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Improving Health Outcomes With Less Cost? Provision of Mobile Clinic in Developing Economies

Fang Liu[1], Pengfei Guo[2], Yulan Wang[3] and Yuejuan Xi[4]

Abstract

Consider a public healthcare system consisting of a hospital, a mobile clinic (MC), and a population of potential patients. The government is concerned about the system's healthcare spending and the population's health outcomes. It decides the frequency and capacity of the MC service to maximize the social welfare that consists of two terms: the system's long-run average healthcare cost and the population's average quality-adjusted life year (QALY). We characterize the population's natural disease progression using a Markov cohort model and derive the average healthcare cost incurred for the system and the average QALY in closed form for a given MC service. We show that the government is more likely to provide the MC service when (i) it puts more weight on the population's average QALY, (ii) the MC treatment becomes more efficient, or (iii) the hospital treatment cost is much higher relative to the MC treatment cost. We further show that when conditions (ii) and (iii) are met or the disease progresses faster, the provision of the MC service is more likely to result in a win–win outcome, leading to both healthcare cost reduction and QALY improvement. The optimal MC delivery policy highly hinges on the disease's progressive speed. Specifically, when the MC service is designated to serve a specific target population, once the MC service is provided, it shall be provided either every period or every other period if the disease is fast-progressive. If the disease is slow-progressive, the long-run average healthcare cost exhibits a zigzag pattern with the MC delivery cycle when the relative treatment cost-saving per person induced by the provision of the MC service is positive. Last, we conducted a real case study. Our analysis reveals that the optimal implementation of the MC program results in a 119.5% improvement in QALY and a 5% reduction in healthcare costs. The results are robust in probabilistic sensitivity analysis with a relative performance gap within 11.5% when factoring in the uncertainty of the parameters.

Keywords

Mobile Clinic, Delivery Cycle, Stochastic Model, Public Healthcare

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1 Introduction

In many countries, the public healthcare systems are facing the unprecedented challenge of handling escalating healthcare demands with earmarked budgets, whereas the operational cost of the healthcare system is rapidly increasing. Meanwhile, traditional healthcare facilities, such as hospitals, are often located in densely populated regions, as the construction and operation of such facilities are costly, especially for governments in underdeveloped countries. As a result, individuals residing in low-income and rural communities face significant barriers to accessing healthcare (Hill et al., 2014). One of the primary obstacles is the long traveling distance between their communities and healthcare facilities, which imposes substantial hardships on those seeking medical treatment. For instance, in the Zambezia province of Mozambique, the average time required to reach a health facility on foot is three

[1]Durham University Business School, Durham University, UK
[2]College of Business, City University of Hong Kong, Kowloon, Hong Kong
[3]Faculty of Business, The Hong Kong Polytechnic University, Kowloon, Hong Kong
[4]School of Mathematics, Southwestern University of Finance and Economics, Chengdu, China

Corresponding authors:
Yulan Wang, Faculty of Business, The Hong Kong Polytechnic University, Hong Kong.
Email: yulan.wang@polyu.edu.hk

Yuejuan Xi, School of Mathematics, Southwestern University of Finance and Economics, Chengdu, China.
Email: yuejuanxi@swufe.edu.cn

hours. Consequently, these populations tend to seek hospital care and receive necessary medical treatments only when their health conditions have reached critical stages.

In response, many governments have implemented mobile clinic (MC) programs alongside traditional hospitals, aiming to reduce public healthcare costs while maintaining high-quality services for local communities. To date, mobile healthcare units have been deployed in countries such as India, Pakistan, and South Africa to achieve various public health objectives, including the control of infectious diseases, provision of medical and clinical treatment, vaccinations, and health education (Khanna and Narula, 2017). This approach is motivated by the significant cost savings that MCs can achieve through their ability to provide community-tailored care in high-risk areas, thereby reducing avoidable hospital admissions and emergency department (ED) visits. For instance, an asthma-focused MC can generate savings of $3,500 per child by decreasing ED visits and hospitalizations through improved asthma management (Hill et al., 2014). Moreover, the operation of MC programs enhances access to care for many remote segments of the population (Khanna and Narula, 2017). Notable examples include the MCs funded by the Ministries of Health of both the governments of Iraq and the Kurdistan Region of Iraq (KRI), which provide basic healthcare and treatments in Iraq and KRI (WHO, 2015), and the mobile hospital train funded by Lifeline Express that offers cataract surgery in rural parts of China (Wong et al., 2018). These programs contribute to improved health outcomes for remote communities, reduce the incidence of severe ailments requiring hospital visits, and increase the population's quality-adjusted life years (QALYs).

While some governments have implemented MC operations, many public healthcare systems continue to rely predominantly on hospitals to serve remote communities due to the currently insufficient understanding of the implications of MCs. Implementing an MC program involves significant operational costs, including initial setup costs such as vehicle utility costs, MC administrative costs, and personnel salaries, as well as the treatment costs per person, such as consumable equipment and medicines. The benefits that MCs offer to remote communities may be limited by several factors. First, the capacity of the MC is limited (Deo et al., 2013), allowing only a limited number of individuals to be treated during each visit. Second, the treatment provided by MCs may be imperfect and might not sufficiently improve individuals' health status. Therefore, it is crucial to characterize the impact of operating MC services on key performance measures of the public healthcare system, including healthcare costs and population health outcomes. Specifically, we are interested in examining the following research questions:

1. Whether and how shall the government operate the MC service, that is, how frequently and with what capacity shall the government dispatch the MC to visit the remote community?
2. How do the disease characteristics affect the frequency of providing the MC service?
3. What is the impact of providing the MC service on the healthcare cost and the population's health outcomes in terms of QALY?
4. Under what conditions can the inclusion of the MC operation into a public healthcare system lead to both healthcare cost reduction and QALY improvement?

To answer the above questions, we consider a public healthcare system consisting of a hospital, an MC,[1] and a target population of potential patients in a remote community in developing economies. The MC provides basic specialized diagnostic and treatment services for a specific chronic disease, such as diabetic retinopathy (DR) and hypertension, which not only controls but also improves the patient's health conditions. We consider a discrete-time infinite horizon setting in which the target population's health progress is modeled as a Markov cohort model. Specifically, the target population is divided into three segments according to their health states: asymptomatic segment (Segment I), symptomatic segment (Segment II), and treatment segment (Segment III). In each period, a fraction of the population progresses from Segment I to Segment II, and from Segment II to Segment III. Individuals in Segment I do not require any medical services, while individuals in Segment II may be treated by the MC service. Depending on the success of their treatments, they either revert back to Segment I or remain in Segment II. Once individuals progress to Segment III, they immediately visit the hospital. The treatment by the hospital can be either successful, under which they revert back to Segment I, or unsuccessful, under which they exit the target population.

The government provides the MC service to the target population at fixed intervals.[2] A setup cost is incurred for each MC visit. During the MC's on-site visits, population's health conditions can be identified in a negligible time through simple diagnosis or basic health screenings. The MC provides treatments to individuals in Segment II, incurring associated treatment costs. If individuals transit to Segment III, they visit the hospital, which incurs related treatment costs. Due to limited financial resources, the government in developing economies cares about the healthcare cost borne by the public healthcare system. Meanwhile, the government is also concerned about the target population's health outcomes measured by the individual's average QALY, hereafter referred to as the average QALY. As such, when determining the optimal frequency and capacity for providing the MC service to the remote community, the government aims to maximize the social welfare comprised of two terms: the average QALY and the long-run average healthcare cost incurred by the hospital and the MC.

Our study makes the following contributions. First, we derive the closed-form expressions for the long-run average healthcare cost and the average QALY. We find that the long-run average healthcare cost highly hinges on the magnitudes of the disease progression rates and the relative treatment cost-saving per person with the provision of the MC service. We show that the average QALY decreases in the MC delivery cycle and increases linearly in the quality-of-life (QoL) of both Segments I and II. When the government emphasizes more on the average QALY, the MC service shall be provided more frequently. Once the government provides the MC service, it is always in its best interest to serve everyone in Segment II. Undoubtedly, the provision of the MC service always helps improve the average QALY. We further show that the government is more likely to provide the MC service when (i) it puts more weight on the average QALY, (ii) the MC treatment becomes more efficient, or (iii) the hospital treatment cost is much higher relative to the MC treatment cost. Moreover, when the last two conditions are met or the disease progresses faster, the provision of the MC service is more likely to reduce healthcare costs while improving the average QALY, resulting in a win–win outcome.

Second, we characterize the optimal MC delivery policy for both fast- and slow-progressive diseases when the MC service is designated to serve a specific target population. We show that if the disease is fast-progressive, once the MC service is provided, it shall be provided either every period or every other period. If the disease is slow-progressive, the long-run average healthcare cost exhibits a zigzag pattern with the MC delivery cycle when the relative treatment cost-saving per person induced by the provision of the MC service is positive. When the government becomes more concerned about the average QALY (i.e., a larger weight is assigned to the average QALY), both the average QALY and the long-run average healthcare cost increase under optimality. This implies that when the government is more concerned about the population's health outcomes, the provision of MC service can improve the average QALY but at the cost of increasing the average healthcare cost. We also identify the sufficient and necessary conditions for the provision of the MC service to result in reductions in healthcare costs and improvements in QALY for both types of diseases.

Last, we conducted extensive numerical experiments and examine a real-world case, both of which align with our theoretical findings. The case study investigates the operation of the MC program in 70 remote villages in Zichuan District, Zibo, China. Our analysis shows that the most effective approach is to deliver the MC program in Zichuan District, China, every 12 weeks. Such implementation can lead to a 119.5% improvement in QALY and a 5% reduction in healthcare costs, yielding an incremental cost-effectiveness ratio (ICER) of −43 CNY per year. The results are robust in probabilistic sensitivity analysis with a relative performance gap within 11.5% when accounting for parameter uncertainties. We also extend the model to include multiperiod intervention impacts and hospital capacity constraints. All the main insights remain intact. We refer the interested readers to the Online Appendix for the related analyses and discussions.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. In Section 3, we present the model setup, including the Markov cohort model and the MC operation. We also investigate a benchmark case in which the MC service is not provided. We then characterize the system performance with the provision of the MC service and investigate the government's optimal MC delivery decision in Section 4. In Section 5, we further examine how system parameters affect the provision of the MC service via extensive numerical experiments. We also conduct a real case study. Concluding remarks are provided in Section 6. All of the proofs are relegated to Online Appendix A.

2 Literature Review

The studies on healthcare operations management that examine the operation of the public healthcare system can be divided into three main categories, according to how far away the service provider delivers healthcare service to patients. To one extreme, healthcare service is only provided at the hospitals, and patients all come to hospitals for treatments. Consequently, congestion and long waiting times occur, which become the major concerns of the healthcare operation. Scholars have considered various scenarios to minimize system congestion and reduce waiting times; see, for example, Liu et al. (2010), Luo et al. (2012), Feldman et al. (2014), Liu and Ziya (2014), Liu (2016), and Kong et al. (2020). On the other extreme, healthcare service is provided to each household, and patients do not need to travel outside their home to receive customized service. The main challenge for this emerging healthcare delivery mode is the justification of its effectiveness in terms of accessibility, quality, and cost. In Klein et al. (2013), they study the goal, potential benefits, and challenges of patient-centered medical home programs initiated in the United States. They find that, in general, patient-centered medical home can increase the accessibility and quality of care as well as limit costs. However, individual variations such as the medical home setup may limit the benefit of the patient-centered medical home.

Our work is closely related to the above studies in the sense that we study an in-between healthcare delivery mode where additional MC services are provided together with the conventional hospital. Scholars recently have begun to study the in-between delivery mode, including the e-visits and telemedicine service system (Bavafa et al., 2018, 2021; Rajan et al., 2022, 2019) and community-based care services in fixed healthcare stations (Deo et al., 2015; Deo and Sohoni, 2015). Differently, we investigate the operation of an MC, which serves as a mobile hospital staffed with physicians and nurse practitioners on the van, bus, or train, in a public healthcare system. Previous work by Deo et al. (2013), De Vries et al. (2021a), De Vries et al. (2021b), and Alban et al. (2022) has also examined the operation of mobile health units. Specifically, Deo et al. (2013) consider the community-based healthcare delivery system for chronic diseases by assuming a fixed schedule of equally spaced visits. They then study the capacity allocation across different patients to maximize the patients' health gain measured by QALY. De Vries et al. (2021a) investigate the optimal visit frequencies of mobile family planning services to maximize the total expected clients reached. De Vries et al. (2021b) consider a setting where the patients need to be referred by mobile screening teams to the health facility for treatment. They then investigate the optimal deployment of mobile screening teams for human African trypanosomiasis (HAT), a lethal neglected tropical disease, to minimize the average expected prevalence of HAT. Alban et al. (2022) analyze the optimal allocation of limited mobile healthcare units. They use the Bass diffusion model to capture the adoption dynamics. In contrast to the above four studies, we utilize a Markov cohort model to model the population-level disease progression of a chronic disease. We consider a public healthcare system comprised of a hospital, an MC, and a target population, where the MC can provide treatments to the individuals in partial remission. We then derive the optimal delivery policy of the MC service to maximize the social welfare. We also conduct a real case study to examine the cost-effectiveness of providing the MC service. Our work also contributes to the related health economics literature examining the effects of the MC service on the public healthcare system. We note that effects such as reducing cost, decreasing ED visits, and improving the health outcome have been empirically investigated in Yu et al. (2017). By contrast, we construct a Markov cohort model to examine the long-run effects of providing the MC service and derive the optimal MC delivery policy for the government to maximize social welfare.

Our work is closely related to the stream of research on stochastic models of disease progression. Armitage and Doll (1954) model the development of cancer in the human body as a six-state continuous-time Markov Chain. Marshall and Jones (1995) characterize the progression of DR as a four-state birth and death Markov Chain. Other works studying the disease progression include Hauskrecht and Fraser (2000) and Shechter et al. (2008). See the review note of Kulkarni (2012) and references therein for the related studies. It is worth pointing out that all the aforementioned studies consider the disease progression at the individual patient level. In contrast, we consider the disease progression at the population level via a Markov cohort model.

Our work is also related to the stream of research on medical decision-making regarding intervention policies for chronic disease. Drawing on Markov models in medical decision problems (see, e.g., Sonnenberg and Beck, 1993), previous research has developed decision-analytic Markov models to assess the costs and benefits of various interventions, such as postpartum depression screening among U.S. women (Wilkinson et al., 2017). However, these studies often do not consider the frequency and capacity constraints of interventions. In contrast, we explicitly examine these factors within a public healthcare system. We show that optimizing these factors can lead to a win–win outcome under certain conditions.

3 Model Setup and Preliminaries

In this section, we first present a Markov cohort model for a target population (i.e., the remote community). We then describe the operation of the hospital and the MC program and study a benchmark case in which the MC service is not provided. Table 1 summarizes the key notations used in the paper. Also, let $a \wedge b \equiv \min\{a, b\}$ and $(a-b)^+ \equiv \max\{a-b, 0\}$. Throughout this paper, the terms "increasing" and "decreasing" mean "nondecreasing" and "nonincreasing," respectively.

3.1 Markov Cohort Model

The Markov cohort model is a deterministic disease progression model that has been adopted in the healthcare decision-making research to study the population trajectories across different states (Iskandar, 2018). Here, we utilize the Markov cohort model to characterize the dynamics of the chronic disease population in discrete time over an infinite horizon. Consider a target population of potential patients living in a remote community without local hospitals, who are likely to develop a chronic disease such as diabetes or cardiovascular disease. Without loss of generality, we normalize the population size to be one.

Specifically, individuals in Segment I are in remission and do not require any treatment. Individuals in Segment II are symptomatic but unaware of the severity of their illness. That is, their symptoms do not significantly affect their daily lives, and they do not take any action. For example, DR patients in Segment II (diabetic macular edema [DME] and stage) may experience slight eye asymmetry, while hypertensive patients in Stage II (early organ damage) may have subtle heart symptoms. Due to limited local medical resources, regular primary office visits are not available in the community. Individuals visit the distant hospital to seek treatment only when they develop more severe symptoms associated with Segment III. The case study of the MC program in Zichuan District, China, aligns with this scenario, where the MC program operates in a community lacking access to regular office visits (see Section 5.2). Interviews with the MC program authorities in Zichuan revealed that nearly all individuals rely on the MC for medical services. We assume that all individuals in Segments I and II seek care through the MC, which offers services similar to those provided by the regular office visits as discussed in Bavafa et al. (2019), Bavafa et al. (2021), and Rajan et al. (2022), where all individuals in Segments I and II attend regular office visits. Individuals who are diagnosed in Segment I require only lifestyle modifications and routine screenings. The MC provides appropriate treatments to those diagnosed in Segment II, enabling them to revert back to Segment I. For DR patients, the MC conducts ocular diagnostics and administers anti-vascular endothelial growth factor (anti-VEGF) injections to those in the DME stage. For hypertensive patients, the MC performs diagnostic assessments, including cardiac and renal function tests, and provides treatments such as medications if early organ damage is detected. We assume that individuals in

Table 1. Summary of key notations.

Notation	Description
λ	Natural disease progression rate from Segment I to Segment II
μ	Natural disease progression rate from Segment II to Segment III
n	Length of one delivery cycle, where $n \in \overline{\mathbb{N}}$, $\mathbb{N} = \{1, 2, \dots\}$ and $\overline{\mathbb{N}} = \mathbb{N} \cup \{\infty\}$
c_r	Average hospital treatment cost per person
π	Probability of the hospital failing to treat an individual in Segment III
$K(n, Q)$	Setup cost of MC service
Q	Capacity of MC service
δ	Probability of the MC failing to treat an individual in Segment II
c_m	MC treatment cost per person
S_∞	Number of individuals in Segment II in the long run without MC service
S_t	Number of individuals in Segment II at the beginning of the tth period, $t = 1, 2, \dots, n$
$\bar{S}_n$	Number of individuals in Segment II at the beginning of the visiting period when $Q = 1$ and the delivery cycle is n
$\mathcal{AC}(n, Q)$	Long-run average healthcare cost given the MC delivery cycle n and capacity Q
σ_1	QoL score for staying in Segment I for one period
σ_2	QoL score for staying in Segment II for one period
$\mathcal{QALY}(n, Q)$	Average QALY given the MC delivery cycle n and capacity Q
ϕ_c	Relative treatment cost-saving per person
$\Delta_{\text{cost}}(n, Q)$	Percentage cost reduction with the provision of the MC service given its delivery cycle n and capacity Q
$\Delta_{\text{qaly}}(n, Q)$	Percentage QALY improvement with the provision of the MC service given its delivery cycle n and capacity Q
θ	Weight the government assigns to the average QALY
$\mathcal{SW}(n, Q)$	Social welfare given MC delivery cycle n and capacity Q
n^*	Optimal MC delivery cycle that maximizes the social welfare
n_c^*	Optimal MC delivery cycle to minimize the long-run average healthcare cost
n_q^*	Optimal MC delivery cycle to maximize the average QALY

Note. MC = mobile clinic; QoL = quality-of-life; QALY = quality-adjusted life year.

Segment I cannot directly progress to Segment III. A similar assumption has been adopted in the medical literature; see, for example, Menn et al. (2012). Denote $\lambda \in (0, 1]$ as the fraction of Segment I population who would progress to Segment II in one time period. Then, $1 - \lambda$ fraction of Segment I population remains in Segment I. Similarly, denote $\mu \in (0, 1]$ as the fraction of Segment II population transiting to Segment III, and the remaining $1 - \mu$ fraction stays in Segment II. We refer to λ (μ) as the *progression rate* from Segment I (II) to Segment II (III). Note that if $\lambda = 0$ ($\mu = 0$), no Segment I (Segment II) population progresses to Segment II (Segment III). Therefore, no MC service (hospital visit) is required. We thus omit these two trivial and uninteresting cases. Due to issues involving resource allocation, staff scheduling, and logistical arrangements, we define a time period as one week, which is the shortest possible interval between any two consecutive MC visits to the remote community. Our model is applicable to noninfectious chronic diseases, particularly those characterized by slow progression, that emphasize the importance of long-term regular monitoring and treatment in Stage II to prevent progression to Stage III.

Stability of the Target Population Size. As the disease progresses, patients may die or enter a critical condition, which we refer to as exiting the target population. In this study, we assume the target population is "stationary" or in a "steady state," meaning the prevalence of the disease remains constant, with the rates of incidence and outflow being equal (Rothman et al., 2008). Such an assumption is aligned with the observations in the existing studies about chronic diseases (see, e.g., Buttorff et al., 2017; Mathur et al., 2017). Mathur et al. (2017) show that the prevalence of DR remains stable over time among patients with Type 2 diabetes; Buttorff et al. (2017) find that the prevalence of multiple chronic conditions also remains stable over time. It is worth pointing out that the stationary population, an important demographic model assumption, has been widely adopted in both chronic diseases models (Alho, 1992; Preston, 1987; Shih et al., 2007) and epidemic models (Inaba and Nishiura, 2008; O'Regan et al., 2010). Here, we adopt this assumption to facilitate the understanding and analysis of the population dynamics. We also consider a model with an "open population," with the rates of incidence and outflow being unequal, in Online Appendix E.

3.2 Public Healthcare System and Two Performance Measures

Consider that an MC service with treatment capacity Q is provided to the target population every n periods, where $n \in \overline{\mathbb{N}}$, $\mathbb{N} = \{1, 2, \dots\}$, and $\overline{\mathbb{N}} = \mathbb{N} \cup \{\infty\}$. Then, n is the delivery cycle of the MC service, indicating how frequently the MC visits the target population. For ease of reference, we use (n, Q) to denote the delivery policy of the MC service. Note that when $n = \infty$, the MC service is never provided. We call the periods in which the MC visits the population the *visiting* periods and

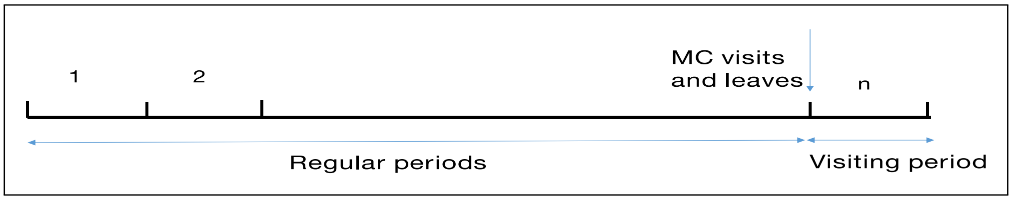

Figure 1. Illustration of the mobile clinic (MC) service provision in an n-period delivery cycle.

other periods the *regular* periods. Then, an n-period delivery cycle consists of $n-1$ regular periods followed by one visiting period; see Figure 1 for the illustration. In the regular periods, the target population progresses according to the Markov cohort model. At the beginning of the visiting period, the MC visits the target population and treats all (or a fraction of) individuals in Segment II, then the MC leaves, and those who are not treated by the MC progress according to the Markov cohort model. In reality, the MC typically stays in the community for only a few hours. To simplify the model and better align with reality, we assume that the MC visit is instantaneous, and the impact of MC visits lasts only for the visiting period. We further consider a multiperiod intervention impact model, which is relegated to Online Appendix B.

Cost Measure: Long-Run Average Healthcare Cost. One of the primary concerns regarding the provision of MC services in addition to existing hospital services is whether the operation of the MC can help reduce public healthcare costs (Yu et al., 2017). The operation of the MC involves costs, including setup expenses for MC visits to the target population and variable costs associated with health screenings and basic treatments. However, the MC service may also help reduce the number of individuals visiting the hospital, thereby decreasing hospital treatment costs. Below, we discuss the hospital and MC operation in our setting.

Hospital. In each period, a fraction of the target population visits the hospital for treatments upon progressing to Segment III. Let c_r denote the average hospital treatment cost per person. We assume that the treatment provided by the hospital is instantaneous but fails with probability $\pi \in (0,1]$. If the treatment succeeds, individuals revert back to Segment I; if it fails, individuals may die or enter a critical condition where we normalize their QALY to zero. We do not impose that a successful treatment restores the patient to "full health" but rather to a baseline state, which we refer to as "healthy." A similar assumption is also adopted by Bavafa et al. (2021). We assume the hospital is not capacity-constrained due to the low population density in the remote community. We further examine a scenario with a capacity-constrained hospital in Online Appendix C and show that our main results remain qualitatively unchanged.

MC. The treatment provided by the MC fails with probability $\delta \in [0,1)$; that is, by receiving the MC treatment, individuals in Segment II can revert back to Segment I with probability $1-\delta$. Note that $\delta = 0$ implies that the MC treatment is 100% perfect. The MC treats at most Q individuals in Segment II with a treatment cost c_m per person.[3] We assume $c_r > c_m$ because the hospital treatment is usually more costly than the MC treatment. In each visiting period, the MC visits the target population and incurs a setup cost $K(n,Q)$, which increases in Q and decreases in n. Specifically, $K(n,Q) = \kappa_1 Q + \kappa_2/n + K$, where κ_1 is the setup cost for each unit of MC capacity required to treat a single patient, κ_2/n is the externality cost incurred for each MC visit that could be used to serve other populations,[4] and K represents a fixed setup cost. In particular, when the MC is required to serve only a specific target population and provides medical service using a reusable physical instrument, such as providing screening and health education service (Khanna and Narula, 2017), then the setup cost is fixed regardless of capacity, that is, $\kappa_1 = \kappa_2 = 0$. In this special case, we have $K(n,Q) = K$.

Denote $\mathcal{AC}(n,Q)$ as the *long-run average healthcare cost* borne by the public healthcare system. Then, we have

$$\mathcal{AC}(n,Q) = \lim_{T\to\infty} \frac{\sum_{t=1}^{T} (\text{hospital treatment costs in period } t + \text{MC operation and treatment costs in period } t)}{T}.$$

Health Outcome Measure: QALY. One goal that the government provides the MC service is to improve the health performance of the target population. In this regard, we use the average QALY as a measure to evaluate the effect of providing the MC service on the population's health outcomes (Weinstein et al., 2009). Recall that we assume individuals who progress to Segment III immediately seek hospital treatment. Those who are successfully treated revert back to Segment I, while those for whom treatment is unsuccessful may either die or enter a critical condition where their QALY is normalized to zero. As a result, the QALY does not include Segment III. Let an individual's QoL score for staying in Segments I and II for one period be σ_1 and σ_2, respectively. Naturally, $0 \leq \sigma_2 < \sigma_1 \leq 1$, where 1 implies that an individual is in perfect health and 0 indicates that an individual is no longer alive. In other words, each individual receives a QALY of σ_1 (σ_2) per period staying in Segment I (II). Then, an individual's QALY can be derived as

$$\begin{aligned}\text{QALY}_{\text{ind}} = &\text{ time periods staying in Segment I} \times \sigma_1 \\ &+ \text{ time periods staying in Segment II} \times \sigma_2.\end{aligned}$$

It is important to note that QALY_{ind} is a measure of the value and benefit of health outcomes of an individual in Segments I and II. This measure does not correspond to the number of years an individual may live. This distinction is crucial because, while the provision of MC services may significantly enhance individuals' health outcomes, it does not necessarily extend their lifespan.

The average QALY is computed by averaging over all the individuals who have entered and exited the population over the infinite horizon. Because the hospital's failure rate is always positive, an individual will exit the population in some finite period with probability one, and the number of individuals who have entered the population will go to infinity as time goes to infinity. We number the individuals in the order of arrival over $[0, \infty)$. Then, for a given MC delivery policy (n, Q), the average QALY can be written as

$$\mathcal{QALY}(n, Q) = \lim_{N \to \infty} \frac{\sum_{k=1}^{N} \text{QALY}_{\text{ind}} \text{ of the } k\text{th individual entering the population}}{N}.$$

3.3 Benchmark: No Provision of the MC Service

In this section, we analyze a benchmark case in which the government does not provide the MC service to the target population, that is, $n = \infty$. Recall that in each period, the health conditions of individuals in Segments I and II progress according to the Markov cohort model as follows: a fraction λ of individuals in Segment I progresses to Segment II, while a fraction μ of individuals in Segment II progresses to Segment III. Those who reach Segment III immediately visit the hospital for treatment: a fraction $1-\pi$ of them is successfully treated and reverts back to Segment I; the remaining fraction π fails the treatment and exits the system, while the same fraction of individuals enters Segment I. All treatments are assumed to be conducted instantaneously. Consequently, the size of individuals in Segment III is always zero. Denote the number of individuals in Segment II at the beginning of period t by S_t. Then, it evolves as follows:

$$S_{t+1} = \lambda + \alpha S_t, \; t = 1, 2, \dots, \tag{1}$$

where $\alpha := 1 - \lambda - \mu$ and $\alpha \in [-1, 1)$. When the progression rates λ and μ are sufficiently large (small) such that $\lambda + \mu > 1$ ($\lambda + \mu < 1$), it is equivalent to $\alpha < 0$ ($\alpha > 0$). In this context, we refer to α as the "disease progression index." We call a disease a *fast-progressive disease* if $\alpha \in (-1, 0)$ and a *slow-progressive disease* if $\alpha \in [0, 1)$. The special case $\alpha = -1$ ($\lambda = \mu = 1$) is discussed in Online Appendix A. In the medical literature (see e.g., Bellomo et al., 2012; McNaught et al., 2004), certain common diseases are classified as fast-progressive, such as acute kidney injury, acute liver failure, and acute myeloid leukemia. Others are classified as slow-progressive, such as Alzheimer's disease, Type 2 diabetes, and Parkinson's disease.

Denote the long-run average Segment II size as S_∞. Then, $1 - S_\infty$ is the long-run average Segment I size. The following lemma describes the health status of the target population and the performance of the public healthcare system when the government does not provide the MC service.

Lemma 1. *When no MC service is provided (i.e., $n = \infty$), we have the following:*

1. *The long-run average Segment II size is $S_\infty = \lambda/(\lambda + \mu)$.*
2. *The average number of hospital visits in each period is $\lambda\mu/(\lambda + \mu)$.*
3. *The long-run average healthcare cost and average QALY are, respectively,*

$$\mathcal{AC}_\infty = \frac{\lambda\mu}{\lambda + \mu} c_r \text{ and } \mathcal{QALY}_\infty = \frac{1}{\pi}\left(\frac{\sigma_1}{\lambda} + \frac{\sigma_2}{\mu}\right).$$

Lemma 1 shows that the size of Segment II decreases in μ but increases in λ. The long-run average healthcare cost $\mathcal{AC}_\infty$ is linear in the hospital treatment cost c_r and increases in the progression rates λ and μ. Undoubtedly, the public healthcare system incurs a higher cost if the disease progresses faster and the treatment becomes more expensive. The $\mathcal{QALY}_\infty$ decreases in λ, μ and the hospital treatment failure rate π. That is, individuals' average QALY becomes smaller when the disease progresses faster and the treatment is more likely to fail. Moreover, the progression rate from Segment I to Segment II (λ) has a greater impact on $\mathcal{QALY}_\infty$ than the progression rate from Segment II to Segment III (μ), as the QoL in Stage I is higher than in Stage II.

4 Analysis: When the MC Service Is Provided

In this section, we analyze the scenario in which the MC service is provided. First, in Section 4.1, we characterize the evolution of the population's health status under a given MC delivery policy. We then derive the corresponding system performance, including the long-run average healthcare cost and the average QALY. Next, in Section 4.2, we derive the optimal delivery policy for the MC service, analyze its properties, and examine its impact on the system performance. We also identify the conditions under which the provision of the MC service leads to a win–win outcome, simultaneously lowering healthcare costs and improving the average QALY.

4.1 System Performance With the Provision of the MC Service

In this subsection, we assume that the MC delivery policy is given and examine the evolution of the population's health status and the corresponding system performance.

4.1.1 Evolution of the Population's Health Status. When the MC service is provided to the target population every n periods, the number of individuals in each segment would evolve in a cyclic pattern every n periods in the long run. In the regular period $t = 1, 2, \dots, n-1$, the MC does not visit the target population, and the population evolves according to (1). The number of individuals in Segment II in the regular period t satisfies the following transition equation:

$$S_{t+1} = \lambda + \alpha S_t,\ t = 1, 2, \dots, n-1.$$

In the visiting period n, the MC visits the target population and treats $Q \wedge S_n$ individuals in Segment II, with those successfully treated reverting back to Segment I. The rest of the population evolves according to the Markov cohort model. Specifically, a fraction λ of individuals in Segment I progresses to Segment II. However, the fraction of individuals in Segment II transitioning to Segment I depends on S_n, the initial number of individuals in Segment II at the beginning of the visiting period. Given S_n, $(1-\delta+\delta\mu)(Q \wedge S_n) + \mu(S_n - Q)^+$ individuals transit to Segment I, while $\delta(1-\mu)(Q \wedge S_n) + (1-\mu)(S_n - Q)^+$ individuals remain in Segment II at the end of the visiting period. Among those who transit to Segment I, $(1-\delta)(Q \wedge S_n)$ are treated successfully by the MC, $(1-\pi)\delta\mu(Q \wedge S_n) + (1-\pi)\mu(S_n - Q)^+$ are treated successfully by the hospital, and $\pi\delta\mu(Q \wedge S_n) + \pi\mu(S_n - Q)^+$ are the new arrivals into the target population.

Consequently, at the beginning of the next cycle, the number of individuals in Segment II is

$$S_1 = \lambda(1 - S_n) + \delta(1-\mu)(Q \wedge S_n) + (1-\mu)(S_n - Q)^+.$$

Denote $\bar{S}_n$ as the number of individuals in Segment II at the beginning of the visiting period when the capacity of the MC is $Q = 1$. The following lemma characterizes the number of individuals in Segment II in each period of a delivery cycle in the long run.

LEMMA 2. *Given the MC service delivery policy (n, Q), then*

$$\bar{S}_n = \frac{\lambda(1-\alpha^n)}{(1-\alpha)(1-\delta\alpha^n + (1-\delta)\lambda\alpha^{n-1})}.$$

In the long run, the number of individuals in Segment II at the beginning of the tth period of a delivery cycle is

$$S_t = \frac{\lambda}{1-\alpha} - \frac{(1-\delta)(1-\mu)(Q \wedge \bar{S}_n)\alpha^{t-1}}{1-\alpha^n}, \qquad t = 1, 2, \dots, n.$$

In particular, the number of individuals in Segment II at the beginning of the visiting period n asymptotically converges to that of the benchmark without the provision of the MC service, that is, $\lim_{n\to\infty} S_n = S_\infty$.

A comparison of the results stated in Lemma 2 with those in Lemma 1 shows that when the disease is slow-progressive ($0 \le \alpha < 1$), S_t, the number of individuals in Segment II in any period t is always smaller than that of the case where no MC service is provided, that is, $S_t < S_\infty$ for all $t = 1, 2, \dots, n$. However, when the disease is fast-progressive ($-1 < \alpha < 0$), $S_t < S_\infty$ if t is an odd period but $S_t > S_\infty$ if t is an even period. That is, the number of individuals in Segment II exhibits a zigzag pattern in t ($t = 1, 2, \dots, n$) over the entire delivery cycle. We further examine S_n and obtain the following:

LEMMA 3. *S_n, the number of individuals in Segment II at the beginning of the visiting period n, has the following properties:*

1. *When $0 \le \alpha < 1$, S_n increases in n and $S_n < S_\infty$.*
2. *When $-1 < \alpha < 0$, we have that*
   i. *for all odd delivery cycles, that is, $n = 2m-1$ ($m \in \mathbb{N}$), S_{2m-1} increases in m and $S_{2m-1} < S_\infty$;*
   ii. *for all even delivery cycles, that is, $n = 2m$ ($m \in \mathbb{N}$), S_{2m} decreases in m and $S_{2m} > S_\infty$.*

As shown in Lemma 3, the number of individuals in Segment II waiting for the MC treatments highly hinges on the characteristics of the disease, α, and the length of the delivery cycle, n. Lemmas 2 and 3 together reveal that when the disease is slow-progressive ($0 \le \alpha < 1$), the number of individuals in Segment II waiting for the MC treatments monotonically increases and converges to S_∞, the one without the MC provision, as the length of the delivery cycle increases. In contrast, when the disease is fast-progressive ($-1 < \alpha < 0$), the number of individuals in Segment II waiting for the MC treatments converges to S_∞ in a zigzag pattern as the number of periods in a delivery cycle increases. This is because the increment of S_n represents the net change, which

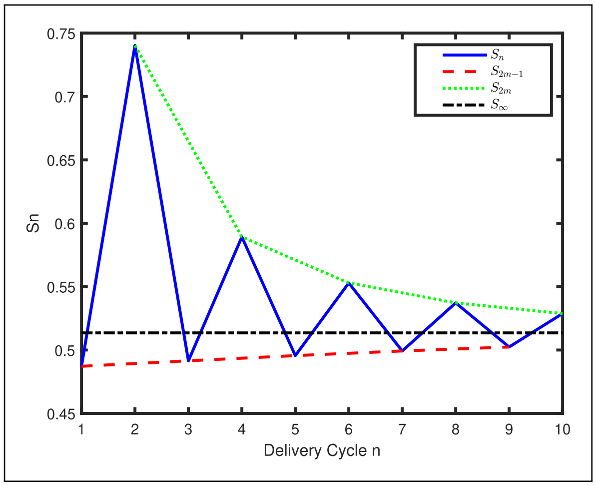

Figure 2. S_n for a fast-progressive disease: $\lambda = 0.95$, $\mu = 0.9$, $Q = 1$, and $\delta = 0$.

is influenced by the number of individuals progressing from Stage I to Stage II, offset by those progressing from Stage II to Stage III. In fast-progressing disease scenarios, the number of individuals progressing from Segment I to Segment II and those exiting Segment II changes over time. At times, the former surpasses the latter, while at other times the reverse occurs, resulting in a zigzag pattern in S_n; see Figure 2 for the illustration.

4.1.2 The Long-Run Average Healthcare Cost. In each regular period t, $t = 1, 2, \ldots, n-1$, μS_t individuals visit the hospital to seek treatment, and hence the public healthcare system incurs a hospital treatment cost $\mu S_t c_r$. In the visiting period n, the MC visits the target population and incurs a setup cost $K(n, Q)$. It then provides the treatment to $Q \wedge S_n$ individuals in Segment II with a treatment cost $(Q \wedge S_n)c_m$. Among the individuals in Segment II who are either not treated due to the MC capacity constraint or treated by the MC but have failed, $\mu(S_n - Q)^+ + \delta\mu(Q \wedge S_n)$ individuals progress to Stage III and visit the hospital to seek treatment. This results in a hospital treatment cost $\mu(S_n - Q)^+ c_r + \delta\mu(Q \wedge S_n)c_r$. Taking the average of the foregoing costs, we can write the long-run average healthcare cost $\mathcal{AC}(n, Q)$ as

$$\mathcal{AC}(n,Q) = \frac{\mu \sum_{t=1}^{n-1} S_t c_r + \mu(S_n - Q)^+ c_r + \delta\mu(Q \wedge S_n)c_r + \left(Q \wedge S_n\right) c_m + K(n,Q)}{n}. \quad (2)$$

The following theorem characterizes $\mathcal{AC}(n, Q)$ in closed form.

Proposition 1. *Given the MC service delivery policy (n, Q), the system's long-run average healthcare cost is*

$$\mathcal{AC}(n,Q) = \frac{\lambda\mu}{\lambda+\mu}c_r - \frac{\phi_c\left(Q \wedge \bar{S}_n\right)}{n} + \frac{K(n,Q)}{n}, \quad (3)$$

where

$$\phi_c = \frac{(1+\lambda)(1-\delta)\mu}{\lambda+\mu}c_r - c_m. \quad (4)$$

Moreover, $\lim_{n\to\infty} \mathcal{AC}(n,Q) = \mathcal{AC}_\infty = \lambda\mu c_r/(\lambda+\mu)$.

Recall that the MC provides treatments to individuals in Segment II that prevent them from progressing to Stage III and seeking treatment at the hospital. The term $[(1+\lambda)(1-\delta)\mu/\lambda+\mu]c_r$ can be understood as the adjusted per person hospital treatment cost when the MC service is provided. Then, ϕ_c stated in (4) represents the relative treatment cost-saving per person with the provision of the MC service. We can further rewrite the long-run average healthcare cost in (3) as follows:

$$\mathcal{AC}(n,Q) = \underbrace{\mathcal{AC}_\infty}_{\text{long-run average cost without MC}} + \underbrace{\frac{K(n,Q)}{n} + \frac{(Q \wedge \bar{S}_n)}{n}c_m}_{\text{MC costs}} - \underbrace{\frac{\mu(1+\lambda)(1-\delta)\left(Q \wedge \bar{S}_n\right)}{(\lambda+\mu)n}c_r}_{\text{hospital treatment cost reduction due to MC}},$$

where the first term is the long-run average healthcare cost borne by the hospital in the benchmark case without the provision of the MC service; the second term is the costs related to the MC operation, consisting of the setup cost $K(n, Q)/n$ and the MC treatment cost $[(Q \wedge \bar{S}_n)/n]c_m$; and the third term is the reduction of the hospital treatment cost as a result of providing the MC service under which less individuals in Segment III seek the hospital service. Clearly, the reduction in the hospital treatment cost decreases as the failure rate of the MC treatment δ increases, under which fewer individuals in Segment II are treated successfully, and increases in the hospital unit treatment cost c_r. We can further obtain the following lemma.

Lemma 4. *Given the MC service delivery policy (n, Q), the long-run average healthcare cost $\mathcal{AC}(n, Q)$ is concave and increasing in the MC treatment failure rate δ. It has the following monotonicity properties with respect to the MC delivery cycle length n:*

1. *When the relative treatment cost-saving per person with the provision of the MC service $\phi_c \le 0$, $\mathcal{AC}(n, Q)$ decreases in n. Moreover, it is always larger than that of the case where without the provision of the MC service, that is, $\mathcal{AC}(n, Q) > \mathcal{AC}_\infty$.*
2. *Otherwise,*
   i. *if $0 \le \alpha < 1$, $\mathcal{AC}(n, Q)$ first decreases and then increases in n;*
   ii. *if $-1 < \alpha < 0$, $\mathcal{AC}(2m-1, Q)$, $m \in \mathbb{N}$ first decreases and then increases in m. When the externality cost associated with each visit $\kappa_2 = 0$, $\mathcal{AC}(2m, Q)$ first decreases,*

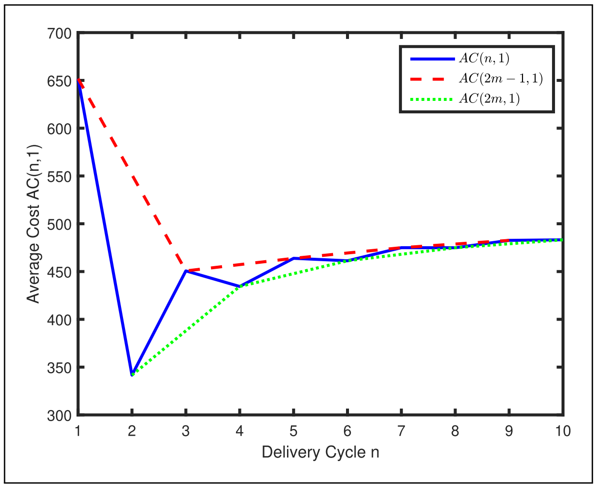

Figure 3. $\mathcal{AC}(n,1)$ for a fast-progressive disease: $\lambda = 0.95$, $\mu = 0.9$, $c_r = 1122.6$, $c_m = 126.9$, $\kappa_1 = 20$, $\kappa_2 = 500$, $Q = 1$, $K = 70$, and $\delta = 0$.

then increases and finally decreases again in m if the setup cost per visit $K + \kappa_1 Q > \phi_c Q$, but if $K + \kappa_1 Q \leq \phi_c Q$, $AC(2m, Q)$ first increases and then decreases in m.

Lemma 4 indicates that the magnitude of ϕ_c plays a critical role in the performance of the long-run average healthcare cost $\mathcal{AC}(n, Q)$. Particularly, when such cost-saving is negative, it indicates the provision of the MC does not help reduce the public healthcare cost. On the contrary, when such cost-saving is positive, the provision of the MC service may help reduce public healthcare cost. Moreover, in such a situation, the shape of $\mathcal{AC}(n, Q)$ depends on the magnitude of α. In particular, for the slow-progressive disease ($0 \leq \alpha < 1$), $\mathcal{AC}(n, Q)$ is *unimodal* in n. However, for the fast-progressive disease ($-1 < \alpha < 0$), $\mathcal{AC}(n, Q)$ is *multimodal* and exhibits a zigzag pattern; see Figure 3 for the illustration. The solid blue line depicts $\mathcal{AC}(n, 1)$, the dashed red line depicts $\mathcal{AC}(2m-1, 1)$, and the dotted green line depicts $\mathcal{AC}(2m, 1)$. Recall from Lemma 3 and Figure 2 that when the disease is fast-progressive, the number of individuals in Segment II, S_n, exhibits a zigzag pattern that oscillates around the long-run average without the provision of the MC service, S_∞, depicted by the dash-dotted black line. As S_n has multiple local maxima, if the MC service is deployed during a period when S_n is not at one of its peaks, this will result in insufficient treatment of patients in Segment II, leading to higher average healthcare costs. This underlying force drives the zigzag pattern observed in the average healthcare cost as depicted in Figure 3, where $\mathcal{AC}(n, 1)$ has multiple local minima.

4.1.3 The Average QALY. In each regular period, individuals in Segment I receive a QoL of σ_1 while individuals in Segment II receive a QoL of σ_2. In the visiting period, individuals in Segment I still receive a QoL of σ_1; however, because the MC visits the target population at the beginning of the period, the QoL that individuals in Stage II receive in this time period depend on both whether they obtain the treatment from the MC and whether the MC treatment is successful or not. If individuals in Segment II receive the MC treatment and are successfully restored to Segment I, then their QoL in the visiting period is σ_1. Otherwise, their QoL in the visiting period is σ_2. We stop counting individuals' QoL when they exit the system.

In general, the average QALY is difficult to compute because computing each individual's QALY is complicated. However, we can apply the periodic Little's Law (see Sigman and Whitt, 2019; Whitt and Zhang, 2019), which is an extension of Little's Law (Little, 2011), to compute the average QALY. Given the MC service delivery cycle n and treatment capacity Q, by the periodic Little's Law, the average QALY is given by

$$\mathcal{QALY}(n, Q) = \frac{\text{Total QALY of the target population in a delivery cycle}}{\text{Total arrivals in a delivery cycle}}.$$

The following theorem summarizes the results regarding the average QALY.

THEOREM 1. *Given the MC service delivery policy* (n, Q)*, the average QALY is*

$$\mathcal{QALY}(n, Q) = \frac{1}{\mu\pi}\left[\frac{(\lambda+\mu)\sigma_1}{\lambda - (1+\lambda)(1-\delta)[(Q \wedge \bar{S}_n)/n]} - \left(\sigma_1 - \sigma_2\right)\right], \quad (5)$$

which decreases in n, and is convex and decreasing in δ. Moreover, $\lim_{n\to\infty} \mathcal{QALY}(n, Q) = \mathcal{QALY}_\infty = (\sigma_1/\lambda + \sigma_2/\mu)/\pi$.

Theorem 1 shows that reducing the MC treatment failure rate is an effective means to enhance the population's health outcome in terms of the average QALY. Moreover, there exists an increasing marginal return to the MC treatment failure rate reduction: a further reduction of the MC treatment failure rate leads to an increase in the marginal improvement of the average QALY. We can further rewrite (5) as follows:

$$\mathcal{QALY}(n, Q) = \underbrace{\mathcal{QALY}_\infty}_{\text{average QALY without MC}} + \underbrace{\frac{\lambda+\mu}{\lambda\mu\pi}\left[\frac{1}{1 - [(1+\lambda)(1-\delta)/\lambda][(Q \wedge \bar{S}_n)/n]} - 1\right]\sigma_1}_{\text{QALY improvement due to MC}}, \quad (6)$$

where the first term corresponds to the average QALY in the benchmark case without the provision of the MC service, and the second term represents the amount of the average QALY improvement due to the provision of the MC service. Note that both terms decrease in π, the failure rate of the hospital treatment. Thus, a more effective hospital treatment is always beneficial to the population's health outcomes, and the hospital treatment and the MC service act as complements in terms of improving the QALY. From (6), we know that the amount of QALY improvement induced by the MC service is linearly increasing in the QoL of the Segment I population, σ_1, but independent of the QoL of the Segment II population, σ_2. This is because the MC service only prolongs the individuals' time staying in Segment I but has no impact on their time staying in Segment II. However, the average QALY increases linearly in both σ_1 and σ_2. Also, the amount of QALY improvement increases in the MC treatment capacity Q until $Q = \bar{S}_n$ and becomes independent of Q afterward.

4.2 The Optimal Operation of the MC Service

The government cares not only about the target population's health outcomes but also the healthcare cost borne by the public healthcare system. The government determines the delivery cycle n and treatment capacity Q of its MC service to maximize the social welfare $\mathcal{SW}$ comprised of the long-run average healthcare cost incurred by the hospital and the MC and the average QALY as follows:

$$\max_{n\in\bar{\mathbb{N}},Q} \quad \mathcal{SW}(n,Q) = \theta\mathcal{QALY}(n,Q) - (1-\theta)\mathcal{AC}(n,Q), \tag{SW}$$

$$\text{s.t.} \quad 0 \le Q \le \bar{S}_n, \tag{7}$$

where $\theta \in [0,1]$ is the weight the government assigns to the average QALY, measuring the degree to which the government cares about improving the average QALY, while $1-\theta$ measures the extent to which the government cares about reducing the healthcare cost. The condition (8) is the capacity constraint, indicating that it is never in the government's best interest to set the MC treatment capacity greater than $\bar{S}_n$, the maximum number of individuals in Segment II that need to be treated (which is derived under an assumption $Q=1$). Let $(n^*, Q^*) = \min\{(n,Q)\ |(n,Q) \in \arg\max_{n\in\bar{\mathbb{N}},Q\le\bar{S}_n}\{\mathcal{SW}(n,Q)\}\}$ be the smallest maximizer of the social welfare function (SW). Here, we consider the "min" in terms of lexicographical ordering, denoted by "$\preccurlyeq$," which is defined as follows: $(n_1,Q_1) \preccurlyeq (n_2,Q_2)$ if and only if $n_1 < n_2$, or $n_1 = n_2$ and $Q_1 \le Q_2$. Clearly, when it is optimal not to provide the MC service ($n^* = \infty$), the MC capacity is zero ($Q^* = 0$). Let n_q^* and n_c^* denote the optimal delivery cycle when the government aims to solely maximize the average QALY ($\theta = 0$) or solely minimize the healthcare cost ($\theta = 1$), respectively. Recall from Theorem 1 that $\mathcal{QALY}(n,Q)$ decreases with n. It naturally follows that $n_q^* = 1$. To facilitate the analysis, let n_d denote the optimal delivery frequency n that maximizes the social welfare when the MC treatment capacity $Q = \bar{S}_n$, and $k_m := c_r/c_m$ the ratio of the hospital treatment cost to the MC treatment cost.

4.2.1 Properties of Optimal Delivery Policy. Although the social welfare function $\mathcal{SW}(n,Q)$ is explicitly defined, the complexity of the expressions for $\mathcal{QALY}(n,Q)$ and $\mathcal{AC}(n,Q)$ makes it challenging to obtain a closed-form solution for (n^*,Q^*). Nevertheless, we can still derive certain properties of n^* and Q^*.

THEOREM 2. *The social welfare function $\mathcal{SW}(n,Q)$ is convex in Q. Furthermore, the optimal solution (n^*,Q^*) has the following properties:*

1. *The optimal delivery cycle satisfies $1 \le n^* \le n_c^*$.*
2. *The optimization problem (SW) has a unique optimal solution (n^*,Q^*), specified as follows:*
   i. *If $n^* < \infty$, then $(n^*,Q^*) = (n_d, \bar{S}_{n_d})$;*
   ii. *If $n^* = \infty$, then $(n^*,Q^*) = (\infty, 0)$.*

Theorem 2 shows that the optimal delivery cycle n^* is bounded by $n_q^* = 1$ and n_c^*. That is, the MC service is delivered least frequently when the government cares solely about reducing the healthcare cost ($\theta = 0$) and most frequently when the government cares solely about improving the QALY ($\theta = 1$). Once it becomes optimal to deliver the MC service, it is optimal to provide it at a capacity sufficient to treat all the individuals in Segment II. In the following, we identify scenarios in which it is more likely for the government to find it optimal to provide the MC service.

To facilitate the analysis and ease of understanding, we define a weight-adjusted social welfare improvement corresponding to the provision of an MC service—delivered every n periods with a treatment capacity of $\bar{S}_n$—that incorporates the government's assigned weight, θ, into the average QALY as follows:

$$\begin{aligned} I_n &= \phi_c\bar{S}_n + \frac{\theta n(\mathcal{QALY}(n,\bar{S}_n) - \mathcal{QALY}_\infty)}{1-\theta} \\ &= \phi_c\bar{S}_n + \frac{\theta\sigma_1(\lambda+\mu)(1+\lambda)(1-\delta)\bar{S}_n}{(1-\theta)[\lambda-(1+\lambda)(1-\delta)\bar{S}_n/n]\lambda\mu\pi}, \end{aligned} \tag{8}$$

where $\theta \in [0,1)$, the first term $\phi_c\bar{S}_n$ represents the treatment cost savings in one cycle from providing the MC service, while the second term captures the weight-adjusted improvement in QALY in one cycle from the service (i.e., $n(\mathcal{QALY}(n,\bar{S}_n) - \mathcal{QALY}_\infty)$), with a coefficient of $\theta/(1-\theta)$.

THEOREM 3. *I_n increases in θ and k_m and decreases in δ. Suppose there exists a finite integer n such that $I_n > \kappa_1\bar{S}_n + \kappa_2/n + K$, then it is optimal for the government to provide the MC service ($n^* < \infty$). Further, if the disease is fast-progressive ($-1 < \alpha < 0$) and the externality cost per MC visit is zero ($\kappa_2 = 0$), then the possible values of n^* are 1, 2, or ∞. Specifically,*

1. *If $I_2 < \kappa_1\bar{S}_2 + K$, then $(n^*,Q^*) = (\infty,0)$.*
2. *If $I_2 \ge \kappa_1\bar{S}_2 + K$, then*

i. $(n^*, Q^*) = (1, \bar{S}_1)$ *if* $2I_1 - I_2 \geq 2\kappa_1\bar{S}_1 - \kappa_2\bar{S}_2 + K$;
ii. $(n^*, Q^*) = (2, \bar{S}_2)$ *if* $2I_1 - I_2 < 2\kappa_1\bar{S}_1 - \kappa_2\bar{S}_2 + K$.

By the monotonicity property of I_n, we have that the government is more likely to provide the MC service when (i) it puts a higher weight on improving the average QALY, (ii) the MC treatment becomes more efficient, or (iii) the hospital treatment cost is much higher relative to the MC treatment cost. Theorem 3 indicates that when there exists a delivery cycle such that the associated weight-adjusted social welfare improvement I_n surpasses the setup cost of the MC service, it is optimal for the government to provide the MC service. Theorem 3 further shows that in the absence of externality costs, the MC service shall be provided either every period or every other period for the fast-progressive disease.

4.2.2 Impact on System Performance. We identify sufficient conditions for the emergence of a win–win outcome in which the implementation of an MC service leads to both a reduction in healthcare costs and an improvement in the average QALY. To facilitate the analysis, and recalling the average healthcare cost stated in (3), the cost reduction associated with the provision of the MC service, when delivered every period with a capacity of $\bar{S}_1$, can be expressed as $C_M := \phi_c\bar{S}_1 - \kappa_1\bar{S}_1 - \kappa_2 - K$.

THEOREM 4. *C_M is increasing in λ, μ, and k_m, and decreasing in δ. If $C_M > 0$, it is optimal to provide the MC service ($n^* < \infty$). Furthermore, the following results hold:*

1. *The provision of the MC service always improves the average QALY.*
2. *The optimal average QALY with the provision of the MC service is higher than that without, while the long-run average healthcare cost is lower than that without, that is, $\mathcal{QALY}(n^*, Q^*) > \mathcal{QALY}_\infty$ and $\mathcal{AC}(n^*, Q^*) < \mathcal{AC}_\infty$.*

Theorem 4 shows that when delivering the MC service, every period leads to a cost reduction ($C_M > 0$), it is optimal to provide the MC service. Under optimality, the inclusion of the MC operation into the public healthcare system leads to both healthcare cost reduction and QALY improvement. By Theorem 4, we have that the win–win outcome is more likely to happen when (i) the disease progresses faster; (ii) the MC treatment becomes more efficient; or (iii) the hospital treatment cost is higher relative to the MC treatment cost. We can further show the following result.

PROPOSITION 2. *Assume no externality cost incurs for each MC visit ($\kappa_2 = 0$). When the MC service is provided, under optimality, both $\mathcal{QALY}(n^*, Q^*)$ and $\mathcal{AC}(n^*, Q^*)$ increase in θ.*

Proposition 2 shows that both the optimal average QALY and the long-run average healthcare cost increase as the government becomes more concerned about the population's health outcomes. This implies that with the provision of MC service, the average QALY improves, but at the cost of increasing the average healthcare cost. Recall that ϕ_c stated in (4) represents the relative treatment cost-saving per person with the provision of the MC service, and κ_1 is the setup cost for each unit of MC capacity required to treat a single patient. We thus define $\bar{\phi}_c := \phi_c - \kappa_1$, which represents the net relative cost saving per person with the provision of the MC service.

PROPOSITION 3. *Assuming no externality cost per MC visit ($\kappa_2 = 0$), the provision of the MC service reduces the long-run average healthcare cost only if $\bar{\phi}_c > 0$ and one of the following three conditions holds:*

1. *$0 \leq \alpha < 1$ and $K < \bar{\phi}_c\bar{S}_1$;*
2. *$0 \leq \alpha < 1$, $\bar{\phi}_c\bar{S}_1 < K < \bar{\phi}_c\bar{S}_\infty$, and $\theta \leq \theta_0$, where $\theta_0 \in [0, 1)$ satisfies $\mathcal{AC}(n^*(\theta_0), \bar{S}_{n^*(\theta_0)}) < [\lambda\mu/(\lambda + \mu)]c_r \leq \mathcal{AC}(n^*(\theta_0) - 1, \bar{S}_{n^*(\theta_0)-1})$;*
3. *$-1 < \alpha < 0$ and $K < \bar{\phi}_c\bar{S}_2$.*

Proposition 3 shows that whether the provision of the MC service can help the government reduce its healthcare spending depends on multiple factors, including the net relative treatment cost-saving per person with the provision of the MC service $\bar{\phi}_c$, the disease progression index α, and the fixed setup cost of providing the MC service K. Specifically, the following two conditions are the prerequisites for cost reduction: (1) $\bar{\phi}_c$ is positive and (2) K is less than a certain threshold. When the above prerequisites are satisfied, the provision of the MC service always leads to a reduction of the healthcare cost for the government when the disease is fast-progressive ($-1 < \alpha < 0$). However, for the slow-progressive disease ($0 \leq \alpha < 1$), cost reduction has more rigid requirements: either the fixed MC setup cost is intermediate-low ($\bar{\phi}_c\bar{S}_1 < K < \bar{\phi}_c\bar{S}_\infty$) and the government's emphasis on improving the average QALY is not high ($\theta \leq \theta_0$) or a further reduction in the MC setup cost ($K < \bar{\phi}_c\bar{S}_1$) is required.

5 Discussion

In this section, we examine the impact of the system parameters on the provision of the MC service, long-run healthcare cost, and average QALY through extensive numerical experiments. We then present a real case study of the MC operation in Zichuan District, Zibo, China, to investigate the outcomes of the MC program initiated by the Chinese government in 2019.

5.1 The Impact of System Parameters on the System Performance

To facilitate our understanding of the impact of providing the MC service, let

$$\Delta_{\text{cost}}(n, Q) = \frac{\mathcal{AC}_\infty - \mathcal{AC}(n, Q)}{\mathcal{AC}_\infty} \quad \text{and}$$
$$\Delta_{\text{qaly}}(n, Q) = \frac{\mathcal{QALY}(n, Q) - \mathcal{QALY}_\infty}{\mathcal{QALY}_\infty}.$$

Then, $\Delta_{\text{cost}}(n, Q)$ and $\Delta_{\text{qaly}}(n, Q)$ represent the *percentage cost reduction* and the *percentage QALY improvement* with the provision of the MC service, respectively. They can be further derived as

$$\Delta_{\text{cost}}(n, Q) = \frac{(\lambda + \mu)(\phi_c(Q \wedge \bar{S}_n) - K(n, Q))}{\lambda \mu c_r n}$$

and

$$\Delta_{\text{qaly}}(n, Q) = \frac{(\lambda + \mu)\sigma_1}{\lambda\sigma_2 + \mu\sigma_1}\left[\frac{1}{1 - [(1+\lambda)(1-\delta)/\lambda](Q/n)} - 1\right],$$

where $\Delta_{\text{cost}}(n, Q) \leq 1$ and $\Delta_{\text{qaly}}(n, Q)$ satisfies the following result.

PROPOSITION 4. *The percentage QALY improvement with the provision of the MC service, $\Delta_{\text{qaly}}(n, Q)$ monotonically decreases in δ, and it is always positive and less than $C(1/\delta - 1)$, that is, $0 < \Delta_{\text{qaly}}(n, Q) \leq C(1/\delta - 1)$, where $C = [\sigma_1(1 + \lambda)/(\lambda\sigma_2 + \mu\sigma_1)] > 1$.*

Proposition 4 implies that the provision of the MC always improves the population's health outcomes. However, the percentage QALY improvement $\Delta_{\text{qaly}}(n, Q)$ is bounded above by $C(1/\delta - 1)$, which decreases in δ, the failure rate of the MC treatment. That is, the population's health outcomes can be further improved when the treatment effectiveness of the MC service increases.

We also define the ICER as follows:

$$\text{ICER} = \frac{\mathcal{AC}(n^*, Q^*) - \mathcal{AC}_\infty}{\mathcal{QALY}(n^*, Q^*) - \mathcal{QALY}_\infty},$$

where the ICER measures the incremental healthcare cost incurred per unit of QALY improvement under the optimal delivery policy (n^*, Q^*) compared to that of the case without the MC service. Note that the ICER is widely adopted in the healthcare economics literature to evaluate the outcomes of one or more interventions; see, for example, Freedberg et al. (1998). Here, we adopt the ICER to analyze the cost-effectiveness of providing the MC service to improve the population's health outcome. When the ICER is negative, the provision of the MC service also results in a positive healthcare cost-saving; otherwise, it is costly to improve the QALY via the provision of the MC service.

We set the parameter values as follows unless otherwise specified: $\pi = 0.3$, $\delta = 0.4$, $\sigma_1 = 0.8$, $\sigma_2 = 0.7$, $\lambda = 0.4$, $\mu = 0.4, \kappa_1 = 20, \kappa_2 = 500, K = 70, c_r = 1122.6, c_m = 126.9$, and $\theta = 0.6$. In particular, the values of treatment cost parameters are derived from the data provided by National Health Commission of the People's Republic of China (2021). We estimate the hospital treatment cost per patient as $c_r = 1122.6$ CNY and the MC treatment cost per patient as $c_m = 126.9$ CNY, based on the average hospitalization cost per patient and the medication cost. Based on Theorem 2, to numerically solve the optimization problem (SW), we first set $Q = \bar{S}_n$, thereby reducing the problem (SW) to a one-dimensional optimization problem focused on optimizing n. We then iterate over n from 1 to 100 (a sufficiently large value based on our parameter settings) to find the optimal n^*. Subsequently, we set $Q^* = \bar{S}_{n^*}$. In cases where multiple policies achieve the maximum, we select the optimal policy based on lexicographical order. If the social welfare function reaches its maximum at $n = 100$, we set $(n^*, Q^*) = (\infty, 0)$.

Impact of the MC Treatment Failure Rate $\boldsymbol{\delta}$. We first examine how the MC treatment failure rate δ affects the provision of the MC service and the system performance by varying δ from 0.1 to 1 with a step size of 0.1 (Table 2). As the MC treatment failure rate increases, more individuals in Segment II cannot successfully revert back to Segment I, and a fraction of them progress to Segment III, resulting in more hospital visits. Thus, the government has less incentive to provide the MC service. As shown in Table 2, a larger δ leads to a weaker, less frequent delivery of the MC service (i.e., a weakly larger n^*). Particularly, it is never in the government's interest to provide the MC service when $\delta \geq 0.7$. A larger MC treatment failure rate also reduces both the social welfare and average QALY, as $\mathcal{SW}(n^*, Q^*)$ and $\mathcal{QALY}(n^*, Q^*)$ are decreasing in δ.

Impact of the Disease Characteristics $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$. We next investigate how the disease characteristics, λ and μ, impact the optimal MC operation and system performance by varying λ and μ from 0.05 to 0.95 with a step size of 0.1, respectively. The results are summarized in Tables 3 and 4. Table 3 demonstrates that the ICER is more likely to be negative when λ becomes larger. Specifically, when λ is sufficiently high ($\lambda \geq 0.25$), the ICER is negative, indicating that both the average QALY is increased and the average healthcare cost is decreased. Interestingly, as λ increases, the optimal delivery cycle first increases, then decreases, and finally increases again. Additionally, we observe that as λ increases, both the social welfare and average QALY decrease, while the average healthcare cost and optimal MC capacity increase.

Tables 3 and 4 exhibit similar patterns as λ and μ vary, except that the optimal MC capacity Q^* increases in λ but decreases in μ. This is because, for diseases with a faster progression rate from Stage I to Stage II, a larger number of individuals in Segment II require treatment by the MC service. Conversely, as the progression rate from Stage II to Stage III increases, fewer individuals remain in Segment II, reducing the need for MC capacity.

Table 2. The optimal MC operation and the system performance under different δ.

δ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
n^*	4.0	4.0	6.0	8.0	14.0	35.0	∞	∞	∞	∞
Q^*	0.498	0.498	0.500	0.500	0.500	0.500	0	0	0	0
$\mathcal{SW}(n^*, Q^*)$	−68.8	−73.5	−77.0	−79.6	−81.3	−82.2	−82.3	−82.3	−82.3	−82.3
$\mathcal{AC}(n^*, Q^*)$	203.5	213.3	216.5	220.8	223.3	224.5	224.5	224.5	224.5	224.5
$\mathcal{QALY}(n^*, Q^*)$	21.1	19.6	15.9	14.5	13.4	12.8	12.5	12.5	12.5	12.5
$\Delta_{\text{cost}}(n^*, Q^*)$	9.3%	5.0%	3.6%	1.7%	0.6%	−0.0%	0	0	0	0
$\Delta_{\text{qaly}}(n^*, Q^*)$	68.8%	57.1%	27.4%	16.1%	7.1%	2.2%	0	0	0	0
ICER	−2.4	−1.6	−2.4	−1.8	−1.4	0.1	—	—	—	—

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio. "—" represents the case where there is no valid value.

Table 3. The optimal MC operation and the system performance under different λ.

λ	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
n^*	6.0	10.0	9.0	8.0	8.0	8.0	8.0	8.0	9.0	9.0
Q^*	0.110	0.273	0.385	0.467	0.530	0.579	0.619	0.653	0.680	0.704
$\mathcal{SW}(n^*, Q^*)$	19.5	−33.0	−56.9	−73.1	−85.3	−94.8	−102.4	−108.8	−114.1	−118.6
$\mathcal{AC}(n^*, Q^*)$	66.7	123.1	170.8	206.4	233.6	255.4	273.1	288.0	300.3	311.0
$\mathcal{QALY}(n^*, Q^*)$	77.0	27.1	19.0	15.7	13.6	12.3	11.4	10.7	10.0	9.6
$\Delta_{\text{cost}}(n^*, Q^*)$	−33.7%	−0.5%	1.1%	1.5%	1.7%	1.8%	1.7%	1.7%	1.7%	1.6%
$\Delta_{\text{qaly}}(n^*, Q^*)$	30.1%	14.8%	15.4%	16.6%	15.7%	15.0%	14.5%	14.0%	12.0%	11.7%
ICER	0.9	0.2	−0.8	−1.4	−2.2	−2.9	−3.4	−3.7	−4.7	−4.9

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio.

Table 4. The optimal MC operation and the system performance under different μ.

μ	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95
n^*	4.0	12.0	9.0	8.0	8.0	9.0	9.0	9.0	10.0	11.0
Q^*	0.805	0.727	0.615	0.533	0.471	0.421	0.381	0.348	0.320	0.296
$\mathcal{SW}(n^*, Q^*)$	15.5	−34.6	−57.4	−73.2	−85.2	−94.8	−102.6	−109.1	−114.5	−119.2
$\mathcal{AC}(n^*, Q^*)$	107.1	125.1	171.9	206.6	233.6	255.3	273.4	288.7	301.5	312.6
$\mathcal{QALY}(n^*, Q^*)$	97.2	25.8	18.9	15.7	13.6	12.2	11.3	10.7	10.1	9.7
$\Delta_{\text{cost}}(n^*, Q^*)$	−114.7%	−2.1%	0.5%	1.4%	1.8%	1.8%	1.6%	1.4%	1.3%	1.1%
$\Delta_{\text{qaly}}(n^*, Q^*)$	82.3%	16.0%	18.2%	17.4%	15.0%	11.5%	10.2%	9.2%	7.5%	6.2%
ICER	1.3	0.7	−0.3	−1.3	−2.3	−3.8	−4.3	−4.6	−5.4	−6.0

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio.

Table 5. The optimal MC operation and the system performance under different c_r: $c_r = k_m c_m$.

k_m	1	3	5	7	9	11	13	15	17	19
n^*	∞	∞	∞	15.0	8.0	6.0	4.0	4.0	3.0	3.0
Q^*	0	0	0	0.500	0.500	0.500	0.499	0.499	0.493	0.493
$\mathcal{SW}(n^*, Q^*)$	−2.7	−23.0	−43.3	−62.7	−81.0	−98.1	−113.9	−128.9	−142.5	−155.8
$\mathcal{AC}(n^*, Q^*)$	25.4	76.1	126.9	177.7	224.2	268.1	310.6	348.1	385.6	418.9
$\mathcal{QALY}(n^*, Q^*)$	12.5	12.5	12.5	13.5	14.5	15.3	17.2	17.2	19.5	19.5
$\Delta_{\text{cost}}(n^*, Q^*)$	0	0	0	0.4%	1.9%	4.0%	5.8%	8.6%	10.6%	13.1%
$\Delta_{\text{qaly}}(n^*, Q^*)$	0	0	0	8.0%	16.1%	22.6%	37.8%	37.8%	56.2%	56.2%
ICER	—	—	—	−0.6	−2.1	−3.9	−4.1	−6.9	−6.5	−9.0

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio. "—" represents the case where there is no valid value.

Table 6. The optimal MC operation and the system performance under different θ.

θ	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
n^*	11.0	11.0	10.0	10.0	10.0	9.0	8.0	7.0	6.0	3.0	1.0
Q^*	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.493	0.345
$\mathcal{SW}(n^*, Q^*)$	−220.3	−196.8	−173.4	−150.0	−126.5	−103.1	−79.6	−56.1	−32.3	−7.4	47.5
$\mathcal{AC}(n^*, Q^*)$	220.3	220.3	220.3	220.3	220.3	220.4	220.8	221.5	223.0	250.1	682.6
$\mathcal{QALY}(n^*, Q^*)$	13.9	13.9	14.1	14.1	14.1	14.3	14.5	14.9	15.3	19.5	47.5
$\Delta_{\text{cost}}(n^*, Q^*)$	1.9%	1.9%	1.9%	1.9%	1.9%	1.8%	1.7%	1.3%	0.7%	−11.4%	−204.0%
$\Delta_{\text{qaly}}(n^*, Q^*)$	11.3%	11.3%	12.5%	12.5%	12.5%	14.1%	16.1%	18.8%	22.6%	56.2%	280.0%
ICER	−3.0	−3.0	−2.7	−2.7	−2.7	−2.3	−1.8	−1.3	−0.5	3.6	13.1

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio.

Table 7. The optimal MC operation and the system performance under different κ_1.

κ_1	0	40	80	120	160	200	240	280	320	≥360
n^*	8.0	9.0	11.0	15.0	22.0	41.0	∞	∞	∞	∞
Q^*	0.500	0.500	0.500	0.500	0.500	0.500	0	0	0	0
$\mathcal{SW}(n^*, Q^*)$	−79.1	−80.1	−80.9	−81.5	−81.9	−82.2	−82.3	−82.3	−82.3	−82.3
$\mathcal{AC}(n^*, Q^*)$	219.5	221.5	223.0	223.9	224.5	224.8	224.5	224.5	224.5	224.5
$\mathcal{QALY}(n^*, Q^*)$	14.5	14.3	13.9	13.5	13.2	12.9	12.5	12.5	12.5	12.5
$\Delta_{\text{cost}}(n^*, Q^*)$	2.2%	1.3%	0.7%	0.3%	−0.0%	−0.1%	0	0	0	0
$\Delta_{\text{qaly}}(n^*, Q^*)$	16.1%	14.1%	11.3%	8.0%	5.3%	2.8%	0	0	0	0
ICER	−2.5	−1.7	−1.1	−0.6	0.0	0.7	—	—	—	—

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio. "—" represents the case where there is no valid value.

Table 8. The optimal MC operation and the system performance under different κ_2.

κ_2	0	100	200	300	400	500	600	700	800	900	1000
n^*	1.0	2.0	3.0	5.0	7.0	8.0	10.0	12.0	14.0	15.0	17.0
Q^*	0.345	0.466	0.493	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
$\mathcal{SW}(n^*, Q^*)$	−44.5	−68.5	−75.0	−77.6	−78.9	−79.6	−80.1	−80.4	−80.7	−80.8	−81.0
$\mathcal{AC}(n^*, Q^*)$	182.6	209.0	216.8	218.1	219.5	220.8	221.3	221.7	222.0	222.4	222.6
$\mathcal{QALY}(n^*, Q^*)$	47.5	25.2	19.5	16.0	14.9	14.5	14.1	13.8	13.6	13.5	13.4
$\Delta_{\text{cost}}(n^*, Q^*)$	18.7%	6.9%	3.5%	2.9%	2.2%	1.7%	1.4%	1.3%	1.1%	1.0%	0.9%
$\Delta_{\text{qaly}}(n^*, Q^*)$	280.0%	101.8%	56.2%	28.3%	18.8%	16.1%	12.5%	10.2%	8.6%	8.0%	7.0%
ICER	−1.2	−1.2	−1.1	−1.8	−2.1	−1.8	−2.1	−2.2	−2.3	−2.1	−2.2

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio.

Effect of the Ratio of the Hospital Treatment Cost to the MC Treatment Cost. In Table 5, we investigate how the ratio of the hospital treatment cost to the MC treatment cost $k_m = c_r/c_m$ impacts the optimal MC operational decisions and the system performance by varying k_m from 1 to 19 with a step size of 2. Table 5 implies that the ICER is more likely to be negative when k_m becomes larger. That is, when the hospital treatment is significantly more expensive than the MC treatment ($k_m \geq 7$), the provision of the MC service can help not only improve the average QALY but also reduce the average healthcare cost. In contrast, when k_m is rather small ($k_m \leq 5$), it is never in the government's best interest to provide the MC service. The MC service, if provided, will be provided more frequently (i.e., with a shorter delivery cycle n^*) as k_m increases.

Impact of the Weight That the Government Assigns to the Average QALY. We now examine how the government's emphasis on improving the QALY affects the provision of the MC service by varying θ, the weight that the government assigns to the average QALY. Table 6 shows that as θ increases, the ICER weakly increases and the MC service is provided more frequently (i.e., a smaller n^*). When θ is less than a threshold ($\theta \leq 0.8$), the ICER is negative, and the provision of the MC service results in both the average QALY improvement and healthcare cost reduction. When θ becomes sufficiently large ($\theta \geq 0.9$), the provision of the MC service leads to the average QALY improvement, but at the cost of increasing the healthcare cost. We also observe that the social welfare $\mathcal{SW}(n^*, Q^*)$ becomes larger as θ increases.

Impact of the MC Setup Costs κ_1 and κ_2. Last, we examine the impact of the MC setup costs, κ_1 and κ_2, on the provision of the MC service and system performance. We vary κ_1 from 0 to 360 with step size 40 and κ_2 from 0 to 1000 with step size 100. As the setup cost increases, the MC service becomes more costly. Nonsurprisingly, Tables 7 and 8 show that accordingly, the government provides the MC service less frequently (i.e., a weakly larger n^*) with a weakly larger capacity Q^*; it stops providing the MC service when the setup cost becomes sufficiently large. Consequently, both the social welfare $\mathcal{SW}(n^*, Q^*)$ and the average QALY $\mathcal{QALY}(n^*, Q^*)$ decrease as κ_1 and κ_2 increase.

5.2 A Case Study of the MC Operation in Zichuan District, Zibo, China

In Zichuan District, Zibo, China, 70 villages are located more than 5 kilometers away from the local health centers, and they have limited access to regular medical services. Since July 2019, Zichuan District has launched a "walking doctor, mobile hospital" medical program, which delivers medical service to the remote community to treat chronic diseases such as hypertension, heart disease, and diabetes. In this case study, we focus on the MC's operation to manage eye-related symptoms and complications for DR patients by providing diagnostic services and administering anti-VEGF injections to those diagnosed in the DME stage. It is worth noting that individuals may receive insulin therapy, a crucial component of early stage diabetes management, which can typically be provided through village health centers when abnormal blood sugar levels are detected. Here, we consider the MC intervention at the DME stage, as village health centers lack the necessary medical equipment for diagnosis and treatment, and patients need to seek treatment at a distant hospital. The International Classification of DR classifies DR into three categories, nonproliferative DR (NPDR), DME, and proliferative DR (PDR), which is the most widely used classification (see Wilkinson et al., 2003). Specifically, the three stages of the disease progression are as follows:

- Stage I: NPDR. Individuals in this stage are in remission and asymptomatic. They do not require any treatment.
- Stage II: DME. Individuals in this stage are in partial remission but remain under control. Their condition can be diagnosed and treated through the administration of anti-VEGF injections via the MC.
- Stage III: PDR. Individuals in this stage are in a serious condition. They require immediate treatment by the hospital, which cannot be done by the MC.

5.2.1 Data Collection and Variables. In 2019, the population of the permanent residents in the remote villages of Zichuan District was 9456, among whom 490 were suffering from diabetes (Dazhong Daily News, 2019). Based on Zhang et al. (2022) and Chen et al. (2020), we set $c_r = 8353.37$ CNY, $c_m = 252.82$ CNY, $\kappa_1 = 17.02$ CNY, $\kappa_2 = 736.92$ CNY, and $K = 300$ (see Online Appendix D for the details on the estimation of these parameter values).

The MC visits the remote villages every n weeks, $n \in \overline{\mathbb{N}}$. Based on Srikanth (2015), we can estimate the annual progression rates from Stage I to Stage II and from Stage II to Stage III to be $\lambda_y = 0.32$ and $\mu_y = 0.54$, respectively (see Online Appendix D for details). By the Chapman–Kolmogorov equation (see Ross, 2019, Chapter 4.2), we compute the weekly transition matrix by taking the 1/52th power of the yearly transition matrix and obtain the weekly progression rates from Stage I to Stage II and from Stage II to Stage III to be $\lambda = 0.0138$ and $\mu = 0.0233$, respectively. Consequently, $\alpha = 0.9629$, that is, DR is a slow-progressive disease when the progression rate is measured in weeks. By Zhang et al. (2022), the QoL scores for staying in Stage I and Stage II are $\sigma_1 = 0.79$ and $\sigma_2 = 0.7$, respectively.

As the success rate of injection-only anti-VEGF agents (which treat the DR patient in Stage II) ranges from 30% to 50% (Yuen, 2020), we first take the average and set the MC treatment failure rate $\delta = 0.6$. We later conduct the probabilistic sensitivity analysis by varying the parameter value of δ between 0.5 and 0.7. When a person progresses to Stage III, he/she needs to be immediately treated by the hospital, which has a surgical success rate of 80.6% (Venincasa et al., 2018). Accordingly, the hospital treatment failure rate is $\pi = 0.194$.

5.2.2 The Optimal MC Provision. When there is no provision of the MC service ($n^* = \infty$), it can be calculated that the long-run average healthcare cost is approximately 8904.9 CNY per week, with an average QALY of about 8.7. When the MC service is provided, we can derive the optimal delivery cycle n^* and MC treatment capacity Q^* for the operation of the MC service in Zichuan District and the resulting system performance based on the weight (θ) assigned by the government to the average QALY by utilizing the parameter values stated in Section 5.2.1. The outcomes are summarized in Table 9.

Improving Health Outcome of Remote Populations. Table 9 reveals that operating the MC service significantly improves the average QALY for populations in remote villages of Zichuan District. For example, when the weight parameter $\theta = 0.8$, the MC service is provided to the remote villages every 12 weeks, increasing the average QALY from 8.7 to 19 compared to that when the MC service is not provided.

Reducing Healthcare Cost. The provision of the MC service to treat DR patients can lead to substantial cost savings for the public healthcare system by reducing the number of hospital visits. For example, when $\theta = 0.8$, the MC service is provided to the remote villages every 12 weeks, lowering the long-run average healthcare cost to 8459.7 CNY per week. This results in an annual cost savings of $(8904.9 - 8459.7) \times 52 \times 4 \approx 9.3 \times 10^4$ CNY, for an MC service covering four communities in Zichuan.

Cost-Effectiveness of Providing the MC Service. Table 9 shows that the ICER increases as the weight parameter θ increases. Notably, the ICER is negative only when $\theta \leq 0.8$, under which both the QALY increases and the healthcare cost is reduced. The study by Li et al. (2021) shows that mHealth

Table 9. The optimal MC operation and the system performance under different θ: $\pi = 0.194$, $\delta = 0.6$, $\sigma_1 = 0.79$, $\sigma_2 = 0.7$, $\lambda = 0.0138$, $\mu = 0.0233$, $\kappa_1 = 17.02$, $\kappa_2 = 736.92$, $K = 300$, $c_r = 8353.37$, $c_m = 252.82$.

θ	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
n^*	24.0	23.0	23.0	22.0	21.0	20.0	19.0	16.0	12.0	5.0	1.0
Q^*	0.292	0.288	0.288	0.283	0.279	0.274	0.268	0.250	0.218	0.126	0.032
$\mathcal{SW}(n^*, Q^*)$	−7821.4	−6967.7	−6113.2	−5257.9	−4401.2	−3541.9	−2678.3	−1804.7	−901.8	200.4	9009.5
$\mathcal{AC}(n^*, Q^*)$	7821.4	7822.3	7822.3	7826.7	7835.5	7849.7	7870.9	7996.0	8459.7	14148.4	129075.2
$\mathcal{QALY}(n^*, Q^*)$	13.7	13.9	13.9	14.2	14.4	14.7	15.1	16.3	19.0	34.5	173.3
$\Delta_{\text{cost}}(n^*, Q^*)$	12.2%	12.2%	12.2%	12.1%	12.0%	11.8%	11.6%	10.2%	5.0%	−58.9%	−1349.5%
$\Delta_{\text{qaly}}(n^*, Q^*)$	58.1%	60.7%	60.7%	63.6%	66.8%	70.2%	74.1%	88.6%	119.5%	298.9%	1902.4%
ICER	−215.7	−206.1	−206.1	−196.0	−185.1	−173.6	−161.3	−118.5	−43.0	202.8	730.1

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio.. n^* is in weeks, $\mathcal{AC}$ is in CNY per week, $\mathcal{QALY}$ is in years, and the ICER is in CNY per year.

interventions for patients with Type 2 diabetes mellitus result in an ICER of CNY −22.02 per patient per year. As the MC intervention involves in-person medical services, it provides a more efficient treatment method than mHealth interventions. Here, the ICER ranges from CNY −215.7 to 730.1 as shown in Table 9, depending on the government's choice of θ. Compared to mHealth intervention, a lower ICER under the MC provision indicates higher cost savings.

We further investigate the individual benefits of optimizing the MC's treatment capacity (Q) and delivery cycle (n) separately; see Online Appendix F for the details. We show that this may result in inefficient resource allocation and hinder the achievement of maximum social welfare.

5.2.3 Probabilistic Sensitivity Analysis. The above results are obtained for the known parameter values. In reality, the specific parameter values may be uncertain, but the decision makers have some prior knowledge of their distributions. We now consider such a scenario by applying the probabilistic sensitivity analysis, which has been used in the health economics literature (see, e.g., Briggs, 2000; Chen et al., 2017) to examine the impact of parametric uncertainty on the system outcomes. Suppose the government assigns a weight of $\theta = 0.8$ to the average QALY. This is a reasonable choice, as it represents the highest weight (as shown in Table 9) that the government can assign to QALY improvement while still maintaining a negative ICER. We consider the values of parameters λ, μ, δ, π, σ_1, and σ_2 follow a Beta distribution and those of c_m, c_r, κ_1, κ_2, and K follow a Gamma distribution. For brevity, the detailed discussion about the ranges of the values of those parameters and their distributions is relegated to Online Appendix D. We consider the probability distribution for one parameter at a time and simulate the population trajectories over a 20-year period with weekly time steps and 2000 sample paths. For each parameter, Table 10 reports the corresponding optimal policy, along with the mean values of social welfare, average healthcare cost, average QALY, percentage cost reduction, percentage QALY improvement, and ICER. The respective standard deviations are shown in parentheses. To quantify the difference between the deterministic and random scenarios as presented in Tables 9 and 10, we follow the approach of Chen et al. (2017) and define a *relative performance gap* as $\delta = (\mathcal{R} - \mathcal{D})/\mathcal{R}$, where $\mathcal{R}$ represents the optimal policy and system performance in the random scenario, and $\mathcal{D}$ represents those in the deterministic scenario. The result is reported in the last row of Table 10. If the relative gap remains within an acceptable tolerance level, $\bar{\delta}$, that is, $\delta < \bar{\delta}$, the policy or performance is deemed robust. Table 10 then indicates that the values of the optimal delivery policy and the system performances remain robust in the uncertain environment, with a relative performance gap within 11.5%. These observations imply the robustness of our proposed model of the MC program.

6 Conclusion

In underdeveloped countries, the individuals living in remote communities often have poor access to healthcare due to issues such as logistical constraints and long traveling distances. The MC, an emerging means to provide the healthcare service, can overcome such access-related barriers by visiting remote communities and delivering healthcare services on site. In this paper, we consider a public healthcare system consisting of a hospital, an MC, and a target population of potential patients in a remote community in developing economies. The government is concerned about both the population's health outcome and the healthcare spending. The government needs to decide whether and how to operate the MC to the target remote population so as to maximize the social welfare that consists of two terms: the average QALY and the long-run average healthcare cost incurred by the hospital and the MC.

We first characterize the dynamics of the target population and derive the average healthcare cost and the average QALY for a given MC delivery policy. We then investigate the optimal operation of the MC service. We show that the government is more likely to provide the MC service more frequently when (i) it puts more weight on the average QALY, (ii) the MC treatment becomes more efficient, or (iii) the hospital treatment cost significantly exceeds the MC treatment cost. Moreover, when either of the latter two conditions is met or

Table 10. Probabilistic sensitivity analysis of the MC service in Zichuan District.

	Optimal policy		System performance					
	n^*	Q^*	$\mathcal{SW}$	$\mathcal{AC}$	$\mathcal{QALY}$	$\Delta_{cost}(\%)$	$\Delta_{qaly}(\%)$	ICER
Disease parameters								
λ	12	0.233	−900.6(0.8)	8458.7(2.2)	19.0(0.0)	5.0(0.0)	119.6(0.0)	−42.2(0.2)
μ	12	0.231	−896.9(1.3)	8451.4(3.4)	19.0(0.0)	5.2(0.0)	120.6(0.0)	−43.4(0.3)
MC parameters								
δ	12	0.246	−893.4(2.4)	8448.4(6.2)	19.1(0.0)	5.2(0.0)	121.2(0.0)	−40.9(0.5)
c_m	12	0.222	−901.7(0.3)	8459.0(1.3)	19.0(0.0)	5.0(0.0)	119.5(0.0)	−43.1(0.1)
κ_1	12	0.219	−901.8(0.0)	8459.9(0.1)	19.0(0.0)	5.0(0.0)	119.5(0.0)	−43.0(0.0)
κ_2	12	0.219	−901.5(0.3)	8458.3(1.4)	19.0(0.0)	5.0(0.0)	119.5(0.0)	−44.6(0.7)
K	12	0.228	−898.6(1.4)	8444.0(6.9)	19.0(0.0)	5.2(0.0)	119.5(0.0)	−45.1(0.9)
Hospital parameters								
π	12	0.233	−899.5(0.7)	8462.3(0.0)	19.1(0.0)	5.0(0.0)	120.0(0.0)	−42.8(0.1)
c_r	12	0.219	−901.5(0.5)	8458.0(2.7)	19.0(0.0)	5.2(0.0)	119.5(0.0)	−44.6(0.2)
QoL parameters								
σ_1	12	0.218	−901.5(0.2)	8459.7(0.0)	19.0(0.0)	5.0(0.0)	119.7(0.0)	−43.0(0.0)
σ_2	12	0.218	−901.8(0.0)	8459.7(0.0)	19.0(0.0)	5.0(0.0)	119.5(0.0)	−43.0(0.0)
Relative gap	0	0%–11.4%	−0.9%–0%	−0.2%–0%	0%–0.5%	0%–3.8%	0%–1.4%	−1.9%–4.7%

Note. MC = mobile clinic; ICER = incremental cost-effectiveness ratio; QoL = quality-of-life. $\mathcal{AC}$ is in CNY per week, $\mathcal{QALY}$ is in years, and the ICER is in CNY per year. The analysis uses time steps of 20 years and 500 sample paths. All values are rounded to one decimal place.

the disease progresses faster, the provision of the MC service is more likely to achieve a win–win outcome by both reducing the healthcare cost and improving QALY. Lastly, we conducted extensive numerical experiments and investigate a real-world case. The findings align well with our theoretical results. The case study of the MC program in Zichuan District, China, shows that when the government's concern level about the average QALY is set at 0.8, the optimal delivery frequency for the MC program is every 12 weeks. Compared to not providing the MC service, this results in an ICER of −43 CNY per year, a 119.5% improvement in QALY, and a 5% reduction in healthcare costs. The results remain robust in probabilistic sensitivity analysis with a relative performance gap within 11.5% when accounting for parameter uncertainties.

In this study, we assume that individuals in Segment III immediately seek hospital treatment, which is considered instantaneous. After treatment, they either revert back to Segment I or exit the population. Given the importance of the time patients spend in the hospital, a potential extension is to develop a tractable model that incorporates the duration individuals stay in Segment III. Our study focuses on a fixed, predetermined delivery policy for the MC service provision. However, in practice, the flow of information can affect the delivery policy, allowing for dynamic adjustments. Therefore, it would be interesting to investigate how the delivery policy could be dynamically modified based on data gathered by the government. In this study, we examine the impact of the MC provision on a homogeneous population living in a remote community without local hospitals, where individuals in Segment II are unaware of their illness and lack access to regular office visits due to the distance to the hospital. However, hospitals can sometimes be established in rural areas as well. In such a situation, considering individuals who might actively seek treatment from hospitals while still in Segment II presents a promising direction for future research. Finally, this study considers how the MC service should be delivered to potential patients suffering from a specific chronic disease. Future research could explore the optimal MC delivery policy for patients dealing with multiple chronic conditions.

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ORCID iDs

Fang Liu https://orcid.org/0000-0003-3271-1846
Pengfei Guo https://orcid.org/0000-0002-0447-3556
Yulan Wang https://orcid.org/0000-0003-4184-590X
Yuejuan Xi https://orcid.org/0000-0001-6523-114X

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Notes

1. We assume that a central hospital serves the surrounding villages, and the government establishes an MC team for each central hospital. Examples include the Health on Wheels program in Kenya (Smith, 2024) and the "walking doctor, mobile hospital" program in Zichuan District, Zibo, China.
2. For example, the mobile antiretroviral treatment (ART) team, comprising a medical doctor, clinical officer, nurse, laboratory staff, and pharmacist, visits the rural Mumbwa district of Zambia every two weeks (Dube et al., 2010).
3. In our study, the MC is delivered to the village, under which the travel cost to the MC can be ignored for most patients. For patients with disabilities, the disutility of traveling to the MC can be incorporated into the MC treatment cost c_m. This adjustment does not alter the structure of our model.
4. For example, in the MC program dedicated to DR treatment in Zichuan District, Zibo, China, there are four remote communities served by a single MC. When the MC serves one community, the other three must wait for their turn. We define the resulting health deterioration in these waiting communities as an externality cost. This cost arises because the delayed treatment for individuals in Segment II may lead to their progression from diabetic macular edema to the more severe proliferative DR.

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