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Strategies for Achieving the United States Health System's Quadruple Aim by Enhancing the Primary Care Level

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by Enhancing the Primary Care Level

by

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Dedication

I dedicate my doctoral dissertation to my mother Rita, my sister Pamela, and my beloved father, Arturo, who will forever be my greatest inspiration.

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Abstract

The quadruple aim is an approach to optimize the performance of the health system in the United States and consists of four dimensions. The main objective is to improve the population's health, followed by reducing cost, improving patients' experience, and increasing providers' satisfaction. In the present doctoral dissertation, I explore three strategies that help accomplish the quadruple aim at the primary care level. The analysis combines data science and operation research principles to address health system engineering questions.

Each strategy proposed in this document emphasizes one objective more than another; however, all of them in conjunction serve to attain the four goals of the quadruple aim directly or indirectly. The first strategy involves restoring house call services as a setting to deliver primary care services. The second strategy examines efficiency and fairness in care access to home-based primary care practices, considering two divergent approaches, proactive and reactive care. The analysis involves medical and non-medical conditions (i.e., social determinants of health) as part of the selection criteria to admit patients. The third strategy relates to financial implications for primary care practices of using a reimbursement model that pays for performance and considers a factor that primary care practices can control. Under this strategy, I evaluate the two most recent Medicare alternative payment models, the 'comprehensive primary care plus' and the 'primary care first,' regarding profit, revenue, and patient selection.

The main findings indicate that the house call setting better achieves, on average, the objectives measured in this study for solo, small, and medium primary care practices. Similarly, small home-based primary care practices that provide proactive care seemingly more efficient and equitable than those that are more reactive. Regarding the value-based payments models, the comprehensive primary care plus resembles a more stable reimbursement model for a primary care practice; however, the primary care first reimbursement model further emphasizes the performance component. The disadvantage of the primary care first payment model is its high variability in all output variables and an inclination to select less severe patients. In contrast, the comprehensive primary care plus holds a high percentage of fee-for-service (i.e., a volume-based payment).

It is expected that the research findings will influence public policy development to enrich the primary care level, and thus, improve the overall population health. I also anticipate that the correct implementation of these strategies will impact everyone who uses the health system, contribute to increasing the satisfaction among primary care providers, and reduce costs in the system.

Chapter 1: Introduction

As the first contact between the patient and the health system, the primary care level has the potential to improve population health while overcoming health disparities and reducing costs [1, 2, 3]. However, the supply-demand for primary care is unbalanced in the United States; the growth of older adults and the shortage of primary care providers increase the difficulties of timely access to primary care services [4, 5]. The population 65 years and older is rising worldwide and more rapidly than any other age group [4]. In the United States, this population will make up to 20% of the total population by 2030 [5]. The World Health Organization has promoted the benefit of emphasizing primary care as a strategy to approach an aged population [6]. Similarly, studies show that focusing on the primary care level drops the use of emergency rooms, decreases hospitalizations, reduces total healthcare costs, and decreases morbidity and mortality in the community [7].

The reimbursement structure utilized to pay for primary care services is one factor that considerably affects the development of primary care in the United States. For decades, the fee-for-service payment model has been the most used reimbursement system to pay for primary care services, accounting for an average of 73.1% of the revenue across primary care practices [8]. The fee-for-service payment method increases the healthcare costs; augments cases of overdiagnosed and overtreated patients; and undermines the efforts toward a coordinated, continuous, first contact, and comprehensive primary care [9]. Considering that the fee-for-service payment model is deemed an obstacle to improving care delivery, the United States health system has driven a transition toward value-based

payments, which better support new care delivery models. These care delivery and reimbursement models strive to reestablish the worth of primary care services and reach a better overall health system performance [10].

The patient-centered medical home is one of the reinforced care delivery models that has emerged in the United States to enhance the primary care level. The model underpins five principles: quality and safety, comprehensive care, coordinated care, patient-centered, and accessible care [11], demonstrating the potential to improve the provision of care to older adults [12, 13]. The implementation of the patient-centered medical home model in some states has resulted in a 15% reduction in adult emergency department visits and a 21% decrease in adult ambulatory-care-sensitive inpatient stays [14, 55]. Nevertheless, only 7% and 19% of solo and small practices, respectively, have been certified as patient-centered medical home practices [55]; considering that these practice sizes deliver more than 50% of primary care services in the United States [15, 16,]. According to [17], solo and small practices will remain essential in the United States health system, particularly in rural areas.

The Centers for Medicare & Medicaid Services Innovation has included the Independence at Home Demonstration program as part of the patient-centered medical home initiative. The purpose is to determine whether a delivery model founded on home-based primary care (i.e., a house call model) improves population health while reducing cost [18]. Thus, the home-based primary care model —which operates under the patient-centered medical home principles—, changes the care location from the office to the patient's home to bring care close to people living in underserved areas, suffering functional impairment, or experiencing transportation barriers [18]. The home-based primary care is a precise, intensive primary care program directed toward 'high-need, high-cost' patients

[19, 20]. Although there is not a clear definition of high-need high-cost patients, multiple chronic conditions, advanced age, behavioral problems, functional impairments, and significant risk of adverse events are general characteristics of this group, small in proportion, and responsible for a substantial level of healthcare use and expenditure [20, 21, 22]. Although the eligibility criteria for Medicare demonstrations and certified home health agencies reduce access to specific groups, the benefits of house call could be extended to all individuals who prefer to be cared for in their own homes [23, 55]. Regarding the future of home-care, [24] outlines the need for more responsive home-care benefits, which should be in accordance with people's demands, pointing out the potential of innovating within the field of home-care before inpatient hospital care.

The home-based primary care and patient-centered medical home models present some challenges, and thus, opportunities to restructure their design and implementation. First, several studies in recent years relate health outcomes, such as the development of chronic conditions, to social determinants of health [25, 26, 27], a concept defined by the World Health Organization as 'the conditions in which people are born, grow, live, work and age' [28]. Although the evidence suggests that the patient-centered medical home model reduces hospitalizations, increases savings, and improves care quality [29, 30, 31], it has not significantly reduced health disparities [32, 33, 34, 2]. Second, some studies advise that directing interventions exclusively to high-need high-cost individuals may not considerably decrease costs; focusing on patients across risk levels has a more meaningful effect on diminishing health spending and developing cost-efficiency [35, 36]. This idea originated from a study conducted by [37] in 1985, in which he introduced the concept of 'population strategy' for preventive medicine, arguing that 'a large number of people at a small risk may

give rise to more cases of diseases than the small number who are at a high risk.' In this regard, the proactive care strategy reduces costs, as well as aligns with value-based payment models [38]. Consequently, strengthening primary care to move steadily from reactive to more proactive and inclusive care seems to be a proper approach to reduce costs and achieve health equity.

Compatible with the principles of the patient-centered medical home and home-based primary care models, the Center for Medicare & Medicaid Innovation has proposed and tested alternative payment models for primary care practices since 2012 [39]. The most recent alternative payment models are the comprehensive primary care plus and the primary care first. However, some concerns have also arisen regarding these reimbursement models [40]. First, the proposed Medicare alternative payment models could place primary care practices at financial risk since the compensations received under the pay-for-performance component relies on factors that the practice has little or no control over, such as visits to emergency department for random reasons [41]. Hence, a correct design of an alternative payment model to estimate pay-for-payment based on aspects managed by the practice is still a subject of discussion [42]. Second, fees and payments under alternative payment models could not be sufficient to cover patients' needs in small primary care practices [40]. This problem would have a notable impact on rural primary care practices since most of them are small and provide care to a more severe patient panel than those located in urban areas [43, 44]. Third, the alternative payment models should consider payment based on patients' severity to ensure that a primary care practice admits individuals across risk levels and has enough resources for their care, especially for more complex patients [41]. The Center for Medicare & Medicaid Innovation has dismissed this

aspect, proposing a payment model that uses flat fees and payments for all admitted patients and services [45].

Notwithstanding the above, the demographics changes in the United States create the necessary conditions to pay attention to innovative payment systems and care delivery models, such as house call, given the multiple benefits of offering care at home for patients and providers [46, 47, 48, 49]. Eventually, the purpose of all emerged care delivery and payment models is to encourage the so-called 'quadruple aim' proposed by [50] in 2014. The 'quadruple aim' is an expansion of the so-called 'triple aim' developed by the Institute for Healthcare Improvement in 2007 to optimize the performance of the United States health system [51, 52, 53, 14, 55]. Improving the health of the United States population is the primary goal of the quadruple aim; reducing costs, improving the patient experience, and improving the provider experience are included as secondary goals, and they contribute to the achievement of the primary objective [50]. The present doctoral dissertation encompasses strategies at the primary care level to achieve the quadruple aim supported with numerical evidence and considering demographic changes the country is experiencing (e.g., an aged population). The achievement of the quadruple aim, and specifically, the secondary goals, became the cornerstones of all subsequent Chapters in this document.

1.1 Intellectual Merit

Developing knowledge at the primary care level of how changes in the care delivery such as reestablishing house call services and reinforcing preventive medicine approach, as well as operating a suitable value-based payment model, can contribute to improving the

overall performance of the United States health system through reducing costs, improving the patients' experience, and increasing the providers' satisfaction.

1.2 Broader Impact

The research findings will provide numerical evidence for developing public policy to enhance the United States health system through the primary care level. The design and implementation of the proposed strategies will impact the experience of everyone who uses the United States health system, particularly disadvantaged older adults who suffer from multiple chronic conditions. An adequate execution of the strategies will also increase the well-being of primary care providers and reduce costs in the overall health system. The numerical evidence may also contribute to analysts in other countries worldwide who demand improvements in their health systems.

1.3 Outline

The present doctoral dissertation is divided into five parts. Chapter 2 evaluates if a house call setting better supports achieving the secondary goals of the quadruple aim. The results are contrasted with caring provided at the office for different practice sizes. Chapter 3 explores efficiency and fairness in care access of two divergent strategies: proactive and reactive care among small home-based primary care practices. Also, it assesses the association between social determinants of health and chronic conditions using probabilistic classification models as selection criteria across risk levels. Chapter 4 analyzes the comprehensive primary care plus and the primary care first payment models on key performance metrics (e.g., profits and revenues), considering the effect of the Bice-

Boxerman continuity of care index as a factor controllable by the primary care practice. Chapter 5 presents the main conclusions of the three strategies offered in Chapters 2, 3, and 4. At the end of this document, I present the references and in Appendices A, B, C, D, and E, the published and under review papers.

Chapter 2: Reducing Costs

In this Chapter, I examine three primary care settings, office-care, house call, and mixed-care, which combines office-care and house call. This analysis aims to identify which of the care settings assist in achieving the secondary goals of the quadruple aim. The analysis considers solo, small, medium, and large primary care practices. I have developed a multi-objective integer programming model that captures elements of a practice from a strategic point of view. The formulation minimizes a set of objective functions, each of which relates to a secondary goal of the quadruple aim. Thus, the total cost of care services and the total number of care workers are associated with 'cost reduction.' Similarly, the total rejected (or accepted) demand relates to 'patients' satisfaction,' and the panel size connects with a 'better experience' for providers (i.e., a smaller panel size increases the providers' satisfaction) [54].

The optimization model is solved using the Nash bargaining solution to obtain a Pareto optimal solution, which is also 'fair' to all secondary goals. I compare the care settings across practice sizes and secondary goals using a metric proposed in this study to summarize the results. The analysis uses instances supported by the literature, which can be adjusted to consider each primary care practice's particular attributes. Appendix C displays the paper 'Office-based and home care for older adults in primary care: a comparative analysis using the Nash bargaining solution' that relates to research topic 1. This article was published in the *Socio-Economic Planning Sciences* journal in 2019 [55].

2.1 Contributions Research Topic 1

The contributions of research topic 1 are the following:

(i) This is the first study that compares primary care delivery settings from a strategic level of care planning, using multi-objective optimization to model conflicting objectives associated with each of the most critical stakeholders in the healthcare industry (i.e., patient, payer, and provider) to guide the achievement of long-term goals of primary care practices.

(ii) This is the first study that uses the Nash bargaining solution as the solution method to solve the multi-objective optimization model to evaluate primary care settings.

(iii) The provision of numerical evidence that serves to identify which of the primary care delivery settings strengthens the achievement of the quadruple aim for solo, small, medium, and large primary care practices.

2.2 Main Results Research Topic 1

The numerical results show that none of the explored settings provides the smallest solution to the objective functions of the integer programming formulation such that the healthcare stakeholders are satisfied simultaneously. The outcomes demonstrate that the best environment to provide primary care services depends on the secondary goal of the quadruple aim that the primary care practice would like to emphasize, not seeming to rely on the practice size. For the instances analyzed, house call still better achieves, on average, the goals measured in this study for solo, small, and medium primary care practices, considering the metric proposed in this study to summarize the information. Including large

practices, settings based on house call strengthen the achievement of the secondary goals of the quadruple aim compared with care at the office.

2.3 Future Directions Research Topic 1

Future directions regarding research topic 1 include performing a similar analysis considering Medicare alternative payment models. The evaluation based on value-based payment models will force the inclusion of characteristics such as continuity of care and support providers (e.g., psychologists, dentists, and pharmacists). These new perspectives may render different results to those obtained in the present study. Furthermore, I want to expand the analysis to include other metrics to measure the secondary goals of the quadruple aim, incorporating, for instance, qualitative techniques to measure satisfaction. Similarly, identifying and evaluating different suitable approaches to summarize the data extracted from the models, including distinct weights for every secondary goal, is another future path.

Chapter 3: Improving the Experience of the Patients

A significant aging trend in the United States, followed by a shortage of primary care providers, has made timely access to care more challenging. The patient-centered medical home and home-based primary care models have emerged to enhance primary care and highlight the level as the proper entrance to the health system. Two challenges have arisen, although the benefits of these care delivery models. The first challenge relates to the home-based primary care model. This model focuses on high-need high-cost patients (i.e., the home-based primary care follows a reactive approach); however, directing attention across patients' risk levels (i.e., attaining proactive care) reduces costs more effectively and improves health outcomes [37]. The second problem relates to the patient-centered medical home model, which has not been shown to reduce health disparities and address patients' social determinants of health [32].

Therefore, in this Chapter, I explore reactive and proactive care strategies, with and without the inclusion of social determinants of health, to understand how efficient and equitable small home-based primary care practices on care access are when operating under each of these approaches. I propose a multi-objective optimization model for these primary care practices that maximizes access of individuals at distinct risk levels. The optimization model still prioritizes the most critical individuals while following the five patient-centered medical home principles: quality and safety, comprehensive care, coordinated care, patient-centered, and accessible care. Additionally, I propose a redefinition of 'high-need' patients that aligns with proactive care, characterizing individuals based on their medical and non-

medical conditions. I solve the models using the weighted sum method to describe the traditional reactive approach and the generalized non-symmetric Nash bargaining solution to account for the preventive medicine strategy.

Appendix D displays the complete article titled 'Reactive or proactive care? Assessing efficiency and equity of care access among critical patients while considering medical and non-medical conditions.' Up to date, this paper is under review in the *Socio-Economic Planning Sciences* journal.

3.1 Contributions Research Topic 2

The contributions of research topic 2 are the following:

(i) This study presents the first multi-objective optimization model at the tactical level of care planning that includes the five patient-centered medical home components, which can be extended to include preventive medicine and social determinants of health to support decision-making for home-based primary care practices.

(ii) The study provides a redefinition of 'high-need' patients that comprises medical and non-medical conditions and aligns with a preventive medicine strategy.

(iii) The study provides numerical evidence of the proactive and reactive care approaches by examining the trade-off between efficiency and fairness of care access for small home-based primary care practices.

3.2 Main Results Research Topic 2

Based on the parameters under consideration, the results indicate that proactive care seemly more efficient and equitable than reactive care regarding care access to small primary care practices. This outcome emphasizes preventive medicine as a reasonable pathway to improve patients' experience. The experiments conducted in this study for small home-based primary care practices indicate that, on average, proactive care that applies only medical conditions as the selection criterion is 4.9% more efficient in care access than reactive care. Furthermore, the same scenario compared to the proactive care strategy that includes non-medical conditions is on average 4.7% fairer across the analyzed metrics and cases. Nevertheless, if the analysis considers patients with a high probability of worsening their health conditions, proactive care that incorporates non-medical factors is fairer and more efficient.

3.3 Future Directions Research Topic 2

I would like to extend the analysis to verify the premise adopted in this study, which establishes that focusing on patients at different risks level reduces cost in the long term. Similarly, as future work, I want to explore further the association between social determinants of health and chronic diseases using distinct datasets to identify patterns that connect diverse patient panels. Furthermore, expanding the analysis to include medium and large primary care practices is another future direction.

Chapter 4: Increasing Satisfaction of the Providers

This Chapter analyzes the two recent Medicare alternative payment models, the comprehensive primary care plus and the primary care first, which comprise fee-for-service, traditional capitation, and pay-for-performance components. The main objective of these reimbursement models is to advance toward value-based care. However, the models confer some doubts since the pay-for-performance fraction of the total revenue contemplates factors not entirely controlled by the practice, potentially increasing the admission of healthier patients, and affecting the profit of small primary care practices. In this study, the pay-for-performance component is modified in both reimbursement models to include a non-controllable agent, the hierarchical condition category score, and a controllable factor, the Bice-Boxerman continuity of care index, to predict hospital admissions.

The adjustment of the pay-for-performance component in both models allows evaluating the performance of the practice considering the providers' effort to reduce the likelihood of hospital admission of each accepted patient. I have developed a mixed-integer programming formulation and analyzed the adjusted pay-for-performance component's main elements using a factorial design considering profit per team, revenue for performance per team, and severity of patient selection as the output variables. The complete article 'Controllable and non-controllable factors to measure performance in primary care practices under Medicare alternative payment models' is in Appendix E. This article is under review in the *Operations Research for Health Care* journal.

4.1 Contributions Research Topic 3

The contributions of research topic 3 are the following:

(i) A mixed-integer programming formulation for hybrid reimbursement models that combines fee-for-service, traditional capitation, and pay-for-performance components and measures the process of the primary care practice to reduce a potential adverse event.

(ii) Evidence for small primary care practices and policymakers about the strengths and limitations of the comprehensive primary care plus and the primary care first reimbursement models when including controllable and non-controllable factors, particularly the Bice-Boxerman continuity of care index and the hierarchical condition category score, to estimate pay-for-performance.

4.2 Main Results Research Topic 3

The results reveal that the pay-for-performance component, precisely the regression coefficients and the hospital admission threshold, have a significant effect on the profit and revenue for performance per team with a tendency of the primary care first to admit less severe patients than the comprehensive primary care plus. Also, the inclusion of the Bice-Boxerman continuity of care index as part of the pay-for-performance increases the practice's continuity of care. However, the effects in the revenue and profit of a primary care practice in a period are more notable under the primary care first payment model because the proportion of pay-for-performance in the total revenue under the comprehensive primary care plus is minimal. A high percentage of the revenue in both reimbursement

models is fee-for-service, even though comprehensive primary care plus and primary care first are considered value-based payment models. Similarly, the primary care first downside is its sensitivity to changes in the pay-for-performance, displaying high variability in the output variables considered in the analysis.

4.3 Future Directions Research Topic 3

As future research directions of research topic 3, I would like to explore further the association between controllable factors and hospital admissions, considering actions directly conducted by primary care practices. Also, I want to analyze reimbursement models for primary care practices, proposing innovative payment models that improve profit, promote quality of care, and support patients' admission at different risk levels.

Chapter 5: Conclusions

In the present doctoral dissertation, I have explored three strategies that contribute to accomplishing the United States health system's quadruple aim by improving the primary care level, which has converged to the following main findings. First, investing in expanding house call services to serve all individuals, especially older adults, could be a reasonable alternative to improve —primarily— physicians' well-being. The overall score that integrates the underlying objectives of each stakeholder (i.e., patients, payers, and providers) supports the premise that settings based on house call strengthen the achievement of the secondary goals compared to office-based physician settings. Thus, care at home is an element of a health system that contributes by some means to improve population health.

Second, efficiency and equity in care access under the home-based primary care model do not seem to arise as a trade-off. A proactive view can unite these (apparently) conflicting metrics. Hence, increasing health investments toward balancing reactive and proactive care might produce positive returns that include higher efficiency and equity at the primary care level, cost reduction in the health system, and better population health outcomes. Third, there is a need for a value-based reimbursement model that renders less uncertainty to primary care practices and provides considerable weight to the quality of care in the total revenue. The drawbacks of the comprehensive primary care plus and the primary care fist payment models describe aspects that policymakers and primary care practices should carefully consider before implementing the models. The findings also assist as a

framework to expand the analysis and include factors that measure the practice structure and care delivery process to assess its performance.

As broader future research directions, care coordination across the system represents one of the critical aspects to improve patients' experience and require further analysis to emphasize primary care as the core level for this endeavor. Similarly, telemedicine and telehealth's financial and operational implications in rural primary care practices and their impact on the quadruple aim are gaining visibility given the rise of these services in the last year in response to the pandemic. Thus, these care services require a careful examination to adequately incorporates them into the health system.

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Appendix B includes the copyright authorization of the complete article published in the Socio-Economic Planning Sciences Journal, which is in Appendix C. Appendices D and E present papers under review.

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Office-based and home-care for older adults in primary care: A comparative analysis using the Nash bargaining solution

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Appendix C: Office-based and Home-care for Older Adults in Primary Care: A Comparative Analysis Using the Nash Bargaining Solution

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Office-based and home-care for older adults in primary care: A comparative analysis using the Nash bargaining solution

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ABSTRACT

Three care delivery settings are compared in this study: office-based care, home-care, and mixed-care, i.e., office-based care combined with home-care, in solo, small, medium, and large primary care practices. The objective of this paper is to identify which of these settings better achieves the secondary goals of the so-called quadruple aim, i.e., reducing costs, improving the patient experience, and improving the physician experience. A multi-objective integer programming formulation is developed to capture the elements of strategic health care planning. The formulation considers the minimization of four objective functions: the total cost of care workers, the total number of care workers, the total rejected demand and unsatisfied preferred care location, and the total panel size of the providers. Instead of computing the entire Pareto frontier, we used the Nash bargaining solution to determine a single Pareto optimal solution for the problem. The approach was tested using real world instances, which can be adjusted to any specific primary care practice. The numerical results show that none of the settings provides the smallest values in all objective functions. The choice of a setting for a primary care practice depends on the secondary goals that the practice desires to emphasize, and, in most cases, it is independent of the type of practice size. For the analyzed instances, a calculated overall score for each setting determined that, on average, the settings based on home-care strengthen the achievement of the secondary goals of the quadruple aim more so than in comparison to the office-based physician settings.

1. Introduction

The population of those who are 65 years and older is increasing worldwide and more rapidly than any other age range [20]. By 2020, it is expected that the percentage of elderly people will be higher than the percentage of the population under 15 years of age in 35 countries [26]. In the United States (US), the population percentage over 85 of age will increase faster, and residents 65 years-and-older will make up one-fifth of the total population by 2030 [56]. The World Health Organization (WHO) has promoted the benefit of emphasizing primary health care (PHC) as a strategy to deal with the aging population [68]. Studies show that focusing on PHC reduces the use of emergency departments (EDs), decreases hospitalizations, reduces the total healthcare costs, and reduces morbidity and mortality in the community [62].

The patient centered medical home (PCMH) is one of the reinforced models that has emerged in the US to enhance PHC. PCMH has demonstrated potential to improve the provision of care to older adults [3,40]. Concretely, the implementation of the PCMH model in some states has resulted in a 15% reduction in adult ED visits and a 21% decrease of adult ambulatory-care-sensitive inpatient stays [46]. Nonetheless, only 7% of solo practices and 19% of small practices, respectively, are certified as PCMH [42] even though they deliver more than 50% of the primary care in the US [8,42]. According to Squires and Blumenthal [63], solo and small practices will continue having a role in the US healthcare system, especially in rural areas.

As part of the PCMH model, the Centers for Medicare & Medicaid Services (CMS) has included a demonstration program of house-calls to determine whether a delivery model founded on home-based primary care (HBPC) can improve outcomes while reducing cost [14]. Moreover, Cornwell [18] also argues that the demographics changes in the US create the opportunity to pay more attention to home-care models given the multiple benefits of providing care to elderly people at home [19,36,55,67]. Even though the eligibility criteria for the demonstration and for the current Medicare-certified home health agencies reduce access to a specific group of patients, the benefit of house-call models could be extended to all older adults who prefer to be cared for in their own homes [33]. Regarding the future of home-care, Landers et al. [38] outline the need for more responsive home-care benefits, which have to

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be in accordance with the elderly people's needs. They point out the potential for innovation within the field of home-care, prior to the need for a hospital stay.

The ultimate purpose of all emerged models is to encourage the so-called quadruple aim proposed by Bodenheimer and Sinsky [9] in 2014. The quadruple aim is an expansion of the so-called triple aim developed by the Institute for Healthcare Improvement (IHI) in 2007 as an approach to optimize the performance of the US healthcare system [23,24,43,46]. Improving the health of the US population is the primary goal of the quadruple aim. Reducing costs, improving the patient experience, and improving the provider experience are included as secondary goals, and they contribute to the achievement of the primary goal [9].

Given the growing interest in home-care and team-based care in PHC, this study intends to answer the following questions: Does the home-care setting support the achievement of the secondary goals of the quadruple aim in primary care practices more so than in comparison with office-based setting? Furthermore, could a mixed-care setting, i.e., office-based care combined with home-care, offer a better alternative to enhance simultaneously the benefits for the organization, the patient, and the physician across all primary care practice sizes? To answer these questions, a multi-objective integer programming formulation was developed. The optimization problem is solved using the Nash bargaining solution, which is defined in Subsection 3.2.

The contributions of this study are: (1) the first work that considers conflicting objective functions, i.e., the total cost of care workers, the total number of care workers, the total rejected demand and unsatisfied preferred care location, and the total panel size of the providers, from a strategic level to analyze different primary care settings through the development of a multi-objective integer-programming formulation; (2) the use of the Nash bargaining solution as a method to solve the optimization formulation, which has not previously been applied in primary care delivery settings; and (3) numerical results that identify which of the primary care delivery settings, i.e., office-based, home-care, or mixed-care, better aligns to the secondary goals of the quadruple aim for solo, small, medium, and large primary care practices.

The remainder of the article is structured as follows. Section 2 reviews the literature of multi-objective optimization in home-care, office-based, and mixed-care settings. Section 3 explains the formulation of the problem (Subsection 3.1), the solution method (Subsection 3.2), and the description of the scenarios (Subsection 3.3). Section 4 describes the results, while Section 5 discusses the findings. Finally, Section 6 presents the conclusions of this work.

2. Literature review

The organization, patient, and physician have conflicting objectives in a healthcare system. The quadruple aim encompasses these contrasting objectives under a single framework [61]. Multi-objective optimization deals with conflicted objective functions, providing, in many cases, more than one solution. These solutions are called efficient solutions, and they represent a subset of the feasible set. The images of the efficient solutions in the criterion space are called Pareto optimal solutions, and the set of all Pareto optimal solutions is referred to the Pareto frontier [22].

Few studies were found that computed an approximation of the Pareto frontier in home-care. Those studies were conducted at an operational level. Barrera et al. [4] considered two objective functions: minimize the total number of care workers and minimize the balance workload. To solve the optimization problem, they used two methods: an approach where they considered the number of care workers as the dominant objective function, and a two-stage heuristic approach. Milburn and Spicer [47] published a study where they minimized three objective functions: the total travel cost, the number of different nurses seen by patients, and the nursing workload. They solved the optimization problem using a meta-heuristic approach. In the work of Duque et al. [21], the service level, i.e., the preferences of the caregiver and the patient, was maximized, and the total distance traveled by all caregivers was minimized. They used a two-stage approach, considering the service level as the most important objective function to be accounted for in the first-stage. Additionally, Braekers et al. [13] considered two objective functions: the total cost, i.e., the sum of the travel and the overtime costs, and the patient preferences regarding the nurse and visit time. The authors used the exact ε-constraint method for small instances and a meta-heuristic approach (a multi-directional local search) for more realistic size instances. Liu et al. [45] considered two objective functions: the minimization of the total operational cost and the minimization of the patient satisfaction measured as the total additional service length. They also used the ε-constraint method for small instances, and they used three heuristic methods for large-scale problems: NSGA-II, a multi-objective simulated annealing method (MOSA), and a problem-based constructive heuristic. Finally, Carello et al. [15] considered the three healthcare perspectives: the organization's, the nurse's, and the patient's. The authors minimized the total overtime cost, the nurses' utilization rates, and the reassignments under continuity of care. The optimization problem was solved using the threshold method, where one of the objective functions is minimized, and the others are considered as constraints. Table 1 summarizes the previous studies in home-care.

There are also few studies that used a multi-objective approach in office-based settings [1]. Qu et al [53]. considered two objective functions to formulate open-access scheduling in primary care outpatient settings. They maximized the expected number of consulted patients while minimizing the variance. They proposed a recursive approach to determine the non-dominated points. In another study, Schacht [58], at a tactical level, explored the efficient allocation of capacity for pre-scheduled and walk-ins patients through minimizing the capacity violation, maximizing the minimum free capacity, and minimizing the number of walk-ins who are not treated within the requested session, i.e., morning or afternoon. The author utilized the lexicographic method, considering the capacity violation as the most important criterion. In the same year, a study was published that aimed to match the patients and the providers properly [17]. Chen et al [17]. maximized the satisfaction degree of the patients, maximized the number of treated

Table 1
Summary of the multi-objective studies in home-care settings and the included perspectives in the objective functions.

	Organization's Perspective	Provider's Perspective	Patient's Perspective	Strategic Level
Barrera et al [4].	✓	✓		
Milburn and Spicer [47]	✓	✓	✓	
Duque et al [21].		✓	✓	
Braekers et al [13].	✓		✓	
Liu et al [45].	✓		✓	
Carello et al [15].	✓	✓	✓	
Present study	✓	✓	✓	✓

Table 2
Summary of the multi-objective studies in office-based settings and the included perspectives in the objective functions.

	Organization's Perspective	Provider's Perspective	Patient's Perspective	Strategic Level
Qu et al [53].		✓	✓	
Schacht [58]		✓	✓	
Chen et al [17].		✓	✓	
Present study	✓	✓	✓	✓

patients, and minimized the workload of the providers. The authors designed the ordinal-weighting average non-dominated sorting genetic algorithm II (OWA-NSGA-II) to solve the problem. Table 2 shows a summary of the previous works in terms of the healthcare perspectives considered in the objective functions for office-based settings.

To the best of our knowledge, there has been no research that studies office-based and home-care settings using multi-objective optimization at a strategic level. In addition, no previous literature has studied home-care and office-based care as a single setting at any level of care planning. There was a drawback to the reviewed papers; they either computed the entire Pareto frontier, which does not provide a single solution to the optimization problem, and left that task to the decision makers, or they ranked the objective functions, which suggests the establishment of an order criterion first. In this paper, we use the Nash bargaining formulation approach to compute a single Pareto optimal solution. With our approach, a fair solution is obtained among all objectives under consideration.

3. The formulation, solution method, and scenarios

In this section, we provide a detailed description of the proposed multi-objective integer programming formulation, the Nash bargaining solution method, and the instances used for the different scenarios.

3.1. Problem formulation

Our work addresses the problem of comparing primary care delivery settings to determine which of them better achieves the secondary goals of the quadruple aim, i.e., reducing cost, improving the patient experience, and improving the provider experience. At the same time, our formulation can guide the achievement of the long-term goals of existing primary care delivery settings. The set of constraints and objective functions proposed in this study can be used to decide which patients are served (acceptance rate), when (time slot and day in the planning period), where (office-based, home-care, or mixed-care), and by whom (single provider or a team).

The formulation allows the inclusion of different primary care providers, e.g., primary care physicians (PCPs), nurse practitioners (NPs), physician assistants (PAs). In addition, the proposed formulation gives the option to incorporate healthcare teams to deliver the services. The demand can differ per provider, team, or location, and it is known at the beginning of the planning period. Depending on the instances used (e.g., high demand, long travel times, or low rejection rates), the number of care workers currently serving in the primary care practice could not be enough to provide the care at a specific required level. The addition of external providers, which we named as "extra", helps to address this issue and brings a new dimension to the strategic analysis, regarding how many care workers the practice should employ.

Hulshof et al. [34] proposed a taxonomy to classify resource capacity planning in health care, which guided our formulation. The authors defined strategic planning as the level that focuses on the "structural decision making". Our paper fits within three different care services defined in the taxonomy: ambulatory, home, and residential care. The taxonomy looks at primary process of care delivery, i.e., the resource capacity planning and control decision making that relate directly to the delivery of the health care service. This classification considers two dimensions, care services (i.e., ambulatory, emergency, surgical, inpatient, home, and residential care) and hierarchical levels (i.e., operational, tactical, and strategic level). Table 3 describes the criteria of the strategic level according to Hulshof et al. [34] and the inclusion or not of those criteria in the present formulation.

Table 3
Strategic level criteria from Hulshof et al. [34] considered/included in the formulation.

Criteria	Description	Inclusion
Placement policy	Eligible patients for home-care/office-based settings	
Regional coverage	Type and location of the centers	
Service mix	Offered services	✓
Case mix	Type and volume of the demand	✓
Panel size	Number of patients served by a provider	✓
Districting	Zone under care	
Capacity dimensioning	Number of care workers-providers	✓
Facility layout	Design of the center	

3.1.1. Sets and parameters

The set $\mathscr{P} = \{1,2,\cdots,P\}$ comprises the primary health care providers that are available in the practice and those that can be required temporarily, in an auxiliary manner. The latter are labeled as "extra". For instance, there could be a set $\mathscr{P} = \{1,2,3,4\}$ where 1 refers to a physician, 2 refers to a nurse, 3 refers to a extra-physician, and 4 refers to a extra-nurse. It is assumed that for every provider currently available, there is an extra provider of the same profession, e.g., a physician and an extra-physician.

The set $\mathscr{A}$ is a subset of the set $\mathscr{P}$, and it includes the providers that are available in the practice, not considering the extra ones. For instance, the set $\mathscr{A} = \{1,2\}$ is the subset of the set $\mathscr{P} = \{1,2,3,4\}$ since 1 and 2 refer to the providers available. For each $p \in \mathscr{A}$, we assume that $p + |\mathscr{A}|$ is the extra provider analogous to the provider, $p \in \mathscr{A}$. The formulation gives the option to consider different costs for the extra providers and the providers in the set $\mathscr{A}$. Each provider, $p \in \mathscr{P}$, has an associated set, $\mathscr{W}_p$. The value $|\mathscr{W}_p|$ represents the total number of care workers of the provider, $p \in \mathscr{P}$.

The set $\mathscr{H} = \{1,\cdots,H\}$ contains the health services. They are defined based on the health care provider and whether the care is delivered by a single provider or by several providers at the same time. Thus, the available health services are determined by the type of primary care delivery setting. The parameter $\boldsymbol{\alpha}_{ph}$ takes the value of 1 if the provider, $p \in \mathscr{A}$, delivers the health service, $h \in \mathscr{H}$, and it takes the value of 0, otherwise. The demand for the health service, location, $l \in \mathscr{L}$, at the beginning of the planning period is captured by the parameter $\boldsymbol{\psi}_{hl}$.

The set $\mathscr{L} = \{1,2\}$ is the service location. The value of $l = 1$ refers to office care, and the value of $l = 2$ refers to home-care. The service location depends on the primary care delivery setting. Particularly in mixed-care settings, the care service location depends on the preference of the patient. The parameter $\boldsymbol{\gamma}_{pl}$ represents the cost of the provider, $p \in \mathscr{P}$, that services at the location, $l \in \mathscr{L}$. The rooms available within which to serve patients in the office is provided by the parameter η. It is known that the home-care programs in the US focus on a bounded geographic area to limit the travel times [59]. Based on this observation, we assume that the parameter β is the maximum travel time from a

patient's home to another patient's home within the radius where the practice operates. In other words, the parameter β is basically the worst case scenario for the travel time. Considering that the worst case scenario can not only remove the uncertainty in the travel time but also leads to obtaining a robust solution (from the optimization model). Furthermore, this assumption allows us to disregard some aspects pertaining to the operational level when building a strategic plan.

Each day, $k \in \mathscr{K}$, of the planning period is divided in time slots. The time slot, $j \in \mathscr{J}$, has a duration of δ, and each day, $k \in \mathscr{K}$, has a daily operating time of t, thus, $|\mathscr{J}| = t/\boldsymbol{\delta}$. A health service has a duration of δ. Thus, the number of required time slots to travel is determined by the parameter $\boldsymbol{\beta}' = \boldsymbol{\beta}/\boldsymbol{\delta}$. It is assumed that $t \geq 2\boldsymbol{\beta} + \boldsymbol{\delta}$ for delivery settings that include care at home. The parameter $\boldsymbol{\xi}_{hl}$ represents the maximum allowable percentage of rejected demand that requests the health service $h \in \mathscr{H}$. This applies for $l = 1$ and $l = 2$, i.e., office-based and home-care delivery settings, respectively. For mixed-care delivery settings, the parameter $\boldsymbol{\xi}_{hl}$ represents the maximum allowable percentage of the rejected demand and the demand whose preferred care location, $l \in \mathscr{L}$, is unsatisfied for the health service, $h \in \mathscr{H}$. In addition, the parameter μ provides the option to assign a different penalty to the rejected demand.

3.1.2. Decision variables

The decision variable, $d_{hljk} \in \mathbf{Z}^{+}$, is the demand for the health service, $h \in \mathscr{H}$, at the location, $l \in \mathscr{L}$, in the time slot, $j \in \mathscr{J}$, on the day, $k \in \mathscr{K}$. The decision variable, $\bar{d}_{hljk} \in \mathbf{Z}^{+}$, is the rejected demand for the health service, $h \in \mathscr{H}$, at the location, $l \in \mathscr{L}$, in the time slot, $j \in \mathscr{J}$, on the day $k \in \mathscr{K}$. The decision variable, $\tilde{d}_{hljk} \in \mathbf{Z}^{+}$, is the demand that asks for the health service, $h \in \mathscr{H}$, in the time slot, $j \in \mathscr{J}$, on the day, $k \in \mathscr{K}$, but the preferred care location, $l \in \mathscr{L}$, is not satisfied. The decision variable, $d^{T}_{hljk} \in \mathbf{Z}^{+}$, is the actual demand that receives the health service, $h \in \mathscr{H}$, at the location, $l \in \mathscr{L}$, in the time slot, $j \in \mathscr{J}$, on the day, $k \in \mathscr{K}$, i.e., the demand after deleting the rejected demand and after changing the care location of the unmatched demand.

The decision variable, $x_{pwljk} \in \{0,1\}$, is equal to 1 when the care worker, $w \in \mathscr{W}_p$, provider, $p \in \mathscr{P}$, is in charge of a patient at the location, $l \in \mathscr{L}$, in the time slot, $j \in \mathscr{J}$, on the day, $k \in \mathscr{K}$, and it is 0, otherwise. In addition, the variable, $y_{pw} \in \{0,1\}$, takes the value of 1 if the care worker, $w \in \mathscr{W}_p$, provider, $p \in \mathscr{P}$, is scheduled during the planning period, and it takes the value of 0, otherwise. The decision variable, $s_p \in \mathbf{Z}^{+}$, is the so-called panel size of the provider, $p \in \mathscr{P}$, i.e., the number of patients under the care of the provider, $p \in \mathscr{P}$, during the planning period. Since the maximum value that the decision variable s_p, $p \in \mathscr{P}$ can take is $|\mathscr{J}||\mathscr{K}|$, we establish this value as the upper bound of the variable, i.e., the decision variable $s_p \leq |\mathscr{J}||\mathscr{K}|$, $\forall\ p \in \mathscr{P}$. Table 4 lists the sets, parameters, and decision variables of the formulation.

3.1.3. Objective functions

Four objective functions are considered in the formulation. Objective function z_1 and objective function z_2 make reference to the organization's perspective, objective function z_3 to the patient's perspective, and objective function z_4 to the provider's perspective. Fig. 1 summarizes and integrates the relationship among the secondary goals of the quadruple aim [9], the healthcare perspectives (patient, provider, and organization), and the objective functions of the formulation that we propose in this study. Additionally, Fig. 1 shows the location of the analyzed primary care delivery settings in the healthcare system.

The first objective function, z_1 (1), minimizes the total cost of the care workers during the planning period, and the second objective function, z_2 (2), minimizes the number of scheduled care workers during the planning period:

Table 4
Sets, parameters, and decision variables of the formulation.

Sets, Parameters, & Variables	Description
Set	**Description**
$\mathscr{P}$	Set of primary health care providers. It includes available and extra providers.
$\mathscr{A} \subset \mathscr{P}$	Subset of the set $\mathscr{P}$. It only includes the available providers.
$\mathscr{W}_p$	Set of care workers associated to the provider $p \in \mathscr{P}$.
$\mathscr{H}$	Set of health services available.
$\mathscr{L}$	Set of health service locations: $l = 1$ for office care and $l = 2$ for home-care.
$\mathscr{K}$	Set of days of the planning period.
$\mathscr{J}$	Set of time slots for each $k \in \mathscr{K}$.
Parameter	**Description**
$\boldsymbol{\psi}_{hl}$	Demand for the health service, $h \in \mathscr{H}$, at the location, $l \in \mathscr{L}$, at the beginning of the planning period.
$\boldsymbol{\alpha}_{ph}$	1: if provider, $p \in \mathscr{A}$, is associated to the health service, $h \in \mathscr{H}$. 0: otherwise.
$\boldsymbol{\xi}_{hl}$	Maximum allowable proportion of rejected demand and unsatisfied demand in respect to the preferred care location.
$\boldsymbol{\gamma}_{pl}$	Cost of the provider, $p \in \mathscr{P}$, when care is delivered at the location $l \in \mathscr{L}$.
η	Numbers of available rooms.
β	Time spent traveling from one patient's home to another patient's home.
δ	Time duration of a time slot.
$\boldsymbol{\beta}'$	Number of used time slots in each travel.
t	Daily operating time of the primary care practice.
μ	Penalty for rejected demand.
Variable	**Description**
x_{pwljk}	1: if care worker, $w \in \mathscr{W}_p$, provider, $p \in \mathscr{P}$, is scheduled at $l \in \mathscr{L}$, $j \in \mathscr{J}$, $k \in \mathscr{K}$. 0: otherwise.
y_{pw}	1: if care worker, $w \in \mathscr{W}_p$, provider, $p \in \mathscr{P}$, is scheduled during the planning period. 0: otherwise.
s_p	Panel size of the provider, $p \in \mathscr{P}$, during the planning period. This decision variable has an upper bound equal to $|\mathscr{J}||\mathscr{K}|$.
d_{hljk}	Demand for $h \in \mathscr{H}$, $l \in \mathscr{L}$, $j \in \mathscr{J}$, and $k \in \mathscr{K}$.
$\bar{d}_{hljk}$	Rejected demand for $h \in \mathscr{H}$, $l \in \mathscr{L}$, $j \in \mathscr{J}$, and $k \in \mathscr{K}$.
$\tilde{d}_{hljk}$	Demand that asks for $h \in \mathscr{H}$, $j \in \mathscr{J}$, and $k \in \mathscr{K}$, and whose preferred care location, $l \in \mathscr{L}$, is not matched.
d^{T}_{hljk}	Demand for $h \in \mathscr{H}$, $l \in \mathscr{L}$, $j \in \mathscr{J}$, and $k \in \mathscr{K}$ after removing $\bar{d}_{hljk}$ and changing $\tilde{d}_{hljk}$.

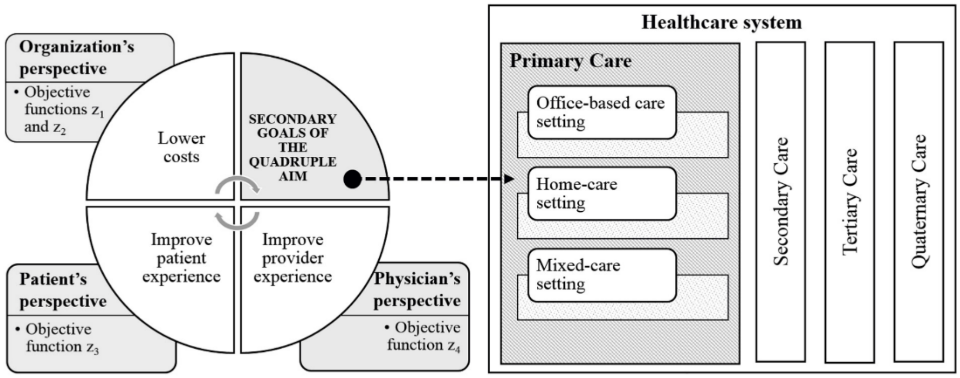


Fig. 1. The secondary goals of the quadruple aim associated with each objective function, and the formulated primary care settings in the healthcare system.

$$z_1 = \min \sum_{p\in\mathscr{P}} \sum_{w\in\mathscr{W}_p} \sum_{l\in\mathscr{L}} \sum_{j\in\mathscr{J}} \sum_{k\in\mathscr{K}} \gamma_{pl} x_{pwljk} \tag{1}$$

$$z_2 = \min \sum_{p\in\mathscr{P}} \sum_{w\in\mathscr{W}_p} y_{pw}. \tag{2}$$

The third objective function, z_3 (3), minimizes the weighted sum of the total rejected demand and the total unmatched preferred care location of the demand during the planning period:

$$z_3 = \min \mu \sum_{h\in\mathscr{H}} \sum_{l\in\mathscr{L}} \sum_{j\in\mathscr{J}} \sum_{k\in\mathscr{K}} \bar{d}_{hljk} + \sum_{h\in\mathscr{H}} \sum_{l\in\mathscr{L}} \sum_{j\in\mathscr{J}} \sum_{k\in\mathscr{K}} \tilde{d}_{hljk}. \tag{3}$$

The fourth objective function, z_4 (4), minimizes the total panel size of the providers during the planning period:

$$z_4 = \min \sum_{p\in\mathscr{P}} s_p. \tag{4}$$

3.1.4. Constraints

equations 5–17 are the constraints of the formulation. Constraint (5) ensures that the total scheduled demand for the health service, $h \in \mathscr{H}$, at the location, $l \in \mathscr{L}$, in the planning period is equal to the demand that asks for the health service, $h \in \mathscr{H}$, at the location, $l \in \mathscr{L}$, at the beginning of the planning period. The demand is assigned to days and time slots in order to plan the service, although the request is not for a specific day and time slot.

$$\sum_{j\in\mathscr{J}} \sum_{k\in\mathscr{K}} d_{hljk} = \psi_{hl}, \quad \forall\, h \in \mathscr{H}, \forall\, l \in \mathscr{L}. \tag{5}$$

Constraint (6) ensures that the rejected demand, i.e., $\bar{d}_{hljk}$, and the demand whose preferred care location is unmatched, i.e., $\tilde{d}_{hljk}$, cannot be greater than the percentage ξ_{hl} of the demand d_{hljk} for all combinations of health service, $h \in \mathscr{H}$, and the location, $l \in \mathscr{L}$, in each time slot, $j \in \mathscr{J}$, on the day, $k \in \mathscr{K}$:

$$\bar{d}_{hljk} + \tilde{d}_{hljk} \le \xi_{hl} d_{hljk}, \quad \forall\, h \in \mathscr{H}, \forall\, l \in \mathscr{L}, \forall\, j \in \mathscr{J}, \forall\, k \in \mathscr{K}. \tag{6}$$

Constraint (7) adjusts the demand d_{hljk}, eliminating the rejected demand, $\bar{d}_{hljk}$, and changing the location, $l \in \mathscr{L}$, of the unmatched demand, $\tilde{d}_{hljk}$, for each health service, $h \in \mathscr{H}$, location, $l \in \mathscr{L}$, time slot, $j \in \mathscr{J}$, and day $k \in \mathscr{K}$:

$$d_{hljk} - \tilde{d}_{hljk} + \tilde{d}_{hbjk} - \bar{d}_{hljk} = d^T_{hljk}, \quad \forall\, h \in \mathscr{H}, \forall\, l \in \mathscr{L}, \forall\, b \in \{1,2\} \setminus \{l\}, \forall\, j \in \mathscr{J}, \forall\, k \in \mathscr{K}. \tag{7}$$

Constraint (8) guarantees that the adjusted demand, d^T_{hljk}, that needs to receive care from a provider, $p \in \mathscr{A}$, at a location, $l \in \mathscr{L}$, on the day, $k \in \mathscr{K}$, is satisfied by the available care workers in the set $\mathscr{W}_p$, $p \in \mathscr{A}$ and by its analogous extra care workers in the set $\mathscr{W}_{(p+|\mathscr{A}|)}$, $p \in \mathscr{A}$. Constraint (8) also guarantees that each care worker provides service to only one patient in each time slot:

$$\sum_{h\in\mathscr{H}} \alpha_{ph} d^T_{hljk} = \sum_{w\in\mathscr{W}_p} x_{pwljk} + \sum_{w\in\mathscr{W}_{(p+|\mathscr{A}|)}} x_{mwljk}, \quad \forall\, p \in \mathscr{A}, \forall\, m = p + |\mathscr{A}|, \forall\, l \in \mathscr{L}, \forall\, j \in \mathscr{J}, \forall\, k \in \mathscr{K}. \tag{8}$$

Constraint (9) makes sure that the care worker, $w \in \mathscr{W}_p$, $p \in \mathscr{P}$, cannot provide care at a home and care at the office during the same time slot, $j \in \mathscr{J}$, on the day, $k \in \mathscr{K}$:

$$\sum_{l\in\mathscr{L}} x_{pwljk} \le 1, \quad \forall\, p \in \mathscr{P}, \forall\, w \in \mathscr{W}_p, \forall\, j \in \mathscr{J}, \forall\, k \in \mathscr{K}. \tag{9}$$

Constraint (10) ensures that the care worker, $w \in \mathscr{W}_p$, $p \in \mathscr{P}$, that provides care at a home in a time slot, $j \in \mathscr{J}$, on the day, $k \in \mathscr{K}$, cannot provide office care or care at home in the previous and in the next β' time slots because of the travel time:

$$\sum_{\substack{n=j-\beta' \\ n\neq j}}^{j+\beta'} x_{pwlnk} \le 2\beta'(1 - x_{pw2jk}), \quad \forall\, p \in \mathscr{P}, \forall\, w \in \mathscr{W}_p, \forall\, l \in \mathscr{L}, \forall\, j = \{1 + \beta', \ldots, |\mathscr{J}| - \beta'\}, \forall\, k \in \mathscr{K}. \tag{10}$$

Constraints (11) and (12) prevent a care worker, $w \in \mathscr{W}_p$, $p \in \mathscr{P}$, from providing care at home in the first and the last β' time slots of the day, $k \in \mathscr{K}$, since the travel time is considered to be part of the working time:

$$x_{pw2jk} = 0, \quad \forall\, p \in \mathscr{P}, \forall\, w \in \mathscr{W}_p, \forall\, j \le \beta', \forall\, k \in \mathscr{K} \tag{11}$$

$$x_{pw2jk} = 0, \quad \forall\, p \in \mathscr{P}, \forall\, w \in \mathscr{W}_p, \forall\, j \ge |\mathscr{J}| - \beta' + 1, \forall\, k \in \mathscr{K}. \tag{12}$$

Constraint (13) establishes that the adjusted demand, d^T_{h1jk}, that asks for the health services in the set $\mathscr{H}$, at location $l = 1$ (i.e., office care), during a time slot, $j \in \mathscr{J}$, on a day $k \in \mathscr{K}$, must be less or equal to the rooms available, η:

$$\sum_{h\in\mathscr{H}} d^T_{h1jk} \le \eta, \quad \forall\, j \in \mathscr{J}, \forall\, k \in \mathscr{K}. \tag{13}$$

Constraint (14) determines whether a care worker, $w \in \mathscr{W}_p$, $p \in \mathscr{P}$, is scheduled during the planning period:

$$\sum_{l\in\mathscr{L}} \sum_{j\in\mathscr{J}} \sum_{k\in\mathscr{K}} x_{pwljk} \le |\mathscr{J}||\mathscr{K}| y_{pw}, \quad \forall\, p \in \mathscr{P}, \forall\, w \in \mathscr{W}_p. \tag{14}$$

Constraint (15) ensures that the total scheduled time slots for the care worker, $w \in \mathscr{W}_p$, $p \in \mathscr{P}$, at all locations during the planning period cannot be greater than the panel size for the provider, $p \in \mathscr{P}$:

$$\sum_{l\in\mathcal{L}}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}} x_{pwljk} \le s_p, \quad \forall\, p\in\mathcal{P}, \forall\, w\in\mathcal{W}_p. \tag{15}$$

Constraints (16) and (17) represent the domain of the decision variables. For the decision variable, s_p, we impose an upper bound equal to $|\mathcal{J}||\mathcal{K}|$:

$$x_{pwljk},\ y_{pw} \in \{0,1\} \tag{16}$$

$$s_p,\ d_{hljk},\ \bar{d}_{hljk},\ \tilde{d}_{hljk},\ d^{T}_{hljk} \in \mathbf{Z}^{+}. \tag{17}$$

3.2. Solution method

Computing the entire Pareto frontier of a multi-objective integer programming formulation in a reasonable amount of time and without using a large amount of computational resources is challenging. Furthermore, the entire Pareto frontier does not provide a convenient solution to the policy makers, i.e., which Pareto optimal solution better fits the needs of a primary care practice [66]. A typical approach to obtain a Pareto optimal solution of a multi-objective problem is to determine a weighted sum of the objective functions. However, this method requires giving a proper weight to each objective function, which is not always an obvious task. In addition, small changes in the weights of the objective functions could result in large changes in the solution and vice versa [25].

The Nash bargaining solution is an approach that provides a single Pareto optimal solution, which satisfies a set of axioms to obtain a "fair" bargain for all players [48,49]. The axioms proposed by Nash [49] (i.e., individual rationality, Pareto optimality, symmetry, linear invariance, and independence of irrelevant alternatives) confer the fairness upon the unique solution of the bargaining problem [64]. This is the advantage of the Nash bargaining solution in comparison to any other method that provides a single Pareto optimal solution.

In multi-objective problems, the objective functions can be considered as "players" [66]. In the bargaining problem the players, collaborate with each other to obtain a higher payoff from an initial state, i.e., the so-called *status quo* [60]. A possible approach to compute the *status quo*, d_i, of the player, i, is to maximize each objective function, $z_i(x)$, independently, over the feasible set, $\mathcal{X}$, of the optimization problem, as shown in the formulation 18 [66]:

$$\begin{aligned} d_i &= \max z_i(x) \\ \text{s.t.}\ \ & x\in\mathcal{X} \end{aligned} \tag{18}$$

The Nash bargaining formulation for the multi-objective optimization problem is shown in (19). The solution x^* is called the Nash bargaining solution and satisfies the five axioms proposed by Nash [49]:

$$\begin{aligned} x^* = \arg\max & \textstyle\prod_{i=1}^{g} (d_i - z_i(x)) \\ \text{s.t.}\ \ & x\in\mathcal{X} \\ & d_i \ge z_i(x),\ \forall\, i\in 1,\dots,g \end{aligned} \tag{19}$$

In the above formulation, g represents the number of objective functions of the multi-objective problem. Solving problem (19) is not a trivial, favorably, it is equivalent to problem (20) [16,57]:

$$\begin{aligned} & \max \gamma \\ \text{s.t.}\ \ & \gamma \le \sqrt[g]{\textstyle\prod_{i=1}^{g}(d_i - z_i(x))} \\ & \gamma \ge 0 \end{aligned} \tag{20}$$

Problem (20) can be transformed to a second-order cone program as is shown in problem (21), where k is the smallest integer value that satisfies the inequality $2^k \ge g$ [5]. Commercial solvers, such as, Gurobi [29], can solve (21) to optimality.

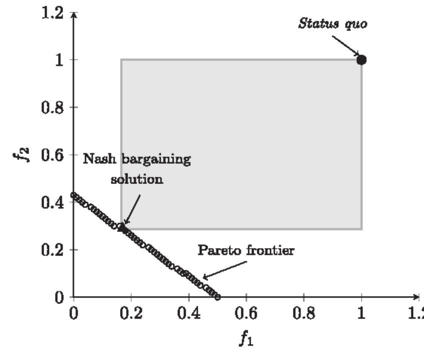


Fig. 2. Example of the concepts related to the solution method.

$$\begin{aligned} & \max \gamma \\ \text{s.t.}\ \ & 0 \le \gamma \le \Gamma \\ & 0 \le \Gamma \le \sqrt{\tau_1^{k-1}\tau_2^{k-1}} \\ & 0 \le \tau_i^{l} \le \sqrt{\tau_{2i-1}^{l-1}\tau_{2i}^{l-1}} \quad \text{for } i = 1,\dots,2^{k-l} \text{ and } l = 1,\dots,k-1 \\ & 0 \le \tau_i^{0} = d_i - z_i \quad \text{for } i = 1,\dots,g \\ & 0 \le \tau_i^{0} = \Gamma \quad \text{for } i = g+1,\dots,2^k \\ & x\in\mathcal{X} \end{aligned} \tag{21}$$

Fig. 2 illustrates an example of the concepts described above for a minimization problem with two objective functions, f_1 and f_2. The black circle is the *status quo* when the objective functions are maximized separately. The white circles depict the Pareto frontier. The gray area represents the largest rectangle defined by the *status quo* and a Pareto optimal solution. This Pareto optimal solution, is the Nash bargaining solution and it is depicted in a black triangle.

The proposed formulation in this study and the described solution method were implemented in a computer with a Intel(R) Core (TM) i7-5700 CPU @ 3.40 Hz 3.40 GHz processor. The problem was solved using Julia 0.6.1 [6] and Gurobi 6.5.2 [29].

3.3. Description of the scenarios

The comparative analysis of the three care delivery settings, office-based, home-care, and mixed-care, was performed using the same set of constraints and objective functions presented in Section 3.1 with slight differences. The home-care setting formulation uses the constraints (5)–(8), (10)–(12), and (14)–(17). The decision variable, $\tilde{d}_{hljk}$, which is related to the unmatched preferred location of the demand, is dismissed from the constraint (6) and from the left side in constraint (7) (second and third terms) since this decision variable requires the inclusion of both service locations: home and office. It also applies to constraint (17). The second term in the objective function z_3 in (3) was deleted. For the office-based setting formulation, the constraints were (5)–(8), (13), and (14)–(17). The same adjustments performed above were made for the office-based setting in constraints (6), (7), and (17) and in the objective function z_3 in (3). The mixed-care setting used the constraints (5)–(17), and the objective functions in (1)–(4).

We designed five scenarios for the different practice sizes. Scenarios 1 and 2 refer to office-based settings since they are the most common in the provision of primary care in the US [8,42]. Scenario 1 is based on the general practice of employing only PCPs [30]. However, given the relevance of teamwork for primary care [24], we included NPs in scenario 2, who are the non-physician providers more often employed in the office-based practices in the US [39]. Scenario 3 refers to home-care settings and it was established for the provision of routine care, this implies, shorter service times in comparison to a current home-care visit. PCPs and NPs were included in scenario 3 since, according to Leff

Table 5
The list of sets and parameters for each scenario considering, as example, a practice size of 25 PCPs

Sets & Parameters	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
$\mathscr{P}$	1:PCP 2: e-PCP	1: PCP 2: NP 3: e-PCP 4: e-NP	1: PCP 2: NP 3: e-PCP 4: e-NP	1: PCP 2:e-PCP	1: PCP 2: NP 3: e-PCP 4: e-NP
$\mathscr{W}_p$	{1, ...,25}PCP {1, ...,25}e-PCP	{1, ...,25}PCP {1, ...,25}NP {1, ...,25}e-PCP {1, ...,25}e-NP	{1, ...,25}PCP {1, ...,25}NP {1, ...,25}e-PCP {1, ...,25}e-NP	{1, ...,25}PCP {1, ...,25}e-PCP	{1, ...,25}PCP {1, ...,25}NP {1, ...,25}e-PCP {1, ...,25}e-NP
$\mathscr{H}$	{1}	{1,2,3}	{1,2,3}	{1}	{1,2,3}
$\mathscr{L}$	{1}(Office)	{1}	{2}(Home)	{1,2}	{1,2}
$\mathscr{J}$	{1, ...,21}	{1, ...,21}	{1, ...,21}	{1, ...,21}	{1, ...,21}
$\mathscr{K}$	{1, ...,5}	{1, ...,5}	{1, ...,5}	{1, ...,5}	{1, ...,5}
$\boldsymbol{\psi}_{hl}$	$[150 \times \lvert\mathscr{W}_1\rvert]$	$\begin{bmatrix} 70 \times \lvert\mathscr{W}_1\rvert \\ 34 \times \lvert\mathscr{W}_2\rvert \\ 46 \times \lvert\mathscr{W}_p^{\bullet}\rvert \end{bmatrix}$ $\lvert\mathscr{W}_p^{\bullet}\rvert = min\{\mathscr{W}_1, \mathscr{W}_2\}$	$\begin{bmatrix} 70 \times \lvert\mathscr{W}_1\rvert \\ 34 \times \lvert\mathscr{W}_2\rvert \\ 46 \times \lvert\mathscr{W}_p^{\bullet}\rvert \end{bmatrix}$ $\lvert\mathscr{W}_p^{\bullet}\rvert = min\{\mathscr{W}_1, \mathscr{W}_2\}$	$[75 \times \lvert\mathscr{W}_1\rvert \;\; 75 \times \lvert\mathscr{W}_1\rvert]$	$\begin{bmatrix} 35 \times \lvert\mathscr{W}_1\rvert & 35 \times \lvert\mathscr{W}_1\rvert \\ 17 \times \lvert\mathscr{W}_2\rvert & 17 \times \lvert\mathscr{W}_2\rvert \\ 23 \times \lvert\mathscr{W}_p^{\bullet}\rvert & 23 \times \lvert\mathscr{W}_p^{\bullet}\rvert \end{bmatrix}$ $\lvert\mathscr{W}_p^{\bullet}\rvert = min\{\mathscr{W}_1, \mathscr{W}_2\}$
$\boldsymbol{\alpha}_{ph}(p \in \mathscr{A})$	$1\begin{bmatrix} 1 \\ 1 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \end{array}\begin{bmatrix} 1 & 2 & 3 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \end{array}\begin{bmatrix} 1 & 2 & 3 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$	$1\begin{bmatrix} 1 \\ 1 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \end{array}\begin{bmatrix} 1 & 2 & 3 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$
$\boldsymbol{\xi}_{hl}$	$\begin{array}{c} 1 \\ 2 \\ 3 \end{array}\begin{bmatrix} 1 & 2 \\ 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \\ 3 \end{array}\begin{bmatrix} 1 & 2 \\ 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \\ 3 \end{array}\begin{bmatrix} 1 & 2 \\ 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \\ 3 \end{array}\begin{bmatrix} 1 & 2 \\ 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \\ 3 \end{array}\begin{bmatrix} 1 & 2 \\ 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix}$
$\boldsymbol{\gamma}_{pl}$	$\begin{array}{c} 1 \\ 2 \end{array}\begin{bmatrix} 1 \\ \$70 \\ 100 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array}\begin{bmatrix} 1 \\ \$70 \\ \$55 \\ \$100 \\ \$80 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array}\begin{bmatrix} 2 \\ \$70 \\ \$55 \\ \$100 \\ \$80 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \end{array}\begin{bmatrix} 1 & 2 \\ \$70 & \$70 \\ \$100 & \$100 \end{bmatrix}$	$\begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array}\begin{bmatrix} 1 & 2 \\ \$70 & \$70 \\ \$55 & \$55 \\ \$100 & \$100 \\ \$80 & \$80 \end{bmatrix}$
$\boldsymbol{\eta}$	25	25	–	25	25
$\boldsymbol{\beta}$	-	-	20 min	20 min	20 min
$\boldsymbol{\delta}$	20 min	20 min	20 min	20 min	20 min
$\boldsymbol{\beta'}$	-	-	1 time slot	1 time slot	1 time slot
t	7 h	7 h	7 h	7 h	7 h
μ	\$165	\$165	\$165	\$165	\$165

et al. [41], they are the commonly hired home-care providers. Scenarios 4 and 5 refer to mixed-care settings, which combine office-based and home-care in a single setting. These two scenarios are extensions of scenarios 1 and 2, respectively, in which the home-care component is incorporated. To the best of our knowledge, there is no literature that describes mixed primary care delivery settings.

The instances used for the five scenarios were selected based on the information extracted from the literature [2,8,28,28,32,42,44,51,54,69,70]. Nonetheless, the parameters can be adjusted to any specific primary care practice. Table 5 shows the instances used for the scenarios. For comparative purposes, it is assumed that, in all cases, the care is provided to any age range.

3.3.1. Resources

The set $\mathscr{P}$ considers PCPs and extra-PCPs (e-PCPs) in scenarios 1 and 4. The set $\mathscr{P}$ includes PCPs, nurse practitioners (NPs), e-PCPs, and extra-NPs (e-NPs) in scenarios 2, 3, and 5. Thus, the scenarios 2, 3, and 5 are shared-care settings [69]. Based on the current categories of primary care practice sizes in the US (i.e., solo [1 PCP], small [2 to 5 PCPs], medium [6 to 20 PCPs], and large [> 20 PCPs]) [8,42], we consider different sizes of the set $\mathscr{W}_p$, $p \in \mathscr{P}$. The set $\mathscr{W}_p$ ranges from $\{1\}$ to $\{1, ..., 25\}$ PCPs, which implies 25 sub-scenarios for each scenario. The previous values of the set $\mathscr{W}_p$ are also replicated in the scenarios in which NPs are included. For instance, where there are 5 PCPs in a practice, it is assumed there will be an additional 5 NPs. The set $\mathscr{W}_p$ of e-PCP and the set $\mathscr{W}_p$ of e-NP are assumed to be equal to $\{1, ..., 25\}$ for all practice sizes.

The scenarios 1 and 4 provide one health service since they only have PCPs as providers. Scenarios 2, 3, and 5 provide three health services given that the set $\mathscr{A}$ includes both PCPs and NPs. The health services can be provided by a PCP, a NP, or a team compounded by a PCP and a NP. The number of rooms, η, available are the same as the practice size, i.e., if there are 5 PCPs, then there are 5 rooms in scenarios 1, 2, 4, and 5.

3.3.2. Times

All scenarios contemplated operating activities during business days, thereby the set $\mathscr{K} = \{1, ..., 5\}$ days. The parameter t is equal to 7 h of daily operating time, which is equivalent to 35 working-hours during the planning period. These working-hours-per-week are in accordance with the study conducted by Grisham [28]. The author reported that 53% of physicians in the US spend between 30 and 45 h per week seeing patients. The parameter δ is assumed to be equal to 20 min since, as stated by Linzer et al. [44], a routine primary care session ranges between 15 and 20 min, and, according to Grisham [28], 59% of physicians spend between 13 and 24 min with the patient. Hence, considering t to be equal to 420 min, the cardinality of the set $\mathscr{J}$ corresponds to 21 time-slots per day. In order to simplify the analysis, it was considered that the travel time between patients' homes takes 20 min on average.

3.3.3. Demand

The weekly demand for PCPs in scenarios 1 and 4 was estimated based on a panel size of 2500 patients, i.e., 150 patients per PCP per week [54]. For scenarios 2, 3, and 5, the total weekly demand for PCP was kept the same as in scenarios 1 and 4. However, since the personnel in scenarios 2, 3, and 5 increases because of the addition of NPs, the total demand was distributed amongst the three health services. The demand for NPs was calculated based on the average panel size of 567 patients per NP, i.e., 34 patients per NP per week, which was estimated in the study developed by Xue and Tuttle [70]. The same study determined that a NP sees an average of 80 patients per week; therefore, it is assumed that the 46 remaining patients correspond to the weekly demand served by a team. Since the weekly demand of 150 patients for a PCP is kept constant across the scenarios, the demand for a PCP is 70 patients in those scenarios where a NP is included. All scenarios consider a maximum of combined rejected demand and unmatched preferred care location of the demand up to 100%.

3.3.4. Costs

The values of the parameter $\boldsymbol{\gamma}_{pl}$ are based on the current procedural terminology (CPT) codes, which report medical services and procedures for insurance claims [2]. The CPT codes 99213 and 99355 are used to estimate the costs of a PCP and the cost of an e-PCP, respectively. Since the cost of a NP is 18% lower than a PCP [51], the values of a NP and of an e-NP were calculated by reducing 18% of the cost of a PCP and of an e-PCP, respectively. The costs of a PCP, a NP, an e-PCP, and an e-NP were assumed to be the same for office-based and for home-care settings across all scenarios. The penalty μ for rejecting demand was estimated using an urgent care center visit cost [32].

4. Results

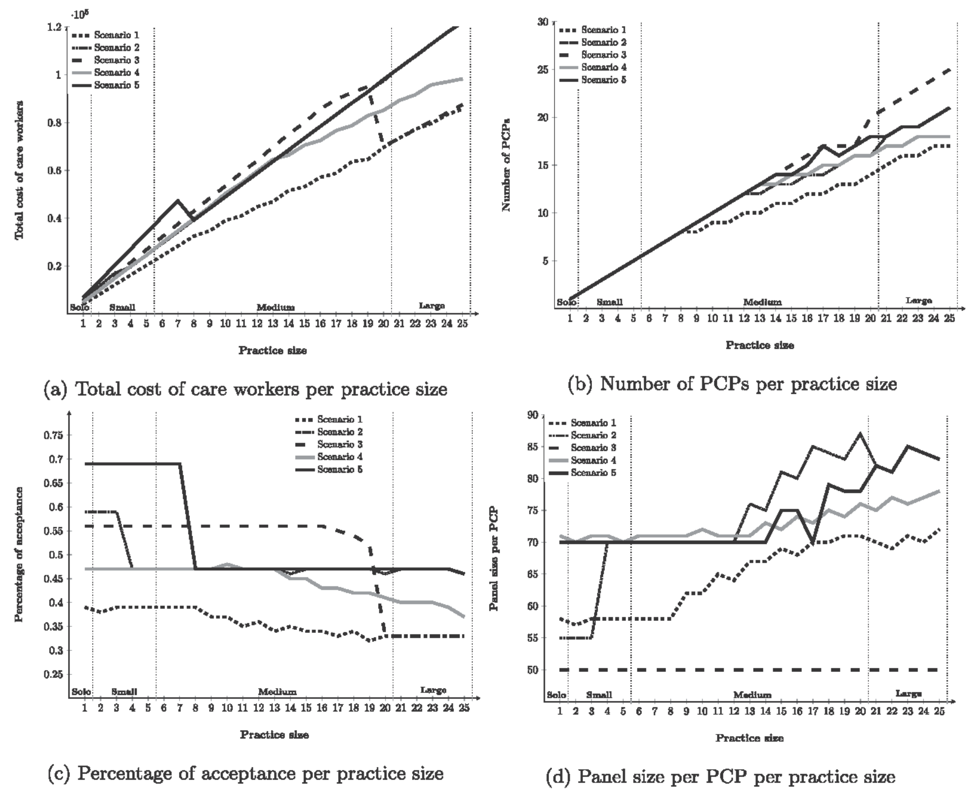
In this section, we describe the results of the Nash bargaining solutions for each scenario and for the different types of primary care practice sizes, i.e, solo, small, medium, and large. In addition, based on the Nash bargaining solution results, we compute a score for each healthcare perspective and an overall score to contrast the different scenarios for each type of practice size. With these metrics, we can determine, on average, which of the scenarios fits better for the achievement of the secondary goals. The following information is considered for the analysis: the total cost of the care workers, the number of PCPs, the percentage of acceptance (i.e., the total accepted demand divided by the total demand), and the panel size per PCP. The results represent the aspects of one week of operating time, totaling 35 working-hours.

4.1. Nash bargaining solution

Fig. 3 depicts separately the results of the Nash bargaining solutions from each healthcare perspective. Fig. 3a summarizes the total cost of the care workers, including the NP costs when they correspond for each practice size. The type of setting that produced lower costs crosswise to the practice sizes was the office-based physician (scenario 1). The worst setting in terms of the cost of the care workers depends on the practice size. Particularly, in solo and small practices, a mixed-care setting with PCPs and NPs (scenario 5) resulted in higher costs of care workers due to the inclusion of NPs in all sizes. In the largest sizes of medium practices, a mixed-shared care setting (scenario 5) also produced higher cost, but practice sizes ranging between 8 and 19 PCPs generated greater costs when they were based on pure home-care service (scenario 3). For large practices, the Nash bargaining solutions excluded NPs in all scenarios; thus, the cost of care workers was based exclusively upon PCPs.

Associated with the cost of the care workers is the required number of PCPs per practice size (Fig. 3b). Solo and small practices can use any setting since either of them required the same minimum amount of PCPs. The same conclusion can be obtained for the first three sizes of medium practices. For medium practices beginning with size 9 and including large practices, the smallest number of PCPs was obtained using the office-based physician care setting (scenario 1). The Nash bargaining solutions required, on average, 2.8 less PCPs (2.14 standard deviation [SD]) than the actual medium practice sizes and a mean of 6.8 less PCPs (0.84 SD) than the actual large practice sizes in scenario 1. Likewise, the highest amount of PCPs for medium and large practice sizes was mainly reached using the home-care setting (scenario 3), which utilized the total size of PCPs in each practice.

The acceptance rate in Fig. 3c exhibits that the mixed-shared care setting (scenario 5) has the lowest rejection rate in solo, small, and large practices. In over half of the medium practice sizes, the highest rate of acceptance was reached by using the home-care setting (scenario 3). The office-based physician care setting (scenario 1) accomplished



(a) Total cost of care workers per practice size

(b) Number of PCPs per practice size

(c) Percentage of acceptance per practice size

(d) Panel size per PCP per practice size

Fig. 3. Nash bargaining solutions per scenario and per practice size.

the lowest acceptance rate across all practice sizes.

Scenario 1: Office-based physician care setting. Scenario 2: Office-based shared-care setting. Scenario 3: Home shared-care setting. Scenario 4: Mixed physician care setting. Scenario 5: Mixed-shared care setting.

Fig. 3d shows that the minimum panel size per PCP across the practice sizes was obtained using the home-care setting (scenario 3). The highest panel size per PCP for solo and small practices was mainly reached using the mixed-care setting with the set of providers compounded by PCPs (scenario 4). For practice sizes over 13 PCPs, the highest panel size was obtained using the office-based shared care setting (scenario 2). Table 6 summarizes the results considering the best and the worst setting for each perspective and for each practice size.

4.2. Healthcare perspectives and overall scores

The score for each healthcare perspective, i.e, the organization's, the patient's, and the physician's was calculated as the difference between the total occurrence of the scenario, labeled as the “best setting”, and the total occurrence of the scenario, labeled as the “worst setting”, display in Table 6. The patient's perspective and the physician's perspective scores consider the percentage of acceptance and the panel size per PCP, respectively. Since the organization's perspective is associated with the dimensions of i. the total cost of the care workers and, ii. the number of PCPs, this score was calculated using weights equal to $\frac{1}{2}$ for each dimension. The purpose of using weights in the organization's perspective was to obtain a single score that included both dimension i and dimension ii. For instance, scenario 5 has a score equal to 0 in the organization's perspective for small practices. This value was calculated as follows: $(0.5 \times 0 + 0.5 \times 4) - (0.5 \times 4 + 0.5 \times 0) = 0$. The first and the second terms refer to the occurrence of scenario 5 labeled as “best setting” in dimension i and dimension ii, and the third and the fourth terms refer to the occurrence of scenario 5 labeled as “worst setting” in dimension i and dimension ii.

Table 7 summarizes the scores for the different combinations of the healthcare perspectives and the scenarios. In addition, an overall score for each scenario and for each type of practice size was calculated adding the three healthcare perspectives. For instance, the score for small practices in scenario 5 is equal to 1 since the scores for the organization's, patient's, and physician's perspectives are 0, 1, and 0, respectively. Based on the scoring system for each healthcare perspective, a negative overall score means that the scenario appears more times as a “worst setting” in the analyzed practice size. The results in Table 7 show that the home-care setting (scenario 3) has the highest score for solo, small, and medium practices. The mixed physician care setting (scenario 4) has the highest scores for large practices.

Fig. 4 shows the scores of the three healthcare perspectives: the organization's, the patient's, and the physician's for each scenario and for all types of primary care practice sizes. The scores of the healthcare perspectives in Table 8 were scaled to positive numbers. The zero values are in the center of the plots, and thus, the outer layers of the plots denote higher scores. Each axis of the radar plots represents a scenario, where scenario 1 is denoted by S1, scenario 2 by S2, and so on. The scores of the healthcare perspectives of each scenario are connected to

Table 6
Summary of the best and the worst setting per perspective and per practice size according to the Nash bargaining solution.

		Total Care Workers' Cost		No. of PCPs		Percentage of Acceptance		Panel Size per PCP	
Practice Size	PCP	Best Setting	Worst Setting	Best Setting	Worst Setting	Best Setting	Worst Setting	Best Setting	Worst Setting
Solo	1	1	5	1,2,3,4,5	-	5	1	3	4
Small	2	1	5	1,2,3,4,5	-	5	1	3	4,5
	3	1	5	1,2,3,4,5	-	5	1	3	4
	4	1	5	1,2,3,4,5	-	5	1	3	4
	5	1	5	1,2,3,4,5	-	5	1	3	2,4,5
Medium	6	1	5	1,2,3,4,5	-	5	1	3	4
	7	1	5	1,2,3,4,5	-	5	1	3	4
	8	1	3	1,2,3,4,5	-	3	1	3	4
	9	1	3	1	2,3,4,5	3	1	3	4
	10	1	3	1	2,3,4,5	3	1	3	4
	11	1	3	1	2,3,4,5	3	1	3	4
	12	1	3	1	2,3,4,5	3	1	3	4
	13	1	3	1	3,4,5	3	1	3	2
	14	1	3	1	3,5	3	1	3	2
	15	1	3	1	3	3	1	3	2
	16	1	3	1	3	3	1	3	2
	17	1	3	1	3,5	3	1	3	2
	18	1	3	1	3	3	1	3	2
	19	1	3	1	3,5	3	1	3	2
	20	1	5	1	3	5	1,3	3	2
Large	21	1,3	2,5	1	3	2,5	1,3	3	2,5
	22	3	2,5	1	3	2,5	1,3	3	2,5
	23	1	2,5	1	3	2,5	1,3	3	2,5
	24	1	2,5	1	3	2,5	1,3	3	2,5
	25	1	2,5	1	3	2,5	1,3	3	2,5

1: Office-based physician care setting; 2: Office-based shared-care setting; 3: Home shared-care setting; 4: Mixed physician care setting; 5: Mixed-shared care setting.

Table 7
Scores based on the best and the worst settings from Table 6.

Practice	Scenario	Organization's Perspective	Patient's Perspective	Physician's Perspective	Overall Score
Solo	1	1	−1	0	0
	2	0.5	0	0	0.5
	3	0.5	0	1	1.5
	4	0.5	0	−1	−0.5
	5	0	1	0	1
Small	1	4	−4	0	0
	2	2	0	−1	1
	3	2	0	4	6
	4	2	0	−4	−2
	5	0	4	−2	2
Medium	1	15	−15	0	0
	2	−0.5	0	−8	−8.5
	3	−10.5	11	15	15.5
	4	−1	0	−7	−8
	5	−4	3	0	−1
Large	1	4.5	−5	0	−0.5
	2	−2.5	5	−5	−2.5
	3	−1.5	−5	5	−1.5
	4	0	0	0	0
	5	−2.5	5	−5	−2.5

Scenario 1: Office-based physician care setting. Scenario 2: Office-based shared care setting. Scenario 3: Home shared care setting. Scenario 4: Mixed physician care setting. Scenario 5: Mixed-shared care setting.

form polygons: the gray area represents the organization's, the area surrounded by sphere markers represents the patient's, and the area surrounded by black lines represents the physician's. Similar scores across the scenarios generate regular polygons in the plot. For instance, the scores of the organization's perspectives are more similar crosswise the scenarios than the patient's and physician's perspectives, for solo and small practices.

According to Fig. 4, and for the instances used, the organization's perspective is enhanced in the office-based physician setting (scenario 1) in all types of practice sizes since the scores are higher toward that direction. Likewise, the patient's perspective is higher in the mixed-shared care setting (scenario 5) for solo, small, and large practices. The home-care setting (scenario 3) strengthens the patient's perspective in medium practices, and office-based shared-care setting (scenario 2) also strengthens the patient's perspective for large practices. From the physician's perspective, the home-care setting (scenario 3) is better across all types of practice sizes.

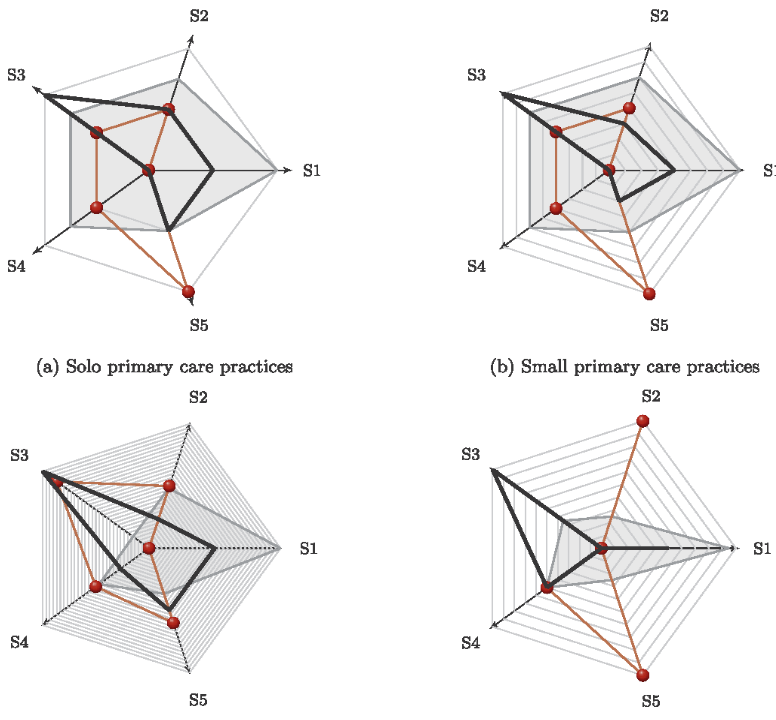
Organization's perspective: gray area. Patient's perspective: area surrounded by sphere markers. Physician's perspective: area surrendered by black lines.

S1: Office-based physician care setting. S2: Office-based shared care setting. S3: Home shared care setting. S4: Mixed physician care setting. S5: Mixed-shared care setting.

4.3. Sensitivity analysis

In this subsection, we performed a sensitivity analysis for the parameter β and for the parameter γ_{pl}, specifically, for the cost of home-care providers. Table 8 shows the scores of the healthcare perspectives and overall scores for values of the parameter β equal to 40 and 60 min. Table 9 displays the scores after including an additional cost for travel time. In both cases, the other parameters and sets shown in Table 5 remained unchanged.

Even though, the overall scores in solo and small practices changed mainly in favor of mixed-shared care settings (scenario 5), Table 8 shows that the highest scores for the three healthcare perspectives, i.e., the organization, the patient, and the physician, were achieved in the same scenarios as those with $\beta = 20$ minutes (Table 7). However, to compensate the longest travel times, the Nash bargaining solutions contemplated the inclusion of extra-PCPs in solo and small practices.



(a) Solo primary care practices (b) Small primary care practices
(c) Medium primary care practices (d) Large primary care practices

Fig. 4. Diagrams of the scores of each healthcare perspective for each scenario.

Table 8
Healthcare perspectives and overall scores for values of the parameter β equal to 40 min and 60 min.

		β = 40 min				β = 60 min			
Practice	Scenario	Organization's Perspective	Patient's Perspective	Physician's Perspective	Overall Score	Organization's Perspective	Patient's Perspective	Physician's Perspective	Overall Score
Solo	1	1	−1	0	0	1	−1	0	0
	2	0.5	0	0	0.5	0.5	0	0	0.5
	3	−1	0	1	0	−1	0	1	0
	4	0.5	0	−1	−0.5	0.5	0	−1	−0.5
	5	0.5	1	0	1.5	0.5	1	0	1.5
Small	1	3	−4	0	−1	4	−4	0	0
	2	2	0	0	2	2	0	0	2
	3	1.5	0	4	5.5	−2	0	4	2
	4	2	0	−4	−2	2	0	−4	−2
	5	0.5	4	0	4.5	1	4	0	5
Medium	1	6.5	−14	0	−7.5	7	−1	0	6
	2	−6	12	−10	−4	−6	12	−12	−6
	3	7.5	−2	15	20.5	5.5	−14	15	6.5
	4	−4.5	5	−7	−6.5	−2.5	3	−5	−4.5
	5	−10	14	−3	1	−10.5	13	−5	−2.5
Large	1	0.5	0	1	1.5	0	0	0	0
	2	−5	5	−5	−5	−4.5	5	−3	−2.5
	3	4.5	−5	4	3.5	5	−5	5	5
	4	0	0	0	0	0	0	0	0
	5	−5	5	−5	−5	−4	4	−5	−5

Scenario 1: Office-based physician care setting. Scenario 2: Office-based shared care setting. Scenario 3: Home shared care setting. Scenario 4: Mixed physician care setting. Scenario 5: Mixed-shared care setting.

Table 9
Healthcare perspectives and overall scores when the travel time cost is included.

		Cost for travel time			
Practice	Scenario	Organization's Perspective	Patient's Perspective	Physician's Perspective	Overall Score
Solo	1	1	−1	0	0
	2	0.5	0	0	0.5
	3	0	0	1	1
	4	0.5	0	−1	−0.5
	5	0.5	1	0	1.5
Small	1	4	−4	0	0
	2	2	0	0	2
	3	0	0	4	4
	4	2	0	−4	−2
	5	2	4	0	6
Medium	1	6	−12	0	−6
	2	−2.5	1	0	−1.5
	3	−14	12	15	13
	4	6.5	−4	−6	−3.5
	5	3.5	1	−12	−7.5
Large	1	0	0	0	0
	2	0	4	0	4
	3	−5	0	5	0
	4	5	−5	0	0
	5	0	5	−5	0

Scenario 1: Office-based physician care setting. Scenario 2: Office-based shared care setting. Scenario 3: Home shared care setting. Scenario 4: Mixed physician care setting. Scenario 5: Mixed-shared care setting.

This would explain the reduction in the scores related to the organization's perspectives in home-care settings (scenario 3), and therefore, the changes in the overall scores. The extra-providers are less required in mixed-care settings (scenarios 4 and 5) since these settings have the option of changing the preferred care location of the demand. The values of the panel sizes per PCP for home-care settings (scenario 3) were always smaller than the values of the scenarios 1, 2, 4, and 5 in solo and small practices for the parameter β equal to 20 min, nonetheless, the values were even smaller when the travel time increased. From the patient's perspective, the acceptance rates were not notably affected by the increment in travel times.

For medium and large practices the phenomenon was different. The Nash bargaining solutions excluded the extra-providers in home-care settings (scenario 3) affecting the acceptance rates, which decreased with longer travel times. The scores for the physician's perspectives were higher in home-care settings (scenario 3) since the panel sizes per PCP were decreasing. All of this triggered that the scores for the organization's perspectives improved.

In summary, for solo and small practices the preferred setting is independent of the type of practice size and of the travel time. The variation relies on the secondary goals of the quadruple aim (i.e., reducing cost, improving the patient experience, and improving the provider experience) on which the type of practice will focus. For medium and large practices, the scores of the organization's and the patient's perspectives vary with the travel time and with the size, but not the score of the physician's perspective which is the same for all types of practice sizes and for the different values considered for the parameter β. Thus, for short travel times (i.e., $\boldsymbol{\beta} = 20$ minutes), the overall score per scenario in each type of practice size suggests that on average, the home-care setting performs better in solo, small, and medium practices but in large practices, the mixed physician care setting is best. For large travel time (i.e., $\boldsymbol{\beta} = 60$ minutes), the mixed-shared care setting aligns better the secondary goals of the quadruple aim in solo and small practices, whereas home-care setting aligns the goals better in medium and large primary care practices.

Table 9 shows the healthcare perspectives and the overall scores when the cost of travel time is incorporated. To include the travel cost, we double the values of the parameter $\boldsymbol{\gamma}_{pl}$ related to the home-care providers. For instance, according to Table 5, the cost of a PCP is \$70 and the travel time takes 1 time slot, thus, we increased the cost of a PCP that provides care at home to \$140, i.e., in our case, the travel time has the same cost than the provision of the health service [65].

The results depicted in Table 9 did not defer much from the results obtained in Table 7 in solo and small practices. The healthcare perspectives, i.e., the organization's, the patient's, and the physician's, achieved their maximum scores in scenarios 1, 5, and 3, respectively. However, the overall scores determined that the best settings shifted from the home-care (scenario 3) to the mixed-shared care (scenario 5) since the total costs of the care workers increased more for pure home-care and, additionally, the mixed-care settings have the option of relocating the demand to office-based.

In medium and large practices, the home-care settings (scenario 3) behaved similar to solo and small practices when the cost of the travel time was included. This is, the panel sizes of a PCP, the rates of acceptance, and the number of PCPs remained constant, but the total costs of the care workers increased. The scores computed based on the Nash bargaining solutions, determined that the highest values for the organization's perspective was obtained in mixed physician care settings (scenario 4) because the number of PCPs decreased when the cost of travel time was included, this implied that the panel sizes of a PCP increased and the acceptance rates decreased. Furthermore, because of the relocation of the demand, the total costs of the care workers also decreased. A solution to reduce the unmatched demand for a care location is to give a value different to 100% to the parameter $\boldsymbol{\xi}_{hl}$ in the location $l = 2$ (home), or to adjust the penalties for the rejected demand and the demand whose preferred care location is not matched in the objective function z_3.

In summary, when the traveling cost is included, the organization's perspectives in medium and large practices are more affected by an increase in the costs. For the other scenarios and practice sizes, the highest scores for each healthcare perspective do not change. The negative effects of the costs on the organization's perspectives, i.e., on the total costs of the care workers and on the number of PCPs, modify the overall scores, and therefore, in some cases, it also modifies the settings that better achieve the secondary goals of the quadruple aim. Notwithstanding the adjustment, they are still led by those primary care settings that include home-care.

Table 10 summarizes the main results obtained in the four experiments conducted in this study. Experiments 1, 2 and 3 differ in the travel times, where the parameter β takes the values of 20, 40, and 60 min. Experiment 4 considers the inclusion of a travel cost. The overall score for each setting determined that, on average, the settings based on home-care, i.e., home shared care setting (scenario 3), mixed physician care setting (scenario 4), and mixed-shared care setting (scenario 5) enhance the achievement of the secondary goals of the

Table 10
Summary of the results obtained in the experiments conducted in the present study.

Practice	Experiment 1	Experiment 2	Experiment 3	Experiment 4
	($\boldsymbol{\beta} = 20$ min)	($\boldsymbol{\beta} = 40$ min)	($\boldsymbol{\beta} = 60$ min)	($\boldsymbol{\beta} = 20$ min, travel time cost)
Solo	Scenario 3	Scenario 5	Scenario 5	Scenario 5
Small	Scenario 3	Scenario 3	Scenario 5	Scenario 5
Medium	Scenario 3	Scenario 3	Scenario 3	Scenario 3
Large	Scenario 4	Scenario 3	Scenario 3	Scenario 2

Scenario 1: Office-based physician care setting. Scenario 2: Office-based shared care setting. Scenario 3: Home shared care setting. Scenario 4: Mixed physician care setting. Scenario 5: Mixed-shared care setting.

quadruple aim across the experiments. Specifically, the relevance of the home-care setting (scenario 3) can be observed from Table 10 since it is preferred in around 56%, i.e., 9 out of 16 of the experimental cases. This is highlighted further by the fact that in each type of practice size, the home-care setting (scenario 3) is indicated as the best scenario in at least one of the experiments conducted.

5. Discussion

The Nash bargaining solutions obtained from the analyzed scenarios using the multi-objective integer programming formulation state that there is not a unique primary care setting that is absolutely preferable over the others when the objective functions are minimized altogether. Nonetheless, we note that the settings incorporating home-care, enhance the achievement of the secondary goals of the quadruple aim more than the office-based physician settings. In most cases, the choice of the setting is independent of the type of practice size and depends only on the secondary goals of the quadruple aim on which the type of practice wants to emphasize.

Considering the changing demographics that the US faces with an aging population and the implications, home-care for health promotion and disease prevention provides multiple advantages for this group of people, which are not completely captured by a mathematical formulation. One of these advantages is the comfort of not having to travel. Elderly people have more chances of suffering of non-financial barriers, e.g., transportation issues, which hinders the timely access to primary care [35,50]. Also, older adults with mental health conditions, such as dementia, can become overwhelmed in unfamiliar places [71], which could affect the provision of care. The care workers, on the other hand, generate closeness with the patient, more accurate understanding of his/her needs, and a clearer assessment of the environmental and social situations of the older adult [19,67,71], which then allow the promotion of patient-centered care. Consequently, pure home-care or mixed-care settings provide more advantages for elderly people than office-based care settings, statement that is in accordance with the numerical results obtained in this study. Furthermore, the satisfaction of the patient (objective function z_3) is related to the acceptance rate, which is higher across the practice sizes that include home-care in most of the experiments conducted.

The projected shortage by 2035 of more than 44,000 PCPs in the US health care system [40,52] increases the need to plan for care under a restricted number of PCPs. However, there is a trade-off among the number of PCPs (objective function z_2), the demand acceptance rate (objective function z_3), and the appropriate panel size (objective function z_4) since a reduced panel size implies the need for more PCPs to keep an "acceptable" rate of demand served. The solution proposed by several authors is to transform the current office-based physician practices into shared-care practices and to confer more autonomy to non-physician providers to administer primary care [8,10–12].

The costs for the practices in hiring NPs and physician assistants (PAs) (objective function z_1) will eventually increase, as they take effect in the mixed-shared care settings for practice sizes of less than 7 PCPs and where the utilization of NPs is greater in that range. The benefits of the inclusion of non-physician primary care providers are noticed in the percentages of rejected demand, which are lower in the settings that include NPs. However, only some states in the US allow for NPs to provide care without the supervision of a PCP [37]. A low 53% of the office-based practices in the US have employed a NP or PA in primary care [31]. Faster actions are required on this matter to increase the engagement in shared-care practices given the evidence of cost-reduction when incorporating NPs [51], the benefits of working in teams for patients that suffer from chronic diseases [69], and the support in reducing the shortage of PCPs [27]. Thus, whether an office-based physician practice wants to expand to a shared-care practice or not, it would be preferable to turn into a mixed-shared care setting, since it incorporates non-physician providers and increases the satisfaction of the older adults to its full extent at the same time.

The poor working conditions that PCPs experience have a direct relation to the estimated shortage since they increase the burnout and, consequently, the turnover. However, an appropriate panel size (objective function z_4) balances the supply-demand relationship; therefore, it could increase the access to primary care and improve the satisfaction of the PCPs since they have more time to spend with their patients, shortened waiting times, and the promotion of coordination and continuity of care [7,54]. According to Raffoul et al. [54], current panel sizes in the US primary care practices admit a minimum of 1200 patients per PCP (approximately 74 served patients per PCP per week). Thus, the settings in which the Nash bargaining solutions require a weekly panel size of less than 74 patients per PCP could be considered as the settings that provide a higher satisfaction for the PCPs. For instance, the Nash bargaining solutions for practice sizes of less than 12 PCPs, in short radius, reach weekly panel sizes fewer than 74 patients in all settings; hence, the selection of the care setting up to that practice size would rely on the other factors, i.e., the satisfaction of the patients and cost-reduction.

6. Conclusions

A multi-objective integer programming formulation was developed to incorporate the three healthcare perspectives, the organization's, the patient's, and the physician's under a single framework. The Nash bargaining solution was used to address the trade-off amongst the different perspectives. The numerical results allow the identification, from a strategic level, of which primary care delivery settings, i.e., office-based, home-care, or mixed-care better achieves the secondary goals of the quadruple aim for different primary care practice sizes. We computed scores for each of the healthcare perspectives based on the five scenarios of our model and for different types of practice sizes. The numerical results show that the choice of the correct setting for a primary care practice depends on which of the secondary goals of the quadruple aim the practice wants to emphasize and not necessarily on the type of practice size. In general, the office-based physician setting reduced the costs of the practices, the mixed-shared care setting increased the acceptance rate, and the home-care setting reduced the panel size per PCP. An overall score that integrates the three perspectives was calculated for each scenario. The numerical results supported the premise that the settings based on home-care strengthen the achievement of the secondary goals of the quadruple aim in comparison to the office-based physician settings. In addition, the home-care setting was indicated more times as the best setting across the experiments conducted in this study and, in each type of practice size, it obtained the highest score in at least one of the experiments. In future work, we will consider the duration of the health services as a stochastic parameter to study its effect on the three healthcare perspectives.

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Appendix A. Supplementary data

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Appendix D: Reactive or Proactive Care? Assessing Efficiency and Equity of Care Access Among Critical Patients While Considering Medical and Non-medical Conditions

Reactive or proactive care? Assessing efficiency and equity of care access among critical patients while considering medical and non-medical conditions

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Abstract

A significant aging trend in the United States, followed by a shortage of primary care providers, has made timely access to primary care more difficult. The patient-centered medical home (PCMH) and home-based primary care (HBPC) models emerged to enhance this level of care. However, two problems arose in the HBPC/PCMH model. First, HBPC focuses on 'high-need high-cost' (HNHC) patients (i.e., reactive care), but directing attention across risk levels (i.e., proactive care) reduces costs more effectively and improves health outcomes. Second, the PCMH model has not been shown to reduce health disparity, and consequently, address social determinants of health (SDH). In this study, we explore reactive and proactive care strategies, with and without the inclusion of SDH, to understand how efficient and equitable the approaches are on care access, including admissions, wait times, and total care services for different risk groups. We propose a multi-objective optimization model for HBPC practices that maximizes access at distinct risk levels, yet prioritizes the most critical, while following the five PCMH components: quality and safety, comprehensive care, coordinated care, patient-centered, and accessible care. Additionally, we propose a redefinition of 'high-need' patients that aligns with proactive care, characterizing individuals based on their medical and non-medical conditions. We solve the models using the weighted sum method to describe the traditional reactive approach and the generalized non-symmetric Nash bargaining solution to account for the preventive medicine strategy. The outcomes for a small HBPC practice indicate that, on average, proactive care that uses medical conditions as the selection criterion is 4.9% more efficient in care access than reactive

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care. Furthermore, compared to the proactive care strategy that includes non-medical conditions, it has an average increment in fairness of 4.7% across the analyzed metrics and scenarios. Nevertheless, if the analysis considers patients with a high probability of worsening health conditions, proactive care that incorporates non-medical factors is fairer and more efficient. While high-risk patients' access is higher under reactive care, including the SDH into proactive care guarantees admissions, lower wait times, and care services provided to HNHC patients at significant risk of an adverse event.

Keywords: preventive medicine, medical home model, social determinants of health, Nash bargaining solution, home-care, chronic conditions

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1. Introduction

As the first contact between the patient and the health system, the primary care level has the potential to improve population health while overcoming health disparities and reducing costs [75, 79, 38]. However, the supply-demand for primary care is unbalanced in the United States (US); the growth of older adults and the shortage of primary care physicians (PCPs) increase the difficulties of timely access to care services [32, 70]. In this regard, the patient-centered medical home (PCMH) approach emerges as a value-based care model to transform primary care in the US [74]. The model is underpinned by five principles: quality and safety, comprehensive care, coordinated care, patient-centered, and accessible care [2]. Furthermore, home-based primary care (HBPC), which operates under PCMH principles, changes the care location from the office to the patient's home, in an attempt to bring care close to people living in underserved areas, suffering functional impairment, or experiencing transportation barriers [16]. HBPC is a precise, intensive primary care program directed toward 'high-need, high-cost' (HNHC) patients [78, 23]. Although there is not a clear definition of 'HNHC patients,' multiple chronic conditions, advanced age, behavioral problems, functional impairments, and significant risk of adverse events are general characteristics of this group, small in proportion, and responsible for a substantial level of healthcare use and expenditure [3, 11, 78].

However, the HBPC/PCMH model presents two main challenges in its design and implementation. First, several studies in recent years relate health outcomes, such as the development of chronic conditions, to social determinants of health (SDH) [22, 28, 6], a concept defined by the World Health Organization as "the conditions in which people are born, grow, live, work and age" [80]. Although the evidence suggests that the PCMH model reduces hospitalizations, increases savings, and improves the quality of care [1, 27, 53], the model has not been shown to have a significant impact on reducing health disparities [30, 61, 76, 79]. Second, some studies advise that directing interventions exclusively to HNHC individuals may not significantly decrease costs; focusing on patients across risk levels has a more meaningful effect on diminishing health spending

and developing cost-efficiency [54, 55]. This idea originated from a study conducted by Rose [69] in 1985, in which he introduced the concept of 'population strategy' for preventive medicine and argued that "a large number of people at a small risk may give rise to more cases of diseases than the small number who are at a high risk." In this regard, the proactive care strategy reduces costs, as well as aligns with value-based care models, supporting the quadruple aim of the US health system [35]. Consequently, strengthening primary care to move steadily from reactive to more proactive and inclusive care seems the proper approach to reduce costs and achieve health equity.

In this study, we aim to provide further evidence on efficiency and fairness in health access regarding the addition of a dimension associated with SDH and the inclusion of preventive medicine as a care delivery approach in the HBPC/PCMH model. We formulate a multi-objective optimization (MOO) model for HBPC practices that maximizes the access of individuals at different risk levels. The formulation assists in representing proactive and reactive care strategies and can extend to include, as a selection criterion, the relationship between SDH and the number of chronic conditions through probabilistic classification models. We use the generalized non-symmetric Nash bargaining solution (NBS) to incorporate preventive medicine (i.e., proactive care) since it accounts for the overall welfare of the system while promoting balance among risk levels, yet emphasizing the most critical. We describe the classical approach of targeting HNHC patients (i.e., reactive care) using the weighted sum method (WSM).

The contributions of this study are as follows: (i) the first MOO formulation at the tactical level of care planning that includes the five PCMH components, which can be extended to include preventive medicine and SDH to support decision making for practices that provide HBPC; (ii) a redefinition of 'high need' patients that comprises medical and non-medical conditions and aligns with a preventive medicine strategy; (iii) the analysis of proactive and reactive care through the study of the trade-off between efficiency and fairness of care access for small HBPC practices.

We organize the article into seven sections. In Section 2, we present the literature review. In Section 3, we describe the MOO formulation and solution methods. Section 4 describes the scenarios performed in the study, and Section 5 reports the results. The discussion and conclusion are presented in Sections 6 and 7, respectively. Additionally, Appendix A presents an application of the identification approach to select patients, while Appendix B contains complimentary tables for the results section.

2. Literature review

Balancing the access of individuals across risk levels and organizing their care plans based on health conditions is a tactical decision that raises questions about "what, where, how, when, and who" [43, 4]. Because resources are limited, increased access to a health system by high-risk individuals affects lower risk groups' wait times, admissions, and number of care services received in a planning period, and vice versa. These

perspectives expose an underlying, conflicting multi-criteria problem that falls within the MOO arena, a decision-making discipline that optimizes more than one objective function simultaneously. In many cases, a MOO formulation offers more than one alternative from which to obtain a suitable solution. MOO formulations that determine a set or an approximation of Pareto optimal solutions are uncommon in home-care studies [37], despite the multi-criteria nature of care delivery problems.

Barrera et al. [7], at the operational level, minimize the number of workers and their workload for multi-period planning. The formulation allows care workers to perform different actions in a solo manner but not as a team. The authors use an exact and meta-heuristic lexicographic approach to solve the mixed-integer programming (MIP) formulation. Milburn and Spicer [57] minimize the total travel costs, number of nurses seen by a patient, and nurse workload at the operational level of care planning. The second objective function in their formulation ensures continuity of care and, thus, patient-centered care since it limits the number of different nurses that can visit a patient. Similarly, the formulation includes home monitoring devices for a more accessible care service, which can substitute for a small fraction of nurse visits. They solve the MIP problem using a meta-heuristic approach. Duque et al. [34], at the operational level, minimize the total travel distance of care workers and maximize the service level (i.e., the preferences of the patients and the care workers). The formulation has patient-centered elements since it measures patient-provider compatibility and ensures a reduced number of different care workers who visit a patient during a planning period. The authors use a meta-heuristic two-stage approach, where the service level considered in the first stage is relaxed in the second stage. Braekers et al. [14] minimize the sum of the travel and overtime costs and minimize patient preferences, at an operational level, for a single period. The authors consider patients' care-worker preferences, penalizing when a patient does not receive a care service from a preferred nurse. The authors use the exact ε-constraint method and a meta-heuristic approach to solve the MIP formulation. Liu et al. [51], at an operational level, minimize the total operational cost (i.e., the salaries of the teams) and maximize patients' satisfaction (i.e., the full additional service length). In the MOO formulation, the authors use the word 'team' to refer to a set of nurses who visit a patient; however, they do not provide further details about the teams. The formulation, similarly, restrains the number of teams assigned to a patient in a planning period. They use the exact ε-constraint and three heuristic methods to solve the MIP problem. Carello et al. [17] minimize the overtime cost, utilization rate of the nurses, and number of patient-nurse reassignments at an operational level. The authors include continuity of care as a critical aspect of the formulation, classifying patients at different levels according to their continuity of care demand. The authors solve the integer programming (IP) problem using the threshold method, which minimizes an objective function while adding the others as constraints. Decerle et al. [31], at the operational level of care planning, minimize three objective

functions representing the total working times of the providers, quality of service, and difference in working time among types of nurses. The formulation considers visits by two care workers (i.e., 'synchronized visits'); its accomplishment is part of the quality of service measurements. They solve the multi-objective problem using an evolutionary algorithm proposed by the authors. Mendoza-Alonzo et al. [56], at the strategic level, compare three types of primary care delivery settings: home-care only, office-based only, and practices that provide both services. They minimize the total care-workers costs, number of care workers, total rejections, and overall panel size of the providers. The authors include care services delivered by a single care worker and by multidisciplinary teams in the MOO formulation. To solve the IP problem, the authors use a solution method based on the Nash bargaining problem. Table 1 summarizes previous home-care studies regarding whether the PCMH model's five components are included, the addition of at least one objective function that relates to access, and the inclusion of patient stratification and SDH in their MOO formulations.

Table 1: Summary of multi-criteria home-care studies and whether the critical components are included

Study	**C1**	**C2**	**C3**	**C4**	**C5**	**SDH**	**Access**	**Risk levels**	**Tactical level**
Barrera et al. [7]									
Milburn and Spicer [57]				✓	✓				
Duque et al. [34]				✓					
Braekers et al. [14]				✓					
Liu et al. [51]		✓		✓			✓		
Carello et al. [17]				✓				✓	
Decerle et al. [31]	✓		✓						
Mendoza-Alonzo et al. [56]		✓							
Present study	✓	✓	✓	✓	✓	✓	✓	✓	✓

C1: quality and safety; C2: comprehensive care; C3: coordinated care; C4: patient-centered; C5: accessible service; SDH: social determinants of health

Table 1 implies and relates to some gaps in the literature. First, none of the current MOO formulations for home-care settings assist in decision-making practices under the HBPC model since the multi-criteria literature, to date, includes no research that captures the five components of the PCMH model concurrently. Second, promoting equitable access across patient groups with different risk conditions and conflicting interests is a tactical decision that previous MOO studies have not addressed. Consequently, there is no indication of proactive medicine in current multi-criteria studies. Third, the current selection criteria for healthcare access do not allow targeting individuals before the first hospital admission or before the development of a chronic

disease. These tools use information regarding prior hospitalizations [13, 73, 68, 29, 26] or current medical conditions [13, 39, 73, 71, 72, 68, 29, 25, 26] as indicators of HNHC patients. Preventive medicine challenges policymakers to redefine the concept of 'high-need' patients and, thus, patients selection criteria used in primary care settings to include individuals from different risk levels. In outpatient settings, patient selection is an area of operation research that requires more consideration since few studies in optimization include, for instance, patients' health conditions [33, 21]. Furthermore, none of them include aspects related to the dimension of SDH.

3. The MOO formulation

The present MOO formulation is a pure integer linear programming model for decision making that outlines care plans to a set of accepted regular patients who receive care in a practice that operates under the HBPC/PCMH model. Recording each patient's diagnosis of chronic health condition allows classification into different risk groups. Each objective function describes a risk level and consequently, aims to maximize the access of patients who belong to its represented group. In this study, the term 'access' involves admissions, wait times, and the number of care services provided in the planning period. Thus, the MOO formulation can answer the following questions pertinent to patient accessibility at different risk levels: (i) considering the limited resources, which individuals should the HBPC practice admit? (admission criterion); (ii) which accepted patients should receive care first? (wait-time criterion); (iii) how many care services of each type can the practice offer to each admitted individual in a planning period? (number of care services criterion).

We classify the constraints of the MOO formulation in five groups following the PCMH principles: comprehensive care, patient-centered, coordinated care, accessible service, and quality and safety. Comprehensive care focuses on the broad view of patient health rather than specific medical problems. The provision of care in the MOO problem revolves around a set of multidisciplinary teams. A set of core providers (e.g., PCPs and nurse practitioners [NPs]) forms the team and a set of support providers (e.g., psychologists and pharmacists) assists all teams in the primary care practice. The core care workers are exclusive to one particular team, this means that they do not provide any care service to the panels of the other teams during the planning period. Conversely, the support care workers do not relate to a specific team; hence, they can serve all of them in the planning period. We assume that all teams have an equal minimum number of core care workers, and thus, the practice has sufficient providers to form the teams. Similarly, patient-centered is the component that relies on a strong relationship between the patient and the care team. In our formulation, the same multidisciplinary team provides all care services to a patient throughout the planning period, striving to deliver high-quality care.

Coordinated care aims to reduce unnecessary procedures and avoids the problem of working in silos. Each team has a weekly set of time slots reserved for care coordination. We assume that all team members (i.e., core and support providers) attend the meetings of their corresponding teams; thus, their schedules must coincide during the sessions. For the accessible service component, the practice offers care services that include home-care visits and e-care. We assume that the care worker has a travel time before and after delivering a care service, considering the travel time as the longest distance or the worst-case scenario from a patient's home to another patient's home, within the geographic area served by the practice. When the service is e-care, or the provision of a home-care visit is in the first or last time slot of the planning period, the travel time is after or before the care service, respectively. The care services may range from services administered by a single provider to services delivered by a multidisciplinary team.

Quality and safety is the component of the PCMH model that promotes the use of available data to make informed shared decisions. In our formulation, critical inputs of the model relate to the number, types, and periodicity of care services required to manage the medical and non-medical conditions of an individual. Periodicity parameters are included in the formulation because the services provided at home by a support care provider, such as a dentist or psychologist, may require different intervals between sessions than other care services offered by the practice. Furthermore, having a single periodicity for the rest of the care services promotes a better distribution of care delivery to the patient across the planning period, assisting in filling the gaps when an HBPC practice confronts a deficit of providers, such as PCPs. Defining this frame must involve a multidisciplinary team, the family, and the patient and should consider the available information and evidence-based practice to determine the ideal and minimum set of care services to reach a desirable patient outcome in a planning period.

3.1. Objective functions

The MOO formulation considers $|\mathcal{J}|$ objective functions, each of them representing a group of patients under a risk level. Expressions (1) show the objective functions for the preventive care strategy that includes both medical and non-medical conditions as enrollment criteria. Thus, the objective function f_j maximizes access to receiving care at home to the set of patients, $\mathcal{I} = \{1, \dots, I_j\}$, who belong to the risk level, $j \in \mathcal{J}$,

$$f_j = \max \sum_{i\in\mathcal{I}_j}\sum_{c\in\mathcal{C}}\sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} \pi_{ji}\big(|\mathcal{S}| - s\big)x_{jicst}, \quad \forall j \in \mathcal{J}. \tag{1}$$

The term $(|\mathcal{S}|-s)x_{jicst}$ represents the product between the decision variable, $x_{jicst} \in \{0,1\}$, and the difference between the total number of time slots $|\mathcal{S}|$ in the planning period and the time slot, $s \in \mathcal{S}$. The parameter π_{ji} is the probability of an individual, $i \in \mathcal{I}_j$, who is at the risk level, $j \in \mathcal{J}$, of worsening in the next period (that generally

refers to years [9]). Therefore, to augment access, each objective function maximizes the weighted sum of the term $(|\mathcal{S}|-s)x_{jicst}$, 'weighted' by the probability π_{ji}, for all care services, $\mathcal{C} = \{1,\ldots,C\}$, provided by the teams, $\mathcal{T} = \{1,\ldots,T\}$, to regular patients from the set, $\mathcal{I}_j = \{1,\ldots,I_j\}$, who are part of the group, $j \in \mathcal{J}$, in a planning period.

The value of the objective function, f_j, $j \in \mathcal{J}$, increases when the following occurs: (i) the practice admits patients who have a higher likelihood of worsening; (ii) the practice provides as many care services as possible in the planning period to patients with a higher probability of worsening; (iii) the teams deliver care services in time slots as close as possible to the beginning of the planning period (i.e., short wait times). The probability of an individual's health condition worsening comprises the non-medical frame, using the SDH to compute the likelihood. In the traditional approach (or reactive care), the selection criterion is based solely on medical conditions. Therefore, removing the SDH component in Expressions (1), the MOO formulation can be extended to account for the traditional approach and preventive medicine that consider medical conditions only.

3.2. Constraints

The following subsection describes the constraints of the MOO formulation and its relationship with the five components of the PCMH model. Table 2 lists the sets, parameters, and decision variables of the formulation.

3.2.1. Comprehensive care

Constraints (2)-(12) relate to the comprehensive care component. In particular, constraints (2)-(7) describe those associated to the core providers. Constraint (2) ensures that the core care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{c}$, is a member of exactly one team throughout the planning period. Thus, the decision variable, $\tilde{y}_{pkt} \in \{0,1\}$, takes the value of 1 if and only if the core care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{c}$, is part of the team, $t \in \mathcal{T}$,

$$\sum_{t\in\mathcal{T}} \tilde{y}_{pkt} = 1, \quad \forall p \in \mathcal{P}^{c}, \forall k \in \mathcal{K}_p. \tag{2}$$

Constraint (3) ensures that the team, $t \in \mathcal{T}$, has at least one core care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{c}$,

$$\sum_{k\in\mathcal{K}_p} \tilde{y}_{pkt} \geq 1, \quad \forall p \in \mathcal{P}^{c}, \forall t \in \mathcal{T}. \tag{3}$$

Constraint (4) guarantees that the core care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{c}$, as part of the team, $t \in \mathcal{T}$, receives at most one duty, $d \in \mathcal{D}$, in the time slot, $s \in \mathcal{S}$,

Table 2: Sets, parameters, and decision variables of the formulation

Notation	Description
Set	*Description of the set*
$\mathcal{C}$	set of care services
$\mathcal{C}^{\mathrm{h}} \in \mathcal{C}$	set of home care services
$\mathcal{C}^{\mathrm{e}} \in \mathcal{C}$	set of e-care services
$\mathcal{C}^{\mathrm{hss}} \in \mathcal{C}^{\mathrm{h}}$	set of home care services provided by a single support care provider, $p \in \mathcal{P}^{\mathrm{s}}$
$\mathcal{D}$	set of duties of a care worker
$\mathcal{I}_j$	set of patients from group, $j \in \mathcal{J}$
$\mathcal{J}$	set of group of patients/states/risk levels
$\mathcal{K}_p$	set of care workers of provider, $p \in \mathcal{P}$
$\mathcal{P}$	set of primary care providers
$\mathcal{P}^{\mathrm{c}} \in \mathcal{P}$	set of core care providers
$\mathcal{P}^{\mathrm{s}} \in \mathcal{P}$	set of support care providers
$\mathcal{S}$	set of time slots in the planning period
$\mathcal{T}$	set of teams
$\mathcal{W}$	set of weeks in the planning period
Parameter	*Description of the parameter*
α	times slots required for a team meeting
β	maximum number of time slots (i.e., the worst-case scenario) for traveling in the geographic area where the practice serves
δ_{ji}	periodicity in time slots of the care services, $c \in \mathcal{C}, c \notin \mathcal{C}^{\mathrm{hss}}$, for the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$
δ_{jic}	periodicity in time slots of the care service, $c \in \mathcal{C}^{\mathrm{hss}}$, for the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$
ζ_j	relative severity of the group, $j \in \mathcal{J}$
η_{jic}^{min}	minimum number of time slots of care service, $c \in \mathcal{C}$, that the practice should assign to the patient, $i \in \mathcal{I}_j$, who belongs to the group, $j \in \mathcal{J}$, if he or she is accepted
η_{jic}^{max}	maximum number of time slots of care service, $c \in \mathcal{C}$, that the practice should assign to the patient, $i \in \mathcal{I}_j$, who belongs to the group, $j \in \mathcal{J}$, if he or she is accepted
ι_w	first and last time slot of the week, $w \in \mathcal{W}$
π_{ji}	likelihood of the patient, $i \in \mathcal{I}_j$, $j \in \mathcal{J}$, moving to the next state/group/level, $j+1 \in \mathcal{J}$
ρ_j	disagreement point for the group, $j \in \mathcal{J}$
σ_{pc}	1 iif the provider, $p \in \mathcal{P}$, delivers the care service, $c \in \mathcal{C}$
Variable	*Description of the variable*
h_{jic}	time slots of care service, $c \in \mathcal{C}$, that the practice assigns to the patient, $i \in \mathcal{I}_j$, who belongs to the group, $j \in \mathcal{J}$ (integer)
m_{st}	1 iif the meeting session of the team, $t \in \mathcal{T}$, begins in the time slot, $s \in \mathcal{S}$ (binary)
$\tilde{x}_{jit}$	1 iif the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, belongs to the panel of the team, $t \in \mathcal{T}$(binary)
x_{jicst}	1 iif the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, receives the care service, $c \in \mathcal{C}$, in the time slot, $s \in \mathcal{S}$, by the team, $t \in \mathcal{T}$ (binary)
$\tilde{y}_{pkt}$	1 iif the care worker, $k \in \mathcal{K}_p$, provider, $p \in \mathcal{P}$, is part of the team, $t \in \mathcal{T}$ (binary)
y_{pkdst}	1 iif the care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}$, does the duty, $d \in \mathcal{D}$, in the time slot, $s \in \mathcal{S}$, as part of the team, $t \in \mathcal{T}$ (binary)

$$\sum_{d \in \mathcal{D}} y_{pkdst} \leq \tilde{y}_{pkt}, \quad \forall p \in \mathcal{P}^{\mathfrak{c}}, \forall k \in \mathcal{K}_p, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}. \tag{4}$$

Constraint (5) ensures that every time the core care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathfrak{c}}$, serves a patient in a time slot, other than the first or last one of the planning period, the core care worker cannot receive any duty in the previous or the next β time slots due to traveling,

$$\sum_{d \in \mathcal{D}} \sum_{\substack{s'=s-\beta \\ s' \neq s}}^{s+\beta} y_{pkds't} \leq 2\beta(1 - y_{pk1st}),$$
$$\forall p \in \mathcal{P}^{\mathfrak{c}}, \forall k \in \mathcal{K}_p, \forall s = \{1+\beta, \ldots, |\mathcal{S}| - \beta\} \in \mathcal{S}, \forall t \in \mathcal{T}. \tag{5}$$

Constraint (6) guarantees that the core care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathfrak{c}}$, who delivers a service in the first time slot, $s = 1 \in \mathcal{S}$, of the planning period, has β time slots for traveling after the provision of care,

$$\sum_{d \in \mathcal{D}} \sum_{s'=2}^{1+\beta} y_{pkds't} \leq \beta(1 - y_{pk11t}), \quad \forall p \in \mathcal{P}^{\mathfrak{c}}, \forall k \in \mathcal{K}_p, \forall t \in \mathcal{T}. \tag{6}$$

Constraint (7) assures that the core care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathfrak{c}}$, has β time slots for traveling before delivering a service in the last time slot, $s = |\mathcal{S}| \in \mathcal{S}$, of the planning period,

$$\sum_{d \in \mathcal{D}} \sum_{s'=|\mathcal{S}|-\beta}^{|\mathcal{S}|-1} y_{pkds't} \leq \beta(1 - y_{pk1|\mathcal{S}|t}), \quad \forall p \in \mathcal{P}^{\mathfrak{c}}, \forall k \in \mathcal{K}_p, \forall t \in \mathcal{T}. \tag{7}$$

Constraints (8)-(12) refer to the support providers. Constraint (8) allows that the support care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathfrak{s}}$, is part of more than one team,

$$\sum_{d \in \mathcal{D}} \sum_{s \in \mathcal{S}} y_{pkdst} - 1 \leq |\mathcal{S}| \; \tilde{y}_{pkt} - 1, \quad \forall p \in \mathcal{P}^{\mathfrak{s}}, \forall k \in \mathcal{K}_p, \forall t \in \mathcal{T}. \tag{8}$$

Constraint (9) assures that the support care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathfrak{s}}$, provides at most one duty, $d \in \mathcal{D}$, to only one team, $t \in \mathcal{T}$, in the time slot, $s \in \mathcal{S}$,

$$\sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} y_{pkdst} \leq 1, \quad \forall p \in \mathcal{P}^{\mathfrak{s}}, \forall k \in \mathcal{K}_p, \forall s \in \mathcal{S}. \tag{9}$$

Constraint (10) ensures that every time the support care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathrm{s}}$, serves a patient, the support care worker cannot receive any duty, $d \in \mathcal{D}$, from any of the teams in the previous or next β time slots due to traveling,

$$\sum_{d \in \mathcal{D}} \sum_{\substack{s'=s-\beta \\ s' \neq s}}^{s+\beta} \sum_{t \in \mathcal{T}} y_{pkds't} \leq 2\beta(1 - y_{pk1st}),$$

$$\forall p \in \mathcal{P}^{\mathrm{s}}, \forall k \in \mathcal{K}_p, \forall s \in \{1+\beta, \ldots, |\mathcal{S}|-\beta\} \subset \mathcal{S}, \forall t \in \mathcal{T}. \quad (10)$$

Constraint (11) guarantees that if the support care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathrm{s}}$, serves a patient in the first time slot, $s = 1 \in \mathcal{S}$, of the planning period, then the support care worker has β time slots for traveling after the provision of care,

$$\sum_{d \in \mathcal{D}} \sum_{s'=2}^{1+\beta} y_{pkds't} \leq \beta(1 - y_{pk11t}), \quad \forall p \in \mathcal{P}^{\mathrm{s}}, \forall k \in \mathcal{K}_p, \forall t \in \mathcal{T}. \quad (11)$$

Constraint (12) ensures the support care provider, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathrm{s}}$, has β time slots available for traveling to the patient's home before providing care in the last time slot, $s = |\mathcal{S}| \in \mathcal{S}$, of the planning period,

$$\sum_{d \in \mathcal{D}} \sum_{s'=|\mathcal{S}|-\beta}^{|\mathcal{S}|-1} y_{pkds't} \leq \beta(1 - y_{pk1|\mathcal{S}|t}), \quad \forall p \in \mathcal{P}^{\mathrm{s}}, \forall k \in \mathcal{K}_p, \forall t \in \mathcal{T}. \quad (12)$$

3.2.2. Quality and safety

Constraints (13)-(17) relate to the quality and safety component. Constraint (13) ensures that for an accepted patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, the total assigned time slots, $h_{jic} \in \mathbb{Z}^+$, of the care service, $c \in \mathcal{C}$, is at least η_{jic}^{min} and at most η_{jic}^{max}. The parameters η_{jic}^{min} and η_{jic}^{max} represent the minimum and maximum number of time slots, respectively, of the care service, $c \in \mathcal{C}$, that the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, should receive in the planning period considering their health conditions,

$$\sum_{t \in \mathcal{T}} \tilde{x}_{jit} \eta_{jic}^{min} \leq h_{jic} \leq \sum_{t \in \mathcal{T}} \tilde{x}_{jit} \eta_{jic}^{max}, \quad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}_j, \forall c \in \mathcal{C}. \quad (13)$$

Constraint (14) imposes that the next care service (if any), $c \in \mathcal{C} \setminus \mathcal{C}^{\mathrm{lss}}$ (i.e., excluding the care services provided by single support care workers), is delivered to the accepted patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, at any time, after δ_{ji} time slots. These care services (i.e., $c \notin \mathcal{C}^{\mathrm{lss}}$) are considered 'exchangeable,' having a single periodicity δ_{ji} defined for each patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$,

Constraint (10) ensures that every time the support care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathfrak{s}}$, serves a patient, the support care worker cannot receive any duty, $d \in \mathcal{D}$, from any of the teams in the previous or next β time slots due to traveling,

$$\sum_{d\in\mathcal{D}} \sum_{\substack{s'=s-\beta \\ s'\neq s}}^{s+\beta} \sum_{t\in\mathcal{T}} y_{pkds't} \leq 2\beta(1 - y_{pk1st}),$$
$$\forall p \in \mathcal{P}^{\mathfrak{s}}, \forall k \in \mathcal{K}_p, \forall s \in \{1+\beta, \ldots, |\mathcal{S}| - \beta\} \subset \mathcal{S}, \forall t \in \mathcal{T}. \quad (10)$$

Constraint (11) guarantees that if the support care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathfrak{s}}$, serves a patient in the first time slot, $s = 1 \in \mathcal{S}$, of the planning period, then the support care worker has β time slots for traveling after the provision of care,

$$\sum_{d\in\mathcal{D}} \sum_{s'=2}^{1+\beta} y_{pkds't} \leq \beta(1 - y_{pk11t}), \quad \forall p \in \mathcal{P}^{\mathfrak{s}}, \forall k \in \mathcal{K}_p, \forall t \in \mathcal{T}. \quad (11)$$

Constraint (12) ensures the support care provider, $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathfrak{s}}$, has β time slots available for traveling to the patient's home before providing care in the last time slot, $s = |\mathcal{S}| \in \mathcal{S}$, of the planning period,

$$\sum_{d\in\mathcal{D}} \sum_{s'=|\mathcal{S}|-\beta}^{|\mathcal{S}|-1} y_{pkds't} \leq \beta(1 - y_{pk1|\mathcal{S}|t}), \quad \forall p \in \mathcal{P}^{\mathfrak{s}}, \forall k \in \mathcal{K}_p, \forall t \in \mathcal{T}. \quad (12)$$

3.2.2. Quality and safety

Constraints (13)-(17) relate to the quality and safety component. Constraint (13) ensures that for an accepted patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, the total assigned time slots, $h_{jic} \in \mathbb{Z}^+$, of the care service, $c \in \mathcal{C}$, is at least η^{min}_{jic} and at most η^{max}_{jic}. The parameters η^{min}_{jic} and η^{max}_{jic} represent the minimum and maximum number of time slots, respectively, of the care service, $c \in \mathcal{C}$, that the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, should receive in the planning period considering their health conditions,

$$\sum_{t\in\mathcal{T}} \tilde{x}_{jit}\eta^{min}_{jic} \leq h_{jic} \leq \sum_{t\in\mathcal{T}} \tilde{x}_{jit}\eta^{max}_{jic}, \quad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}_j, \forall c \in \mathcal{C}. \quad (13)$$

Constraint (14) imposes that the next care service (if any), $c \in \mathcal{C} \setminus \mathcal{C}^{\mathfrak{hss}}$ (i.e., excluding the care services provided by single support care workers), is delivered to the accepted patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, at any time, after δ_{ji} time slots. These care services (i.e., $c \notin \mathcal{C}^{\mathfrak{hss}}$) are considered 'exchangeable,' having a single periodicity δ_{ji} defined for each patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$,

Constraint (19) guarantees that the multidisciplinary teams of an HBPC practice do not schedule meeting sessions for care coordination in the same time slots since the support care worker (if any), $k \in \mathcal{K}_p$, $p \in \mathcal{P}^{\mathbf{s}}$, must attend the meetings of all teams,

$$\sum_{t \in \mathcal{T}} m_{st} \leq 1, \quad \forall s \in \mathcal{S}. \tag{19}$$

Constraint (20) ensures that in the week, $w \in \mathcal{W}$, when the decision variable, $m_{st} \in \{0,1\}$, is equal to one, the team, $t \in \mathcal{T}$, begins the meeting session in the time slot, $s \in \mathcal{S}$. The duty, $d = \{3\} \in \mathcal{D}$, of a care worker, $k \in \mathcal{K}_p$, $p \in \mathcal{P}$, suggests a team meeting,

$$\begin{aligned}\sum_{s'=s}^{s+\alpha-1} y_{pk3s't} \geq -\alpha(1-m_{st}) + \alpha\tilde{y}_{pkt}, \quad & \forall w \in \mathcal{W}, \forall p \in \mathcal{P}, \forall k \in \mathcal{K}_p, \\ & \forall s = \{\iota_w + 1, \ldots, \iota_{(w+1)} - \alpha + 1\} \in \mathcal{S}, \forall t \in \mathcal{T}.\end{aligned} \tag{20}$$

Constraint (21) states that a 'weekly' team meeting lasts exactly α time slots,

$$\sum_{s=\iota_w+1}^{\iota_{(w+1)}} y_{pk3st} = \alpha\tilde{y}_{pkt}, \quad \forall w \in \mathcal{W}, \forall p \in \mathcal{P}, \forall k \in \mathcal{K}_p, \forall t \in \mathcal{T}. \tag{21}$$

3.2.4. Patient-centered

Constraints (22)-(24) focus on the elements that ensure continuity of care. Constraint (22) guarantees that the same team, $t \in \mathcal{T}$, delivers all care services to the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, throughout the planning period,

$$\sum_{t \in \mathcal{T}} \tilde{x}_{jit} \leq 1, \quad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}_j. \tag{22}$$

Constraint (23) ensures that the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, receives all time slots, $h_{jic} \in \mathbb{Z}^+$, of the care service, $c \in \mathcal{C}$, in the planning period,

$$h_{jic} = \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} x_{jicst}, \quad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}_j, \forall c \in \mathcal{C}. \tag{23}$$

Constraint (24) ensures that in the time slot, $s \in \mathcal{S}$, the patient, $i \in \mathcal{I}_j$, from the group, $j \in \mathcal{J}$, receives at most one care service from the team, $t \in \mathcal{T}$,

$$\sum_{c \in \mathcal{C}} x_{jicst} \leq \tilde{x}_{jit}, \quad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}_j, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}. \tag{24}$$

3.2.5. Accessible service

Constraint (25) guarantees that the team, $t \in \mathcal{T}$, covers the duty, $d = \{1, 2\} \in \mathcal{D}$, scheduled in the time slot, $s \in \mathcal{S}$, that requires the provider, $p \in \mathcal{P}$. Specifically, if $c \in C^{h}$, then $d = 1 \in \mathcal{D}$ (home-visit), and if $c \in C^{e}$, then $d = 2 \in \mathcal{D}$ (e-visit). The parameter σ_{pc} is a matrix of zeros and ones that combines providers, $\mathcal{P} = \{1, \ldots, P\}$, and care services, $\mathcal{C} = \{1, \ldots, C\}$,

$$\sum_{j \in \mathcal{J}} \sum_{i \in \mathcal{I}_j} \sum_{c \in \mathcal{C}} \sigma_{pc} x_{jicst} = \sum_{k \in \mathcal{K}_p} y_{pkdst}, \quad \forall p \in \mathcal{P}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T},$$
$$c \in C^{h} \Rightarrow d = 1 \in \mathcal{D}, c \in C^{e} \Rightarrow d = 2 \in \mathcal{D}. \quad (25)$$

3.3. Solution methods

The solution method considered for the MOO formulation derives from the bargaining game proposed by Nash [58] in 1950. The bargaining game stands on a set of highly rational players, $\mathcal{J} = \{1, \ldots, J\}$, who collaborate to improve the pay-off of all them [58]. The bargaining problem has multiple applications; one of them is in the MOO field. In MOO, each objective function, $j \in \mathcal{J}$, represents a player who intends to increase their profit cooperatively. As it is well known, a MOO problem may not have a unique solution that simultaneously provides optimum values to all objective functions. However, the cooperative bargaining problem demands finding one solution that is fair to all players. The approach for finding a fair solution requires computing f_j^{max}, which is the so-called disagreement point or *status quo* of the player, $j \in \mathcal{J}$. The *status quo* is the pay-off that the player, $j \in \mathcal{J}$, receives in the eventuality that the parts do not reach an agreement. A method used to compute this value is the heuristic form of estimating the Nadir point [67, 66]: $f_j^{max}(\mathbf{x}) = \max f_j(\mathbf{x}_r^*), 1 \leq r \leq |\mathcal{J}|$, where $\mathbf{x}_r^*$ is the vector that minimizes the jth objective function, and $|\mathcal{J}|$ represents the total number of objective functions (or total players of the game) [36]. Maximizing the product of the difference between the expected cooperative bargaining value $f_j(\mathbf{x})$ and the worst-case value f_j^{max} of each objective function, $j \in \mathcal{J}$, describes the interaction of the players and, hence, the bargaining game [67, 66].

Nash [59] proposed a solution to the bargaining problem, known as the NBS. The NBS is an axiomatic approach that has an advantage over other solution methods, offering a unique and fair Pareto optimal solution to all the bargainers [58, 59]. This characteristic confers supremacy on this method, considering how computationally expensive it is to estimate the entire Pareto frontier and how challenging it is for a decision-maker to select the right solution for a MOO problem. For our MOO formulation, we use the non-symmetric version of the NBS proposed by Kalai [45] since, although it offers relative priorities among players, it still accounts for balancing across them to achieve collective welfare [18]. The generalized non-symmetric NBS determines

a unique Pareto optimal solution that satisfies the axioms described by Nash [59] except for the 'symmetric' assumption. Formulation (26) shows the non-symmetric form of the bargaining problem for $|\mathcal{J}|$ objective functions, which can be easily expressed in the traditional Nash bargaining problem form [19]. Consequently, $\mathbf{x}^*$ denotes the NBS of the non-symmetric bargaining game,

$$\begin{aligned} \mathbf{x}^* = \arg\max \prod_{j=1}^{|\mathcal{J}|} [f_j^{max} - f_j(\mathbf{x})]^{\zeta_j} \\ \text{s.t. } \mathbf{x} \in X \\ f_j^{max} \geq f_j(\mathbf{x}), \quad \forall j \in \mathcal{J}. \end{aligned} \tag{26}$$

In the above formulation, $|\mathcal{J}|$ represents the number of objective functions in the MOO problem, while X is the set of constraints of the MOO formulation, and ζ_j is a positive integer assigned to each, $j \in \mathcal{J}$. The parameter ζ_j exposes the non-symmetry of the bargaining game when it takes different values for each, $j \in \mathcal{J}$. Formulation (27) is equivalent and a more manageable form to solve Formulation (26) [19],

$$\begin{aligned} &\max \gamma \\ &\text{s.t. } \gamma \leq \sqrt[|\mathcal{J}|']{\prod_{j=1}^{|\mathcal{J}|} \prod_{u=1}^{\zeta_j} [f_j^{max} - f_{j,u}(\mathbf{x})]} \\ &0 \leq \gamma, \\ &\mathbf{x} \in X. \end{aligned} \tag{27}$$

In Formulation (27), $|\mathcal{J}|' = \sum_{j=1}^{|\mathcal{J}|} \zeta_j$, $u \in \{1, \ldots, \zeta_j\}$, and $j \in \{1, \ldots, J\}$. Formulation (28) displays the second-order cone program transformation of Formulation (27). This model allows solving to optimality the generalized non-symmetric Nash bargaining game using optimization solvers, such as Gurobi or Cplex. In Formulation (28), g represents the smallest integer value that satisfies the inequality $2^g \geq |\mathcal{J}|'$ [8, 19],

$$\begin{aligned} &\max \gamma \\ &\text{s.t. } 0 \leq \gamma \leq \Gamma \\ &0 \leq \Gamma \leq \sqrt{\tau_1^{g-1} \tau_2^{g-1}} \\ &0 \leq \tau_r^l \leq \sqrt{\tau_{2r-1}^{l-1} \tau_{2r}^{l-1}} \quad \text{for } r = 1, ..., 2^{g-l} \text{ and } l = 1, ..., g-1 \\ &0 \leq \tau_i^0 = f_r^{max} - f_r \quad \text{for } r = 1, ..., |\mathcal{J}|' \\ &0 \leq \tau_r^0 = \Gamma \quad \text{for } r = |\mathcal{J}|' + 1, ..., 2^g \\ &\mathbf{x} \in X. \end{aligned} \tag{28}$$

We aggregate the $|\mathcal{J}|$ objective functions in Expressions (1) to obtain the single objective function in Equation (29), which is the non-symmetric Nash bargaining solution problem,

$$f_1^{'} = \max \prod_{j=1}^{|\mathcal{J}|} \Big[\sum_{i\in\mathcal{I}_j}\sum_{c\in\mathcal{C}}\sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} \pi_{ji}\big(|\mathcal{S}| - s\big)x_{jicst} - \rho_j\Big]^{\zeta_j}. \tag{29}$$

The parameter ρ_j is the *status quo* of the risk level or objective function, $j \in \mathcal{J}$ (i.e., $\rho_j = f_j^{max}$). Thus, regular patients, $\mathcal{I}_j = \{1, \ldots, I_j\}$, who are part of the risk level, $j \in \mathcal{J}$, compete to be accepted and reach the maximum number η_{jic}^{max}, of care services, $c \in \mathcal{C}$, as well as access the earliest time slots in the planning period. The severity of a risk level and the probability of a patient's current health condition worsening regulate the game and ensure an appropriate distribution among and within risk levels. Hence, the parameter ζ_j in Expression (29) gives a relative priority to the group, $j \in \mathcal{J}$, supporting the specification of higher values to the most critical levels, and the likelihood π_{ji} prioritizes the patient, $i \in \mathcal{I}_j$, within the group, $j \in \mathcal{J}$. These parameters are decisive metrics when selecting a patient and, together, confer relative urgency to each individual based on their medical and non-medical conditions.

The reactive approach and the proactive care strategy that include only medical conditions can easily derive from Expression (29). More precisely, for the preventive medicine approach that considers medical conditions only, we remove the parameter π_{ji}, for all individuals, $\mathcal{I}_j = \{1, \ldots, I_j\}$, and for all risk levels, $\mathcal{J} = \{1, \ldots, J\}$, as shown in Expression (30). Similarly, the traditional approach that focuses on HNHC patients requires using the value of the parameter ζ_j as the weight of the objective function, $j \in \mathcal{J}$, in the WSM, and also removing the SDH component as shown in Expression (31),

$$f_2^{'} = \max \prod_{j=1}^{|\mathcal{J}|} \Big[\sum_{i\in\mathcal{I}_j}\sum_{c\in\mathcal{C}}\sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} \big(|\mathcal{S}| - s\big)x_{jicst} - \rho_j\Big]^{\zeta_j}, \tag{30}$$

$$f_3^{'} = \max \sum_{j=1}^{|\mathcal{J}|} \zeta_j \sum_{i\in\mathcal{I}_j}\sum_{c\in\mathcal{C}}\sum_{s\in\mathcal{S}}\sum_{t\in\mathcal{T}} \big(|\mathcal{S}| - s\big)x_{jicst}. \tag{31}$$

3.4. Social determinants of health

The selection criterion proposed in this study for a preventive medicine-based approach comprises two steps to identify 'high-need' patients at each medical risk level, using non-medical characteristics. A person classified at a risk level from a medical viewpoint possesses non-medical characteristics, the SDH that makes him or her unique and distinct from other individuals in the same risk group [63, 62]. Because resources are limited in primary care, interventions must be targeted to the most critical patients in an effort to simultaneously improve their health outcomes and reduce costs [24].

Step 1: Risk-stratification

In **step one** of the approach, we classify a set of individuals at different risk levels, groups, or states, $\mathcal{J} = \{1, \ldots, J\}$. Each risk level indicates a 'number of chronic conditions,' starting from individuals with zero chronic diseases and progressing as the number of states increments. The last state J represents an adverse event, such as a hospital admission. The total number of states $|\mathcal{J}|$ and the number of chronic conditions under each risk level depend on the HBPC practice and the data available to perform the analysis. The classification method arises from the most prevalent characteristic of the patients considered as HNHC in the traditional approach [3] and the conclusion inferred by the currently existing risk stratification tools, which suggest that a person suffering from more chronic conditions is at a considerable risk of an adverse event [49].

Step 2: Individual probability

In **step two** of the approach, we formulate a probabilistic classification model at each risk level defined in step one using SDH as input variables to determine the likelihood of a person's current health condition worsening, as shown in Expressions (32), where, $i \in \mathcal{I}_j$, represents an individual classified in the state, $j \in \mathcal{J}$, and $\mathcal{X}$ symbolizes the set of values of the input variables,

$$\Pr_i(j+1 \mid j, \mathcal{X}) = \pi_{ji}, \quad \forall j \in \mathcal{J}, \forall i \in \mathcal{I}_j. \tag{32}$$

A probabilistic classification model estimates the individual risk probability of a patient who is currently in the state, $j \in \mathcal{J}$, to reach the next state, $j+1 \in \mathcal{J}$, in the subsequent period. We assume that a person cannot improve his or her health condition and cannot skip a level to enter a group that is at a higher risk. The output variable in each state is binary, taking the value of 1 if the person moves to the next state and 0 if he or she stays at the same risk level in the following term. The meaning of the values of the output variable in the last state changes; 1 suggests that the patient experiences the specified adverse event, and 0 otherwise. Step two requires a longitudinal dataset to develop probabilistic classification models.

The proposed two-step identification approach characterizes the individual, $i \in \mathcal{I}_j$, in terms of a risk level, $j \in \mathcal{J}$ (step one), and the probability π_{ji} of an individual's current health condition worsening (step two). Hence, the proposed method can identify lower-risk individuals with a significant chance of health deterioration. These people will potentially be high-risk patients in the upcoming periods. We present an application of the two-step identification approach using the longitudinal household survey conducted by the Health and Retirement Study (HRS) [42] in Appendix A.

Table 3: Characteristics of the scenarios under analysis

Scenario	HBPC/PCMH model	SDH	Target patients	Type of care	Case 1 Severe condition	Case 2 Moderate condition	Case 3 Mild condition	Solution method
A	✓		High-need high-cost	Reactive	✓	✓	✓	WSM
B	✓		Across risk levels	Proactive	✓	✓	✓	NBS
C	✓	✓	High-need	Proactive	✓	✓	✓	NBS

HBPC: home-based primary care, PCMH: patient-centered medical home, SDH: social determinants of health, WSM: weighted sum method, NBS: Nash bargaining solution

4. Description of the scenarios

In this section, we analyze the trade-off between efficiency and equity regarding patients' access (i.e., admissions, wait times, and total care services provided in a planning period) to small practices. They are the most common practice size that operates under the HBPC model in the US health system [48]. We analyze three scenarios A, B, and C, which include elements from the five PCMH components: patients' risk levels based on medical diagnosis, care workers arranged by teams, weekly team meetings for care coordination, patients assigned to the same team throughout the planning period, and telehealth. Scenario A represents the traditional approach that focuses on HNHC patients. We use the WSM to promote the access of HNHC individuals through the weights assigned to each risk level (Expression (31)). In contrast, scenario B incorporates preventive medicine through the generalized non-symmetric NBS (Expression (30)), which offers, by definition, balanced solutions across the risk levels. This scenario describes a proactive HBPC practice that enrolls patients based solely on medical diagnosis. Scenario C analyzes preventive medicine combined with medical and non-medical conditions as the enrollment criteria across risk levels to access an HBPC practice. We use the non-symmetric NBS to solve the mathematical formulation (Expression (29)). Scenarios A, B, and C use constraints (2)- (25). We examine three levels of severity of the patient's panel for each scenario: a severe, a moderate, and a mild-case that denotes a high, medium, and low demand for resources of care services and time slots in the planning period. Table 3 summarizes the scenarios and their characteristics. We code the scenarios using the programming language Julia 1.3.1 [10] and solve the models using the commercial optimization solver Gurobi 9.0 [41] with an optimality gap up to 5%.

4.1. Sets and parameters

Table 4 shows the values of the sets and the parameters of scenarios A, B, and C for each case.

Table 4: Sets and parameters of scenarios A, B, and C for each case

Notation	**Scenarios A-B-C: Severe case**	**Scenarios A-B-C: Moderate case**	**Scenarios A-B-C: Mild case**
$\mathcal{C}$	$\{1,2,3,4,5\}$	$\{1,2,3,4,5\}$	$\{1,2,3,4,5\}$
	1: PCP only	1: PCP only	1: PCP only
	2: NP only	2: NP only	2: NP only
	3: PCP&NP	3: PCP&NP	3: PCP&NP
	4: e-NP only	4: e-NP only	4: e-NP only
	5: SW only	5: SW only	5: SW only
$\mathcal{C}^h \in \mathcal{C}$	$\{1,2,3,5\}$	$\{1,2,3,5\}$	$\{1,2,3,5\}$
$\mathcal{C}^e \in \mathcal{C}$	$\{4\}$	$\{4\}$	$\{4\}$
$\mathcal{C}^{hss} \in \mathcal{C}^h$	$\{5\}$	$\{5\}$	$\{5\}$
$\mathcal{D}$	$\{1,2,3\}$	$\{1,2,3\}$	$\{1,2,3\}$
	1: home-visit	1: home-visit	1: home-visit
	2: e-care	2: e-care	2: e-care
	3: team meeting	3: team meeting	3: team meeting
$\mathcal{I}_j$	$\{1,\ldots,73\}_1$	$\{1,\ldots,73\}_1$	$\{1,\ldots,73\}_1$
	$\{1,\ldots,73\}_2$	$\{1,\ldots,73\}_2$	$\{1,\ldots,73\}_2$
	$\{1,\ldots,73\}_3$	$\{1,\ldots,73\}_3$	$\{1,\ldots,73\}_3$
$\mathcal{J}$	$\{1,2,3\}$	$\{1,2,3\}$	$\{1,2,3\}$
	1: Low-risk	1: Low-risk	1: Low-risk
	2: Rising-risk	2: Rising-risk	2: Rising-risk
	3: High-risk	3: High-risk	3: High-risk
$\mathcal{P}$	{PCP, NP, SW}	{PCP, NP, SW}	{PCP, NP, SW}
$\mathcal{P}^c \in \mathcal{P}$	{PCP, NP}	{PCP, NP}	{PCP, NP}
$\mathcal{P}^s \in \mathcal{P}$	{SW}	{SW}	{SW}
$\mathcal{S}$	$\{1,\ldots,147\}$	$\{1,\ldots,147\}$	$\{1,\ldots,147\}$
$\mathcal{T}$	$\{1,2,3\}$	$\{1,2,3\}$	$\{1,2,3\}$
$\mathcal{W}$	$\{1\}$	$\{1\}$	$\{1\}$
α	4	4	4
β	1	1	1
δ_{ji}	$\delta_{1i} = 21, \quad \forall i \in \mathcal{I}_1$	$\delta_{1i} = 21, \quad \forall i \in \mathcal{I}_1$	$\delta_{1i} = 21, \quad \forall i \in \mathcal{I}_1$
	$\delta_{2i} = 21, \quad \forall i \in \mathcal{I}_2$	$\delta_{2i} = 21, \quad \forall i \in \mathcal{I}_2$	$\delta_{2i} = 21, \quad \forall i \in \mathcal{I}_2$
	$\delta_{3i} = 21, \quad \forall i \in \mathcal{I}_3$	$\delta_{3i} = 21, \quad \forall i \in \mathcal{I}_3$	$\delta_{3i} = 21, \quad \forall i \in \mathcal{I}_3$
δ_{jic}	$\delta_{1i} = 21, \quad \forall i \in \mathcal{I}_1, \forall c \in \mathcal{C}$	$\delta_{1i} = 21, \quad \forall i \in \mathcal{I}_1, \forall c \in \mathcal{C}$	$\delta_{1i} = 21, \quad \forall i \in \mathcal{I}_1, \forall c \in \mathcal{C}$
	$\delta_{2i} = 21, \quad \forall i \in \mathcal{I}_2, \forall c \in \mathcal{C}$	$\delta_{2i} = 21, \quad \forall i \in \mathcal{I}_2, \forall c \in \mathcal{C}$	$\delta_{2i} = 21, \quad \forall i \in \mathcal{I}_2, \forall c \in \mathcal{C}$
	$\delta_{3i} = 21, \quad \forall i \in \mathcal{I}_3, \forall c \in \mathcal{C}$	$\delta_{3i} = 21, \quad \forall i \in \mathcal{I}_3, \forall c \in \mathcal{C}$	$\delta_{3i} = 21, \quad \forall i \in \mathcal{I}_3, \forall c \in \mathcal{C}$
ζ_j	$\zeta_1 = 1$	$\zeta_1 = 1$	$\zeta_1 = 1$
	$\zeta_2 = 2$	$\zeta_2 = 2$	$\zeta_2 = 2$
	$\zeta_3 = 3$	$\zeta_3 = 3$	$\zeta_3 = 3$
η_{jic}^{min}	$\begin{array}{cc} j\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&0&0&0&1\\1&1&0&0&1\\1&1&1&0&1 \end{bmatrix}_{\forall i\in\mathcal{I}_j} \end{array}$	$\begin{array}{cc} j\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&0&0&0&0\\1&1&0&0&0\\1&1&1&0&0 \end{bmatrix}_{\forall i\in\mathcal{I}_j} \end{array}$	$\begin{array}{cc} j\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&0&0&0&0\\1&1&0&0&0\\1&1&1&0&0 \end{bmatrix}_{\forall i\in\mathcal{I}_j} \end{array}$
η_{jic}^{max}	$\begin{array}{cc} j\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1 \end{bmatrix}_{\forall i\in\mathcal{I}_j} \end{array}$	$\begin{array}{cc} j\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&1&1&1&1\\1&1&1&1&1\\1&1&1&1&1 \end{bmatrix}_{\forall i\in\mathcal{I}_j} \end{array}$	$\begin{array}{cc} j\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&0&0&1&1\\1&1&0&1&1\\1&1&1&1&1 \end{bmatrix}_{\forall i\in\mathcal{I}_j} \end{array}$
ι_w	$\iota_1 = \{1, 147\}$	$\iota_1 = \{1, 147\}$	$\iota_1 = \{1, 147\}$
π_{ji}	A: -	A: -	A: -
	B: -	B: -	B: -
	C: $U(0,1,\mathcal{I}_j), \quad \forall j \in \mathcal{J}$	C: $U(0,1,\mathcal{I}_j), \quad \forall j \in \mathcal{J}$	C: $U(0,1,\mathcal{I}_j), \quad \forall j \in \mathcal{J}$
σ_{pc}	$\begin{array}{cc} p\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&0&1&0&0\\0&1&1&1&0\\0&0&0&0&1 \end{bmatrix} \end{array}$	$\begin{array}{cc} p\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&0&1&0&0\\0&1&1&1&0\\0&0&0&0&1 \end{bmatrix} \end{array}$	$\begin{array}{cc} p\backslash c & \begin{array}{ccccc} 1&2&3&4&5 \end{array} \\ \begin{array}{c} 1\\2\\3 \end{array} & \begin{bmatrix} 1&0&1&0&0\\0&1&1&1&0\\0&0&0&0&1 \end{bmatrix} \end{array}$

4.1.1. Providers

The set of providers, $\mathcal{P} = \{1, \ldots, 3\}$, for the analysis are PCPs, NPs, and social workers (SWs), respectively. PCP and NP are the core providers most frequently required since, according to Leff et al. [48], 85% of HBPC practices in the US have PCPs, and 73% of them have NPs. Furthermore, SWs (support providers) have the highest percentage of hires in HBPC practices [48, 47]. Similarly, each team across the scenarios has one PCP and one NP (a teamlet), which only provides care to its patient panel, whereas the SW assists all teams [12]. The set, $\mathcal{C} = \{1, \ldots, 5\}$, represents the care services 'PCP only,' 'NP only,' a 'team' comprised of a PCP and NP, 'e-NP only,' and 'SW only,' respectively. The scenarios describe a small practice size with 3 PCPs, 3 NPs, and 1 SW given that HBPC practices in the US have, on average, 3.2 PCPs, 3.5 NPs, and 0.9 SWs [48]. We explore the duties of the providers, $d \in \{1, \ldots, 3\} \subset \mathcal{D}$, representing home-visits, e-care services, and team meetings.

4.1.2. Patients

The demand for care at home is considered half of a panel size of 2,500 patients per PCP reported for office visits [65]. Thus, the total demand in the planning period is approximately 219 individuals, which we distribute equally across the risk groups for the analysis. The risk levels considered in the scenarios are low, rising, and high; therefore, the set, $\mathcal{J} = \{1, 2, 3\}$, has 73 individuals at each level. Using a uniform distribution with values between 0 and 1, we simulate $n = 73$ probabilities for the parameter π_{ji}, $\mathcal{I}_j = \{1, \ldots, 73\}$ with $\mathcal{J} = \{1, 2, 3\}$, keeping the same values for all risk levels for an unbiased comparison. The parameter ζ_j takes the values of 1, 2, and 3, representing the complexity of the patients belonging to the group, $j \in \mathcal{J} = \{1, 2, 3\}$, respectively, which means group 3 is at a more critical stage than group 2, and group 1 has a less complicated condition than group 2.

To facilitate the interpretation, we assume that all patients, $\mathcal{I}_j = \{1, \ldots, 73\}$, classified under the same risk level, $j \in \mathcal{J}$, demand the same minimum and maximum number of the care service, $c \in \mathcal{C}$, in the planning period [5], where the resources demanded depend on the complexity of the level. Hence, for the severe case, the accepted low-risk, rising-risk, and high-risk individuals should receive all care services, $c \in \{1, 5\} \subset \mathcal{C}$, $c \in \{1, 2, 5\} \subset \mathcal{C}$, and, $c \in \{1, 2, 3, 5\} \subset \mathcal{C}$, respectively, only one time, describing the case when the SW visits all patients [15], and at most from the set, $c \in \{1, 2, 3, 4, 5\} \subset \mathcal{C}$, one time each care service in the planning period. For the moderate case, the accepted patients across risk levels receive the same minimum number of care services provided in the severe case, except for the support care service delivered by the SW. 'SW only' is still part of the set of care services that patients across levels may receive at most (i.e., $c \in \{1, 2, 3, 4, 5\} \subset \mathcal{C}$). In the mild case, the minimum number of care services remains the same as it occurs in the moderate case for each risk level. The minimum is equal to the maximum number of care services provided by core providers

at home, with the addition of ‘e-NP only’ and ‘SW only’ to the maximum number of care services demanded by all patients, as shown in the highlighted rows in Table 4. We establish a minimum frequency of one day for the parameter $\delta_{ji}, j \in \mathcal{J}, i \in \mathcal{I}_j$, which is equivalent to 21 time slots. The parameter $\delta_{jic}, j \in \mathcal{J}, i \in \mathcal{I}_j$, uses the same minimum periodicity for the care service, $c \in \mathcal{C}^{\text{hss}}$, delivered by the support provider.

4.1.3. Practice

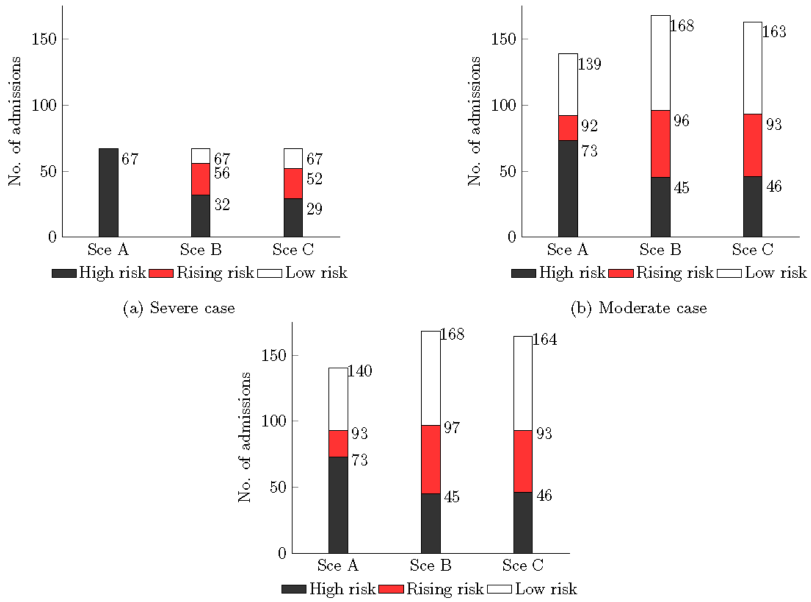
The scenarios represent a planning period of 1 week (seven days). Each day has seven working-hours divided into time slots of 20 minutes each [50, 40], giving 21 time slots per day. The total working hours each week is 35, which is consistent with the study conducted by Grisham [40], which suggests that more than 50% of the physicians in the US work between 30 and 45 hours per week. Consequently, there is a total of 147 time slots in the planning period. The scenarios use four consecutive time slots (i.e., a total of 80 minutes) for care coordination one time per week [46]. Across the scenarios, the parameter β takes the value of a one time slot (i.e., 20 minutes) as the worst-case scenario for traveling [56].

5. Results

We report the results for the severe, moderate, and mild cases through the analysis that connect all patients and the results linked to ‘high-need’ individuals only.

5.1. Analysis of all individuals

Figure 1 presents the results of the severe, moderate, and mild case for scenarios A, B, and C regarding admissions. Efficiency, measured as the total number of admitted individuals in the planning period, is the same for the three scenarios in the severe case (Figure 1a). Fairness, computed as the non-symmetric standardized product of the admissions at each risk level (using ζ_j to distinguish the risk level, $j \in \mathcal{J}$), establishes that scenario B is more equitable. Digging into the results, scenario B recognizes all patients from a risk level as equally critical. In contrast, scenario C admits individuals with probabilities greater or equal to 60% of worsening across levels because of the non-medical component (Table B.1, Appendix B). The pattern of the moderate and mild cases is similar, and both increase total admissions respects to the severe case (Figures 1b and 1c). Still, scenario B is more efficient and fairer across the risk levels. The high demand for support providers restrains admissions in the severe case, creating bottlenecks and dead times for core providers. In the other two cases, scenarios B and C accept more patients from the low-risk level since the demand for care services is more flexible. Scenario A (i.e., the traditional approach) always admits more high-risk individuals in all cases.



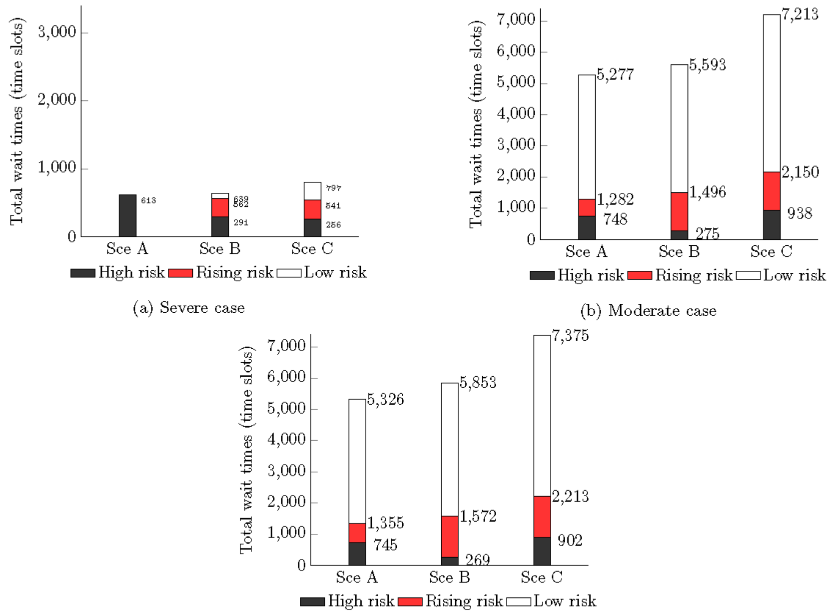
(a) Severe case

(b) Moderate case

(c) Mild case

Figure 1: Outcomes of scenarios A, B, and C: ‘admissions’

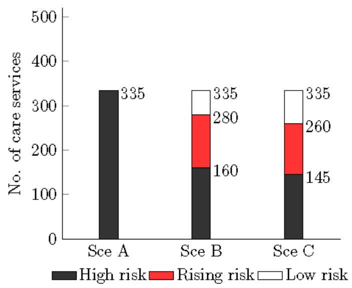
Figure 2 shows the total wait times in time slots for the first care service provided to the accepted patients. In the severe case (Figure 2a), scenario A is more efficient since it reports the lowest total wait time (613-time slots). Still, high-risk patients average nine time slots in wait time for the first appointment (i.e., the sum of wait times divided by the total accepted patients) in all scenarios. The average wait time for rising-risk is higher than for low-risk individuals in scenario B. Conversely, in scenario C, more severe patients, based on medical and non-medical conditions, have shorter wait times for the first appointment than those who are less critical. Thus, regarding equity across risk levels, scenario C is fairer in the severe case. The moderate and mild cases have similar performance, soaring in the sum and average wait times over the risk levels when compared to the severe case, and with shorter wait times when the seriousness of the risk level increases, as shown in Figures 2b and 2c. Still, scenario A presents the smallest total wait times, and B reduces inequity across risk levels in the moderate and mild case.



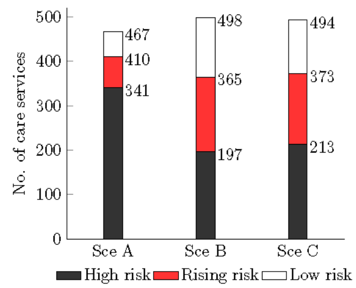
(c) Mild case

Figure 2: Outcomes of scenarios A, B, and C: 'wait times for the first appointment'

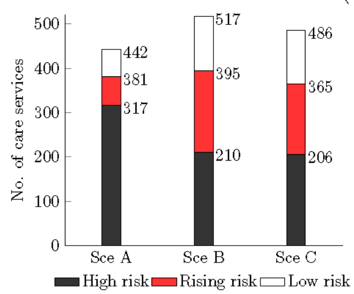
Figure 3 shows the number of care services delivered per case and scenario. All scenarios in the severe case have similar efficiency in the planning period (Figure 3a). In terms of equity, the non-symmetric multiplication of the total number of care services delivered at each risk level shows that scenario B more effectively balances the provision of care across risk levels. If we relax the demand for 'SW only,' then the number of care services delivered increases by at least 30%, as shown in Figures (3b) and (3c). In the moderate and mild case, scenarios A, B, and C expose that the more critical the risk level, the more care services the level receives. Nevertheless, scenario B provides more care services in both cases, and thus, it is more efficient. Scenario C is fairer in the moderate case and scenario B in the severe case.



(a) Severe case



(b) Moderate case



(c) Mild case

Figure 3: Outcomes of scenarios A, B, and C: 'number of care services'

Table 5 summarizes the results for each scenario, case, and metric of access. Across the scenarios and based on the sets and parameters considered in the analysis, scenario B seems a more promising strategy to raise admissions and total care services delivered in a planning period. This care delivery approach better performs on average when the demand for resources is more flexible. Scenario A reduces the wait times for the first appointment, having higher performance when the demand for resources is high and constrained. Therefore, scenario B is more efficient and equitable crosswise the cases and over the metrics of access than scenario A and scenario C.

Table 5: Outcomes including all individuals

		Admissions			Wait times			Care services			Results		
Metric	**Case**	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**
Efficiency	Severe	67	67	67	613	639	780	335	335	335	3	2	2
	Moderate	139	168	163	5277	5593	7213	467	498	494	1	2	0
	Mild	140	168	164	5326	5853	7375	442	517	486	1	2	0
	Results	1 m	3	1	3	0	0	1	3	1	5	6	2
Equity*	Severe	0	21	19	0	4712	8469	0	324403	302385	0	2	1
	Moderate	660	1707	1538	12407	14050	13584	1095104	2869914	2993396	0	2	1
	Mild	731	1749	1527	12693	14094	13717	795917	3866884	2674122	0	3	0
	Results	0	3	0	0	2	1	0	2	1	0	7	2

*Values divided by 10^7

Compared to scenario B, scenarios A and C provide less efficient and fair access, respectively (Table 5). The dashed red line in Figure 4 shows the variations in efficiency, in percentages, across the cases and metrics of access when moving from scenario A to scenario B. The performance varies from a 21% improvement in admissions (moderate case) to a 10% increment in wait times (mild case). Therefore, efficiency increases 4.9%, on average, across the cases with a standard deviation (SD) of 11.7% when shifting from reactive to proactive care that operates using medical conditions only. Similarly, the solid black line in Figure 4 displays the variation in fairness for all access metrics and cases when shifting from scenario C to scenario B. From scenario C to B, fairness ranges from an improvement of 45% in the total number of care services (mild case) to a 44% reduction in the total sum of wait times (severe case). Therefore, fairness increases 4.7%, on average, with a SD of 23% when moving from preventive medicine that includes medical and non-medical conditions to preventive medicine that only considers medical conditions as the selection criterion.

5.2. Analysis of 'high-need' individuals

Table 6 summarizes the results of the most critical patients in terms of non-medical conditions, and Table B.2 in Appendix B displays the quantities used to compute these values. Scenario C is more efficient and fairer for individuals with probabilities greater or equal to 50% of worsening health conditions based on their SDH. The fact that scenario C performs better is an expected outcome since scenario B considers all patients under the same group to be comparable in terms of risk. Therefore, the approach randomly selects patients within a group when the demand for resources is the same. A similar situation occurs in scenario A. For instance, in light of limited resources, the model randomly selects individuals from the high-risk level (the prioritized group under this strategy), considering all patients within this level equally critical.

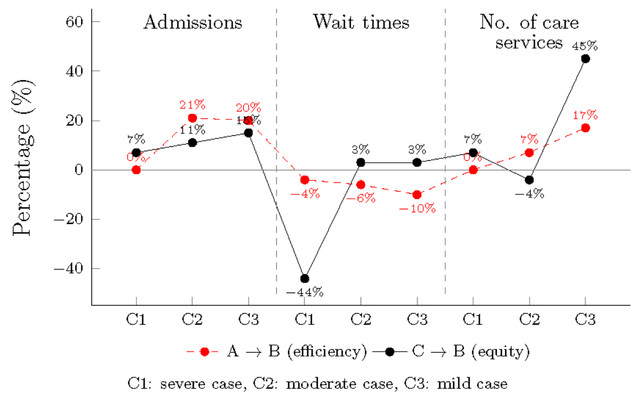


Figure 4: Percentage of variation in efficiency and equity of scenario B, in comparison to scenarios A and C

Table 6: Outcomes including individuals with a ≥ 50% probability of worsening

		Admissions			Wait times			Care services			Results		
Metric	**Case**	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**
Efficiency	Severe	33	40	67	342	333	780	165	200	335	0	1	2
	Moderate	71	87	111	2679	2934	2344	238	254	397	0	0	3
	Mild	72	86	111	2512	2714	2393	232	266	386	0	0	3
	Results	0	0	3	0	1	2	0	0	3	0	1	8
Equity*	Severe	0	1	19	0	4406	8469	0	14181	302385	0	0	3
	Moderate	7	31	257	11641	14105	13263	13405	48438	851661	0	1	2
	Mild	17	37	257	13034	14388	13075	19761	75566	728609	0	1	2
	Results	0	0	3	0	2	1	0	0	3	0	2	7

*Values divided by 10^7

Assuming a set of fixed resources, some of the high-risk patients must suffer the consequences in terms of rejections, wait times, or care services received in a period of planning to grant access to the lower risk levels under a preventive care delivery approach. Figure 5 shows the effect on high-risk patients of moving from the traditional approach that focuses on HNHC patients (i.e., scenario A) to a preventive medicine strategy that redefines the concept of 'high-need' individuals to include SDH (i.e., scenario C). The dashed red line represents the variation in care access across the metrics and cases, between scenarios A and C, including all accepted high-risk patients and using scenario A as the benchmark. The densely dotted gray line, dot-dashed black line, and solid black line depict the variation in care access considering patients with probabilities greater or equal to 25%, 50%, and 75% of worsening, respectively. Although high-risk patients' access reduces by an average of 27% when moving from reactive to proactive care, the new definition of 'high-need' individuals guarantees admissions,

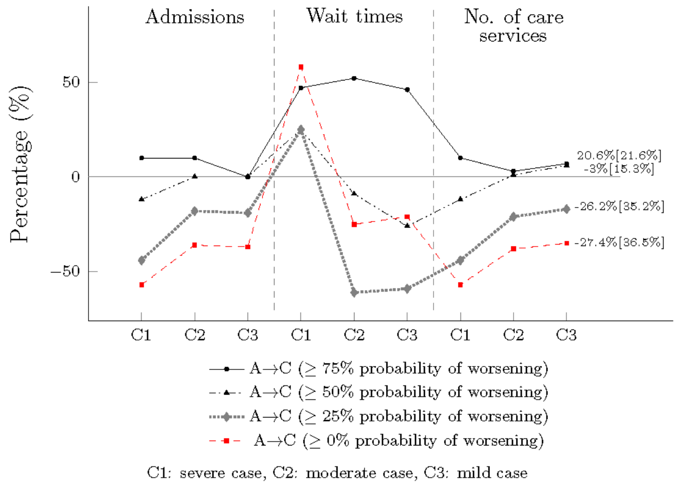


Figure 5: Percentage of variation from scenarios A to C for high-risk patients at different probabilities of worsening

lower wait times, and care services to HNHC patients with a higher likelihood of adverse events.

6. Discussion

In this study, we analyze proactive and reactive care delivery strategies for small HPBC practices to determine efficiency and fairness in three dimensions of access: admissions, wait times, and total care services delivered to individuals in different risk groups. Specifically, for the proactive care approach, we analyze medical conditions as a unique enrollment criterion and non-medical conditions as an additional factor in patient selection. To compare the three approaches, we propose a MOO formulation at a tactical level of care planning that follows the five principles of the PCMH model. The results show that, on average, proactive care is more efficient in care access than reactive care in 4.9% when patient selection is based solely on the medical condition. Similarly, it is 4.7% fairer in care access than the proactive strategy that incorporates non-medical factors as the selection criterion. Proactive care that includes medical and non-medical conditions in patient selection seems to be more efficient and balance access more effectively across risk levels of patients with high probabilities of worsening (i.e., more than 50%). Although moving from reactive to proactive care reduces access among high-risk patients, using broadly non-medical factors to characterize individuals, guarantees access of HNHC patients who, in other circumstances, would go unnoticed as individuals with an elevated likelihood of an adverse event.

As the strategy based on proactive care reduces cost by avoiding or delaying diseases [54, 55], the outcomes imply that it could also make the system more efficient and equitable in promoting access at all risk levels while prioritizing the most critical among and within the groups. The idea that preventive medicine that considers medical conditions only, on average, is more efficient and fairer may relate to the fact that the approach does not operate under a strict patient selection criterion. Consequently, it has more 'freedom' to select individuals, provides time slots for the first appointment, and assigns care services in the planning period to maximize total access. However, given the limited resources at the primary care level, proper selection criteria are crucial to support care access among individuals in greater need of preventive and patient-centered care. The positive impact of preventive medicine on care access and the evidence that the adoption of risk stratification tools is relatively new in primary care practices [77] creates an opportunity to explore selection mechanisms that support proactive care approaches and, simultaneously, reduce health disparities. The approach proposed in this study serves to redefine the concept of 'high need' patients to include individuals from different risk levels and promotes health equity, the missing component of the PCMH model. Similarly, and since most older adults will suffer from a chronic condition at some point [60], the relationship between chronic diseases and SDH must have special consideration when characterizing individuals. Nonetheless, the lack of agreement among the health organizations and institutions regarding what is understood by 'chronic condition' makes the adoption and implementation of the proposed two-step identification approach challenging [44, 9]. Reaching consensus between and within organizations on a single definition would facilitate the pattern search that connects SDH and chronic diseases, ensuring the adequate implementation and use of probabilistic classification models across HBPC practices.

There are some observations to consider from the PCMH components in the MOO formulation. (1) The inclusion of non-medical conditions as part of the selection criteria demands accurate estimations of the 'relative importance' of each risk group: how severe are high-risk patients relative to rising-risk, and how critical are rising-risk patients, in comparison to those who are low-risk? Accurate data collection and coordination through HBPC practices could lead to a more reliable and consistent representation of this critical parameter. (2) Support providers (i.e., psychologists, pharmacists, social workers, and dentists) are essential in strengthening holistic views of patients' health. However, they are not always present in care practices or not in the required numbers [48]. Under the PCMH model, specifically the comprehensive care component, support providers demand as much consideration as core providers. A deficit of support providers decreases admissions and affects the balance in access across the risk levels. As evidenced by the analysis of a small HBPC practice, support providers should be exclusive to a team, which grants more freedom to schedule multidisciplinary team meetings and enables them to deliver integrated care plans to all patients who need it.

(3) Even though weekly meetings and team-based organizations could worsen some of the access metrics, the care coordination factor and team-based approach entail well-studied benefits. The provision of care by a coordinated and multidisciplinary team to the same panel of patients throughout a planning period builds solid team-patient relationships, which highly correlates to positive health outcomes and higher levels of satisfaction among providers and patients. (4) Telehealth, as a complementary service in care plans, improves efficiency and fairness throughout the approaches. The issue that the same care workers who deliver home-visits also provide e-care can reduce in-person treatments and increase wait times until the first face-to-face encounter. The precise effects of e-care depend on several factors, such as the severity of the patient panel, number of care workers, types of care services provided through telehealth, and patients' specific needs.

This study has some limitations. First, coordination among care levels and other methods to ensure accessible services are not part of the formulation and, thus, require further consideration. Second, the analysis and conclusion offered in this study involve small HBPC practices; additional studies should consider medium and large settings.

7. Conclusion

This study examines three strategies of care delivery: the traditional approach that focuses on HNHC patients, the preventive medicine approach that considers medical conditions, and its extension, which includes non-medical factors. The analysis assesses efficiency and equity in care access for patients at different risk levels subject to medical conditions. We propose a MOO formulation that maximizes access while following PCMH principles and can adjust to include reactive and proactive care strategies. As part of the MOO formulation, we propose a two-step identification method, which characterizes an individual based on a risk group, as stated by the number of chronic diseases, and the probability of their health conditions worsening, which relies on SDH. The MOO formulation can manage risk levels and individual likelihood to serve as patient selection criteria in accessing an HBPC practice. Efficiency, understood as the allocation of limited resources to meet the care demands of a set of individuals, and equity, the balanced distribution of these limited resources across different groups of patients, are usually in conflict. However, the outcomes for small HBPC practices state that proactive care based only on medical conditions seems to better support efficiency and equity in care access across risk levels when compared to reactive care that focuses on HNHC patients. If the analysis involves individuals with a 50% or greater probability of their health condition worsening, efficiency and equity in care access increases under the proactive care strategy that includes non-medical factors. Therefore, considering the sets and parameters used in the analysis, efficiency and equity in care access under the HBPC/PCMH model do not seem to arise as a trade-off; these (apparently) conflicting metrics can be strengthened by adopting a proactive

view. Hence, increasing health investments toward balancing reactive and proactive care might produce positive returns that include higher efficiency and equity at the primary care level, cost reduction in the health system, and better population health outcomes. In future work, we plan to extend the analysis to medium and large practices for a more extended planning period and estimating costs to compare the strategies under value-based payment models. Additionally, we plan to explore further the association between SDH and chronic diseases using different datasets to identify patterns that connect diverse patient panels.

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Appendix

Appendix A. Application of the two-step identification approach

We apply the two-step identification approach described in Subsection (3.4) to the public dataset 'RAND HRS Longitudinal File 2016 (V1),' which is a household survey initially conducted in 1992 and, since then, administrated every two-years by the Health and Retirement Study (HRS). The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan [42]. The data includes SDH, such as the demographics, health, financial and housing wealth, income, social security, insurance, family structure, retirement plan, and employment history of people 50 years old and older and their spouses. This application separately examines 11 administrated surveys from 1995/96 to 2016 of respondents 65 years of age and older, disregarding the answers of their spouses and younger individuals. We conduct the analysis using the software R 3.6.1 [64].

Step 1: Risk-stratification

We include the following chronic conditions in the analysis: hypertension, diabetes, lung disease (except asthma), heart disease, stroke/transient ischemic attack, and arthritis/ rheumatism. For each selected respondent, we count the number of diagnosed chronic diseases and classify them depending on whether they have zero (*state 1*), one (*state 2*), or more than one (*state 3*) chronic disease. We classify the older adults under these categories as low-risk, rising-risk, and high-risk, respectively. In the first selection stage, each respondent receives a new identification that concatenates the actual ID and the year of the study, enabling us to include the same older adult as a distinct participant as many times as he or she has answered the survey. Across the years, 10,315 observations have zero chronic conditions (*state 1*), 21,742 report one chronic disease (*state 2*), and 49,665 report more than one chronic condition (*state 3*). In the second selection stage, we randomly select unique older adults across the years, based on their official ID, removing all duplicated observations in each category. Hence, the datasets are reduced to 2,947, 6,702, and 11,179 individuals in states 1, 2, and 3, respectively.

Step 2: Individual probability

State 1 includes patients with zero chronic diseases; thus, the outcome variable for this probabilistic classification model is whether the older adult develops a chronic condition in the next recorded year. Similarly, the outcome variable of *state 2* is whether an older adult continues with one chronic disease or develops one or more additional chronic conditions in the next period. The outcome variable at *state 3* indicates whether a hospital admission occurs in the next period. The hospital admission constitutes *state 4*. Of the older adults in *state 1*, 1,709 remain in the same group in the next period,

and 1,238 shift to *state 2* (removing 574 patients who migrated from *state 1* to *state 3*). Similarly, 3,874 and 2,828 older adults classified in *state 1* report one and more than one chronic condition, respectively, in the next survey (removing 156 respondents who were previously in *state 2* and report zero chronic diseases in the following period). Among 11,179 older adults with more than one chronic condition, 4,478 report hospital admission in the next examination year. To select the set of input variables, we consider one prior survey year. Thus, we match the output variable of a participant chosen from 1995/96 to 2016 with his or her SDH obtained from 1993/94 to 2014, respectively. For instance, if the output variable is from the survey conducted in 2000, we use the SDH reported in 1998 as input variables. We disregard explanatory variables greater than 10% of missing values, categorical variables with more than 95% of values in one category, and continuous variables that correlate 50% or higher. We convert categorical variables using dummy variables and impute the missing values using the median. In total, 121, 134, and 128 input variables result for the probabilistic classification models concerning *states* 1, 2, and 3, respectively.

For each probabilistic classification model, we use 80% of the dataset for training and 20% for testing. To address the imbalanced output variable in the training set, we use the synthetic minority over-sampling technique (SMOTE) [20], which is available in the software R's ROSE package [52]. After balancing the training set, the first model's output variable results in 1,090 observations classified as 0 (zero chronic conditions) and 1,010 classified as 1 (one chronic disease). The second model's output variable has 2,564 and 2,436 observations equal to 0 (i.e., one chronic condition) and 1 (i.e., more than one chronic disease), respectively. The third model has 7,500 observations; the output variable has 3,776 records classified as 0 (i.e., no hospital admission) and 3,724 classified as 1 (i.e., hospital admission). We use ridge, elastic net, and lasso logistic regression with values that range from 0 to 1 for the parameter 'alpha' of the function *glmnet()* in the R software and generalized linear models (GLM), specifically, probit and logit functions. The models related to the GLMs involve the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) for feature selection. The analysis includes the previous models compared to linear, radial, and polynomial support vector machines (SVMs) using the same set of selected variables obtained from the regularization methods and the GLMs. The SVM models include Platt scaling transformation to obtain probabilities. To select the best model for each risk level, we compute the Brier score and log loss.

Table A.1 summarizes, at each risk level, the probabilistic classification models that better perform according to the log loss and the Brier score. A ridge regularization method with 121 input variables performs better at the low-risk level according to the log loss and Brier score. A linear SVM with 26 SDH as input variables is the best probabilistic classification model for the rising-risk group having the lowest Brier score and log loss. Elastic net classifiers with values of 'alpha' 0.8 and 0.9 reach the lowest Brier

Table A.1: Summary of the best performances of probabilistic classification models for the analysis of the HRS dataset based on the log loss and Brier score

	Low Risk		**Rising Risk**		**High Risk**	
	Log loss	**Brier score**	**Log loss**	**Brier score**	**Log loss**	**Brier score**
Type	Ridge Regression	Ridge Regression	Linear SVM	Linear SVM	Elastic net	Elastic net
Log loss	0.6799	0.6799	0.674	0.674	0.6703	0.6703
Brier score	0.2429	0.2429	0.241	0.241	0.247	0.2387
No. variables	121	121	26	26	35	38

score and log loss, respectively, among the probabilistic classification models considered for high-risk older adults; nevertheless, the difference in performance is minimal. The Brier scores are slightly lower than 0.25, while the log loss scores are near 0.69, values considered non-informative for these metrics. The low results relate to the following limitations of the dataset. First, the dataset may have a degree of 'response bias' since the information comes from a survey rather than medical records or federal agency sources, such as the Centers for Medicare and Medicaid Services. Second, most of the input variables considered in the analysis are binary, not providing a much comprehensive description of the social characteristics of older adults. Third, since the survey is administrated every two years, there are long-time periods without information about the progress of the older adults.

Appendix B. Complimentary tables of the results section

Table B.1: Percentage of acceptance at each risk level, distributed across ten ranges according to the SDH selection criterion for scenarios A, B, and C

Case	**Sce**	**Risk level**	**[1.0, 0.9]**	**(0.89, 0.8]**	**(0.79, 0.7]**	**(0.69, 0.6]**	**(0.59, 0.5]**	**(0.49, 0.4]**	**(0.39, 0.3]**	**(0.29, 0.2]**	**(0.19, 0.1]**	**(0.09, 0]**
Severe	A	Low	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
		Rising	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
		High	100%	78%	100%	71%	100%	100%	80%	100%	86%	100%
	B	Low	13%	22%	14%	14%	0%	10%	20%	11%	29%	20%
		Rising	13%	11%	43%	71%	67%	40%	0%	22%	43%	20%
		High	63%	33%	43%	71%	83%	30%	40%	22%	14%	60%
	C	Low	100%	78%	0%	0%	0%	0%	0%	0%	0%	0%
		Rising	100%	100%	86%	0%	0%	0%	0%	0%	0%	0%
		High	100%	100%	100%	71%	0%	0%	0%	0%	0%	0%
Moderate	A	Low	88%	78%	57%	71%	67%	50%	80%	44%	57%	60%
		Rising	13%	11%	43%	14%	17%	40%	20%	33%	29%	40%
		High	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	B	Low	100%	100%	100%	100%	100%	100%	80%	100%	100%	100%
		Rising	100%	89%	86%	43%	50%	80%	60%	56%	43%	80%
		High	50%	44%	71%	57%	83%	60%	80%	89%	57%	20%
	C	Low	100%	100%	100%	100%	100%	100%	100%	100%	100%	40%
		Rising	100%	100%	100%	100%	100%	90%	0%	0%	0%	0%
		High	100%	100%	100%	100%	100%	100%	0%	0%	0%	0%
Mild	A	Low	88%	44%	71%	71%	33%	70%	80%	33%	71%	80%
		Rising	63%	33%	29%	14%	17%	10%	0%	44%	29%	20%
		High	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
	B	Low	100%	89%	100%	100%	83%	100%	100%	100%	100%	100%
		Rising	100%	56%	86%	14%	100%	70%	100%	67%	71%	60%
		High	75%	56%	71%	43%	100%	50%	60%	78%	57%	20%
	C	Low	100%	100%	100%	100%	100%	100%	100%	100%	100%	60%
		Rising	100%	100%	100%	100%	100%	100%	0%	0%	0%	0%
		High	100%	100%	100%	100%	100%	90%	0%	0%	0%	0%

Table B.2: Outcomes of individuals with a 50% probability of worsening in each scenario, case, and risk level to compute efficiency and equity

		Total admissions			**Total sum wait times for first appointment (time slots)**			**Total number of care services**		
Scenario	**Risk level**	**Sce A**	**Sce B**	**Sce C**	**Sce A**	**Sce B**	**Sce C**	**Sce A**	**Sce B**	**Sce C**
Severe	Low risk	0	5	15	0	42	239	0	25	75
	Rising risk	0	14	23	0	128	285	0	70	115
	High risk	33	21	29	342	163	256	165	105	145
Moderate	Low risk	27	37	37	2109	2153	1277	37	66	87
	Rising risk	7	28	37	196	665	661	26	94	134
	High risk	37	22	37	374	116	406	175	94	176
Mild	Low risk	23	35	37	1832	1910	1284	30	60	82
	Rising risk	12	26	37	332	653	669	39	91	131
	High risk	37	25	37	348	151	440	163	115	173

Appendix E: Controllable and Non-controllable Factors to Measure Performance in Primary Care Practices Under Medicare Alternative Payment Models

Controllable and non-controllable factors to measure performance in primary care practices under Medicare alternative payment models

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Abstract

We analyze two recent Medicare alternative payment models, the comprehensive primary care plus (CPC+) and the primary care first (PCF). Both models comprise fee-for-service, traditional capitation, and pay-for-performance (P4P) components. The main objective of these reimbursement models is to advance toward value-based care. However, the models confer some hesitations since the P4P component is based on factors not entirely controlled by the practice, increasing the potential admission of healthier patients and affecting the profit of small primary care practices. We modify the P4P component in both models to include a non-controllable agent (the hierarchical condition category score) and a controllable factor (the Bice-Boxerman continuity of care index) through a probabilistic classification model to predict avoidable hospital admissions. This study aims to determine the impact of adjusting the P4P component on the profit per team, P4P revenue per team, and the admitted patients' severity. We develop a mixed-integer programming formulation and analyze the main elements of the adjusted P4P component using a 2^k factorial design. The results indicate that the regression coefficients and the hospital admission threshold have a significant effect on the profit and revenue for performance per team with a tendency of the PCF to admit less severe patients than the CPC+. Yet, the effects are more notable in the PCF payment model because the P4P proportion of the total revenue under the CPC+ is minimal (16.5% versus $< 1\%$). Similarly, the PCF's downside is its sensitivity to the P4P changes, displaying high variability in the output variables considered in this study.

Keywords: comprehensive primary care plus, primary care first, pay-for-performance, Medicare, rural primary care practices

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1. Introduction

For decades, the fee-for-service (FFS) payment model has been the most used reimbursement system to pay for primary care services in the United States (US), accounting for an average of 73.1% of the revenue across primary care practices [37]. In the last years, the US health system has driven a transition toward value-based payments to reestablish the worth of primary care services. The objective of value-based payments is to reach a better overall health system's performance since the FFS is considered an obstacle to improving care delivery [26]. In fact, the FFS reimbursement model increases the healthcare costs; augments the cases of overdiagnosed and overtreated patients; and undermines the efforts toward a coordinated, continuous, first contact, and comprehensive primary care [7].

Alternative payment models (APMs) that combine three payment methods, the FFS, traditional capitation (TC), and pay-for-performance (P4P), have strengthened in the last ten years as reasonable reimbursement models for primary care services [39]. The TC is a payment method that has coexisted with the FFS over the years, providing a one-time payment in a fixed period for each enrolled patient to cover all care services. It has been exposed as a solution to the health system's overuse presented in the FFS since it shifts the risk from the payers to the primary care practices [35]. However, there are those who think that providing only a per-patient per-month would encourage the primary care practices to admit patients in better health conditions (i.e., the 'cherry-picking' patients) without having an incentive to improve care quality [36, 40]. Thus, since patients with more severe health conditions also require more care services blending the FFS and the TC could increase the primary care practice's profit and reduce the barriers to its implementation [7]. Similarly, the P4P emerges as an alternative to ensure that the primary care practice also improves quality of care. P4P is a payment method that rewards the practice as long as it achieves specific health care outcomes [35].

The Center for Medicare & Medicaid Innovation (CMMI) has proposed and tested APMs for primary care practices since 2012 [13]. The most recent APM tested is the comprehensive primary care plus (CPC+) and promptly, the primary care first (PCF). However, some concerns have arisen regarding these reimbursement models [30]. First, the proposed Medicare APMs could place primary care practices at financial risk since the compensations under the P4P method relies on factors that the practice has little or no control over, such as visits to the emergency department for random reasons [29]. Hence, a correct design of an APM to estimate the P4P based on aspects managed by the practice is still a subject of discussion [39]. Second, fees and payments under APMs could not be sufficient to cover patients' needs in small primary care practices [30]. This problem would have a notable impact on rural primary care practices since most of them are small in size and provide care to a more severe patient panel than those located in urban areas [25, 33]. Third, the APMs should consider payment based

on patients' severity to ensure that a primary care practice admits patients across risk levels and has enough resources for care delivery [29]. The CMMI has dismissed this aspect, proposing payment models (e.g., the PCF) that use flat fees and payments for all admitted patients [17].

This study aims to provide insight into how the two most recent Medicare APMs, the CPC+ and PCF, contribute to profit, revenue for performance, and patient selection in small (rural) primary care practices when modifying the P4P component to include controllable and non-controllable variables. For this initial exploration, we define the Bice-Boxerman continuity of care index (COCI) as the factor that the practice can control since it relates to a high quality of care, fewer avoidable hospitalizations, increasing providers' and patients' satisfaction, and better patients' health [9, 8, 23]. Similarly, we include the hierarchical condition categories (HCC) risk score as the non-controllable factor, which measures demographic and disease conditions of a patient. We propose a mixed-integer programming (MIP) formulation for hybrid reimbursement models that includes the three payment methods, FFS, TC, and P4P. To evaluate the adjusted P4P component in the MIP formulation, we embed a probabilistic classification model. The probabilistic classification model predicts the likelihood of avoidable hospital admissions of each admitted patient using their HCC score and the COCI as the input variables. We use a 2^k factorial design to assess the effect of the probabilistic classification coefficients given the lack of a model that simultaneously utilizes the HCC score and the COCI to predict avoidable hospitalization extensive to any disease [23]. The modification of the P4P and its integration to the MIP formulation allows evaluating the practice performance based on the expected hospital admission rate rather than the actual admission rate. This adjustment changes the paradigm from better outcomes to better processes [18, 38]. We await to contribute to the primary care providers' payment discussion by adding the following aspects: 1. An MIP formulation for hybrid reimbursement models that combines FFS, TC, and P4P and measures the process of the primary care practice to reduce a potential adverse event, 2. Evidence for small primary care practices and policymakers about the strength and limitations of the CPC+ and PCF when including controllable and non-controllable factors, particularly the COCI and the HCC score, to estimate P4P.

We divide this work into nine sections. Section 2 outlines the literature review. We explain in Section 3 the modeling framework and in Section 4, the MIP formulation. Section 5 describes the Medicare APMs, and Section 6, the set of parameters and experiments. Sections 7, 8, and 9 give the results, discussion, and conclusion, respectively.

2. Literature review

The literature of operations analysis concerning primary care hybrid reimbursement models is limited. Agee and Gates [2] analyze two payment methods, the FFS and an alternative framework proposed by the authors. In the proposed payment model, they

modify pricing and incentive strategies. The authors use game theory to perform the analysis, concluding that under certain conditions, including a cooperative structure, the patient could lower the insurance expenses. Similarly, the provider and insurer could reduce administrative costs. Adida et al. [1] examine the FFS and the bundled payment for care improvement (BPCI) initiative for a set of heterogeneous patients. The analysis considers patient selection and flexibility in the level of care. The authors propose two payment methods, a hybrid reimbursement model that combines the characteristics of the FFS and BPCI and the stop-loss mechanisms, a model that modifies the BPCI. The authors conclude that a hybrid payment system improves performance measures, such as the provider's utility and risk. Andritsos and Tang [6] examine three payment methods, FFS, bundled payment (BP), and P4P, to reduce readmissions. The authors analyze a co-productive relationship between the patients' and hospital's characteristics and hospital's and patients' effect in reduction-effort. They use the Stackelberg game to determine the equilibrium point of three decision levels, the payer, hospital, and patient. The authors conclude that the FFS payment model does not control patients' and hospital's readmission reduction efforts, while P4P is better in reducing readmissions contrasted to BP. Guo et al. [20] analyze the FFS and BP methods considering the perspectives of the patients, payers, and providers, regarding social welfare, revisit rate, and waiting time for outpatient elective care services. The authors use a three-stage Stackelberg game, concluding that the implication of shifting from FFS to BP depends on the practice's panel size. For large and small practices, BP defeats the FFS in a greater number of performance metrics, and for medium practices, both reimbursement models perform similarly under specific conditions. Koenecke [24] considers the payers' and providers' perspectives to analyze the transition from FFS and TC payment models. The author minimizes the payers' net cost and maximizes the practice's revenue in a two-stage Stackelberg game. As part of the payers' model, the author includes a P4P payment method (i.e., a bonus or penalty to the practice). They conclude that both payment methods (i.e., FFS and TC) can co-exist at a potential risk of lower practice performance. Table 1 summarizes the studies based on whether the authors analyze hybrid payment models that blend FFS, TC, and P4P, include P4P, explicitly consider the patient's health conditions and continuity of care, focus entirely on primary care practices reimbursement models, and explore a Medicare APM.

The literature up to date points out that no study analyzes hybrid reimbursement models that blend the FFS, TC, and P4P payment methods to compensate primary care providers. Moreover, few studies explicitly consider the impact of patients' health conditions on the models, and none of them assesses care continuity as a fundamental indicator of practices' performance. Similarly, any study explores the impact of established and innovative APMs on primary care practices' key performance metrics; they describe generic reimbursement models, not reflecting on the current Medicare APMs initiatives. The next section describes the characteristics of the general hybrid

Table 1: Summary of studies that analyze value-based payment models

Study	**Hybrid model (FFS, TC, and P4P)**	**P4P**	**Non-controllable factor (PC)**	**Controllable factor (COC)**	**Primary care**	**Medicare APM**
Agee and Gates [2]					✓	
Adida et al. [1]			✓			✓
Andritsos and Tang [6]		✓	✓			
Guo et al. [20]						
Koenecke [24]		✓			✓	
Present study	✓	✓	✓	✓	✓	✓

FFS: fee-for-service, TC: traditional capitation, P4P: pay-for-performance, PC: patient's health conditions, COC: continuity of care, APM: alternative payment model

reimbursement model framed in the present study.

3. Modeling framework

Our modeling framework encompasses the FFS, TC, and P4P payment methods, as shown in Figure 1, supporting different hybrid reimbursement models that may use a combination of the three payment methods. The FFS is a predefined payment that the practice receives for each care service delivered. Thus, the total revenue per patient is higher if they need more care services and longer team-patient encounters. Similarly, the amount received for each beneficiary under the TC correlates with the patient's risk-adjustment score, returning a more significant amount for individuals in the worst conditions to cover all care services required by the patient in a given period. An example of a risk-adjustment model is the HCC developed by the Centers for Medicare & Medicaid Services (CMS) in 1997 and later adopted by private insurances to adjust payment rates [4].

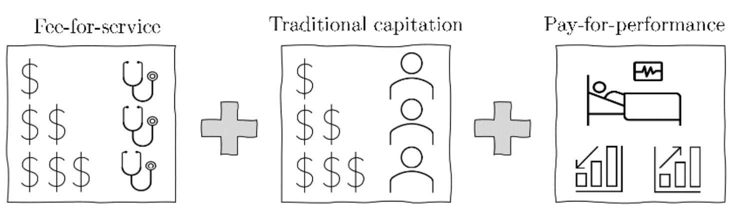


Figure 1: Payment methods comprised in the hybrid reimbursement model

The P4P method is a reward (or penalty) added to the total amount received in a term depending on whether the primary care practice accomplishes a healthcare outcome benchmark. The regulatory entity (e.g., CMS) either establishes the benchmark in advance or obtains it from a regional performance. In our model, we consider the

expected proportion of accepted patients admitted to the hospital, particularly those potentially avoidable at the primary care level, as the quality and utilization indicator of the practice's performance.

To determine the expected proportion of accepted patients who could experience a hospital admission in the next period, we use a probabilistic classification model to compute individual likelihood. The probabilistic classification model considers as input variables patient's risk-adjustment and continuity of care measurements. In particular, the evidence suggests that: (1) the HCC risk score increases the probability of hospital admission as the patient's score rises [21], and (2) the COCI reduces their likelihood of hospital admission as the value increases [8, 19]. The COCI takes values between 0 and 1 and assigns a higher score to patients who receive care from fewer providers in the planning period [10].

In this study to relax the model, we assume that the hybrid reimbursement model operates in primary care practices that work in teams, know their potential patients and care demand at the beginning of a planning period, and admit patients according to their financial needs. The patient's health conditions, the demand for care services, and the individual likelihood of hospital admission are the aspects under consideration to decide on the set of patients to admit in a period that boosts the practice's profit. In the next section, we explain the mathematical structure and elements of the MIP formulation.

4. Mixed-integer programming

Table 2 summarizes the sets, parameters, and decision variables of the MIP formulation. Expression (1) is the objective function; it maximizes the practice's profit, considering the three payment methods and a variable cost that depends on the patient's health conditions in a period.

$$\max \sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}}\sum_{i\in\mathcal{I}}\sigma_{st}v_{ist} + \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}}\xi_{it}x_{it} + \sum_{t\in\mathcal{T}}R_t - \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}}\lambda_{it}x_{it} \tag{1}$$

The first term in Expression (1) represents the amount in FFS earned across periods. Under this method, the practice needs to rise the total office visits delivered to increase its revenue. The decision variable, $v_{ist} \in \mathbb{W}$, is the quantity to be determined, indicating the total number of time slots of the care service, $s \in \mathcal{S}$, delivered to the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$. The care service, $s \in \mathcal{S}$, returns to the practice a total of σ_{st} dollars in the term, $t \in \mathcal{T}$, which could comprise a third-party payer fee, out-of-pocket payment, and geographic adjustment. The second term represents the fee obtained using the TC in a set of terms, granting higher compensations for patients with higher needs. The parameter ξ_{it} is the fee received for the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$, based on their health condition inferred by their risk adjustment score. Under the TC payment

Table 2: Sets, parameters, and decision variables of the formulation

Notation	Description
Set	*Description of the set*
$\mathcal{I}$	set of patients
$\mathcal{S}$	set of care services
$\mathcal{T}$	set of terms
$\mathcal{W}$	set of teamlets
Parameter	*Description of the parameter*
α_t	working time in the term, $t \in \mathcal{T}$ (minutes)
β_j	regression coefficient, $j = \{0, 1, 2\}$
δ_{st}	length of the care service, $s \in \mathcal{S}$, in the term, $t \in \mathcal{T}$ (minutes)
γ_t^P	penalty for failing to achieve a benchmark in the term, $t \in \mathcal{T}$
γ_t^R	reward for achieving a benchmark in the term, $t \in \mathcal{T}$
ε	small number
η_{it}	risk-adjustment score of the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$
λ_{it}	variable cost of caring for the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$
μ	big negative number
M	big positive number
ξ_{it}	fee per accepted patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$ (dollars)
π_t	benchmark in the term, $t \in \mathcal{T}$ (proportion)
σ_{st}	fee per time slot for the care service, $s \in \mathcal{S}$, in the term, $t \in \mathcal{T}$ (dollars)
ϕ_{ist}	number of time slots of the care service, $s \in \mathcal{S}$, demanded by the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$
Variable	*Description of the variable*
a_{wst}	office visits that the teamlet, $w \in \mathcal{W}$, provides of the care service, $s \in \mathcal{S}$, in the term, $t \in \mathcal{T}$ (integer)
b_{iwst}	time slots that the patient, $i \in \mathcal{I}$, receives of the care service, $s \in \mathcal{S}$, from the team, $w \in \mathcal{W}$, in the term, $t \in \mathcal{T}$ (integer)
c_t	1 iff the expected proportion of accepted patients admitted to the hospital, $h_t \in \mathbb{R}$, is above the benchmark π_t in the term, $t \in \mathcal{T}$ (binary)
f_t	total reward (or penalty) for performance estimated for the practice in the term, $t \in \mathcal{T}$ (continuous or integer)
h_t	expected proportion of accepted patients admitted to the hospital in the term, $t \in \mathcal{T}$ (continuous)
m_{it}	Bice-Boxerman continuity of care index of the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$ (continuous)
p_{it}	probability of hospital admission of the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$ (continuous)
r_t	unitary reward (or penalty) in the term, $t \in \mathcal{T}$ (continuous)
R_t	total reward (or penalty) in the term, $t \in \mathcal{T}$ (continuous)
v_{ist}	appointments scheduled for the patient, $i \in \mathcal{I}$, of the care service, $s \in \mathcal{S}$, in the term, $t \in \mathcal{T}$ (integer)
x_{it}	1 iff the practice admits the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$(binary)

method, the practice wants to increase the total admitted patients to maximize the revenue. The decision variable, $x_{it} \in \{0,1\}$, assists in registering an admitted patient, taking the value of 1 if the patient, $i \in \mathcal{I}$, is accepted in the term, $t \in \mathcal{T}$, assuming that the fee for TC is collected at the end of the planning period. The third term describes the total reward (or penalty) for the practice in a planning period (i.e., the P4P). Under this payment method, the practice wants to increase its compensation by improving its performance. The decision variable, $R_t \in \mathbb{R}$, denotes the total reward (or penalty) in the term, $t \in \mathcal{T}$, which rises when the practice's performance exceeds a pre-defined healthcare outcome. The last term is the total variable cost that the primary care practice spends for each accepted patient, $x_{it} \in \{0,1\}$. In particular, the parameter λ_{it} is the cost of caring for the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$. Expressions (2)-(12) are the constraints of the formulation,

$$\phi_{ist} x_{it} = v_{ist}, \quad \forall i \in \mathcal{I}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \tag{2}$$

$$v_{ist} = \sum_{w \in \mathcal{W}} b_{iwst}, \quad \forall i \in \mathcal{I}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \tag{3}$$

$$\sum_{i \in \mathcal{I}} b_{iwst} = a_{wst}, \quad \forall w \in \mathcal{W}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \tag{4}$$

$$\sum_{s \in \mathcal{S}} a_{wst} \delta_{st} \leq \alpha_t, \quad \forall w \in \mathcal{W}, \forall t \in \mathcal{T}, \tag{5}$$

$$(\mu - \varepsilon)(1 - c_t) + \varepsilon \leq h_t - \pi_t \leq (M + \varepsilon) c_t, \quad \forall t \in \mathcal{T}, \tag{6}$$

$$h_t \sum_{i \in \mathcal{I}} x_{it} = \sum_{i \in \mathcal{I}} p_{it} x_{it}, \quad \forall t \in \mathcal{T}, \tag{7}$$

$$p_{it} = \bar{f}\big(\eta_{it}, m_{it} | \beta_0, \beta_1, \beta_2\big), \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{8}$$

$$\sum_{w \in \mathcal{W}} \big(\sum_{s \in \mathcal{S}} b_{iwst}\big)^2 - \sum_{s \in \mathcal{S}} v_{ist} = m_{it} \sum_{s \in \mathcal{S}} v_{ist}\big(\sum_{s \in \mathcal{S}} v_{ist} - 1\big), \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{9}$$

$$r_t = \gamma_t^R (1 - c_t) - \gamma_t^P c_t, \quad \forall t \in \mathcal{T}, \tag{10}$$

$$R_t = r_t f_t, \quad \forall t \in \mathcal{T}, \tag{11}$$

$$f_t = H\big(\sum_{i \in \mathcal{I}} x_{it}\big), \quad \forall t \in \mathcal{T}. \tag{12}$$

Constraint (2) connects the decision variable, $v_{ist} \in \mathbb{W}$, with the decision variable, $x_{it} \in \{0,1\}$. Hence, if the patient, $i \in \mathcal{I}$, is admitted in the term, $t \in \mathcal{T}$, they receive ϕ_{ist} time slots of the care service, $s \in \mathcal{S}$, in the term, $t \in \mathcal{T}$. Note that, for clarity, we include the decision variable, $v_{ist} \in \mathbb{W}$, in the formulation. Constraint (3) ensures that the total time slots of the care service, $s \in \mathcal{S}$, delivered to the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$, is covered by the teamlets. Constraint (4) guarantees that the schedule of the teamlet, $w \in \mathcal{W}$, covers the assigned time slots of the care service, $s \in \mathcal{S}$, of all accepted patients in the term, $t \in \mathcal{T}$. Constraint (5) ensures that the total length

of the care services, $a_{wst} \in \mathbb{W}$, delivered by the teamlet, $w \in \mathcal{W}$, does not exceed the practice working time α_t in the term, $t \in \mathcal{T}$, considering that the care service, $s \in \mathcal{S}$, has a length δ_{st} in the term, $t \in \mathcal{T}$. Constraint (6) establishes that if the proportion, $h_t \in [0, 1]$, of accepted patients admitted to the hospital surpasses the pre-defined benchmark π_t in the term, $t \in \mathcal{T}$, the binary decision variable, $c_t \in \{0, 1\}$, takes the value of 1, and 0 otherwise. Constraint (7) computes the decision variable, $h_t \in [0, 1]$, as the ratio between the expected value of hospital admissions and the total number of accepted patients in the term, $t \in \mathcal{T}$. Constraint (8) determines the likelihood of hospital admission of the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$, with a probabilistic classification model, which uses as input variables the risk-adjustment score η_{it} and the decision variable, $m_{it} \in [0, 1]$, which represents the COCI. Constraint (9) estimates the decision variable, $m_{it} \in [0, 1]$, of the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$. The first term, $\sum_{s \in \mathcal{S}} b_{iwst}$, in the left-hand side represents the number of visits of the patient, $i \in \mathcal{I}$, provided by the teamlet, $w \in \mathcal{W}$, in the term, $t \in \mathcal{T}$. The second term, $\sum_{s \in \mathcal{S}} v_{ist}$, is the total number of appointments of the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$. The linearization of Expressions (9) is shown in Appendix A. Constraint (10) computes the reward (or penalty), $r_t \in \mathbb{R}$, for the practice in the term, $t \in \mathcal{T}$. Consequently, if the binary decision variable, $c_t \in \{0, 1\}$, takes the value of 0, the practice receives a unitary bonus of γ_t^R, and if it is equal to 1, the practice gets a unitary penalty of γ_t^P in the term, $t \in \mathcal{T}$. Constraint (11) determines the total reward (or penalty) of the practice in the term, $t \in \mathcal{T}$. The decision variable, $R_t \in \mathbb{R}$, depends on the decision variables, $r_t \in \mathbb{R}$, and, $f_t \in \mathbb{R}^+$. Constraint (12) estimates the decision variable, $f_t \in \mathbb{R}^+$, as a function H of the total accepted patients in the term, $t \in \mathcal{T}$. This expression is conditional to the characteristics of the reimbursement model under analysis.

5. Medicare alternative payment models

In this section, we describe the general characteristics of the CPC+ and PCF and the formulation adjustments described in Section 4. This study simplifies some of the elements of these two Medicare APMs without significantly modifying their basic structure.

5.1. Comprehensive primary care plus

We consider the fees and payments of the CPC+ Track 1, which focuses on practices that provide care to a less severe patient panel compared to the CPC+ Track 2 [14]. The practices that operate under this payment model receive a monthly care management fee (i.e., TC), a payment under the Medicare physician fee schedule (i.e., FFS), and a performance-based incentive payment (i.e., P4P). The monthly care management fee depends on the complexity of each patient's health conditions. The CPC+ Track 1 uses the HCC risk-adjustment model to classify patients into four risk groups. Under Track 1, the CPC+ pays the conventional FFS amounts. Similarly, it rewards the practice if

it meets a performance threshold based on quality, utilization, and patient experience [3].

The objective function of the MIP formulation presented in Section 4 remains the same for the CPC+ Track 1. In the CPC+ Track 1, the unitary reward (or penalty) for performance, $r_t \in \mathbb{R}$, is multiplied by the total number of admitted patients in the term, $t \in \mathcal{T}$. Hence, we replace Expressions (12) by Expressions (13) to compute the decision variable, $f_t \in \mathbb{W}$, adding it to the set of constraints enumerated in Section 4,

$$f_t = \sum_{i \in \mathcal{I}} x_{it}, \quad \forall t \in \mathcal{T}. \tag{13}$$

5.2. *Primary care first*

We consider the characteristics of the 'general PCF' payment model. The model introduces three payment methods, an up-front population-based payment (i.e., TC), a flat fee rate per visit (i.e., FFS), and an upside or downside performance-based adjustment (i.e., P4P). The population-based payment is the same for every registered patient, but it differs from practice to practice based on the patient panel's average of HCC scores. Consequently, a primary care practice obtains the same fee for patients with high and low needs [17]. Under this APM, the FFS rate is the same for all care services. For the P4P component, acute hospitalization is the utilization measurement that determines the practice's reward in the first year of implementation. The performance is contrasted to a regional achievement to assess P4P. The general PCF also considers leakage, geographic, and continuous improvement adjustments, which we do not include to overcome complexity.

Table 3: Additional sets, parameters, and decision variables of the formulation

Notation	Description
$\mathcal{G}$	set of groups
κ^L_{gt}	lower bound of the risk-adjustment score for the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$
κ^U_{gt}	upper bound of the risk-adjustment score for the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$
ρ_{gt}	fee for a patient in the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$ (dollars)
d_{gt}	1 iff the lower and upper bound resemble in the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$ (binary)
d^L_{gt}	1 iff the average of patients' risk-adjustment scores is greater or equal to κ^L_{gt} in the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$ (binary)
d^U_{gt}	1 iff the average of patients' risk-adjustment scores is less than κ^U_{gt}, the upper bound of the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$ (binary)
e_t	fee per admitted patient that the primary care practice receives in the term, $t \in \mathcal{T}$ (continuous)

The general PCF formulation differs somewhat from the model presented in Section 4. Table 3 describes the additional sets, parameters, and decision variables for the

PCF mathematical formulation. Precisely, we replace the parameter ξ_{it} in Expression (1) that represents the payment per accepted patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$, by the decision variable, $e_t \in \mathbb{R}^+$, which is the fee per admitted patient that the practice receives in the term, $t \in \mathcal{T}$. Expression (14) shows the objective function for the general PCF payment model,

$$\max \sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}}\sum_{i\in\mathcal{I}} \sigma_{st} v_{ist} + \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}} e_t x_{it} + \sum_{t\in\mathcal{T}} R_t - \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{I}} \lambda_{it} x_{it}. \tag{14}$$

Constraint (15) replaces Constraint (12), and Expressions (16)–(20) describe the constraints added to those defined in Section 4. These extra constraints allow estimating the decision variables, $e_t \in \mathbb{R}^+$, and, $f_t \in \mathbb{R}^+$, in the term, $t \in \mathcal{T}$,

$$f_t = \sum_{s\in\mathcal{S}}\sum_{i\in\mathcal{I}} \sigma_{st} v_{ist} + \sum_{i\in\mathcal{I}} e_t x_{it}, \quad \forall t \in \mathcal{T}, \tag{15}$$

$$(\mu - \varepsilon) d^L_{gt} + \varepsilon \leq \kappa^L_{gt} \sum_{i\in\mathcal{I}} x_{it} - \sum_{i\in\mathcal{I}} \eta_{it} x_{it}, \quad \forall g \in \mathcal{G}, \forall t \in \mathcal{T}, \tag{16}$$

$$(\mu - \varepsilon) d^U_{gt} \leq \sum_{i\in\mathcal{I}} \eta_{it} x_{it} - \kappa^U_{gt} \sum_{i\in\mathcal{I}} x_{it} \quad \forall g \in \mathcal{G}, \forall t \in \mathcal{T}, \tag{17}$$

$$d^L_{gt} + d^U_{gt} - d_{gt} \leq 1, \quad \forall g \in \mathcal{G}, \forall t \in \mathcal{T}, \tag{18}$$

$$\sum_{g\in\mathcal{G}} d_{gt} \leq 1, \quad \forall t \in \mathcal{T}, \tag{19}$$

$$e_t = \sum_{g\in\mathcal{G}} \rho_{gt} d_{gt}, \quad \forall t \in \mathcal{T}. \tag{20}$$

Constraint (15) estimates the decision variable, $f_t \in \mathbb{R}^+$, as the sum of the total FFS payment and TC fee obtained in the term, $t \in \mathcal{T}$. Constraint (16) determines whether the parameter κ^L_{gt}, the lower bound of the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$, is also the lower bound for the average accepted patients' risk-adjustment scores of the practice. This value is estimated using the parameter η_{it} that indicates the risk-adjustment score of the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$. Hence, the decision variable, $d^L_{gt} \in \{0, 1\}$, takes the value of 1 in the risk group, $g \in \mathcal{G}$, if the average of the patients' risk-adjustment scores is greater or equal to κ^L_{gt} in the term, $t \in \mathcal{T}$. The variable takes the value of 0 otherwise. Similarly, Constraint (17) determines the upper bounds of the set of admitted patients. The decision variable, $d^U_{gt} \in \{0, 1\}$, takes the value of 1 if the average of the patients' risk-adjustment scores is less than κ^U_{gt}, the upper bound of the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$. The binary decision variable takes the value of 0 otherwise. Constraints (18) and (19) ensure that the practice classifies in only one risk group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$. The decision variable, $d_{gt} \in \{0, 1\}$, takes the value of 1 when the lower and upper bound resemble in the group, $g \in \mathcal{G}$, in the term,

$t \in \mathcal{T}$, and 0 if it is not. Constraint (20) estimates the decision variable, $e_t \in \mathbb{R}^+$, that represents the amount received by the primary care practice per admitted patient in the term, $t \in \mathcal{T}$. It is a function of the parameter ρ_{gt}, the fee for each accepted patient when the primary care practice classifies in the risk group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$.

5.3. Probabilistic classification model

The CPC+ and PCF reimbursement models estimate the P4P component using the HCC score and the COCI framed in a binary logistic regression model that predicts the likelihood of hospital admission. The use in this analysis of a logistic regression model is due to the following: (1) it forms part of the probabilistic classification family, and thus, provides a likelihood of hospital admission and not only a binary outcome, (2) it is mathematically tractable and easy to embed in the MIP formulation given its explicit expression contrasted with other probabilistic classification models, such as naive Bayes and multilayer perceptrons, (3) it is of simple linearization. Thus, we replace Expressions (12) with Expressions (21). The linearization of Constraint (21) is in Appendix B,

$$\ln\Big(\frac{p_{it}}{1-p_{it}}\Big) = \beta_0 + \beta_1\eta_{it} + \beta_2 m_{it}, \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}. \tag{21}$$

6. Sets, parameters, and experiments

This section describes the sets and parameters of the CPC+ and PCF payment models and the experiments to determine the effect of the factors of the adjusted P4P component on key metrics. For the CPC+, we use Constraints (2)–(7), (9)–(11), (13), and (21) and the objective function in Expression (1). For the PCF payment model, we use Constraints (2)–(7), (9)–(11), (15)–(21) and Expression (14) as the objective function.

6.1. Sest and parameters

Table 4 shows the parameters for the CPC+ and PCF. The analysis considers two sets of teams, $\mathcal{W} = \{1, 2\}$ and $\mathcal{W} = \{1, \ldots, 4\}$, representing small primary care practices with two and four teamlets. A physician (and thus, a team) works, on average, 40.03 hours each week on clinical duties (not including paperwork), which is equivalent to eight working-hours each day [34]. We analyze one month that represents one term, $\mathcal{T} = \{1\}$; thus, the parameter α_t is equal to $9,600$ minutes for the term, $t \in \mathcal{T}$. Usually, a term represents one to four months, which are the payment periods of the FFS, TC, and P4P methods [16]. The set of care services included in the analysis are those categorized as 'evaluation and management' (E&M) with current procedural terminology (CPT) codes 99201-99204 and 99211-99214. Under the CPC+, the payments vary based on the consultation length, and for the PCF, it is a flat fee of \$50 for each care service [29].

The CMMI defines a set of four HCC risk-adjustment groups, $\mathcal{G} = \{1, \ldots, 4\}$, for the general PCF payment model. Specifically, the HCC score is less than 1.2 in group 1, between 1.2 and 1.5 in group 2, between 1.5 and 2 in group 3, and greater than 2 in group 4. Under the PCF payment model, the per-patient per-term fee is \$28, \$45, \$100, and \$170, for patients in groups 1, 2, 3, and 4, respectively, groups estimated using the average severity of the patient panel of the practice [12]. We use the same classification to differentiate the risk groups and estimate the parameter ξ_{it} in the CPC+ payment model. The fees under this model in the term, $t \in \mathcal{T}$, are \$6, \$8, \$16, and \$30 for groups 1, 2, 3, and 4, respectively [14].

The practice receives a reward if it does not reach a hospital admission rate of π_t in the term, $t \in \mathcal{T}$. We evaluate the CPC+ and PCF for values of the parameter π_t equal to 25% and 75% in the term, $t \in \mathcal{T}$. The CPC+ offers a reward of \$2.5 per accepted patient per month for exceeding performance in quality and utilization measurements. There is no penalty for poor execution [3]. On the contrary, the PCF provides different compensations depending on the percentile the practice holds relative to a regional benchmark, increasing the practice revenue by up to 34% and reducing it up to 10%. The percentage of reward (or penalty) is computed over the total revenue in FFS and TC in the term, $t \in \mathcal{T}$ [15]. The labor and overhead cost λ_{it} per accepted patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$, is the same for both reimbursement models. We base the estimation using the results from the study conducted by Meyers et al. [28], in which the authors compute costs for different severity levels in rural primary care practices. The values are adjusted to 2020 US dollars and associated to a risk group from the set, $\mathcal{G} = \{1, \ldots, 4\}$. Thus, the cost for each group is \$29, \$43, \$52, and \$65, respectively. In particular, we compute the cost for group 1 as the average proportion of the fee per-patient per-term under the CPC+ and PCF payment models since it is not estimated in the referenced study.

Table 5: Probabilities of each risk group to require a care service

Care service	CPT code	Description	Potential risk group	Prob. Group 1	Prob. Group 2	Prob. Group 3	Prob. Group 4
s=1	99201	Office visit for the E&M of a new patient	1	1	0	0	0
s=2	99202	Office visit for the E&M of a new patient	2	0	1	0	0
s=3	99203	Office visit for the E&M of a new patient	3	0	0	1	0
s=4	99204	Office visit for the E&M of a new patient	4	0	0	0	1
s=5	99211	Problem(s) are minimal	1, 2, 3, 4	0.4	0.3	0.1	0.1
s=6	99212	Problem(s) are self-limited or minor	1, 2, 3, 4	0.3	0.4	0.2	0.2
s=7	99213	Problem(s) are of low to moderate severity	1, 2, 3, 4	0.2	0.2	0.4	0.3
s=8	99214	Problem(s) are of moderate to high severity	1, 2, 3, 4	0.1	0.1	0.3	0.4

We simulate the risk group and HCC score for each patient from the set, $\mathcal{I} = \{1, \ldots, 500\}$ [28], in the term, $t = 1 \in \mathcal{T}$. A similar procedure is applied to estimate the set of time slots ϕ_{ist} of the care service, $s \in \mathcal{S}$, required by the patient, $i \in \mathcal{I}$, in the

Table 4: Parameters of CPC+ and PCF reimbursement models

Notation	Description	CPC+	PCF
α_t	time slots in the term, $t \in \mathcal{T}$	$9,600$	$9,600$
β_0^*	logistic regression coefficient	–1.83	–1.83
β_1^*	logistic regression coefficient	1.34	1.34
β_2^*	logistic regression coefficient	–0.95	–0.95
δ_{st}	length of the care service, $s \in \mathcal{S}$, in the term, $t \in \mathcal{T}$ (minutes)	$\begin{array}{c} s=1\\ s=2\\ s=3\\ s=4\\ s=5\\ s=6\\ s=7\\ s=8 \end{array}\begin{bmatrix} 10\\ 20\\ 30\\ 45\\ 5\\ 15\\ 15\\ 25 \end{bmatrix}$	$\begin{array}{c} s=1\\ s=2\\ s=3\\ s=4\\ s=5\\ s=6\\ s=7\\ s=8 \end{array}\begin{bmatrix} 10\\ 20\\ 30\\ 45\\ 5\\ 15\\ 15\\ 25 \end{bmatrix}$
γ_t^P	penalty for failing to achieve a benchmark in the term, $t \in \mathcal{T}$	\$0	10%
γ_t^R	reward for achieving a benchmark in the term, $t \in \mathcal{T}$	\$2.5	34%
ε	small number	0.0001	0.0001
κ_{gt}^L	lower bound of the risk-adjustment score for the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$	–	$\begin{array}{c} g=1\\ g=2\\ g=3\\ g=4 \end{array}\begin{bmatrix} 0.9\\ 1.2\\ 1.5\\ 2.0 \end{bmatrix}$
κ_{gt}^U	upper bound of the risk-adjustment score for the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$	–	$\begin{array}{c} g=1\\ g=2\\ g=3\\ g=4 \end{array}\begin{bmatrix} 1.2\\ 1.5\\ 2.0\\ 3.0 \end{bmatrix}$
λ_{it}^{**}	variable cost to provide care to the patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$	$\begin{array}{c} g=1\\ g=2\\ g=3\\ g=4 \end{array}\begin{bmatrix} \$29\\ \$43\\ \$52\\ \$65 \end{bmatrix}$	$\begin{array}{c} g=1\\ g=2\\ g=3\\ g=4 \end{array}\begin{bmatrix} \$29\\ \$43\\ \$52\\ \$65 \end{bmatrix}$
μ	big negative number	–10,000	–10,000
M	big positive number	10,000	10,000
ξ_{it}^{**}	fee per accepted patient, $i \in \mathcal{I}$, in the term, $t \in \mathcal{T}$ (dollars)	$\begin{array}{c} g=1\\ g=2\\ g=3\\ g=4 \end{array}\begin{bmatrix} \$6\\ \$8\\ \$16\\ \$30 \end{bmatrix}$	–
π_t	benchmark in the term, $t \in \mathcal{T}$ (percentage)	0.25, 0.75	0.25, 0.75
ρ_{gt}	fee for a patient in the group, $g \in \mathcal{G}$, in the term, $t \in \mathcal{T}$ (dollars)	–	$\begin{array}{c} g=1\\ g=2\\ g=3\\ g=4 \end{array}\begin{bmatrix} \$28\\ \$45\\ \$100\\ \$175 \end{bmatrix}$
σ_{st}	fee for the care service, $s \in \mathcal{S}$, in the term, $t \in \mathcal{T}$ (dollars)	$\begin{array}{c} s=1\\ s=2\\ s=3\\ s=4\\ s=5\\ s=6\\ s=7\\ s=8 \end{array}\begin{bmatrix} \$46\\ \$77\\ \$109\\ \$167\\ \$23\\ \$46\\ \$76\\ \$110 \end{bmatrix}$	$\begin{array}{c} s=1\\ s=2\\ s=3\\ s=4\\ s=5\\ s=6\\ s=7\\ s=8 \end{array}\begin{bmatrix} \$50\\ \$50\\ \$50\\ \$50\\ \$50\\ \$50\\ \$50\\ \$50 \end{bmatrix}$

* The value represents the central point of the cases analyzed
**Each patient relates to a fee based on the group where they classify

term, $t = 1 \in \mathcal{T}$. Table 5 displays different probabilities of demanding a care service for each risk group to ensure that the potential patient receives care according to their risk group without leaving aside each patient's individuality. We assume that the set of patients are new for the practice, and based on their risk groups, each patient, $i \in \mathcal{I}$, requests one of the care services, $s = \{1, \ldots, 4\} \in \mathcal{S}$, one time in the term, $t \in \mathcal{T}$. Similarly, patients can demand the care services from the set, $s = \{5, \ldots, 8\} \in \mathcal{S}$, more than one time in the term, $t \in \mathcal{T}$, totaling 3, 4, 5, and 6 care services for patients classified in the groups 1, 2, 3, and 4, respectively.

We associate the coefficient β_0 with the fact that if a patient receives care from a primary care provider, it should reduce the probability of hospital admissions. This reduction could have an average log odds ratio of –1.83 [11]. Similarly, based on the study conducted by Mosley et al. [32], the HCC risk-adjustment score (i.e., the parameter η_{it}) increases the probability of hospital admission of the patient, $i \in \mathcal{I}$, by a log odds ratio of 1.34 in the term, $t \in \mathcal{T}$. The coefficient β_2 of the decision variable, $m_{it} \in [0, 1]$ (i.e., the COCI), reduces the likelihood of a hospital admission of the patient, $i \in \mathcal{I}$, by 0.18 in the term, $t \in \mathcal{T}$ [9]. These values are used to estimate the range of values of the logistic regression coefficients in the next subsection.

6.2. Design of the experiment

We perform a 2^5 unreplicated full factorial design for the CPC+ and PCF reimbursement models, using a low and high level of each factor in the standard order, totaling 64 experiments. The factors considered in the analysis are the number of teams in the primary care practice (factor A), logistic regression coefficients (factors B, C, and D), the benchmark for hospital admission (factor E), and the reimbursement model (factor F). Factors B, C, D, and E represent the parameters that characterize the adjusted P4P component. Table 6 displays the factors, levels, and estimation of the ranges for the logistic regression coefficients using the central points established for β_0 and β_1.

Table 6: Factors and levels for the 2^k factorial design

Factors			**Levels**	
Notation	**Parameter**	**Description**	**Low**	**High**
A	$\lvert\mathcal{W}\rvert$	Practice size	2	4
B	β_0	Regression coefficient	-2.75 (-1.83*1.5)	-0.92 (-1.83*0.5)
C	β_1	Regression coefficient HCC score	0.67 (1.34*0.5)	2.01 (1.34*1.5)
D	β_2	Regression coefficient Bice-Boxerman COC index	-1.71 (-0.5*[$\lvert -2.75\rvert$ +0.67])	-0.18
E	π^*	Threshold	0.25	0.75
F	Model	Type of reimbursement model	0 (CPC+)	1 (PCF)

$^*\pi_t = \pi, \forall t \in \mathcal{T}$

The output variables are the profit per team, revenue for performance per team, and patients' average of HCC scores. We use Python 3.7 as the programming language for the experiments and Gurobi 9.0 as the MIP solver, applying an optimality gap of 10% to all cases. The analysis of the factorial design is implemented in the software R 4.0.3.

7. Results

This section describes the outcomes obtained in the 2^k factorial design for the three key performance metrics and the sensitivity analysis over the parameter γ_t^R $(t \in \mathcal{T})$, considering the same set of experiments performed in the factorial design.

7.1. Results factorial design

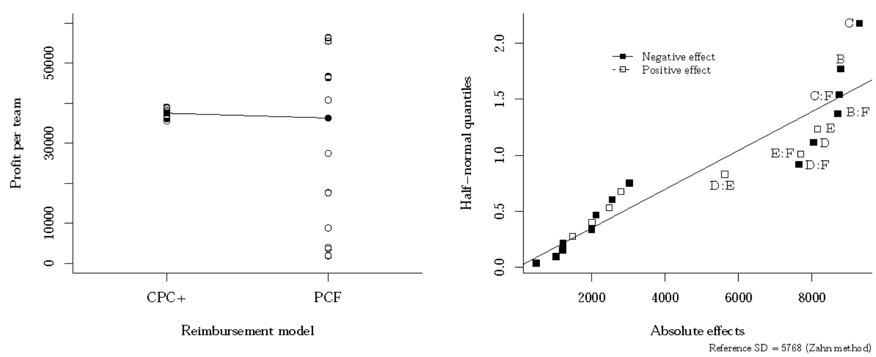
Table 7 displays the results of the second-order Akaike information criterion (AIC) of three analysis of variance (ANOVA) models for each output variable. The ANOVA models 1, 2, and 3 represent a first-, second-, and third-order interaction, respectively. For the output variable 'profit per team,' we use the ANOVA model 2 since it explains an additional 38% of the total variation in the dependent variable. Similarly, we examine the ANOVA model 2 for the output variable 'revenue for performance per team' and the ANOVA model 1 for the 'average of HCC scores,' which considers only the main effects. Appendix C shows the normal probability and residuals versus fitted values plots for each output variable.

Table 7: ANOVA models that best explain the variation in the dependent variable

Output variable	ANOVA model	K	AICc	Delta AICc	AICc weight	Cumulative weight	Log likelihood
Profit per team	1	8	1404.74	0	0.62	0.62	–693.06
	2	23	1405.71	0.97	0.38	1	–666.06
	3	43	1570.04	165.29	0	1	–647.42
Revenue for performance per team	1	8	1259.79	0	0.55	0.55	–620.58
	2	23	1260.19	0.41	0.45	1	–593.3
	3	43	1431.17	171.38	0	1	–577.98
Average HCC scores	1	8	-22.7	0	1	1	20.66
	2	23	–6.49	16.21	0	1	40.05
	3	43	124.82	147.52	0	1	75.19

K: number of estimated parameters for the ANOVA model

7.1.1. *Profit per team*



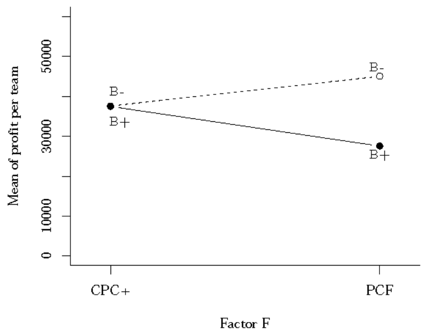
(a) Dot plot distribution depicting the effects of factor F

(b) Half-normal plot of the factor effects

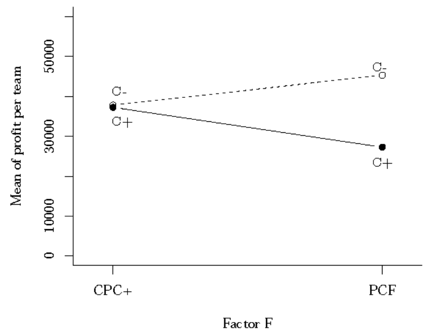
Figure 2: Results profit per team

Figure 2a displays the dot plot of the profit per team for the categorical factor F, where 0 represents the CPC+ and 1, the PCF payment model. PCF shows a high variability across the experiments compared with the CPC+. The PCF model has a standard deviation equal to \$21,526, whereas the CPC+ has a standard deviation equal to \$1,226. The mean profit per team across the experiments is similar in both models. The CPC+ and PCF have an average equal to \$37,526 and \$36,301 per team per month, respectively. Factor F has an estimated negative effect equal to 1,226 on the profit per team represented by the nearly horizontal line. This effect appears relatively small to other factors and interactions, and thus, factor F does not have a significant effect on the profit per team. Figure 2b shows the half-normal plot, where the squares that fall off the straight line represent the significant effects [31]. The white squares such as the interaction of factors E (i.e., the threshold π) and D (i.e., β_2), and E and F represent positive effects on the output variable. In contrast, the black squares, such as the interaction effects of factor F with factors B (i.e., β_0), C (i.e., β_1), and D, denote negative effects on the profit per team.

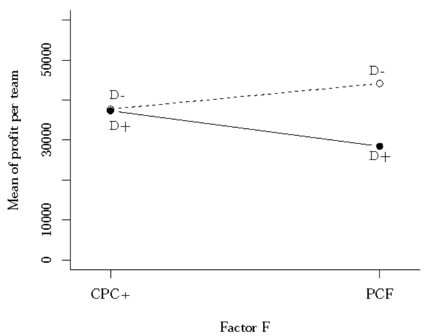
Notwithstanding that factor F by itself does not have a significant effect on the profit per team, its interactions with other factors produce changes in the output variable, as shown in Figure 3. Figures 3a, 3b, 3c, and 3d indicate that if the coefficients of the logistic regression take the highest values and, additionally, the threshold π is about 25%, CPC+ provides higher profit per team in small primary care practices. Note that the profit per team does not vary notably under the CPC+ payment model when turning factors B, C, D, and E from the low to the high level. Conversely, if the coefficients take the smallest values and the benchmark π is high (i.e., 75%), PCF outperforms CPC+.



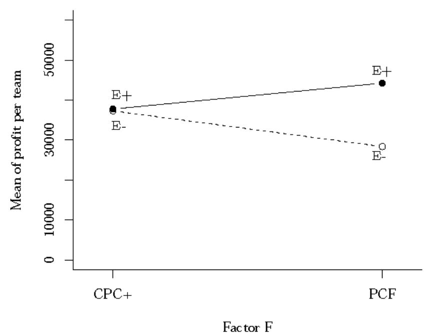
(a) Factors B and F



(b) Factors C and F



(c) Factors D and F

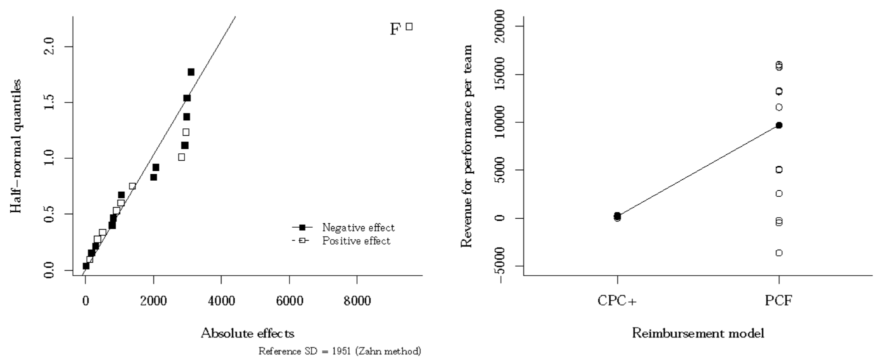


(d) Factors E and F

Figure 3: Interaction effects of factor F and factors B, C, D, and E

7.1.2. Revenue for performance

Factor F has a significant positive effect on revenue for performance per team (Figure 4a). The logistic regression coefficients and their interactions do not seem to impact the output variable significantly. Since the effect of factor F is positive, if the primary care practice operates under the PCF model, the revenue for performance per team on average is higher than the amount obtained under the CPC+ ($9,687 versus $164). However, PCF presents a high variability across the experiments, ranging from $3,628 of penalty to $16,023 of reward, as indicated by Figure 4b. Note that the CPC+ reports a 0.4% average percentage of revenue in P4P, a low rate compared with PCF, which equals an average of 16.5% in the 32 experiments. More than 95% of the total revenue of the CPC+ is FFS, followed by 4.2% in TC fees. In contrast, PCF registers an average of 56.8% in FFS and 26.7% in TC based on the total revenue obtained in a month.



(a) Half-normal plot of the factor effects

(b) Dot plot distribution depicting the effect of factor F

Figure 4: Results revenue for performance per team

Given the imbalance percentage of P4P in the reimbursement models, we analyze the revenue for performance per team for the CPC+ and PCF independently, totaling 32 experiments in each model. Table 8 displays the outcomes of first-order ANOVA models for each reimbursement model, which fully explain the variations in the output variable 'revenue for performance per team.' Factors B, C, D, and E have a high percentage of contribution to the output variable in both reimbursement models. Particularly, if the coefficient β_1 increases from 0.67 to 2.01, the revenue for performance per team reduces since a high value of factor C indicates more likelihood of hospital admission and potentialities to achieve and suppress the established benchmark. Similarly, the regression coefficients β_0 and β_2 reduce the output variable when moving from –2.75 to –0.92 and from –1.71 to –0.18, respectively, since they also relate to an increas-

ing probability of hospital admissions. Conversely, factor E improves the revenue for performance per team when the threshold changes from 25% to 75%, a more flexible benchmark for hospital admission rate. Still, the estimated effect of the factors in the output variable is more notable under the PCF payment model.

Table 8: Effect on revenue for performance per team under the CPC+ and PCF, independently

CPC+					PCF				
Model term	**Effect estimate**	**Sum of squares**	**Percent contribution**	**P-value**	**Model term**	**Effect estimate**	**Sum of squares**	**Percent contribution**	**P-value**
A	27.23	5930	1.7	0.357	A	−1599	20455503	2.1	0.316
B	−65.74	34576	9.9	0.032	B	−5912	279588679	28.1	0.001
C	−131.45	138223	39.5	0.001	C	−6084	296164711	29.7	0.001
D	−65.2	34003	9.7	0.033	D	−4078	133059941	13.4	0.015
E	131.13	137567	39.3	0.001	E	5778	267103795	26.8	0.001

7.1.3. Average of HCC scores

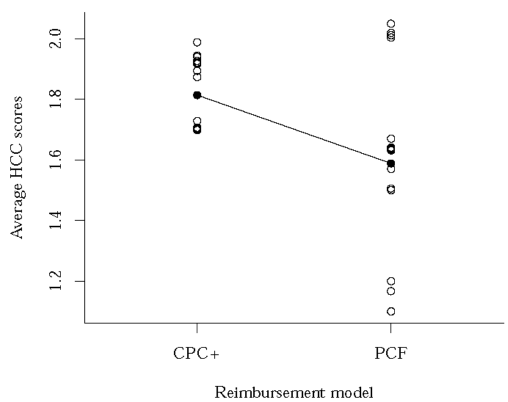


Figure 5: Main effect of factor F in the average of HCC scores

Factor F has the highest effect (p-value > 0.001) on the output variable 'average of HCC scores' of the admitted patients in one month of the planning period. Figure 5 illustrates the variability in the average of HCC scores of the admitted patients for each PCF experiment contrasted to the results of the CPC+. The PCF has a minimum average of HCC scores equal to 1.1 and a maximum of 2.1, while CPC+ varies from 1.7 to 2.0. The average of the HCC scores is smaller for the PCF than the CPC+ (i.e., 1.59 versus 1.81). On average, both payment models accept patients from risk group

3; however, the patient selection from all risk groups differs in the CPC+ and PCF. CPC+ admits higher percentages of patients from groups 3 and 4 (32.2% and 32.1%, respectively) and PCF mainly from groups 1 and 2 (37.9% and 22.6%, respectively). Hence, PCF seems to reach optimal or close to optimal profit when the practice accepts a higher percentage of less severe patients. On the contrary, CPC+ achieves its maximum profit by accepting patients in more severe conditions.

Table 9 presents the results of first-order ANOVA models for the CPC+ and PCF independently. Factor A (i.e., the practice size) has a significant effect on patient admission when the practice operates under the CPC+. A primary care practice with four teams admits less severe patients, contrasted with practices that serve with two teamlets. Factor C has a significant effect on the patient selection under the PCF payment model. The value of the regression coefficient β_1 equal to 0.67 (i.e., a low level) relates to a smaller 'average of HCC scores,' and thus, a less severe admitted set of patients. A higher value of β_1 is associated with slightly more severe patient admissions.

Table 9: Effect on the average of HCC scores under the CPC+ and PCF, independently

CPC+					PCF				
Model term	**Effect estimate**	**Sum of squares**	**Percent contribution**	**P-value**	**Model term**	**Effect estimate**	**Sum of squares**	**Percent contribution**	**P-value**
A	−0.217	0.3502	99.80	< 0.001	A	0.06	0.023	5.54	0.45
B	0.006	0.0003	0.09	0.04	B	0.02	0.000	0.00	0.99
C	0.005	0.0002	0.06	0.11	C	0.21	0.341	82.46	0.01
D	0.005	0.0002	0.06	0.10	D	0.06	0.030	7.26	0.39
E	0.001	0	0.00	0.87	E	-0.05	0.020	4.74	0.48

7.2. Sensitivity analysis

To determine the impact of incrementing the reward of the CPC+ on the output variables, we perform a sensitivity analysis over the parameter γ_t^R $(t \in \mathcal{T})$ for the CPC+ and PCF. Similarly, the analysis examines the impact of reducing the PCF bonus percentage on the profit variability. Table 10 summarizes the CPC+ and PCF results after increasing the reward from \$2.5 to \$100 and reducing the bonus from 34% to 10%; it also presents the outcomes of the traditional FFS payment model. According to the results, the CPC+ performs similarly to the traditional FFS in most of the metrics, reinforcing the issue that the FFS component drives the CPC+ model. The PCF outcomes differ from the FFS, exposing that the PCF has a distinctive structure that diverges from the traditional FFS. Nonetheless, the CPC+ and PCF have in common high COCI values that reasonably relate to its inclusion in the P4P component.

Table 10: Results of modifying the parameter γ_t^R $(t \in \mathcal{T})$ for the CPC+ and PCF

Metric	Statistics	Traditional FFS	CPC+ $\gamma_t^R = \$2.5$	CPC+ $\gamma_t^R = \$100$	PCF $\gamma_t^R = 34\%$	PCF $\gamma_t^R = 10\%$
Profit*	Mean	35850	37526	45719	36301	28862
	SD	1256	1226	6335	21526	17657
FFS*	Mean	41033	40750	40507	21308	20821
	SD	976	1023	1051	11825	12349
TC*	Mean	0	1773	1752	9756	9546
	SD	0	34	36	5670	5836
P4P*	Mean	0	164	9223	9687	2844
	SD	0	130	0	6970	2112
% FFS of the total revenue	Mean	100	95.5	80.0	56.9	64.6
	SD	0	0.3	10.9	10.9	6.0
% TC of the total revenue	Mean	0	4.2	3.5	26.8	31.5
	SD	0	0.1	0.5	10.1	9.1
% P4P of the total revenue	Mean	0	0.4	16.5	16.3	3.9
	SD	0	0.3	11.4	16.1	9.0
HCC	Mean	1.81	1.81	1.61	1.59	1.62
	SD	0.10	0.11	0.15	0.24	0.25
% patients admitted from group 1	Mean	23.3	23.5	30.6	38.2	35.9
	SD	1.6	1.8	7.7	19.4	16.4
% patients admitted from group 2	Mean	14.4	12.5	21.0	22.4	22.3
	SD	4.2	6.4	4.3	11.5	10.9
% patients admitted from group 3	Mean	31.6	32.1	28.4	17.8	18.5
	SD	1.9	2.5	2.6	11.7	10.6
% patients admitted from group 4	Mean	30.7	32.0	20.0	21.6	23.3
	SD	3.9	5.3	8.5	12.8	13.3
% Acceptance	Mean	64.8	64.4	74.2	58.6	56.7
	SD	26.4	26.8	20.0	35.2	36.0
Bice-Boxerman COC index	Mean	0.56	1.00	0.98	0.99	1.00
	SD	0.09	0.00	0.08	0.05	0.01

* per team

Considering the same set of parameters and experiments used for a reward equal to \$2.5, an increment on the bonus to \$100 changes the distribution of the FFS, TC, and P4P revenues to 80%, 3.5%, and 16.5%, respectively, describing a more similar P4P proportion to the PCF model. Notably, another consequence of increasing the reward for performance in the CPC+ model is the variation in the acceptance rate. The model now admits more patients, with a higher rate from the risk group 1 to the detriment of patients from the risk group 4 (Table 10). The ANOVA model in the right side of Table 11 explains 93% of the total variation of the profit per team and indicates that the only factor that has a significant effect on the profit per team is the categorical factor G (i.e., the current model versus the same model with the increased reward). Despite the augmented weight assigned to the P4P component in the CPC+ model, the interactions between the P4P elements and the profit per team remain unchanged and not significant.

According to Table 10, reducing the reward of the PCF decreases slightly the variability (i.e., from $\$21,526$ to $\$17,657$) but also the total profit per team (i.e., from $\$36,301$ to $\$28,862$). 10% of the total reward moderately increases patients' acceptance in risk groups 3 and 4 to compensate for the cutback by increasing the FFS and TC returns. The right side of Table 11 displays the results of the first-order ANOVA model that includes factor H (i.e., PCF model with 34% of reward versus the adjusted model with 10% of bonus). Among the factors analyzed, all of them individually have a significant effect on the output variable. Thus, reducing the parameter γ_t^R $(t \in \mathcal{T})$ decreases the profit per team. Still, the logistic regression coefficients and the threshold to evaluate performance are the main factors, which have the highest effects on the profit per team.

Table 11: Effect of factors G and H on the profit per team under the CPC+ and PCF, respectively

CPC+					PCF				
Model term	Effect estimate	Sum of squares	Percent contribution	P-value	Model term	Effect estimate	Sum of squares	Percent contribution	P-value
A	−2687	1.16E8	7.1	0.004	A	−4765	3.75E8	23.1	0.13
B	−2384	9.10E8	5.6	0.011	B	−15628	3.91E9	241.0	<0.0001
C	−2843	1.29E8	8.0	0.003	C	−15389	3.78E9	233.0	<0.0001
D	−2599	1.08E8	6.7	0.006	D	−14839	3.53E9	217.3	<0.0001
E	2568	1.06E8	6.5	0.006	E	15215	3.70E9	228.0	<0.0001
G	8193	1.07E9	66.2	<0.0001	H	−7360	8.52E8	52.5	0.0209

Factor G: '0' $\gamma_t^R = \$2.5$, '1' $\gamma_t^R = \$100$
Factor H: '0' $\gamma_t^R = 34\%$, '1' $\gamma_t^R = 10\%$

8. Discussion

This study analyzes the two most recent Medicare APMs, the CPC+ and PCF, for small primary care practices, considering estimation costs incurred in rural areas. The CPC+ has been tested since 2017, while PCF is a payment model that is scheduled to begin operating in 2021. We modify the P4P component of these reimbursement models to determine, using the HCC score and the COCI, the expected rate of hospital admissions in a set of admitted patients. The adjustment in the P4P implies focusing on the process rather than outcomes, evaluating the primary care providers' effort in reducing the likelihood of hospital admission rather than centering on the actual hospital admission rate. We analyze the performance of the reimbursement models for one month, considering three output variables: profit per team, revenue for performance per team, and the severity of the admitted patients. Using a factorial design, we alter the logistic regression coefficients, the practice size, and hospital admission benchmark for a planning period. The results indicate that the logistic regression coefficients, as well as the threshold for hospital admissions, have a significant effect on the output variables, particularly in the revenue for performance per team. However, the small

proportion of the P4P component in the total revenue under the CPC+ overshadows the effects. Similarly, the connection of the P4P with the FFS and TC components in the PCF payment model creates high variability in the output variables when modifying the parameters of the P4P.

A reduced variability favors stability to the primary care practices given the predictability of the incomes. The low variation in the output variables is the advantage of the CPC+ over the PCF, an aspect mentioned as a characteristic of the CPC+ [5]. Moreover, CPC+ does not penalize for poor performance; therefore, a worst-case scenario is a reward equal to $0, which renders less uncertainty to a primary care practice. However, the low variation of the output variable under the CPC+ is due to the still high FFS proportion and low rate of P4P in the total revenue. Since Medicare APMs aim to change the current volume-based payment system to a model that promotes value, the PCF reimbursement model is preferred since it adjusts better to this premise of forcing the practice to improve performance to boost profit. Increasing the reward for performance under the CPC+ payment model is insufficient to emphasize the P4P component and make more preponderant the effects of its elements on the output variables. Similarly, a reduction in the percentage of reward in the PCF does not overcome the high variation in the profit per team. The PCF has a more complex association between the elements of the P4P and the other payment components (i.e., FFS and TC), which causes the variability in the results.

The logistic regression coefficients have a more notable impact on the profit per team under the PCF payment model rather than the CPC+. The changes in the profit due to the values of the regression coefficients could be attributable to a direct impact on the P4P revenue and an indirect effect on the patient admission's severity, affecting the FFS and TC components. Hence, considering the proposed P4P, the correct estimation of the coefficients is critical for the PCF. The inclusion of the COCI as part of the P4P component has positively forced each admitted patient to receive care from the same provider. However, this result prompts that the controllable factor effect falls over the value that could take the parameter β_2. Hence, if the coefficient β_2 is not small enough, as the literature currently suggests [23], the adverse effect of a higher HCC score could not have a controllable counterpart that can reduce the likelihood of hospital admission using the proposed logistic regression model. Correcting this issue is convenient to extend the analysis to include other factors over which the primary care practice has control, for instance, patient preference for a particular provider [19] or care coordination and telehealth [22]. Also, the HCC score could not reflect all aspects of a person's health condition; therefore, additional factors, such as social determinants of health, should also be considered for predicting avoidable hospital admissions and estimating the P4P of a practice [27]. Similarly, since the P4P adjustment in the models focuses mainly on the process rather than the health outcomes, defining a realistic threshold is essential to evaluating the practice performance objectively. The

regulatory entities need to consider that the hospital admissions relate to aspects that do not entirely relapse in primary care practice endeavors, such as behavioral and genetic factors.

This study is not exempt from limitations. First, we simplify some characteristics of the reimbursement models, mostly in the PCF, to facilitate the mathematical modeling and comparison. This simplification implies that fees and reward computation could differ slightly from real values in some cases. Second, we consider one controllable variable to grasp the models' responses; however, the real world could be more complex. Thus, as future work, we would like to explore in more detail the association between controllable factors to reduce hospital admissions, considering actions directed from the primary care level. We would also like to propose new payment models that improve profit, promote quality of care, and support patients' admission at different risk levels, starting from CPC+ and PCF structure modifications.

9. Conclusion

This study analyzes the CPC+ and PCF reimbursement models, which have FFS, TC, and P4P components. The CPC+ testing began in 2017 in some states in the US, and the PCF is a more recent APM, whose characteristics the CMMI released in 2019. We modify the P4P component in both models to include the HCC scores as a non-controllable determinant and the COCI as an element that the primary care practice can control. A probabilistic classification model links these elements to predict hospital admissions. The P4P adjustment in the models allows rewarding the practice based on the effort they can make to reduce each patient's likelihood of hospital admission rather than reward (or penalize) based on the actual hospital admissions, which sometimes are due to causes beyond the practice control. The results show that the logistic regression coefficients and the threshold defined to determine whether the practice deserves a reward (or penalty) have a significant effect on the profit per team and revenue for performance per team, becoming more notable on the PCF payment model. The significant factors have less impact on the profit per team in the CPC+ because the P4P component represents only 0.4% of the total revenue, while in the PCF, the P4P constitutes 16.5%. However, the disadvantages of the PCF payment model are its high variability in all of the output variables and its tendency to select less severe patients. The connection among components within the PCF suggests a more susceptible model to any variation in the P4P. Consequently, CPC+ resembles a more stable payment model for a primary care practice, while the PCF further emphasizes the performance component. The limitations of both models and the performance when including controllable and non-controllable factors provide evidence to the policymakers and primary care practices about the aspect to consider before implementing the models. This study also assists as a framework to extend the analysis and include factors that measure the practice structure and care delivery process to assess the practice's performance.

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Appendix

Appendix A. Conversion of Constraints (9) to a quadratic expression

Gurobi 9.0 solves optimization formulations with linear and quadratic constraints and objective functions. Thus, we convert Constraints (9) to a quadratic expression to obtain the value of the decision variable, $m_{it} \in \mathbb{R}^+$, for all, $i \in \mathcal{I}$, and, $t \in \mathcal{T}$.

Let

$$\tilde{v}_{it} = \sum_{s \in \mathcal{S}} v_{ist}, \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{A.1}$$

$$\hat{v}_{it} = \tilde{v}_{it}\big(\tilde{v}_{it} - 1\big), \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{A.2}$$

$$\tilde{b}_{iwt} = \sum_{s \in \mathcal{S}} b_{iwst}, \qquad \forall i \in \mathcal{I}, \forall w \in \mathcal{W}, \forall t \in \mathcal{T}. \tag{A.3}$$

Replacing Expressions (A.1)–(A.3) in Constraint (9) leads to Expressions (A.4), and consequently, Constraint (9) can be replaced by Expressions (A.1)–(A.4),

$$\sum_{w \in \mathcal{W}} \tilde{b}^2_{itw} - \tilde{v}_{it} = m_{it}\hat{v}_{it}, \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}. \tag{A.4}$$

Appendix B. Managing Constraint (21)

We derive an explicit expression for the decision variable, $p_{it} \in \mathbb{R}^+$, in terms of the parameter η_{it} and the decision variable, $m_{it} \in \mathbb{R}^+$, for all, $i \in \mathcal{I}$, and, $t \in \mathcal{T}$, to handle the non-linear constraint in Constraint (21).

Let

$$\ln\Big(\frac{p_{it}}{1-p_{it}}\Big) = \beta_0 + \beta_1\eta_{it} + \beta_2 m_{it}, \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{B.1}$$

$$\frac{p_{it}}{1-p_{it}} = \exp\big\{\beta_0 + \beta_1\eta_{it} + \beta_2 m_{it}\big\}, \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{B.2}$$

$$\frac{1}{\frac{1}{p_{it}} - 1} = \exp\big\{\beta_0 + \beta_1\eta_{it} + \beta_2 m_{it}\big\}, \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{B.3}$$

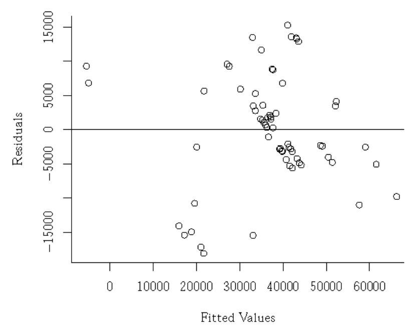
$$\frac{1}{p_{it}} - 1 = \exp\big\{-\big(\beta_0 + \beta_1\eta_{it} + \beta_2 m_{it}\big)\big\}, \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{B.4}$$

$$\frac{1}{p_{it}} = 1 + \exp\big\{-\big(\beta_0 + \beta_1\eta_{it} + \beta_2 m_{it}\big)\big\}, \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}, \tag{B.5}$$

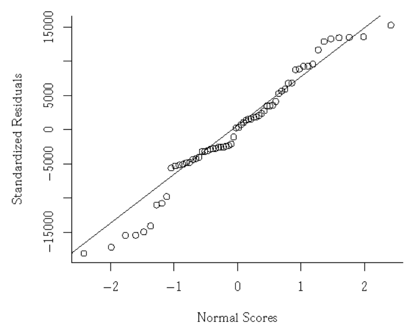
$$p_{it}(m_{it}) = \frac{1}{1 + \exp\big\{-\big(\beta_0 + \beta_1\eta_{it} + \beta_2 m_{it}\big)\big\}}, \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}. \tag{B.6}$$

Then, we use the piecewise linear approximation of the decision variable, $p_{it} \in \mathbb{R}^+$, in Expressions (B.6) in terms of the decision variable, $m_{it} \in \mathbb{R}^+$. Fortunately, the approximation is directly provided by the Gurobi API for Python.

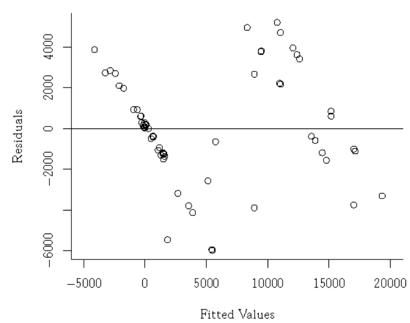
Appendix C. Homoscedasticity and normality of residuals



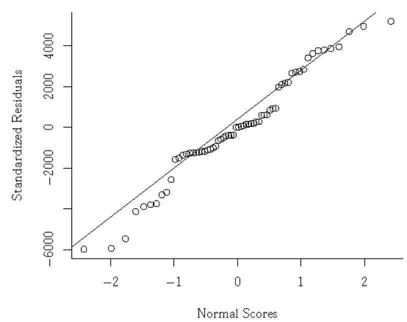
(a) Residuals vs fitted: profit per team



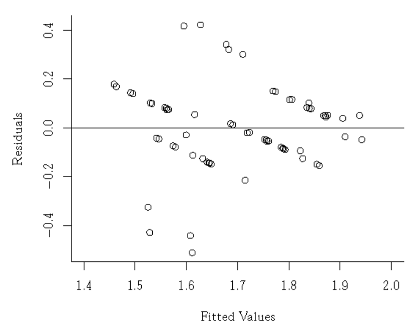
(b) Normal probability plot: profit per team



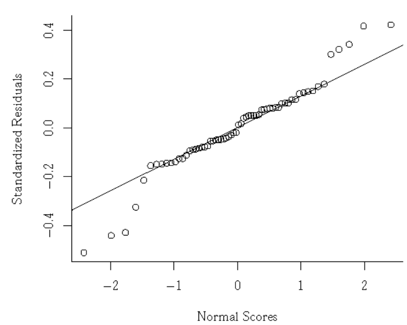
(c) Residuals vs fitted: revenue for performance per team



(d) Normal probability plot: revenue for performance per team



(e) Residuals vs fitted: average of HCC scores



(f) Normal probability plot: average of HCC scores

Figure C.1: Residuals vs fitted and normal probability plots