024). Previous research has approached this problem from both a cash availability and cash need side, but we study two new interventions that target both sides. These interventions take into account the operational challenges of healthcare provision in rural areas, where resupply costs are high leading to long resupply intervals. Previous studies using empirical data focused on urban areas where visit frequencies tend to be high. Second, our work extends the scarce body of operations- and supply chain management literature using field experiments to examine solutions whose potential has been highlighted by Gao et al. (2023) (for examples of field experiments see Berge et al., 2015, Björkman Nyqvist et al., 2019, Vledder et al., 2019, and Acimovic et al., 2022).

The remainder of this paper is structured as follows. Section 4.2 reviews the relevant literature. Section 4.3 provides a description of the field experiment. In Section 4.4 we discuss the methods for analyzing the results of the field experiment. Section 4.5 provides the results of the field experiment. Finally, in Section 4.6 we discuss our findings and conclude.

4.2 Literature review

We first discuss causes of the limited availability of health products and interventions to improve the availability of health products, in both the public and private sector. We then briefly review relevant literature on microentrepreneurs.

4.2.1 Reasons for limited availability of health products

Research points at several causes of the limited availability of health products in developing countries. For public supply chains they include the complexity of the supply chain (Yadav, 2015), unstable and unpredictable funding (Windisch et al., 2011), and a lack of supply chain planning data (Sarley et al., 2009). For private supply chains they include limited reach in rural areas Yadav, 2015, a shortage of trained staff (Lowe and Montagu, 2009), and a lack of working capital (Karamshetty et al., 2022).

CHWs form the final tier of the public supply chain in many LMICs and obtain their products from nearby public health facilities. As such, availability at the CHW level is affected by the low availability at the public health facility level (see above for the causes). CHWs also face travel-related barriers. The journey to a facility is often time-consuming and expensive due to long travel times, poor roads, limited public transportation and a lack of transportation means (Pradhan et al., 2020).

In contrast to CHWs, CHEs operate in the private sector and need funds to order new health products. However, many have insufficient financial resources to maintain sufficient stock to satisfy demand (Hermus, 2021). Some CHEs use their profits to maintain their household instead of reinvesting them in their business (Aarssen, 2022). Cash constraints are a key issue in other parts of the private sector in LMICs as well. For example, (Karamshetty et al., 2022) interviewed providers at 39 private health facilities and identify cash constraints as a major barrier for availability.

4.2.2 Improving the availability of health products

An increasing body of research studies interventions to improve the availability of health products. One stream examines supply chain policies and design decisions. For example, (Vledder et al., 2019) uses a large-scale randomized field experiment in Zambia to evaluate different designs of the public supply chain. Gallien et al. (2021) analyze different inventory policies for the same supply chain.

A second stream of research focuses on the use of mobile tools. These include mobile apps to collect data on stock levels or the use of text messages to report stock levels. Such interventions have successfully reduced stock-outs at health facilities (Barrington et al., 2010; Githinji et al., 2013) and CHWs (Chandani et al., 2014) but also experience implementation challenges such as network connectivity, access to electricity, access to training, and costs (Agarwal et al., 2020; Fruchtman et al., 2021).

Training forms a third type of intervention. Chandani et al. (2014) find no significant differences between product availability for CHWs in Ethiopia who received training on key supply chain skills and supply chain problem solving compared to those that did not. The training did improve supply chain knowledge and competency.

These interventions target various root causes for limited availability of health products, including distribution issues, lack of data, and limited knowledge and skills. Many of these studies also focused on addressing these issues within the public sector. Our study targets a different root cause, namely cash constraints, which are relevant for the private sector. While relieving cash constraints has received some attention in research on microentrepreneurs, as discussed in the next section, it has not been studied before in the context of health product availability.

4.2.3 Microentrepreneurs

Microentrepreneurs operate small businesses with fewer than five employees (Chandy and Narasimhan, 2011). They represent more than half the labor force in developing countries (De Mel et al., 2008; Hipple, 2010). The development of such businesses is therefore a key concern in many countries (Berge et al., 2015).

Small independent neighborhood stores called nanostores are an example of microenterprises (Escamilla et al., 2021). Nanostores share similarities with CHEs. Both serve a small client base in their neighborhood, offer a limited number of products and place small orders (Escamilla et al., 2021). Nanostore shopkeepers are also often cash constrained (Villa et al., 2024). Many cannot access formal sources of credit, and they often extend informal credit to their customers while not receiving credit from their suppliers (Escamilla et al., 2021). Microentrepreneurs also seldom use basic business practices such as record keeping, budgeting, and planning (Chandy and Narasimhan, 2011; McKenzie, 2021).

Several studies examine how to alleviate cash constraints. Boulaksil and van Wijk (2018) show that it is beneficial for suppliers to offer credit to profitable nanostores even in the presence of high default rates. Escamilla et al. (2021) discuss various innovative financing schemes to relieve cashflow problems. Both these interventions target *increasing the cash availability.* Extending credit to CHEs was considered, but HE already provides starting CHEs with products on credit. The financial risk associated with extending additional credit was deemed to high. Hence, an alternative intervention with a similar aim, the cashflow game, was selected.

Ge et al. (2020) find that appropriate sales visit and pricing strategies of suppliers can help nanostores continue to operate. The paper by Villa et al. (2024) is closest to our examination of stock-hubs. The authors find that a higher visit frequency of suppliers to shopkeepers increases the total order volume (and, presumably, sales). These frequent visits allow shopkeepers to limit their on-hand inventory. This reduces the risk that money is tied up in inventory when it is needed to cover families' needs or to order from (other) suppliers. Our stock-hub intervention is similar in aim to that of a higher supplier visit frequency. The key difference is that CHEs are not supplied directly but travel to the stock-hub to replenish their inventories. This is practically and conceptually different in that it 1) brings about travel costs, 2) requires a pro-active decision to obtain a resupply and 3) adds a supply chain actor – the stock-hub coordinator. This makes transferability of the findings by Villa et al. (2024) to our interventions far from trivial.

Business training has also been proposed to improve microentrepreneurs' business practices and sales. A meta-analysis of the effect of training microentrepreneurs shows that, on average, training increases profits and sales by 5 – 10% (McKenzie, 2021). Such training typically focuses on business management practices, such as keeping records, and budgeting. In this research, we study the effect a game that aims to increase awareness on the importance of retaining cash in the business, which has not been studied before.

Studies have investigated the effectiveness of games in teaching inventory management skills to students. Several simulation games exist that provide students first-hand experience in managing a supply chain (Sparling, 2002). Students show increased supply chain knowledge after playing such games and improved performance when playing them repeatedly (Dhumal et al., 2008; Jeong and Hong, 2011; Lau, 2015). The game studied in this research has a different aim compared to the previously mentioned studies. The context in which we study the effectiveness of games is also substantially different. The above studies occurred in classroom settings while CHEs operate an actual business. Second, CHEs tend to have little formal education. Finally, CHEs operate in rural areas which brings its unique set of challenges (as explained in Section 4.1 and 4.2.1).

4.3 Field experiment

In this section we explain our field experiment. Section 4.3.1 starts with a short description of how HE operates and then describes the cash constraint challenge currently faced by CHEs. Section 4.3.2 outlines the two proposed interventions. Sections 4.3.3 and 4.3.4 describe the selection of clusters for the field experiment and the implementation of the interventions.

4.3.1 Cash constraint challenge

HE provides starting CHEs with training and a basket of health products on credit. HE sources the health products using their supply chain and stores them in a central warehouse upon arrival in a country. The operating area in a country consists of clusters, with on average 15 CHEs working in each cluster. HE visits a cluster once a month to resupply CHEs and provide additional training. The CHEs determine their own order quantities and frequencies and the timing of their orders. CHEs can submit their orders using an ordering app, or with a sales representative from the HE office. HE stimulates CHEs to make orders of at least 1,000 Kenyan Shilling (KES; 8 EUR).

To ensure the availability of health products, CHEs require sufficient cash to purchase enough inventory to meet the demand during the resupply interval. Cash constraints have been identified as the primary cause for insufficient stock levels to meet the demand.

"Another challenge was budget constraints, they [CHEs] could only afford products for maybe two weeks" – HE staff member #1

Currently, HE replenishes CHEs' inventory on a monthly basis. The longer the resupply interval, the more cash is needed to purchase the necessary products to meet the demand during this period. CHE cash availability may then also not line up with the next replenishment opportunity. In addition, the recommended minimum order value of 1,000 KES might cause CHEs to postpone their order due to insufficient funds, potentially leading them to spend the cash on other expenses in the meantime.

"So, they [CHEs] were not able to buy things on the moments that we [HE] wanted them to buy, which you know was connected to the fact that they don't save money. So, they either have it and then they buy now or they spend it on something else and then the money is gone." – HE staff member #2

These cash constraints result in consistently small order sizes, which in turn limit profits from sales, and often lead to CHEs not placing orders every month. In 2021, CHEs placed an average of just four orders per year, with an average order value of 1,138 KES (9 EUR), consisting of only seven different products on average out of a total assortment of 100.

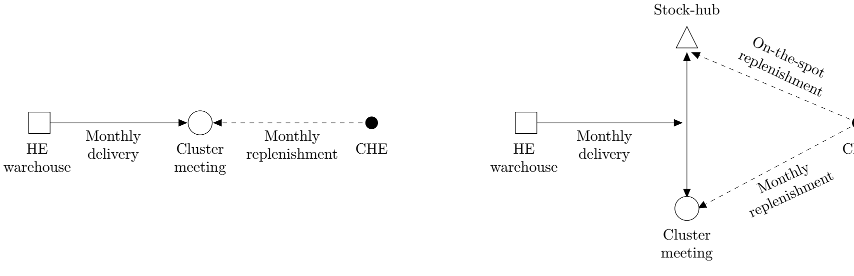
4.3.2 Description of interventions

4.3.2.1 Stock-hubs

The first intervention focuses on increasing the replenishment frequency. CHEs express that more frequent replenishments would enable them to increase their order volumes (Aarssen, 2022), and this strategy has also proven successful in increasing order volumes at nanostore shopkeepers (Villa et al., 2024).

One way to achieve a higher replenishment frequency is to increase the number of visits to the clusters. This option was considered, but logistical constraints such as limited transportation capacity and high costs made this option not economically viable during the field experiment. Doubling the visit frequency would require an additional delivery van which doubles the monthly transportation costs (Hermus, 2021). Increasing the replenishment frequency can then only be achieved by CHEs replenishing more frequently themselves. To enable CHEs to do that, we selected to establish stock-hubs in each cluster, to bring stocks closer to the CHEs.

A stock-hub offers a selection of frequently ordered health products. CHEs operating in the cluster can visit the stock-hub to replenish their inventory on-the-spot with no minimum order requirement. The stock-hub is an add-on to the current replenishment system; CHEs still retain the option to place direct orders with the HE office with the standard encouraged minimum order size. Figure 4.1 provides an overview of both the current replenishment system and the proposed stock-hub system.



(a) Current system (b) Stock-hub system

Figure 4.1: Current and proposed stock-hub replenishment system.

The stock-hub operates as follows. A coordinator manages the stock-hub's inventory and receives a small monetary compensation based on the total sales at the stock-hub. The order process starts with CHEs confirming product availability with the coordinator and ensuring the coordinator's presence at the stock-hub. Then at the stock-hub, CHEs place an order via the ordering app and pay for it using mobile money. The coordinator verifies the payment before packing and handing over the order. HE replenishes the stock-hub during the monthly visit to the cluster. This minimizes the additional resources necessary to implement the stock-hubs, as the replenishment for the stock-hub can be included in the delivery van's regular monthly visit to the cluster. At the stock-hub 20 different products are available. The products as well as the quantity to hold at the stock-hub were determined by HE. HE utilizes an order-up-to level to calculate the necessary replenishment quantity.

4.3.2.2 Cashflow game

As mentioned, one of the contributing factors to cash constraints is that CHEs invest insufficient profits into their business. HE already tries to increase awareness by distributing flyers illustrating expected profit calculations for various re-investment strategies. However, as highlighted in Section 4.3.1, cash constraints persist. This medium may not allow for sufficient internalization of the key messages, highlighting the need to try a different tool. For this reason, we designed a cashflow game which has the main learning goal of internalizing the importance of reinvesting profits into the business.

The game mirrors the CHE business model. It consists of six rounds wherein players sell products to earn game coins, which represent cash. The players can use the coins to order new products. The players need to decide in each round how much of each product to order. In some rounds, players are presented with alternative investment and business opportunities, allowing them to allocate their earned coins differently. Following the game, players engage in a discussion focused on their experiences. Appendix A provides a comprehensive description of the game and the necessary resources to play it.

4.3.2.3 Effect on cash constraints

Figure 4.2 shows the conceptual framework of how the two interventions relate to cash constraints and the availability of health products. The expected effect of the stock-hub intervention is similar to that of a higher replenishment frequency. Both decrease the replenishment interval and thereby decrease the amount of cash needed to cover demand during the replenishment interval (arrow a_1 in Figure 4.2). The stock-hub reduces the cash need for CHEs and thus moderates the negative effect of cash constraints on the availability of health products (arrows a_2 and a_7 in Figure 4.2). The stock-hub also decreases the need for buffer stock thereby reducing the risk that cash is tied-up in inventory. The stock-hub further provides the flexibility for CHEs to make smaller orders. This eliminates the need to accumulate sufficient cash to place an order at the HE office, and reduces the risk that cash is spent outside of the business enabling CHEs to invest more cash in their business (arrow a_3 in Figure 4.2).

The aim of the cashflow game is to increase the awareness of the need to re-invest profits (arrow a_5 in Figure 4.2). We posit that increased awareness will lead to an increase in reinvested profits (arrow a_6 in Figure 4.2). Increasingly reinvesting profits leads to more money in the business which helps to increase sales and thus relieve cash constraints (arrow a_4 in Figure 4.2). An HE sales officer states: "*The CHEs*

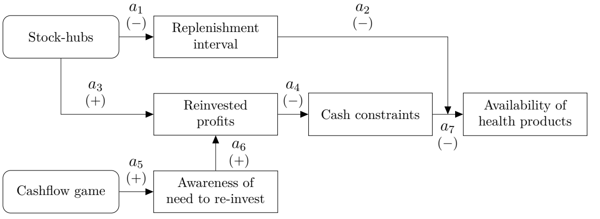


Figure 4.2: Conceptual framework

that know how to reinvest the profit made from selling health products into purchasing new products, perform notably better than CHEs that use the profit for personal use" (Aarssen, 2022, p. 55).

There are several mechanisms in the game intended to help achieve the learning goal. First, to do well in the game, players need to reinvest in products. Players who invest their coins in products will observe a more rapid increase in their sales compared to players who do not invest in products. Second, the game also shows the potential profitability of the business. The discussion at the end of the game prompts players to reflect on the extent to which their cash on hand increased throughout the game. Third, the reflection after the game emphasizes that reinvesting is particularly important when inventory levels are low, i.e., in the beginning of the game. Finally, the game helps to internalize the concept of opportunity costs associated with spending coins outside of the business. When presented with different business opportunities, players must assess the return on their investment.

4.3.3 Selection of clusters for the field experiment

In 2021, HE operated in 60 clusters in Kenya. HE selected six clusters for implementing the stock-hub, mainly focusing on hard-to-reach areas. We randomly selected the clusters for the cashflow game and control group. We first excluded clusters that were selected for a stock-hub or for piloting the interventions (see Section 4.3.4), and where operations started after 2021. We also excluded clusters with less than ten CHEs to increase the sample size. The remaining 23 clusters were stratified into two groups based on their performance, using the average order size per CHE within the cluster in 2021. This stratification balances performance prior to the intervention for the cashflow game and control groups. We randomly selected 10 clusters for each group, with half from each stratum. Fewer clusters were selected for the stock-hub intervention compared to the cashflow game, because the stock-hubs required more resources for implementation.

4.3.4 Implementation phase

4.3.4.1 Pilot implementation

Before the actual implementation, we conducted several pilot implementations. From the 28th of March to the 1st of April 2022, one member of the research team was present in Kenya to guide this process.

HE initiated a pilot stock-hub to: 1) test the hub replenishment process, 2) evaluate CHEs perception and comprehension of the hubs, and 3) conduct a test order at the stock-hub with the CHEs. The pilot was successful and no modifications to the intervention were deemed necessary.

For the cashflow game, HE conducted pilots in 11 clusters involving both HE staff members and CHEs to assess understanding and how the game played out in practice. The pilot implementations of the game led to two modifications: 1) we reduced the game length from eight to six rounds and 2) we improved the pre-game explanation and post-game reflection by creating a game script. Additionally, these pilots served as an opportunity to train HE staff members to lead the game during the implementation phase.

4.3.4.2 Implementation of the interventions

Before the implementation, HE appointed a stock-hub coordinator for each of the six stock-hub clusters. The research team designed and printed all necessary game materials, which were brought to Kenya during the pilot phase.

The implementation of the interventions occurred during the scheduled cluster meetings in May and June 2022. HE sales officers proactively encouraged CHEs to attend these meetings. We obtained informed consent from the CHEs to participate in the field experiment using a consent form. For the game, CHEs played the game led by one or several facilitators. For the stock-hubs, HE delivered the stocks for the hub on the day of the cluster meeting. CHEs were then informed of the stock-hub and received a flyer explaining the concept and listing available products. Unfortunately, the implementation of one of the six stock-hubs was cancelled because the appointed hub coordinator did not carry out the required tasks and a suitable replacement could not be found.

In October and November 2022, refreshers took place. First, HE organized additional information sessions during a cluster meeting in all stock-hub clusters to refresh CHE's knowledge on how the stock-hubs operate. HE staff members explained the order process in the local language, instead of in English. Additionally, a simplified flyer in the local language was distributed. Second, HE hosted refresher sessions in the cashflow game clusters, revisiting and discussing the insights from the game.

4.4 Methodology

In Section 4.4.1 we discuss the quantitative analysis of the field experiment. Section 4.4.2 outlines the details of the qualitative analysis.

4.4.1 Quantitative analysis

4.4.1.1 Outcome

The primary outcome we consider is the total monthly order value per CHE. We have data on all CHE orders between May 2021 and February 2023, consisting of orders placed both directly at the HE office and at the stock-hubs (Figure 4.3). To distinguish between the two types of orders in stock-hub clusters, HE provided separate data detailing the total sales volume at the stock-hubs.

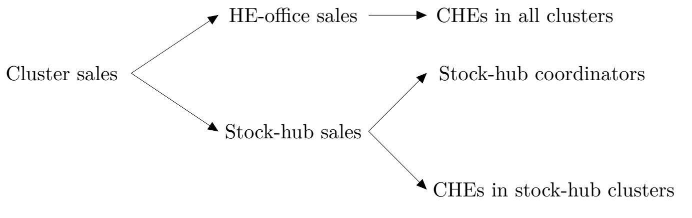


Figure 4.3: Overview of what cluster sales consist of.

For the analysis, we consider the month before the intervention as the reference month, and we exclude the two months when the implementation occurred. We also exclude CHEs that had no orders in the pre-intervention period.

The total order value serves as a proxy for availability. Stock levels, stock-out frequency, stock-out duration, or CHE sales to clients are alternative measures of availability, but HE currently does not collect this data. During the implementation, we attempted to collect stock level and stock-out data by handing out stock record forms to CHEs during cluster meetings or through phone contact by HE sales representatives. However, gathering this data proved challenging as CHEs had difficulty recalling their product inventory levels, and it was difficult to reach them in the field.

4.4.1.2 Difference-in-difference analysis

To estimate how the interventions influenced the total monthly order value per CHE, we perform a difference-in-difference (DiD) analysis. DiD analysis is frequently used to evaluate causal effects of interventions (Callaway and Sant'Anna, 2021). This approach compares the change in the outcome over time between clusters that were enrolled in one of the interventions and clusters that were in the control group. The DiD regression specification is as follows:

$$\begin{aligned} Y_{mc} = &\beta_0 + \beta_1 HUB_c \times POST_m + \beta_2 GAME_c \times POST_m + \beta_3 POST_m + \\ &\Gamma_m + v_c + \epsilon_{mc} \end{aligned} \tag{4.1}$$

where Y_{mc} denotes the total order value in month m of CHE c. The variables HUB_c and $GAME_c$ are binary indicators for stock-hubs and game clusters, respectively. $POST_m$ is a binary indicator that equals zero in the pre-treatment period and equals one in the post-treatment period. We include month-of-year time controls indicated by Γ_m. Finally, we control for CHE-specific heterogeneity, by including CHE-fixed effects, denoted by v_c. Standard errors are clustered by CHE cluster to account for possible serial correlation.

4.4.1.3 Dynamic treatment effects

The DiD formulation in (4.1) estimates a single effect for the post-treatment period, but the effect of treatment may be dynamic, e.g., increasing or decreasing over time. We extend the DiD formulation to include dynamic treatment effects, using the following specification:

$$\begin{aligned} Y_{mc} = &\sum_{i \neq 0} \beta_i \mathbb{1}(\Delta_m = i) \times HUB_c + \sum_{j \neq 0} \beta_j \mathbb{1}(\Delta_m = j) \times GAME_c + \\ &\Gamma_m + v_c + \epsilon_{mc} \end{aligned} \tag{4.2}$$

Here $\mathbb{1}(\Delta_m = i)$ is an indicator variable that is equal to 1 if month m is i months before ($i < 0$) or after ($i > 0$) the reference month. This regression specification also allows to test for parallel trends, which is an important assumption for the validity of the DiD approach. This assumption posits that, in the absence of treatment, the average outcome for the intervention group would have exhibited a similar trajectory to that of the control group (Callaway and Sant'Anna, 2021). To assess parallel trends, we consider the pre-treatment coefficients and assess whether these are significantly different from zero.

4.4.2 Qualitative analysis

In addition to the quantitative analysis, we perform a qualitative analysis to gain additional insight into the observed outcomes and the experiment itself. We set-up a structured interview guide for HE sales officers to interview CHEs. HE sales officers performed these interviews because they have regular contact with the CHEs during the cluster meetings in the field. Appendix B provides an overview of the interview guide. In total, HE sales officers conducted interviews with 27 CHEs, of which 14 CHEs played the cashflow game and 13 CHEs were part of the stock-hub clusters. The interviews took place in September and October 2022. The responses were transcribed by the sales officers and shared with the research team. The sales officers also conducted interviews with each cluster coordinator before the refresher phase of the implementation. The results from these interviews were summarized by an HE staff member and shared with the research team.

In addition, we conducted five one-hour semi-structured interviews with HE staff members in June and July 2023. For this, we designed an interview guide (Appendix B). The staff members were selected because they were closely involved in the design of the experiment and the implementation. These interviews were recorded and transcribed.

To analyze the interview data we coded the qualitative data to identify themes or patterns. We followed an abductive approach (Kovács and Spens, 2005). The conceptual framework presented in Section 4.3.2.3 provided us with a set of pre-existing codes. For data that did not align with the existing codes, we used inductive coding to identify and develop new codes.

4.5 Results

In this section we discuss the results from the field experiment. Section 4.5.1 presents statistics on the CHEs that participated in the experiment. We discuss the results of the stock-hub in Section 4.5.2 and the results of the game in Section 4.5.3. Section 4.5.4 presents an extended conceptual framework based on the main findings.

4.5.1 Data

Table 4.1 presents statistics on the order data for the CHEs in the field experiment. In total, 467 CHEs participated in the field experiment. We observe that the average order value per month was slightly higher for CHEs in the cashflow game clusters, compared to the other two groups. From pre- to post-intervention, the average monthly order value increased for the stock-hub and cashflow game clusters, and it decreased slightly in the control clusters.

Table 4.1: Average order value per month per CHE pre- and post-intervention (in KES) and the number of CHEs per group (HUB, $GAME$, or $CONTROL$).

Intervention	Pre-intervention	Post-intervention	# CHEs
HUB	564.50	672.14	91
$GAME$	639.32	737.31	186
$CONTROL$	543.58	530.54	190

4.5.2 Stock-hubs

We first analyze the effect of the stock-hubs. CHEs mention in the interviews to see the benefits of the stock-hub. They especially value the possibility to purchase new stock if they have a stock-out, and to make orders of any size.

"It [the stock-hub] has helped me in that if my products get finished before cluster meeting, I can easily get products from hub [. . .] without waiting for a month to order." – CHE #7

"It [the stock-hub] has given me a chance to order products worth the money I have [. . .] no matter how little it is." – CHE #8

However, the quantitative analysis shows that there was no significant increase in the monthly order value per CHE for CHEs in the stock-hub clusters. Table 4.2 presents the estimated coefficients from the DiD analysis. The coefficient on the DiD term for the stock-hubs indicates an increase in monthly order value of approximately 120 KES (0.86 EUR), but the effect was not statistically significant. The dynamic treatment effect analysis shows no variation of this effect over time (Appendix 4.C). Considering the order data from stock-hub clusters in more detail, we find that the CHEs placed limited orders at the stock-hub. Figure 4.4 shows the total order value

Table 4.2: Estimated coefficients of the difference-in-difference terms. Standard errors in parentheses. *, **, *** indicate significance levels at the 10%,5%, and 1% levels, respectively.

	(1)
$HUB \times POST$	120.671
	(112.474)
$GAME \times POST$	111.023
	(109.477)
Observations	9,340
Adj. R-sq	0.442

from July 2022 – February 2023 and from the same period a year before in the stock-hub and control clusters. CHEs placing orders at the stock-hub account for only 11% of the total order value at the stock-hub clusters.

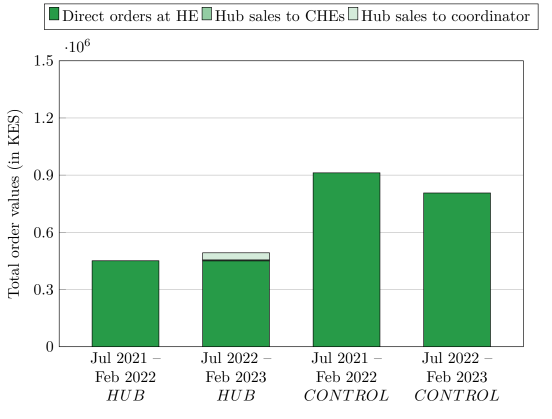


Figure 4.4: Comparison of total order values between July 2021 – February 2022 (pre-intervention) and between July 2022- February 2023 (post-intervention) in the five stock-hub clusters. Control clusters are shown for comparison.

It is predominantly the stock-hub coordinators who purchase products at the stocks. Figure 4.5 shows the order value of the stock-hub coordinators during the same period pre- and post-intervention. Collectively, the five cluster coordinators doubled their order value from pre- to post-intervention. A substantial part of this increase is a result of stock-hub purchases. A t-test shows that the average monthly order value of the hub coordinators increased significantly from July 2022 – February 2023 compared to the same period one year earlier (*one tailed p-value=0.003*).

The qualitative data shows that the limited use of the stock-hubs is due to CHEs experiencing barriers to using the hubs. The main barrier reported was the cost

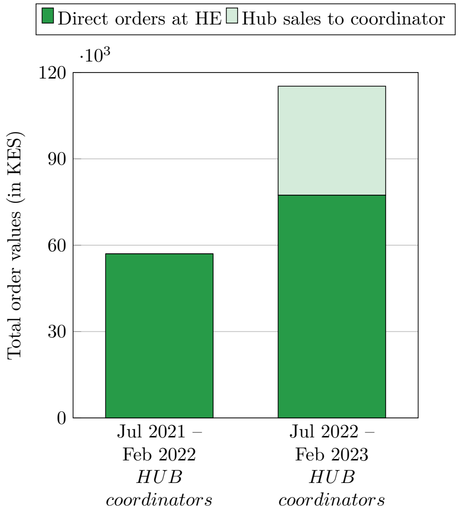


Figure 4.5: Comparison of total order values between July 2021 – February 2022 (pre-intervention) and between July 2022- February 2023 (post-intervention) for the five stock-hub coordinators.

of accessing the stock-hub. All stock-hub coordinators and 6 out of 13 interviewed CHEs reported this as a barrier.

"[. . .] hub coordinator stays far from where I come from, and I use a total of 400 [KES] for transport for me to access it [the stock-hub] which is too expensive." – CHE #1

"The biggest challenge they were telling me was on the distance. [. . .] So, when we give the product to hub coordinators, we realize that some of them were not centrally located and that most CHEs had to use a lot of transport to at least get to near the hub." – HE staff member #3

For most CHEs, the distance to the hub was sufficiently large to require transport. Locations of CHEs were geo-mapped after the intervention for two clusters, revealing that the average straight-line distance between the CHEs and their respective hub locations was 4.3 kilometer, with the maximum distance reaching 9.5 kilometer. While CHEs had access to motorbikes or the ability to arrange other transportation, the potential profits from selling products obtained from the hub often did not outweigh the associated travel costs. This was exacerbated by a significant increase in fuel prices during the implementation period, with fuel costs increasing by 35% between April 2022 and June 2023.[1]

While the proximity of the coordinator's location to the CHEs was a consideration during the coordinator selection process, it was not the primary concern. Instead, HE focused on mitigating the financial risk associated with owning and managing the products stored at the stock-hub. To this end, HE selected coordinators with good historical performance and with access to reliable storage facilities. In addition, they considered the relationship between the coordinator and the other CHEs in the cluster.

"So, the people who are in the central place, their performance was not good in terms of loan performance, orders and others were not of the idea of wanting to keep the products." – HE staff member #4

"Is that one [the hub coordinator] sufficiently reliable, and is the house that they live in is that the right place to keep stocks?" – HE staff member #2

"We are looking at someone who can do good communication with us [HE] [. . .] we were also looking at someone who has a good rapport with all the cluster members and all the cluster members were OK with them having the stocks so that they could be free to visit the hub" – HE staff member #3

Considering the stock-hub where we conducted the pilot implementation[2], we observe a potential way for overcoming the cost of access barrier. The hub sales at the pilot stock-hub represent approximately 45% of the value of all hub sales (Figure 4.6). The key factor that facilitated success was the hub coordinator's ability to consolidate orders from multiple CHEs and bring them to a centralized location within the cluster. By aggregating CHE orders and subsequently delivering them to a central location or at home, the cost of access barrier can be mitigated. This shows that a mobile and pro-active stock-hub coordinator can strongly contribute to the success of a hub, even if their location is not easily accessible to the CHEs.

"The coordinator was a lot more mobile with [. . .] products going into the marketplace, and [. . .] would meet the other CHEs in a lot more central location and

[1]Based on prices reported in `https://tinyurl.com/2s3tryh6` and `https://tinyurl.com/bdd3tcnv`.

[2]This hub was not included in the DiD analysis

hand over some products. So that we saw that was probably the most successful hub." – HE staff member #1

"So basically, I think we should also look for certain traits like. [...] I think this person should also be someone who is social enough to be able to even reach out to their peers and tell them, hey, I have this product. So yeah, they don't even think about ordering from the office because they are here." – HE staff member #5

We identified two additional barriers, which were perceived as relatively minor com-

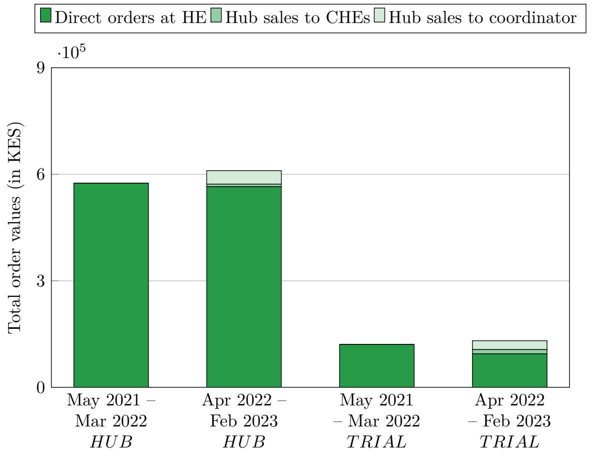


Figure 4.6: Comparison of total order values from May 2021 – March 2022(pre-intervention) and April 2022 – February 2023 (post-intervention) at the five stock-hubs and the pilot stock-hub.

pared to distance. First, some CHEs reported to not be aware of the existence of the stock-hubs. This barrier was addressed during the information sessions in the second phase of the implementation, by having the explanation during the cluster meeting and the information flyers in the local language.

Second, several CHEs reported to prefer to order at HE directly rather than at the hub. CHEs felt like the stock-hub coordinator was benefiting more than them, because they had the impression that the sales profits would go to the hub coordinator. The second phase information session put additional focus on that the stocks at the stock-hub were owned by HE and that the coordinator thus does not receive the profit from the sales. After the second implementation phase, there was a minor improvement in stock-hub sales, but the use of the stock-hub by CHEs remained limited.

"They [the CHEs] were preferring to just come to the cluster [meeting], place their order on their own and just take them on their own, than taking it from the hub coordinators. So, I can say even after training them on what the hub was containing, they were not really convinced on this thing." – HE staff member #4

This shows that willingness to buy from the coordinator is an important success factor. This aspect also emerged as a contributor to the success of the pilot hub. It was reported that CHEs were supportive in terms of buying from this coordinator.

4.5.3 Cashflow game

All the qualitative responses received on the game were positive. From the responses, two main mechanisms through which cash constraints can be addressed emerged. First, CHEs describe that they now have a better understanding of how important it is to reinvest profits into their business. Eight out of 14 CHEs report that after playing the game they are more conscious of how they spend and save their money and as a result are less limited by cash constraints when they place their orders.

"Since I played the game there is a progress and expansion of my business as compared to before the game because I can now set aside the profit I made and use it to place the next order." – CHE #4

"I learned to separate my business money from my personal income to avoid spending a lot and lacking money to place an order" – CHE #6

Second, a new mechanism emerged from the qualitative analysis, namely that CHEs adopted new business practices. CHEs state that the cashflow game led them to improve their record keeping and forecasting.

"My business has improved; I properly keep a record of money I am making monthly hence I know the progress of my business. I have been motivated." – CHE #2

"I think record keeping is probably the biggest [mechanism] [. . .] trying to get them [CHEs] to understand that they need to keep records of how many they sold, how much they have on inventory to try and calculate how much they should order." – HE staff member #1

"I learned to order a lot of stock in order to get more profit. I also learned to order a variety of different products in line with the demand." – CHE #3

The quantitative analysis shows that the game did not lead to a significant increase in the monthly order value per CHE. The coefficient on the DiD term for the cash-flow game suggests an increase in monthly order value per CHE of approximately 111 KES (0.80 EUR), but the increase is not statistically significant. The dynamic treatment effect analysis shows no trend in this effect over time (Appendix 4.C).

Given the contrast between the qualitative and quantitative analysis, we perform an additional DiD analyis comparing the effect of the game for CHEs that were 'high-performing' and 'low-performing' in the pre-intervention period. We classify high-performing as the top 50% of CHEs with the highest monthly order value on average in the pre-intervention period. We then include a three-way interaction between the binary indicators for the game ($GAME$), the post-intervention period ($POST$), and high-performing CHEs ($HIGH$) in the DiD analysis.

Table 4.3 presents the results from this analysis. The results show that low-performing CHEs increased their monthly order value significantly in the post-intervention period. The estimated increase of 191 KES (1.35 EUR) corresponds to an increase of approximately 30% compared to the average monthly order value per CHE in the game clusters. For high-performing CHEs the game had no significant effect on their order values.

Table 4.3: Estimated coefficients of the difference-in-difference terms. Model (3) is equal to Equation (1) plus a three-way interaction between the binary indicators for the game ($GAME$), the post-intervention period ($POST$), and high-performing CHEs ($HIGH$). Standard errors in parentheses. *, **, *** indicate significance levels at the 10%,5%, and 1% levels, respectively.

	(3)
$HUB \times POST$	120.671
	(112.480)
$GAME \times POST$	190.771**
	(78.847)
$GAME \times POST \times HIGH$	-170.497
	(167.384)
Observations	9,340
Adj. R-sq	0.442

4.5.4 Extended conceptual framework

In this section we present an extended conceptual framework in Figure 4.7, based on the qualitative and quantitative evidence. The qualitative findings on the stock-hubs are in line with the expected relationships. CHEs report that the reduced replenishment interval and the absence of a minimum order size are beneficial (arrows a_1 and a_3 in Figure 4.7). Combining evidence from the qualitative and quantitative analysis does reveal important success factors for the stock-hubs to bring about these benefits. First, there should be a low cost of accessing products at the stock-hub. This can be achieved by selecting a central location for the stock-hub or by having a mobile stock-hub coordinator who can consolidate and distribute orders to CHEs. Second, the stock-hub coordinator plays an important role in the success of the stock-hub. The coordinator needs to have a good rapport with the CHEs and the CHEs need to be supportive of buying products from the coordinator.

Considering the stock-hub coordinators, the significant increase in their order values shows that there is significant potential for CHEs to increase their order values and sales and that having closer access to stocks can contribute to increased availability of health products (arrows a_2, a_4, and a_7 in Figure 4.7).

For the cashflow game, we find strong qualitative evidence that the game contributes to more awareness of the need to reinvest cash in the business (arrow a_5 in Figure 4.7). The extended framework also includes the newly emerged relationship that the cashflow game leads to adoption of business practices, such as record keeping and forecasting of demand (arrow a_8 in Figure 4.7). Both business practices lead to better inventory decisions and therefore reduce the probability that cash is tied-up in slow moving inventory. This increases the probability that reinvested profits lead to more sales, and it thus moderates the negative relationship between reinvested profits and cash constraints (arrow a_9 in Figure 4.7). The quantitative analysis shows that the increased awareness of reinvesting and adoption of business practices helped to address cash constraints for CHEs that had low sales performance in the pre-intervention period contributing to better availability of health products (arrows a_4, a_6, a_7, and a_9 in Figure 4.7)

4.6 Conclusion & Discussion

The availability of health products remains a significant challenge in many low- and middle-income countries (LMICs), particularly in rural areas. Community health entrepreneurs (CHEs) that sell health products can help to increase the availability

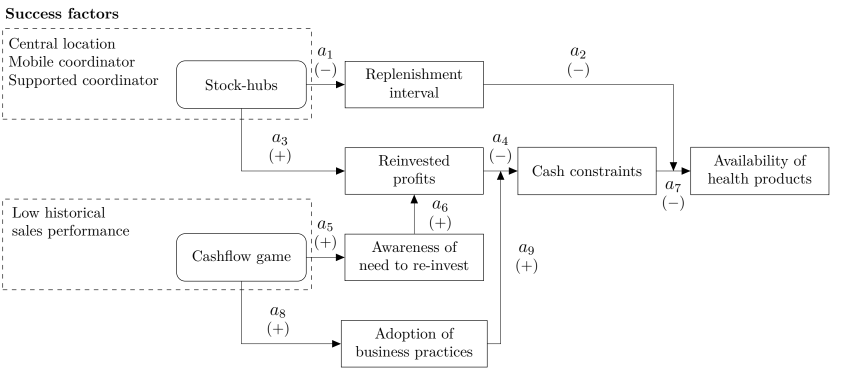


Figure 4.7: Extended conceptual framework

of health products. One of the main challenges faced by CHEs is frequent stock-outs, which are often a result of insufficient cash to purchase products. Potential ways to address these cash constraints include reducing the cash need and increasing the cash availability. It is currently unclear which of these mechanisms can effectively address cash constraints and under which conditions. In this paper, we adopt a mixed-methods approach to answer these questions. We conduct a field experiment in Kenya that tests two interventions aimed at addressing cash constraints. The first involves the establishment of stock-hubs positioned to bring inventory of health products closer to the CHEs, thereby enabling them to make smaller and more frequent orders. The second is a cashflow game designed to enhance the understanding regarding the importance of reinvesting profits into the business. We also collect qualitative data using interviews. This research is in collaboration with social enterprise Healthy Entrepreneurs (HE).

4.6.1 Summary of main findings

The results of the experiment reveal an increase in CHE monthly order values in stock-hub clusters, but this increase was predominantly driven by stock-hub coordinators increasing their order values. We identified that the cost of access was a significant barrier in utilizing the stock-hubs for the CHEs. Despite the stock-hubs being geographically closer to the CHEs than the central warehouse, the expenses incurred in accessing these hubs often exceeded the potential profits derived from ordering and selling products. This was exacerbated by an increase in fuel prices during the intervention period. The hub coordinators, who had zero cost of access, doubled their order values from pre- to post-intervention. Furthermore, we identified informational barriers, such as a lack of awareness regarding the existence of the hub and inadequate understanding of its functioning which were addressed during a refresher training that occurred mid-way during the implementation period.

The primary goal of the cashflow game was to increase the awareness of CHEs regarding the importance of reinvesting profits into their business as a means to foster growth and alleviate cash constraints. After playing the game, CHEs reported improved investment practices. CHEs also mentioned to have adopted business practices, such as record keeping and forecasting. Both practices improve inventory management, reducing the risk of capital being tied up in slow-moving inventory. We show that the cashflow game significanty increased the monthly order value of CHEs who had low sales performance in the pre-intervention period.

4.6.2 Contribution to the literature

This study provides valuable new insights into addressing cash constraints of microentrepreneurs in rural areas. Previously studied interventions that successfully addressed cash constraints, such as increasing the visit frequency by the supplier (Villa et al., 2024), are not feasible in the context of in rural areas due to the high replenishment costs. We show that the establishment of stock-hubs which is similar in aim to an increased supplier visit frequency can successfully address cash constraints, but only under certain conditions (we outline these conditions in Section 4.6.3).

Our study also highlights another successful intervention at addressing cash constraints, the cashflow game. We find that the cashflow game can increase monthly order values by 30%, which exceeds reported increases in profits and sales for other interventions, such as business training for microentrepreneurs (e.g., McKenzie, 2021, reports an average effect of 5-10%). The cashflow game belongs to the set of interventions that target *increasing the cash availability*. Another intervention in this category that successfully addressed cash constraints is the extension of credit to microentrepreneurs (Boulaksil and van Wijk, 2018). An important benefit of the cashflow game is that this intervention carries less financial risk for the credit provider. The risk of default is particularly high in rural areas with high poverty levels.

An important note on the cashflow game is that the positive effect of the game occurred for CHEs that had low sales performance in the pre-intervention period. The cashflow game showed no significant increase in order values for CHEs that had high sales performance in the pre-intervention period. It is reasonable to assume that these CHEs were already less cash constrained in the pre-intervention period and therefore may have already been aware of the intended learnings of the game.

This shows that for these 'high-performing' CHEs additional measures beyond raising awareness are necessary to further increase sales and availability of health products.

One such approach is providing consignment stocks to CHEs. This approach has proven successful in enhancing the availability of health products in private facilities across several LMICs, as evidenced by social enterprise mPharma (mPharma, 2021). The significant increase in orders of the stock-hub coordinators who had access to the consignment stock further demonstrates the potential of this approach. However, there are associated financial risks, because HE will be exposed to the risk of product loss or damage.

4.6.3 Practical implications

The insights from this research highlight several key factors crucial for the successful implementation of a stock-hub. First, the stock-hub coordinator must have good connections with the CHEs in the cluster and the CHEs must be supportive in buying products from the coordinator. Second, the cost of access for the CHEs must be limited. This can be achieved by selecting a central location for the stock-hub or by having a mobile stock-hub coordinator that visits CHEs. It is unlikely that all these factors are met in each cluster, thus necessitating consideration of the need for differentiation. In certain clusters conditions for the establishment of a stock-hub may be more favorable than in others. The decision to allow the successful hubs to continue operating after the intervention concluded further underscores the importance of differentiation and tailored solutions.

The cashflow game is very suitable for large-scale implementation. The game can be played during regularly scheduled cluster meetings or trainings, which means there is no additional transportation cost and staff members can easily be trained to facilitate the game so no additional staff is required. Most of the game materials are reusable, meaning that a limited set of game materials suffices to roll-out the game on a large scale.

This research revealed two successful interventions for addressing cash constraints at CHEs. Addressing these constraints allows CHEs to grow their business and improve the availability of health products within their community. Research on this topic is much needed to ensure continued progress towards the Sustainable Development Goals.

Appendix

4.A Detailed description of the cashflow game

The game is played in a small group of players (for larger groups, several CHEs can be grouped together as one player). Each player starts the game with a basket of four products on credit. Players pay off the credit over six rounds. Printed product cards represent inventory. Each player has a game sheet that provides an overview of the products in the game and the product's order and selling prices. Each game round has a fixed order of actions. First, players sell products that they have on stock. Each round has an associated sales card denoting the demand for each product in that round. Second, CHEs pay their credit payment. Third, CHEs order new products using the coins earned from selling products.

In rounds three to five, the game also includes chance cards which players draw before they order new products in that round. These cards represent business opportunities, such as outside investments or the possibility to take out another loan. The goal of these cards is to present other opportunities to spend coins thereby stimulating discussions on how best to invest coins. The player with the highest profit at the end of the game wins.

CHEs play the game during the regularly scheduled cluster meeting. The estimated time to play the game is between 1 and 2 hours. The resources required are the game items and two people to help manage the game. One person acts as a game facilitator. We set up a script that includes a description of how to explain the game beforehand and discussion/reflection questions for during and after the game. Another person acts as a bank. The bank oversees the exchange of coins for products and vice versa.

4.B Overview of interview guides

Table 4.4 provides an overview of the interview questions for the CHEs. Table 4.5 provides the interview guide for the interview with HE staff members.

Table 4.4: List of questions for CHE and stock-hub coordinator interviews. Note that to the CHEs we referred to the cashflow game as the Biashara game and the stock-hubs as the Hazina hubs.

Cashflow game
1. In what way did playing the Biashara game impact your behavior? How does this impact your business? 2. Besides impact on your business, did the Biashara game have any other impacts? 3. What were your main take-aways from playing the Biashara game?
Stock-hubs
1. Did you use the Hazina hub to order products? Why (not)? 2. In what way did the introduction of the Hazina hub impact your business? 3. Besides impact on your business, did the Hazina hub have any other impacts? 4. Did you have any difficulties ordering products at the Hazina hubs? If yes, what were the difficulties?
Stock-hub coordinators
1. What were the main benefits of the Hazina hub that CHEs told you about? 2. What were the main difficulties of ordering at the hub that CHEs told you about? 3. What activities did you perform to stimulate CHEs to order at the hub? 4. Are there any things you would change to the Hazina hubs?

Table 4.5: List of questions for HE staff interviews. Note that to the CHEs we referred to the cashflow game as the Biashara game and the stock-hubs as the Hazina hubs.

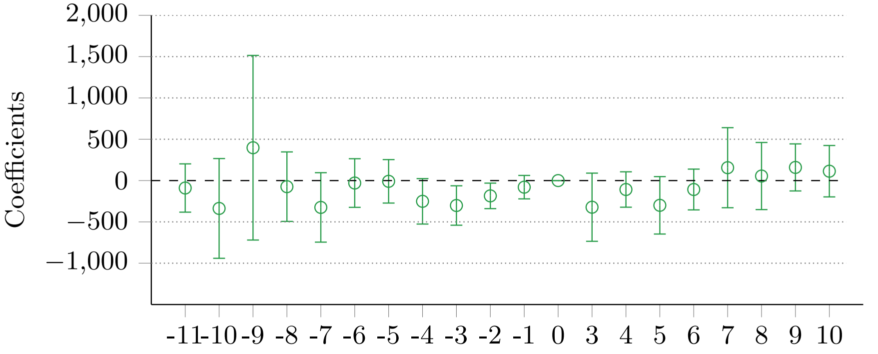
Prior to the field experiment
1. What were the main challenges HE wished to address with this field experiment? 2. While designing the field experiment, we discussed a variety of potential interventions. We will go over four potential interventions that we discussed but decided not to include in the field experiment. Can you explain for each of these why the intervention was not appropriate and/or not feasible to implement? a. Increasing the frequency of deliveries to clusters b. Vendor managed inventory c. Mobile tools for inventory management (reminders, stock reports) d. Inventory management training 3. What were the main reasons for selecting the Hazina hubs and Biashara game for the field experiment?
Hazina hub implementation: Cluster selection
1. What were HE's main criteria for selecting the clusters for the Hazina hubs? 2. What do you think are key characteristics for a cluster to become a successful hub cluster?
Hazina hub implementation: Coordinator selection
1. What are the main requirements that you considered for selecting a hub coordinator? 2. Looking back, are there any requirements that you would add to this list? 3. What kind of agreements did HE make with the hub coordinator? 4. What do you think are the key characteristics that a coordinator should display to have a successful Hazina hub? 5. To what extent do you feel the coordinator is essential for the success of the Hazina hub?
Hazina hub implementation: General
1. What were the main learnings from the pilot implementation of the Hazina hub? 2. Can you describe the implementation process of the Hazina hub, before, during, and after the cluster meeting?
Hazina hub implementation: Products and Replenishment
1. Were there any Hazina hubs that needed replenishment? If yes, can you describe the replenishment process? 2. How was the product basket for the Hazina hubs decided? Were there many changes to this basket over the study period?

Hazina hub results
1. There are some clusters where the Hazina hub works well and in others it does not. Can you provide examples of clusters where the Hazina hub is working well? Why do you think the Hazina hub is successful in these clusters? 2. What do you think were the main barriers for CHEs in using the Hazina hub? 3. Do you think that CHEs felt like they were competing with the coordinator/ that the coordinator was getting an unfair advantage? 4. Looking at the performance differences between the different Hazina hubs, what do you feel are the key factors for a successful Hazina hub?
Biashara game implementation: General
1. What were the main learnings from the pilot implementation of the Biashara game? 2. Can you describe the implementation process of the Biashara game, before, during, and after the cluster meeting?
Biashara game results
1. Do you think the Biashara game changed CHE's behavior? If yes, in what way? 2. Do you think the Biashara game helped loan repayments? Either for CHEs in the experiment or for new CHEs? 3. What are the elements in the game you think helped CHEs most in their business? 4. Did you observe any negative effects on CHE business or behavior of playing the game?
Refreshers
1. What activities did the refreshers consist of and when did they take place? 2. Do you feel the refreshers had an impact?
After the field experiment
1. Were there any external factors that may have influenced the results of the experiment? 2. Were there any changes within HE that may have influenced the results of the experiment? 3. Are there any Hazina hubs still active? What is the sales process like in these hubs? 4. After the experiment finished, you implemented an increased visit frequency to the clusters. How did this affect sales? 5. Did the increased visit frequency increase transportation costs? If yes, do you have an estimate of the increase in costs?
Data collection
1. Can you describe the main challenges related to data collection? For example, collecting data on stock-outs or sales from CHEs to clients. 2. Can you provide an estimate of the percentage increase in fuel prices from 2021 to 2023?

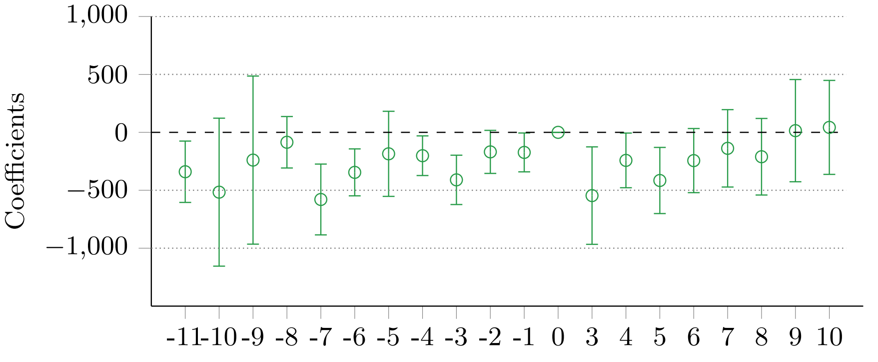
4.C Dynamic treatment effects

Figure 4.8 presents the results of the dynamic treatment effects analysis. We first observe that all except two of the estimated coefficients of the interaction terms for the stock-hubs are insignificant in the pre-treatment period. This indicates that the parallel trends assumption is met. For the cashflow game we do observe numerous coefficients which are statistically different from zero in the pre-treatment period, signaling a violation of the parallel trends assumption.

Second, we observe no clear trend in the estimated coefficients in the post-treatment period. The positive effect of the stock-hubs on order values is highest in the period November 2022 – February 2023, which is after the second implementation phase. For the cashflow game there is no visible increasing trend or tapering off effect.



(a) Stock-hubs



(b) Cashflow game

Figure 4.8: Results from dynamic treatment effects analysis specified in Equation (4.2).

Chapter 5

Conclusion and future research

In this thesis, we study two health service delivery models to improve access to healthcare in underserved rural areas. In Chapters 2 and 3, we consider mobile outreach teams. In Chapter 2, we analyze a decentralized approach for site-to-team assignment decisions. In Chapter 3, we study drivers of the need for outreach teams to provide contraceptive implant removals and which operational decisions can help meet this need. Chapter 4 focuses on community health entrepreneurs (CHEs). In this chapter, we evaluate two interventions to address cash constraints at CHEs.

In Chapter 2, we investigate the effectiveness of a decentralized approach for site reassignment where teams collaborate in team meetings and evaluate what drives the effectiveness. We find that there is a significant trade-off between decentralization and effectiveness. We also reveal several moderators of this trade-off: 1) the number of teams in a team meeting, 2) the number of iterations of team meetings, 3) the site reassignment approach in team meetings, (4) the grouping of teams in team meetings and (5) the accuracy of central planner estimates of baseline client volume. We conclude that, when properly designed, a decentralized decision-making approach has similar effectiveness as a centralized approach and can even be more effective in case of inaccurate information at the central level. We show that this finding remains valid when input parameters evolve over time, team participation varies, and when the objective function is misspecified.

In Chapter 3, we explore drivers of the need for outreach teams to provide contraceptive implant removals. We find that the availability of other providers of implant services (besides the outreach teams) is a driver of the need. Sites in counties with a high density of mid-level health facilities have a relatively low need for outreach removal services, compared to sites in counties with a high density of high-level facilities. Higher poverty levels of the population around the site increase the need for outreach removal services. We also investigate operational decisions that outreach teams can make to better meet the need for outreach removal services. We find that aligning the frequency at which they visit sites with the need for outreach removal services can help to better meet the need. Demand generation methods can help to better meet the need for outreach removal services in high-poverty areas. These results help inform how to select sites and deploy teams to address the gap between access to contraceptive implant insertion and removal services.

In Chapter 4, we adopt a mixed-methods approach to study how to address cash constraints at CHEs. We combine quantitative and qualitative evidence from a field experiment and interviews in collaboration with social enterprise Healthy Entrepreneurs. Our results show that setting up stock-hubs - small consignment stock locations - can help address cash constraints and improve the availability of health products, provided that certain conditions are met. First, the cost of accessing the products must be low, e.g., by selecting a central location for the hub, or by having a stock-hub coordinator collecting and distributing the orders. Second, the stock-hub coordinator must have a good relationship with the CHEs in the cluster and the CHEs must be supportive of buying products from them. Our study also shows that a cashflow game – a game designed to help CHEs internalize the importance of reinvesting profits in their business – addresses cash constraints for CHEs that had low historical sales performance prior to playing the game.

Future research can extend in different directions. One direction is to field test the decentralized decision-making approaches discussed in Chapter 2. Although our research indicates the potential effectiveness of decentralized decision-making, research is needed on the best way to implement it in practice, e.g., whether team meetings would take place online or in-person, how many teams would participate in the meetings, and the optimal frequency of these meetings. This also raises the question of incentives. Future research can consider appropriate incentive structures to encourage teams to participate in team meetings. This is especially important in cases where the overall effectiveness increases as a result of the team meetings but the effectiveness of individual teams might decrease.

Chapter 3 can be extended by integrating contraceptive implant removals into team deployment optimization. This is challenging for two reasons. First, providing an implant insertion now, creates a need for an implant removal in the future. Given that teams operate under severe resource constraints, failing to account for this can easily lead to their capacity being exceeded. Our study in Chapter 3 begins to identify drivers of the need for outreach removal services, but we have not yet considered what influences the timing of a removal. Second, selecting an appropriate objective function that balances the need for outreach removal services with the need for other family planning service provision is key. The choice of objective function affects how removals are prioritized. For example, a frequently used objective in family planning service provision is couple years of protection (CYP), which assign a value to a contraceptive method depending on how long this method protects against pregnancy. Since an implant removal is not assigned any CYP, this objective would under prioritize sites where removals represent a relatively high share of service provision (likely indicating a high need for outreach removal services at these sites).

Building on Chapter 4, future research could examine additional strategies beyond addressing cash constraints to improve the availability of health products. Potential interventions to consider are providing additional credit, consignment stock, inventory management training, or inventory management tools such as mobile apps. Identifying 'underperforming' CHEs relative to their demand potential could help inform where to target these interventions. Research that develops methods to estimate this demand potential is then needed.

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Abstract

Sustainable Development Goal 3 aims to achieve good health and well-being for all, but access to healthcare is still constrained in rural areas in low- and middle income countries. To overcome challenges related to access to healthcare, healthcare delivery in rural areas often makes use of non-traditional delivery models. In this thesis we study two such health service delivery models: mobile outreach teams and community health entrepreneurs. Mobile outreach teams are teams of healthcare workers who visit outreach sites in rural areas to provide healthcare services. Community health entrepreneurs are individuals from rural communities that sell health products within the community they reside in.

In Chapter 2, we investigate the effectiveness of a decentralized approach for outreach site reassignment where mobile outreach teams collaborate in team meetings and evaluate what drives the effectiveness. We propose a mixed-integer programming model for centralized site reassignment. We extend this model to represent the decentralized approach and develop a set of simple decision rules for this approach. We use empirical data from six country outreach programs of the nongovernmental organization MSI Reproductive Choices. Our results suggest that, when properly designed, decentralized decision making performs close to centralized decision making, and even outperforms it in the case of inaccurate information at the central level. The finding remains valid when demand and supply fluctuate, and is insensitive to the chosen objective.

Chapter 3 explores drivers of the need for outreach teams to provide contraceptive implant removals and how operational decisions impact this need. We perform a regression analysis using service delivery data from MSI Reproductive Choices' outreach teams in Uganda and publicly available datasets on demographics and health facilities. Our results show that availability of other providers of removal services and poverty levels around the outreach site are drivers of the need for outreach removal services. We also show that visit frequency and demand generation methods

are important operational decisions that can help meet the need for outreach removal services. These results help inform how to select sites and deploy teams to attain more equitable and inclusive removal service provisioning.

In Chapter 4, we adopt a mixed-methods approach to study how to address cash constraints faced by community health entrepreneurs. We combine quantitative and qualitative evidence from a field experiment in Kenya and interviews in collaboration with social enterprise Healthy Entrepreneurs. The field experiment tests two interventions: stock-hubs and a cashflow game. Our results show that the stock-hubs can successfully address cash constraints and contribute to improving the availability of health products, but only under certain conditions. The cost of accessing the products at the hub must be low, the stock-hub coordinator must have good connections with the CHEs in the cluster, and the CHEs must be supportive in buying products from the coordinator. The cashflow game successfully addressed cash constraints for CHEs that had low historical sales performance. This study provides valuable new insights into addressing cash constraints in areas with high resupply costs and long resupply intervals.

Nederlandse samenvatting (Abstract in Dutch)

Duurzaam ontwikkelingsdoel 3 streeft naar een goede gezondheid en welzijn voor iedereen, maar toegang tot gezondheidszorg is nog steeds beperkt in rurale gebieden in lage- en middeninkomenslanden. Om uitdagingen gerelateerd aan de toegang tot gezondheidszorg te overkomen, wordt gezondheidszorg in rurale gebieden vaak op niet-traditionele manieren geleverd. In dit proefschrift bestuderen we twee modellen voor de levering van gezondheidszorg: mobiele outreachteams en lokale gezondheidsondernemers. Mobiele outreachteams zijn teams van zorgmedewerkers die rurale dorpen – outreachlocaties – bezoeken om gezondheidszorg te leveren. Lokale gezondheidsondernemers zijn individuen uit rurale gemeenschappen die gezondheidsproducten verkopen binnen de gemeenschap waarin zij wonen.

In Hoofdstuk 2 onderzoeken we de effectiviteit van een decentrale methode voor het opnieuw toewijzen van outreachlocaties, waarbij mobiele outreachteams samenwerken in bijeenkomsten, en evalueren we wat de effectiviteit drijft. We stellen een gemengd geheeltallig programmeringsprobleem op voor centrale toewijzing van outreachlocaties. We breiden dit model uit tot een decentrale methode en ontwikkelen een reeks simpele beslissingsregels voor deze methode. We gebruiken empirische data van outreach programma's uit zes landen van niet-gouvernementele organisatie MSI Reproductive Choices. Onze resultaten laten zien dat goed ontworpen decentrale beslissingsmethodes een soortgelijke prestatie hebben als centrale beslissingsmethodes, en decentrale beslissingsmethodes presteren zelfs beter in het geval van onjuiste informatie op centraal niveau. De bevinding blijft geldig wanneer vraag en aanbod fluctueren, en is niet gevoelig voor de gekozen doelfunctie.

Hoofdstuk 3 onderzoekt de drijvende krachten achter de behoefte aan outreachteams om anticonceptiestaafjes te verwijderen en hoe operationele beslissingen deze behoefte beïnvloeden. We voeren een regressieanalyse uit met behulp van dienstverleningsdata van de outreach teams van MSI Reproductive Choices in Oeganda en openbaar toegankelijke datasets over demografische gegevens en gezondheidsfaciliteiten. Onze resultaten laten zien dat de beschikbaarheid van andere aanbieders van de verwijderingsprocedure en armoede rondom de outreachlocatie drijvende krachten zijn achter de behoefte aan outreach teams om anticonceptiestaafjes te verwijderen. We laten ook zien dat de bezoekfrequentie en methoden voor het stimuleren van de vraag belangrijke operationele beslissingen zijn die kunnen helpen om te voldoen aan de behoefte aan outreachteams om anticonceptiestaafjes te verwijderen. Deze resultaten bieden handvaten voor het selecteren van outreachlocaties en het inzetten van teams om een eerlijker en inclusiever aanbod van de verwijderingsprocedure te bereiken.

In Hoofdstuk 4 gebruiken we een mixed-methods aanpak om te bestuderen hoe cashflowproblemen bij lokale gezondheidsondernemers kunnen worden bestreden. We combineren kwantitatieve en kwalitatieve data van een veldstudie en interviews in Kenia in samenwerking met sociale onderneming Healthy Entrepreneurs. De veldstudie test twee interventies: voorraad-hubs en een cashflowspel. Onze resultaten laten zien dat voorraad-hubs cashflowproblemen kunnen bestrijden en daarbij bijdragen aan de beschikbaarheid van gezondheidsproducten, maar alleen onder bepaalde voorwaarden. De kosten om de voorraad-hub te bezoeken moeten laag zijn en de coördinator van de voorraad-hub moet op de juiste manier worden geselecteerd. Het cashflowspel heeft geholpen om cashflowproblemen te bestrijden voor lokale gezondheidsondernemers die historisch gezien slecht presteerden. Deze studie presenteert waardevolle nieuwe inzichten over het bestrijden van cashflowproblemen in gebieden waar herbevoorradingskosten hoog zijn en waar de tijd tussen herbevoorrading lang is.

About the author

Lisanne van Rijn was born on May 3, 1994 in Spijkenisse, the Netherlands. Lisanne graduated in 2015 from the bachelor Econometrics and Operations Research, and in 2017 from the master Econometrics and Management Science, both with a specialization in Operations Research and Quantitative Logistics. For her master thesis, she worked as a research intern at the Humanitarian Research Group at INSEAD business school in Fontainebleau. After graduation, she remained there as a research associate working on research projects for large international humanitarian organizations.

In 2018, Lisanne started working as a PhD candidate at the Econometric Institute, Erasmus University Rotterdam, under the supervision of Prof.dr. Albert Wagelmans and Dr. Harwin de Vries. During her time as a PhD candidate, Lisanne worked on addressing operational challenges related to increasing access to healthcare in underserved rural areas. She presented her work at seminars and conferences in the United States, France, and the Netherlands. Her work has been published in the journal Manufacturing & Service Operations Management. Lisanne is currently working as an assistant professor at the Technology & Operations Management department at the Rotterdam School of Management.

Portfolio

Publications in peer-reviewed journals

van Rijn, L., de Vries, H., Van Wassenhove, L.N. (2024). Site Reassignment for Mobile Outreach Teams: Investigating the Effectiveness of Decentralized Decision-Making. *To appear in Manufacturing & Service Operations Management.*

Working papers

van Rijn, L., de Vries, H., Gutt, D. (2023). Providing Access where it is Needed: Equity and Inclusion through Contraceptive Implant Removals by Mobile Outreach Teams. *Revise and resubmit at Production and Operations Management.*

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PhD courses

Robust Optimization at LNMB
Algorithms and Complexity at LNMB
Networks and Polyhedra at LNMB
Foundations of Operations B at INSEAD
Operations Strategy at INSEAD
Topics in the Philosophy of Science at ERIM
Qualitative Methods at ERIM

Teaching activities

Lecturer for the course Mathematics & Game Theory for the bachelor *Economics and Business Economics.*

Teaching assistant for the courses Academic Writing and Presentation Skills, and Introduction to Analysis for the bachelor *Econometrics and Operations Research.*

Teaching assistant for the course Stochastic Models and Optimization for the master *Econometrics and Management Science.*

Teaching assistant for the course Supply Chain Management 2 for the master *Maritime Economics and Logistics.*

Teaching assistant for the course Health and Humanitarian Logistics for the master *Supply Chain Management.*

Supervisor of 25 bachelor theses for the bachelor *Econometrics and Operations Research.*

Co-reader of 2 master theses for the master *Econometrics and Management Science.*

Referee activities for international journals

Production and Operations Management
BMJ Global Health
European Journal of Operational Research
OR Spectrum

Conference presentations

POMS 2019, Washington D.C., US
LNMB Conference 2022, Online
INFORMS 2022, Indianapolis, US
Netherlands OML Conference 2022, Soesterberg, The Netherlands
LNMB Conference 2023, Soesterberg, The Netherlands
POMS 2023, Orlando, US
POMS International Conference 2023, Paris, France

Other presentations
EI-ERIM-OR seminar, September 2022, Rotterdam, The Netherlands
MSI Reproductive Choices HQ, March 2019, London, United Kingdom

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Sustainable Development Goal 3 aims to achieve good health and well-being for all, but access to healthcare is still constrained in rural areas in low- and middle-income countries. In this thesis we study two health service delivery models to improve access to healthcare in underserved rural areas: mobile outreach teams and community health entrepreneurs.

First, we investigate the effectiveness of a decentralized approach for site reassignment where mobile outreach teams collaborate in team meetings and evaluate what drives the effectiveness. We propose a mixed-integer programming model for centralized site reassignment. We extend this model to represent the decentralized approach and develop a set of simple decision rules for this approach.

Second, we explore drivers of the need for outreach teams to provide contraceptive implant removals. We perform a regression analysis to identify drivers of the need for outreach removal services and how operational decisions impact this need.

Finally, we adopt a mixed-methods approach to study how to address cash constraints at community health entrepreneurs. We combine quantitative and qualitative evidence from a field experiment in Kenya and interviews in collaboration with social enterprise Healthy Entrepreneurs.

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