Journal of the Operational Research Society

ISSN: 0160-5682 (Print) 1476-9360 (Online) Journal homepage: www.tandfonline.com/journals/tjor20

An integrated optimization and analytics approach for planning mental healthcare services

Sheema Noorain, Maria Paola Scaparra, Kathy Kotiadis & Emily Musara

To cite this article: Sheema Noorain, Maria Paola Scaparra, Kathy Kotiadis & Emily Musara (24 Jun 2025): An integrated optimization and analytics approach for planning mental healthcare services, Journal of the Operational Research Society, DOI: 10.1080/01605682.2025.2519996

To link to this article: https://doi.org/10.1080/01605682.2025.2519996

Published online: 24 Jun 2025.

JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY
https://doi.org/10.1080/01605682.2025.2519996

An integrated optimization and analytics approach for planning mental healthcare services

Sheema Noorain[a], Maria Paola Scaparra[b], Kathy Kotiadis[b] and Emily Musara[c]

[a]University of Westminster, London, UK; [b]University of Kent, Canterbury, UK; [c]Kent & Medway NHS and Social Care Partnership Trust (KMPT), Maidstone, UK

ABSTRACT

Mental health services worldwide, including in the UK, face significant constraints that necessitate effective resource planning for delivering high-quality care. The application of analytics in healthcare offers the potential to enhance efficiency and improve care quality. However, achieving this vision is particularly challenging in the context of mental healthcare. This paper focuses on the evaluation and redesign of a Primary Care Mental Health (PCMH) service located in Kent, UK. To address this problem, we propose an analytics-driven approach that integrates the three stages of descriptive, predictive, and prescriptive analytics with an optimization model. Through a comprehensive case study, we illustrate how this integrated approach serves as a valuable tool for experimentation within the PCMH service. We explicitly detail how data analysis and stakeholder engagement informed model development. The findings of our novel multi-skill multi-location model demonstrate the benefits of utilising optimised workforce planning to reduce unmet demand while ensuring equitable workload distribution among clinicians. We also discuss the adaptability of the analytics approach and the potential applicability of the optimization model in mental health and other care settings.

ARTICLE HISTORY
Received 25 August 2023
Accepted 9 June 2025

KEYWORDS
Analytics; health services; optimization; practice of OR; workforce planning

1. Introduction

Mental illness has a significant impact on individuals, society, and the economy. Primary care is now at the forefront of the predicted increase in mental health presentations (Park et al., 2020). Early intervention in primary care reduces subsequent mental health problems and is cost-effective (Le et al., 2021; Van't Veer-Tazelaar et al., 2010). In the UK, one mental health care model of care involves distributing mental health professionals from secondary care to primary care locations (Naylor et al., 2020). These heterogeneous mental health professionals work across multiple General Practitioner (GP)/primary care clinic locations in a geographic patch. In the field of Operations Research (OR), the planning and scheduling of healthcare workers deployed across multiple locations have not been extensively studied (Noorain et al., 2023). Only a limited number of research papers have addressed this topic (Al-Yakoob & Sherali, 2008; Cheng & Kuo, 2016). Moreover, multiple literature reviews investigating the use of OR techniques in mental healthcare services have revealed that the application of OR methods to planning mental healthcare services receives less attention compared to other healthcare domains (Bradley et al., 2017; Howells et al., 2022; Long & Meadows, 2018; Noorain et al., 2019, 2023).

Before COVID-19, mental health services in England were already under considerable strain. Issues included inadequate resourcing, patients' ability to access care and overall patient outcomes (British Medical Association, 2020). Many of these issues have worsened due to the pandemic (HM Government, 2021; NHS Confederation, 2022). The impacts of the COVID-19 pandemic on people's mental health and wellbeing are a significant public health concern; while some are transient, others are likely to be long-term (McCartan et al., 2021; Pierce et al., 2021). Recent data shows that the number of people contacting the NHS seeking help for mental health problems is now at a record high (NHS Digital, 2022). These needs arise within the context of underfunded mental health services facing a care backlog, waiting lists, and a stretched, exhausted, and understaffed workforce (Valentine et al., 2024). Workforce capacity has been a long-term concern, and shortages represent the biggest threat to national ambitions to improve mental healthcare

CONTACT Sheema Noorain s.noorain@westminster.ac.uk University of Westminster, London, UK
Supplemental data for this article can be accessed online at https://doi.org/10.1080/01605682.2025.2519996.

(HM Government, 2021; NHS Confederation, 2022). Potential solutions could be found in telemedicine, which remains controversial, despite its efficiency in reducing the impact of the pandemic (Omboni et al., 2022; Van Der Heijde et al., 2024). In OR literature, studies addressing telemedicine with respect to operational efficiency are limited (Zhou et al., 2023).

In OR literature, optimization modelling has a long history of supporting healthcare decision makers seeking to develop more efficient healthcare systems (Cissé et al., 2017; Goodarzian et al., 2023; Grieco et al., 2021; Leeftink et al., 2018; Kahraman & Topcu, 2018; Marynissen & Demeulemeester, 2019). Despite the widespread use of optimization techniques in healthcare contexts, application in mental healthcare is still sparse (Noorain et al., 2023).

In this article, we consider the pressing challenge of evaluating and redesigning a mental health service to better serve communities. We focus on a primary care network in Kent, UK that aimed to optimize its itinerant mental health clinician schedules across multiple locations. To tackle this problem, we developed a novel multi-skill, multi-location optimization model that assigns clinicians across geographical sites based on demand planning. Our model balances the dual objectives of minimizing unmet demand and balancing workload distribution among clinicians (Al-Yakoob & Sherali, 2008; Carter & Busby, 2023; Cheng & Kuo, 2016; Noorain et al., 2023).

Importantly, we explicitly detail how our exploration of data and analytics directly informed the model structure, demonstrating an iterative nature of model building. This approach not only aligns with current trends in healthcare analytics but extends them by making this process explicit from the start and providing a clear description of the process. This contribution addresses a gap identified in the literature, where the link between data analysis and model formulation is often not explicitly described or is less direct in shaping the model structure (Sir et al., 2017; Wang et al., 2021). By providing this detailed account, we aim to contribute to recent discussions on the need for more comprehensive reporting of OR interventions in healthcare (Lamé et al., 2022).

We ground our model in real-world data from the healthcare provider. Descriptive and predictive analytics were used to address data requirements needed by the optimization model and enabled us to holistically profile service needs. From a healthcare provider's perspective, our combined optimization modelling and data analysis approach provides valuable managerial insights into optimizing mental healthcare delivery. The optimization model matches clinician skills and availability to the changing mental health needs in the community (Attia et al., 2019; Nearchou et al., 2020) while ensuring fair workloads. This case study demonstrates how data-driven workforce planning can reduce unmet demand while ensuring equitable workload distribution, offering healthcare managers practical guidance on standardizing operational procedures and making informed resource allocation decisions. It exemplifies the value of using local data and customized modelling over one-size-fits-all solutions for healthcare challenges (Carter & Busby, 2023; Lamé et al., 2022), while contributing to the limited body of work applying optimization modelling to mental healthcare service planning (Bradley et al., 2017; Howells et al., 2022; Long & Meadows, 2018).

The remainder of this article is organized as follows. In Section 2, we provide a literature review on the various components of this study, such as the application of OR and analytics approaches in mental healthcare. We also discuss a specific body of scheduling literature upon which our optimization model draws. Section 3 provides contextual background on the collaboration with a PCMH service. Section 4 describes the various elements of the integrated approach. Since the novel optimization model is a central contribution, Section 5 provides a comprehensive account of the prescriptive element, including model formulation, and Section 6 examines the computational results from the scenario analysis. Section 7 discusses the study's contributions and Section 8 provides some conclusive remarks.

2. Literature review

We drew on several relevant literature themes to positioning our study. We begin by focusing on optimization in mental healthcare, followed by a broader examination of personnel scheduling in healthcare, particularly on multi-skill multi-location scheduling. We then examine the literature for studies in healthcare that have explicitly applied optimization combined with analytics approaches.

2.1. Optimization in mental health

Operational Research has contributed significantly to designing and organizing processes, optimizing operations, and managing healthcare systems (Hulshof et al., 2012; Rais & Viana, 2011). Optimization for healthcare planning enables simultaneous consideration of multiple constraints and sensitivity analysis to find the best solution (Kahraman & Topcu, 2018) and has been used to determine resource quantity, allocate capacity, scheduling, and allocating appointments to support planning of emergency rooms, primary, outpatient and home care (Cissé et al., 2017; Goodarzian et al., 2023; Grieco et al., 2021; Leeftink et al., 2018; Marynissen & Demeulemeester, 2019).

Despite the widespread use of optimization in healthcare, application in mental healthcare (MH) is only beginning (Noorain et al., 2023). MH systems are generally composed of a diverse range of services that comprise interrelated parts of a whole system and primarily rely on human resources, including a heterogeneous mix of specialists, non-specialists, and community workers (Gask, 2005; Gupta et al., 2019; Kakuma et al., 2011). A handful of studies have developed optimization models in MH, such as to schedule appointments with patient no-show predictions (Samorani & LaGanga, 2015), allocate appointments subject to waiting times (Pagel et al., 2012), assign staff to shifts by considering preferences (Cohn et al., 2009) and workload balancing (Hertz & Lahrichi, 2009), schedule visits to outreach clinic locations (Li et al., 2016) and patients' homes (Hertz & Lahrichi, 2009), and build duty rosters for psychiatric nurses (Bester et al., 2007). It has been established that the strength of optimization planning models in MH so far is that they are developed in real world practical contexts but had a narrow scope and used simplified assumptions (Noorain et al., 2023).

2.2. Personnel scheduling in healthcare

In OR, scheduling problems have been studied extensively (Van den Bergh et al., 2013). In healthcare, personnel scheduling problems have been considered for nurses (Burke et al., 2004; De Causmaecker & Berghe, 2011; Kellogg & Walczak, 2007), and physicians (Brunner et al., 2009; Brunner & Edenharter, 2011; Erhard et al., 2018; Thielen, 2018). Studies have also examined the scheduling of patients in outpatient clinics (Ahmadi-Javid et al., 2017; Cayirli & Veral, 2003), and operating rooms (Cardoen et al., 2010; Samudra et al., 2016; Zhu et al., 2019). Most nurse scheduling problems are addressed within the context of hospitals. Specifically, nurses are allocated to periods of work over a planning period. Such problems consider skill categories, shift types, coverage constraints, work regulations, nurse preferences etc. Although physician scheduling is part of the larger field of personnel scheduling, specific aspects such as demand volatility, cost-intense resource, strict adherence to preferences differentiates it from other types (Erhard et al., 2018). The commonality between nurse and physician scheduling is that the schedules are usually developed in the context of a single location - a hospital.

2.2.1. Multi-skill multi-location personnel scheduling

The literature classifies skills into two categories: hierarchical and categorical. In hierarchical, higher-skilled workers handle more complex tasks, while categorical skills define specific tasks for workers (Afshar-Nadjafi, 2021; De Bruecker et al., 2015). Healthcare staffing and scheduling involving skills have been extensively studied (De Bruecker et al., 2015; Respicio et al., 2018; Vermuyten et al., 2018). However, most studies focus on single-location or departmental scenarios (Dahmen et al., 2018; Restrepo et al., 2017), with only limited research addressing multi-department or multi-location situations (Attia et al., 2019; Nearchou et al., 2020).

Mental healthcare in primary care settings presents distinct scheduling challenges compared to other specialist services. Unlike physical health specialists who typically operate independently with standardized appointment types, primary care mental health nurses work within a hierarchical framework delivering varied interventions across multiple locations (Aurizki & Wilson, 2022; Kenwright et al., 2024). These nurses provide a range of services including bio-psychosocial assessments, risk management, and evidence-based treatments while working collaboratively with GPs and other primary care professionals (McLeod & Simpson, 2017; Price, 2024). This integration requirement and varied skill mix create unique scheduling complexities not present when scheduling other specialists like gynecologists or podiatrists to GP practices.

To the best of our knowledge, Franz et al. (1989) examined the first multi-skill multi-location situation in healthcare, scheduling a hierarchically skilled workforce across rural clinic locations while minimizing costs and maximizing staff preference. Later healthcare applications include studies that scheduled different categories of nurses across hospital wards with costs associated with staff shortages (Maenhout & Vanhoucke, 2013) and centralized scheduling of nurses in multiple departments considering both schedule desirability and costs (Wright & Mahar, 2013).

Beyond healthcare, personnel scheduling across multiple departments or locations has been studied in the service industry, where models enable the movement of employees under specific rules (Van den Bergh et al., 2013). For instance, these studies incorporate skills and worker movements through transfer and labour costs (Attia et al., 2019; Bard & Wan, 2008; Dahmen et al., 2020; Nearchou et al., 2020). Models have also considered fairness, worker preferences, and satisfaction (Al-Yakoob & Sherali, 2007, 2008; Cheng & Kuo, 2016; Kuo et al., 2014). For example, Al-Yakoob and Sherali (2007, 2008) assigned a hierarchical workforce across gas stations while minimizing employee dissatisfaction, Kuo et al. (2014) scheduled multi-skilled employees across airport stations minimizing staffing shortages and skills mismatches, and Cheng and Kuo (2016) developed a model for scheduling food safety inspectors with travel restrictions and fairness considerations.

The heterogeneity of skills in primary care mental health services presents unique challenges tied to both nursing bands and intervention types, requiring models that balance skill-appropriate care delivery with geographical coverage needs. While some parallels exist with home healthcare scheduling in terms of staff-to-visit assignments and location coverage (Cissé et al., 2017; Fikar & Hirsch, 2017), neither these models nor general multi-location scheduling approaches fully address the combination of hierarchical nursing bands, varied intervention types, primary care integration requirements, and consistent geographical coverage needs specific to mental health service delivery.

2.3. Analytics driven approaches to optimization modelling in healthcare

Our integrated descriptive, predictive, and prescriptive analytics approach notably guided model development and provided useful insights. In OR discourse, business analytics is concerned with enabling descriptive, predictive, and prescriptive model building using diverse, real-time, and "big" data sources (Duan et al., 2020; Hindle et al., 2020; Hindle & Vidgen, 2018). The conversation in this body of work has received much attention in the literature (Conboy et al., 2020; Petropoulos et al., 2024), and lately focused on how OR can derive value from analytics (Vidgen et al., 2017) and introducing a framework for the deployment of OR analytics (Hindle & Vidgen, 2018). When considering the application of each of the three stages of analytics in healthcare, researchers have found that predictive analytics is most widely used, followed by prescriptive and then descriptive methods (Galetsi & Katsaliaki, 2020; Lepenioti et al., 2020).

To investigate the integrated use of descriptive and predictive analytics with optimization in healthcare, we conducted a structured literature review. We searched recent review and survey articles (published 2013–2023) for studies explicitly discussing combining these methods. By screening articles by Ahmadi-Javid et al. (2017), Kraus et al. (2020), Noorain et al. (2023), Ortíz-Barrios and Alfaro-Saíz (2020), Vázquez-Serrano et al. (2021), Vishwakarma et al. (2025), Wang and Demeulemeester (2023) , and Yousefi et al. (2020) we identified 5 relevant research studies after removing duplicates (Elleuch et al., 2021; Lee et al., 2015; Ordu et al., 2021; Samorani & LaGanga, 2015; Sir et al., 2017).

We supplemented this with targeted keyword searches on ScienceDirect, yielding 10 additional articles meeting our criteria. In total, 15 studies were identified exemplifying descriptive and predictive analytics integrated with optimization in healthcare. Further details of search strategies and screening are provided in the supplementary material. The articles identified in the literature review are summarized in Table 1. The "descriptive" column categorizes the studies based on how historical data was utilized across three types of analysis. Firstly,

Table 1. Combined use of descriptive and predictive analytics with optimization.

	Descriptive (or date processing)				
Author(s)	Parameter Estimation + Input for Predictive	Data Analysis + Visualisation	Model Validation	Predictive	Optimization Model
Ahmed and Frohn (2021)	✓			ML	MOIP
Andersen et al. (2019)	✓		✓ (P)	MCS	ILP
Elleuch et al. (2021)	✓		✓ (P + O)	ANN	FIM
Jang (2019)	✓			ML	RO
Lee et al. (2015)	✓	✓	✓ (P + O)	ML	MINLP
Mizan and Taghipour (2022)	✓		✓ (P)	ML	MOMILP
Moradi et al. (2022)	✓		✓ (P)	ML	MILP
Olya et al. (2022)	✓		✓ (P)	ML	MIP
Ordu et al. (2021)	✓		✓ (P)	TSF	DES + IP
Samorani and LaGanga (2015)	✓		✓ (O)	DM	SO
Sir et al. (2017)	✓	✓		CART	MIP
Uriarte et al. (2017)	✓	✓		DM	DES + SMO
Wang et al. (2021)	✓	✓	✓ (O)	REG + TSF	MIP
Yaspal et al. (2023)	✓	✓	✓ (P)	ML	MOMILP
Zimmerman et al. (2021)	✓		✓ (O)	DF	MILP + DES

ANN: Artificial Neural Network; ML: Machine Learning; TSF: Time Series Forecasting; DM: Data Mining; REG: Regression; CART: Classification and Regression Tree; MCS: Markov Chain Simulation; MIP: Mixed-Integer Programming; DES: Discrete-event Simulation; SMO: Simulation-based Multi-Objective Optimization; SO: Stochastic Optimization; IP: Integer Programming; MOMILP: Multi-Objective Mixed Integer Linear Programming; MINLP Mixed-Integer Nonlinear Programming; RO: Robust Optimization; FIM: Fuzzy Interval Mathematical Model; ILP: Integer Linear Programming; MOIP: Multi-Objective Integer Programming.

data was used as inputs for predictive analytics techniques and estimating optimization model parameters using summary statistics. Secondly, data was analyzed to produce visualizations and uncover patterns and trends. Thirdly, data was used to validate either the predictive model or both the predictive and prescriptive optimization models. The "predictive" column specifies the type of predictive method applied in each study, whilst the "optimization model" column provides information on the type of model developed. This categorization allows for a clear understanding of how historical data is leveraged in different stages of the analytics process, from descriptive analysis to predictive modelling and optimization model development and validation.

Our literature review revealed three distinct approaches to integrating analytics with optimization in healthcare. The first and most basic approach uses descriptive analytics primarily for parameter estimation. Zimmerman et al. (2021), Samorani and LaGanga (2015), and Ahmed and Frohn (2021) used historical data to estimate parameters like arrival rates and service times. While demonstrating data's value for model inputs, these studies do not leverage analytics to shape model structure.

A second group of studies shows stronger integration between data analysis and model formulation. Elleuch et al. (2021) and Olya et al. (2022) used operational pattern analysis to inform both their predictive models and optimization parameters. Jang (2019) applied machine learning for predictions that fed into robust optimization. Mizan and Taghipour (2022) used machine learning to forecast workloads, incorporating these insights into their model structure through probabilistic scenarios. Andersen et al. (2019) utilized Markov Chain simulation alongside descriptive analytics to develop capacity constraints.

The third and most sophisticated approach uses analytics to fundamentally shape model structure and validation. Wang et al. (2021) analyzed demand patterns using penalized distributed lag nonlinear models, with findings directly motivating their model constraints for handling nonstationary demand. Sir et al. (2017) employed Classification and Regression Trees to identify key operational thresholds that became specific constraints. Lee et al. (2015) combined time-motion studies and machine learning to validate their simulation and optimization models, though the connection between analysis and model structure remains somewhat implicit.

Several studies demonstrate innovative approaches to handling data limitations. Ordu et al. (2021) and Uriarte et al. (2017) used simulation to bridge descriptive and prescriptive analytics. Yaspal et al. (2023) combined time series forecasting with multi-objective optimization. However, these studies typically do not explicitly connect their methodological choices to findings from descriptive analysis. Moradi et al. (2022) and Olya et al. (2022) address validation but focus less on how analytics shaped their initial model formulation.

This literature review reveals several important gaps our study addresses. While optimization has been widely applied in healthcare, its use in mental healthcare remains limited. Personnel scheduling research, particularly in multi-skill multi-location contexts, has focused primarily on solution approaches rather than practical implementation in healthcare settings. Additionally, while analytics-driven optimization is emerging, most studies use analytics mainly for parameter estimation rather than informing model construction. Our study makes two key contributions that address these gaps. First, we extend mental healthcare optimization beyond narrow scheduling problems by developing a comprehensive multi-skill, multi-location model that considers real-world complexities like workload fairness and skill distribution. Second, we demonstrate how analytics can systematically inform optimization model development, from using descriptive findings to shape constraints and objectives, to employing predictive techniques for handling data limitations. This analytics-driven approach makes explicit the often implicit connection between data analysis and model building in existing literature.

3. Background and problem statement

Primary care providers continue to encounter barriers when referring patients to secondary mental healthcare settings (Pomerantz et al., 2008). At the time of the study, several change imperatives had highlighted the need for integrating mental health services into primary healthcare (NHS England, 2020). Several key benefits of the primary care mental health model were highlighted, including the closer integration of primary, secondary, and tertiary mental healthcare and improved patient access to services.

Several new models of PCMH services were in various stages of development across the UK. There was significant variability in the service models of newly established PCMH services. These services existed on a spectrum between a simple attached specialist working within the primary care setting and a fully integrated multidisciplinary team drawn from primary and specialist services. The deployment of these models represented a significant opportunity to consider how services could be redesigned to ensure the most effective and appropriate care provision.

One such PCMH service was the focus of our study. We developed this approach in collaboration with a real-world PCMH service provided by the Kent and Medway Mental Healthcare Trust (KMPT) based in Kent, UK. The service worked alongside GP clinics and primary care partners and interfaced with KMPT services to provide care to people experiencing mild/moderate mental health conditions who do not require secondary care mental health services. The service offered short-term interventions lasting at most six months. The clinician team provided mental health consultations and, where appropriate, may refer patients to external services (such as education, housing, employment, benefits and voluntary sector) at which point patients exit the PCMH service. The workforce comprised 12 multi-skilled clinicians deployed to 57 GP clinic locations to provide patient consultations across four types of appointments (further detailed in Appendix Figure A2: PCMHS Patient Pathway). Stakeholders were interested in exploring appointment durations for different appointment types offered by the clinic: Assessment (A), Follow-up (F), Community (C), and Telephone (T). An assessment appointment is the first encounter where a clinician assessed a newly referred patient's needs and risks. Based on this assessment, the clinician determined if the patient could be referred to other services immediately or if a follow-up appointment was needed. Follow-up appointments were conducted either in person or over the telephone (dubbed a telephone appointment). Depending on the assessment outcomes, a patient could have multiple follow-up appointments. Community appointments were provided to patients requiring ongoing medication administration by a clinician to support their transition from secondary care to the community.

During problem exploration, stakeholders reported that the service was on the verge of expansion on two fronts: expanding service capacity by hiring more clinicians and adding more clinic locations to their service provision. These advances were being made in response to county-level population health forecasts' predictions. However, stakeholders conveyed high levels of uncertainty and a lack of clarity around current and future capacity and demand. Furthermore, stakeholders were aware of differences in clinician experience and variations in operating procedure. As such, stakeholders were keen to understand the service quantitatively, uncover operational patterns, and explore opportunities to improve service efficiency. The service was driven by the goal of providing the right intervention, by the right professional, at the right time and location. Stakeholders sought our help to investigate current efficiency and consider several options for service transformation.

At the time, the PCMH service was reporting high-level summaries of Key Performance Indicators (KPIs) generated from heterogeneous data sources. The lack of integration and visualization presented the stakeholders a disjointed view of the service. There was tacit consensus amongst stakeholders that service data was inadequately leveraged for better decision-making. As such, we identified a course of actions that interlinked three areas of investigation: the presence and underutilization of historical data with a potential for generating insights, elements of uncertainty regarding future service transformation, and the planning of a multi-skilled workforce across multiple locations. We further describe the components of the analytical framework in the next section.

4. Overview of integrated optimization and analytics approach

In this project, we developed an optimization model through a series of facilitated workshops with the stakeholder group. The component described in this article was part of a modelling framework called PartiOpt (Participative Optimization) (Noorain, 2024) which is based on Participative Simulation (PartiSim) (Kotiadis, 2007; Kotiadis et al., 2014; Kotiadis & Robinson, 2008; Tako & Kotiadis, 2012; 2015; 2018). The conceptual modelling that preceded the work described here is discussed in the thesis Noorain (2024). However, we will focus on how the analytics approach shaped the optimization model.

Our analytics approach consisted of three main stages: descriptive, predictive, and prescriptive (Figure 1). In the descriptive analytics phase, we gathered and integrated heterogeneous data from several electronic patient record systems used by the PCMHS to manage administrative and clinical processes. The process began by identifying sources and transforming raw data through data linkage into a format that enabled historical data analysis. We identified critical components within the service, including patient waiting times, length of stay, clinician utilization, workload distribution, appointment types and durations, and clinic location demand. We then explored performance measures related to these components using visualization, statistical summaries, and drill-down tables. The data gathered in this stage served as inputs for the predictive and prescriptive stages.

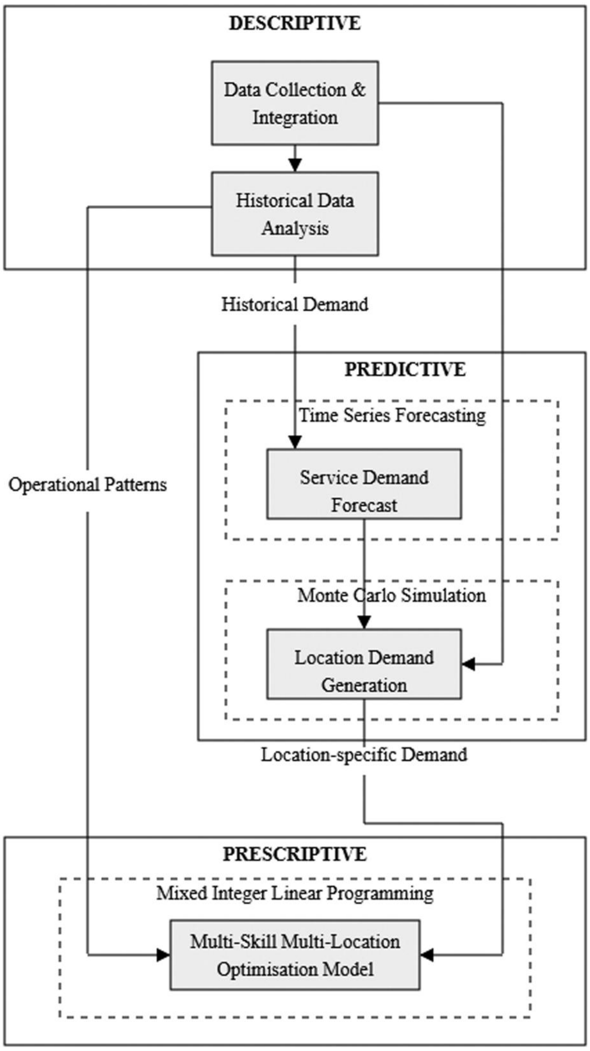


Figure 1. Integrated optimization and analytics approach.

The predictive analytics stage focused on the demand for appointments. Alongside the descriptive analysis, a monthly service level demand forecast was generated using historical data and time series forecasting. We forecasted demand for the entire service. This addressed stakeholders' concerns about the need to hire more clinicians due to the expected increase in service demand.

During the validation of the initial optimization model, we identified the need for location-specific appointment demand, as opposed to the aggregated service-level projections from the time-series forecast. However, location-specific data had issues, such as missing values and inconsistent patterns. Monte Carlo simulation was used to fill gaps in historical data to determine monthly demand for each clinic location. For locations with available data, a distribution was fitted to monthly appointments, and data was generated. For locations lacking data, stakeholders were asked to describe appointment patterns based on their expert experience. We then used this information to generate simulated demand data.

In the prescriptive analytics stage, a multi-skill multi-location optimization model was built using Mixed-Integer Linear Programming (MILP). Inputs to the model were obtained from both preceding stages of the multi-methodology. The main aim of this stage was to use the model to compare service performance for several alternative operational strategies while ensuring both efficiency in meeting demand and fairness in workload distribution among clinicians. The model allocated clinicians to clinic locations on a given day and shift based on skills and assigns appointments to clinicians. It uniquely balanced two objectives: minimizing unmet demand and balancing the percentage of unassigned hours across clinicians.

4.1. Descriptive analytics

Historical data spanning four years was extracted from the service's electronic patient record system used by the PCMH service to manage administrative and clinical processes. This data included information about referrals made to the service, clinician utilization, and patient appointment logs. The data was anonymized and altered only to depict the operational perspective of the service. We began by performing data profiling to clarify the structure, content, relationships, and derivation rules. We then conducted data linkage to join records and create a multi-dimensional integrated dataset. For this purpose, data was migrated to MySQL and transformed. The analysis was then conducted on this enhanced dataset. During the preliminary data analysis, we identified several gaps in information related to clinician working patterns. To redress these gaps, individual clinicians were required to provide a "Job Plan" detailing the division of working hours to various activities, including patient appointments, over a four-week planning horizon.

Two defining operational guidelines of the PCMHs service were that a patient should be assessed within four weeks of a referral and that it offered short-term interventions lasting at most six months. As seen in Figure 2, the waiting time data showed that while 486 patients (28.5%) were assessed within the four-week target, a substantial number of patients waited longer.

The length of stay data depicted in Figure 3 revealed a more complex pattern. While 662 patients (27.4%) had stays of 0–1 month and 986 patients (40.9%) stayed within the target 1–6 month range, there were significant numbers exceeding the six-month guideline. This pattern suggested that while clinicians were managing new referrals and assessments within target times for about a quarter of patients, they were also maintaining a substantial

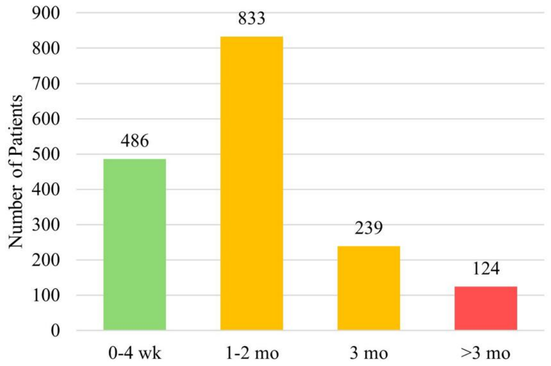


Figure 2. Patient waiting time.

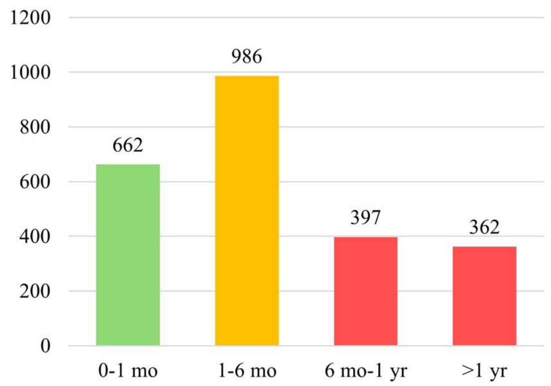


Figure 3. Patient length of stay.

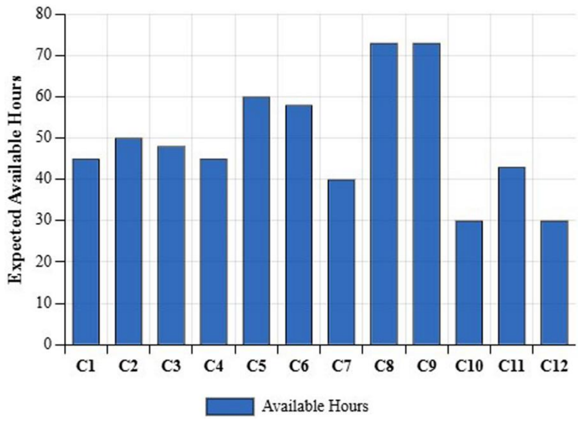


Figure 4. Clinician availability for appointments.

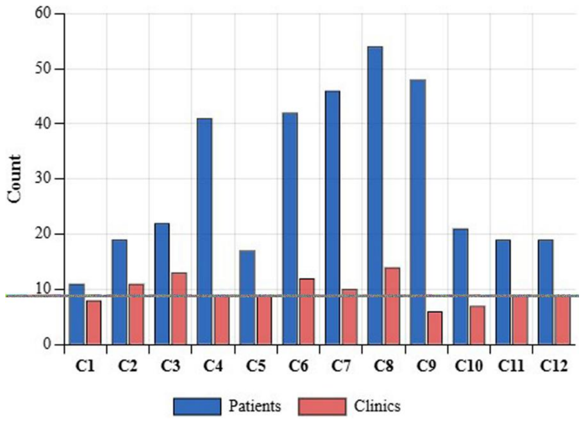


Figure 5. Clinician patient to location distribution.

Table 2. Clinician code and band.

Clinician	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Band	B-8a	B-8a	B-8a	B-7	B-7	B-7	B-7	B-6a	B-6a	B-6b	B-6c	B-6c

number of long-term cases. This created a complex balance between new assessments and ongoing care that likely contributed to service delays, as evidenced by the high proportion of patients waiting beyond the four-week assessment target.

Next, we looked at clinician related analytics. At the time of this analysis, the services employed 12 multi-skilled clinicians, who were grouped into hierarchical categories called bands. Table 2 depicts the 12 clinicians with a code (C1, C2, … , C12) and their corresponding band. In addition to representing skill class, bands also provided information on clinician employment type. There were five bands: 8a, 7, 6a, 6b and 6c. Clinicians in bands 6b and 6c worked part-time, while all others worked full-time.

Individual clinician working patterns were grouped and quantified based on the time clinicians allocated to each task. Figure 4 depicts the clinician's availability for appointments. Although clinicians engaged in various activities, this study focused solely on appointment planning, due to its direct impact on service efficiency. Appointments were the primary task that clinicians conduct consistently, with other activities scheduled around these slots.

Our analysis revealed that actual time distribution contrasted with both management and clinician expectations. Figure 4 shows considerable variation in appointment availability across clinicians of the same band. For instance, band 7 clinicians (C4–C7) show availability ranging from 40 to 65 h. C8 and C9 demonstrate the highest availability at around 70 h. Given these variations, stakeholders proposed standardizing clinician availabilities based on job plans and historical data - suggesting five, seven, eight, three and four weekly 3-h clinic shifts for Band 8a, 7, 6a, 6b, and 6c clinicians, respectively.

We then analyzed the clinician caseload for active patients in the service, as seen in Figure 5. The 12 clinicians conducted appointments across 57 different clinic locations. Figure 5 shows varying distributions of clinic locations and patients among clinicians within the same band.

For example, band 8a clinicians C1, C2, and C3 managed 11, 19, and 22 patients across 8, 11, and 13 different clinic locations respectively. The distribution ratio between clinics and patients revealed an inefficient pattern – for instance, C1's ratio of 11 patients across 8 locations indicated they frequently

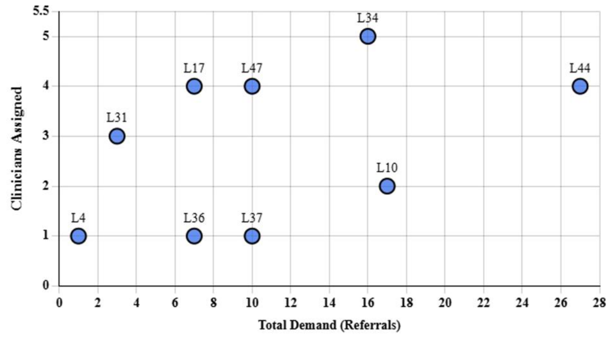


Figure 6. Notable examples of demand-clinician allocation mismatch.

travelled to see just one patient at a location. Similar patterns were observed for clinicians C2 and C5. This suggests a need for both caseload redistribution and reducing the dispersal of clinics per clinician.

A further drill-down on the distribution of clinicians to clinic locations based on the demand (active referrals) was conducted, as seen in Figure 6, which displays the distribution for a few selected locations. The analysis showed that clinician allocation does not necessarily correspond to demand. A striking example was seen when comparing locations with similar clinician staffing but vastly different referral volumes: L44 managed approximately 27 referrals with four clinicians, while L17 handled just 7 referrals with the same number of clinicians. Similarly, both L37 and L47 had similar referral volumes (10 referrals) but had one and four clinicians staffing respectively. L34 had five clinicians despite having lower demand (16 referrals) than L44 which had four clinicians.

Although this analysis showed undesirable variation in the distribution (full distribution shown in Appendix Figure A3), an operational decision was made to preserve these allocations in favour of continuity of care. Stakeholders suggested that higher clinician counts in clinics with currently low referrals might reflect historically higher demand patterns. This data-driven insight was corroborated with stakeholders, where clinicians emphasized the importance of maintaining consistent staffing for long-term clinic relationships and managing potential future demand increases. This combination of historical data analysis and clinician expertise informed the decision to maintain these allocations, even where current referral numbers appeared low.

Additionally, clinicians expressed varying preferences for appointment durations for each type, with a belief that most appointments lasted over 60 min. To analyze appointment durations, we analyzed the historical data and identified two appointment duration profiles, Pa and Pb, shown in Table 3. In profile Pa, we observed that 75% of all historical

Table 3. Appointment types duration distribution.

	(Pa)	(Pb)
Assessment (A)	60	60
Follow-up (F)	45	60
Telephone (T)	30	45
Community (C)	45	60

appointments of a specific type were completed within or below a certain time frame. For instance, 75% of all follow-up appointments took 45 min or less. In profile Pb, we found that 90% of all historical appointments were completed within or below a given duration.

Although we encountered some outliers, such as appointments lasting 120 or 180 min, the overall historical data contradicted clinicians' perceptions that most appointments went beyond 60 min. This analysis presented empirical evidence challenging the clinicians' perceptions and highlighted the need to standardize appointment durations, to promote greater efficiency and consistency.

4.1.1. Summary

The descriptive analytics provided some critical insights about clinician capacity and utilization drawn from a snapshot in the PCMH service timeline. As such, the insights were specific to the chosen period. Some of the imbalances were attributed to time-specific circumstances, such as the hiring and training of new clinicians, new clinics signing up for the service etc. Nevertheless, the investigation did uncover inconsistencies in the distribution of clinician caseloads, variations in clinician availabilities, and skewed perceptions of appointment time durations.

These descriptive analytics findings directly informed the development of our optimization model. The identified inconsistencies in clinician utilization and variations in operational procedures were incorporated as key considerations in the model formulation through constraints and objectives. The standardized appointment durations established from historical data analysis served as input parameters for the model. The model's constraints and objectives were then designed to address these utilization and procedural inconsistencies, aiming to create more balanced schedules that efficiently utilize clinician skills while ensuring equitable workload distribution.

4.2. Predictive analytics

The patient demand for the PCMH service was captured through an electronic patient record system. The service regarded demand as being driven by new referrals and requests for service, including

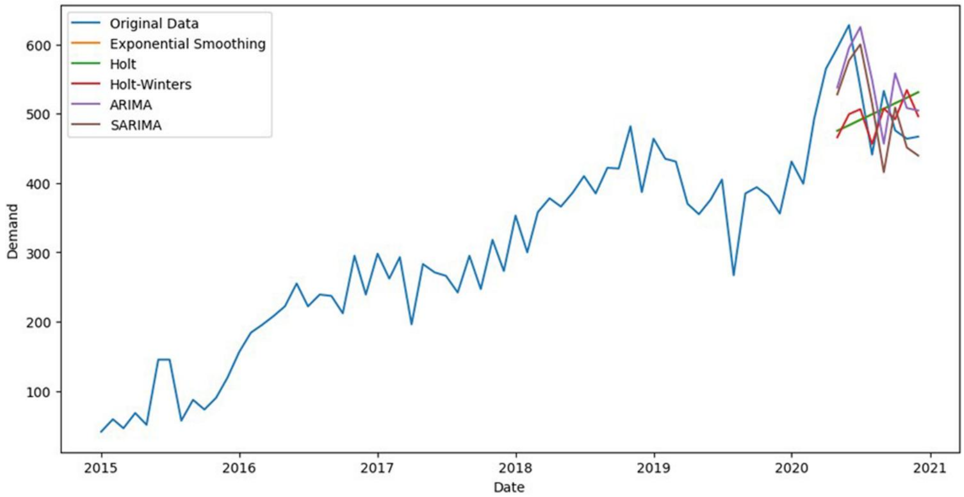


Figure 7. Model validation on service level demand data.

Table 4. Time series modelling validation.

Method	RMSE	MAPE
Exponential Smoothing	79.512822	0.130677
Holt	79.512742	0.130676
Holt-Winters	71.680787	0.101342
ARIMA	72.064192	0.136005
SARIMA	62.962087	0.105795

appointments that are part of the ongoing treatment pathway. Therefore, monthly demand values from January 2015 to December 2020 were extracted for time-series modelling. As seen in Figure 7, several time series models, including Exponential Smoothing, Holt's, Holt-Winters, ARIMA, and SARIMA, were fitted, and model validation was conducted by comparing accuracy measures (see Table 4). The SARIMA (1,1,0)(0,0,0)(12) model emerged as the best-fitting model for the data, as seen in Figure 8.

This SARIMA model suggested that the demand data was differenced once to remove the trend, and the differenced data had a non-seasonal autoregressive component of order 1, meaning the current differenced demand value is influenced by the differenced demand value from one previous time step. No non-seasonal moving average components were included. The data exhibited a seasonal pattern repeating every 12-time steps (eg, monthly data with an annual seasonality), but no seasonal autoregressive, differencing, or moving average terms were included in the model.

Having forecast monthly demand, we proceeded to disaggregate these values to generate monthly demand figures for 57 clinic locations across four appointment types. For locations with sufficient data, we fitted probability distributions to monthly appointment demand and generated multiple scenarios. We illustrate this process for Location 25. We fitted a Negative Binomial distribution to both assessment (Figure 9) and telephone appointments (Figure 10), suggesting overdispersion and greater variability, an approach similar to that used by Ninh et al. (2024) in modelling patient arrivals in clinical trials. For follow-up appointments (Figure 1), a Gaussian Mixture model with three components provided the best fit, implying distinct patterns of low, medium, and high-volume months. This multimodal approach has been effectively used to model elective surgery durations (Bernardelli et al., 2024).

For community appointments (Figure 12), a Zero-Inflated Poisson distribution best captured the data, with many zero-demand days interspersed with Poisson-distributed appointment occurrences. This distribution has been similarly applied to model mental health outpatient services demand (Wang et al., 2021). Using these fitted distributions, we employed Monte Carlo simulation to generate synthetic appointment data for Location 25.

For locations lacking data, stakeholders were asked to describe referral patterns based on their expert experience. This expertise was then used to determine appropriate statistical distributions. These distributions were then embedded into a Monte Carlo simulation to generate data. We illustrate the results of 1000 simulations for location 1 as an example. For instance, we used a Poisson distribution ($\lambda = 5.5$) for follow-up appointments as they made up the most appointments (Figure 13). Assessment appointments were modelled using a Poisson distribution with $\lambda = 0.2$, reflecting their less frequent occurrence (Figure 14).

Community appointments were represented by a Discrete Uniform Distribution ($a = 0$, $b = 2$), indicating an equal likelihood of 0, 1, or 2 appointments (Figure 15). For less frequent appointments such as telephone contacts, a Geometric distribution ($p = 0.05$) was employed (Figure 16). These distributions were chosen based on stakeholder input about the typical patterns and frequencies of different appointment types.

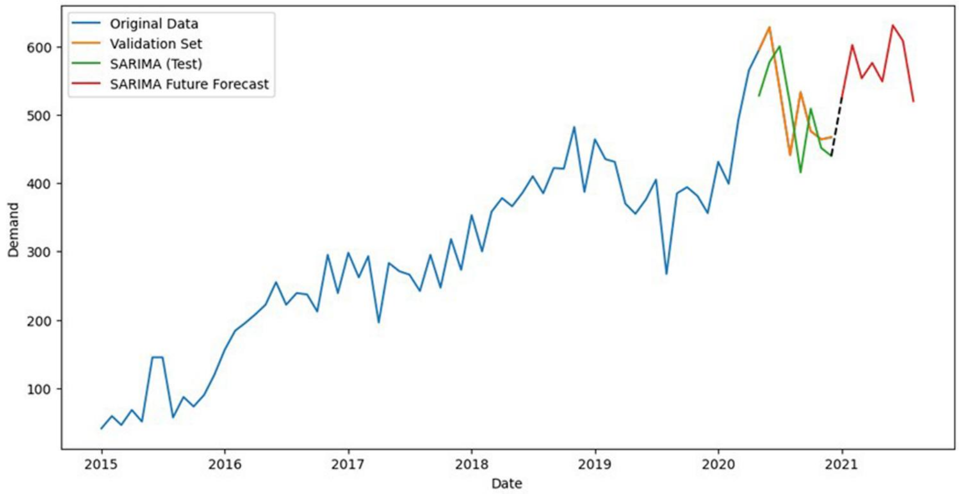


Figure 8. SARIMA model service level demand forecast.

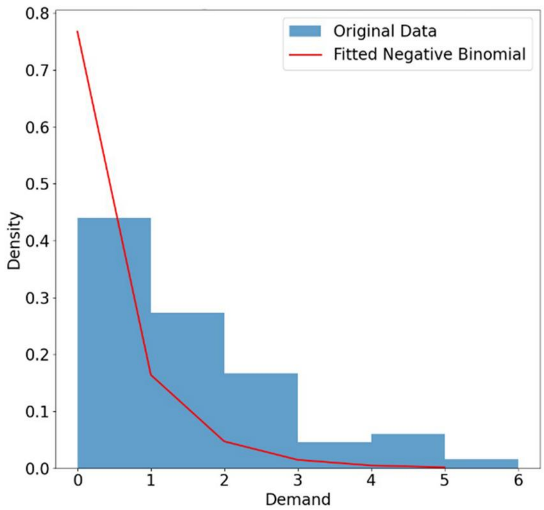


Figure 9. Assessment appointments.

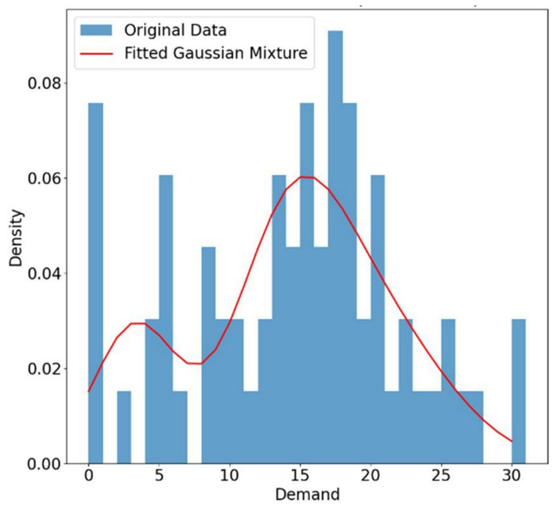


Figure 11. Follow up appointments.

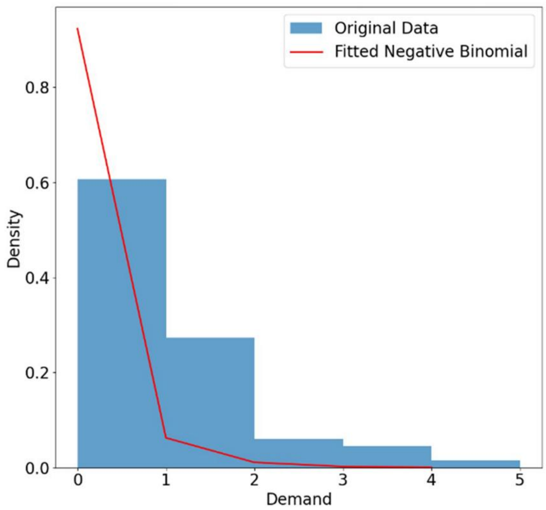


Figure 10. Telephone appointments.

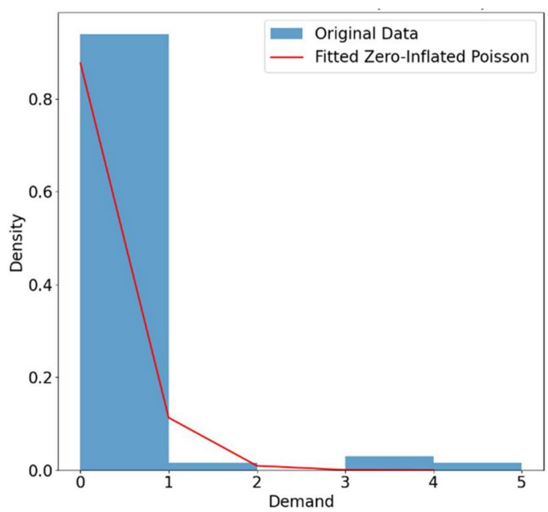


Figure 12. Community appointments.

5. Prescriptive analytics: Optimization model

Building upon insights from the descriptive and predictive analytics stages, we developed a multi-skill multi-location optimization model using Mixed-Integer Linear Programming. This model addressed specific challenges identified earlier, particularly

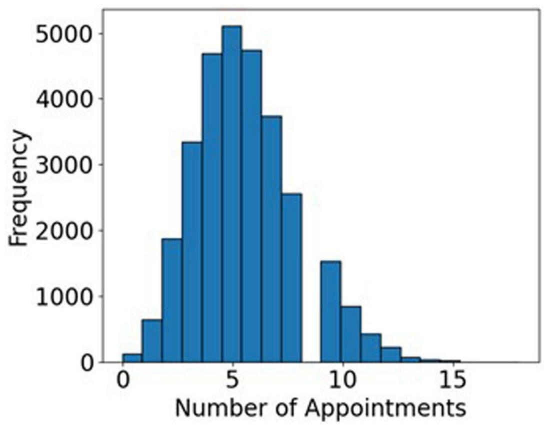


Figure 13. Follow up (Poisson $\lambda = 5.5$).

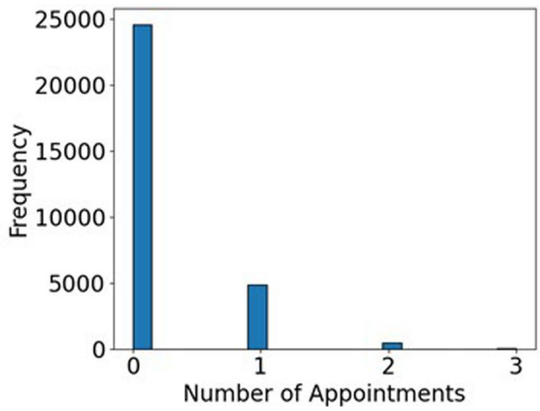


Figure 14. Assessment (Poisson $\lambda = 0.2$).

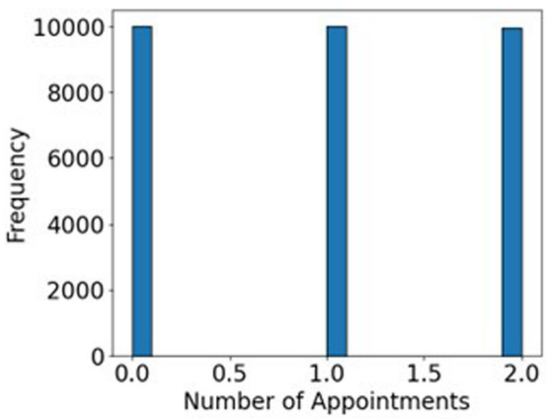


Figure 15. Community (Discrete Uniform, $a = 0$, $b = 2$).

inconsistencies in clinician utilization and variations in operational procedures. The optimization model is based on the following assumptions. A workforce including 12 multi-skilled clinicians must be deployed to 57 primary care clinic locations to conduct four types of appointments. Clinicians get assigned appointments based on their skill set, as displayed in Table 5. For instance, clinicians in bands 8a, 7, and one 6a clinician are skilled to conduct appointment type "assessment", while clinicians 6b and 6c cannot. Additionally, "community"

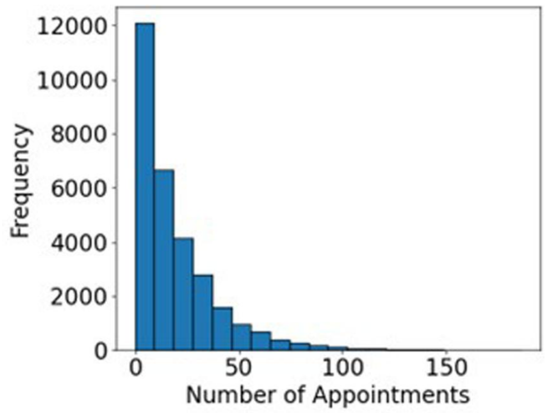


Figure 16. Telephone (Geometric $p = 0.05$).

Table 5. Clinician skill distribution.

Clinician Skill Level	Assessment	Follow-up	Telephone	Community
Band 8a	✓	✓	✓	
Band 7	✓	✓	✓	✓
Band 6a	✓*	✓	✓	✓
Band 6b, 6c		✓	✓	✓

appointments are conducted only by clinicians in bands 7, 6a, 6b and 6c.

Additionally, we assumed that the service operated on weekdays (Monday to Friday) from 9 AM until 6 PM. A working week is made up of 5 days, and a clinician's working day is split into two shifts: AM and PM. In addition to consulting with patients at a clinic, clinicians also carry out other activities, as discussed in Section 4.1. Our application does not include these activities as they were prescheduled and fixed. However, these activities were considered when determining clinician availability in each shift. Clinicians travelled to locations split over two geographic patches to hold clinics across the two shifts (AM and PM).

During each shift, clinicians consulted with patients for four different types of appointments. The demand for each type of appointment at each clinic location was assumed to be known for the planning horizon. This demand data was generated through the methods described in the predictive analytics section. On a given working day, a clinician could be assigned two shifts, either in one clinic or in two separate clinics. A clinician could not be assigned to two locations if the travel distance was greater than a threshold value. The model determined the optimal allocation of clinicians to clinics, appointments and shifts over a planning horizon to minimize the number of unassigned appointments.

While inspired by this real application, the model is general in scope and can handle different numbers of shifts, appointment types, and skills. This flexibility allows for potential application in other healthcare contexts with similar multi-skill, multi-location characteristics.

In the context of this short-term mental health service, continuity of care was defined as clinicians consistently visiting their allocated clinics rather than maintaining patient-specific continuity. This definition aligned with the service's role as a bridge to secondary mental healthcare. By allocating clinicians to predetermined clinic locations, the service balanced the need for consistent care with flexibility to assign patients to the appropriate clinicians based on their needs.

5.1. Model formulation

The model formulation used the following notation. A notation Table is also available in Appendix Table A1.

Objective function:

$$\text{Min}\ \left(\sum_{a\in A}\sum_{l\in L}F_l^a-\sum_{a\in A}\sum_{c\in C}\sum_{l\in L}\sum_{s\in S}X_{cls}^a\right)+MaxZ \tag{1}$$

Subject to:

$$\sum_{c\in C}\sum_{s\in S}X_{cls}^a\le F_l^a\forall l\in L,\quad \forall a\in A \tag{2}$$

$$\sum_{a\in A}R_aX_{cls}^a\le L_s\quad \forall c\in C,\forall l\in L,\forall s\in S \tag{3}$$

$$\sum_{l\in L}\sum_{s\in A}\sum_{a\in A}R_aX_{cls}^a+Z_c^-=H_c\quad \forall c\in C \tag{4}$$

$$X_{cls}^a\le MY_{cls}\quad \forall c\in C,\forall l\in L,\forall s\in S,\forall a\in A \tag{5}$$

$$Y_{cls}\le\sum_{a\in A}X_{cls}^a\quad \forall c\in C,\forall l\in L,\forall s\in S \tag{6}$$

$$\sum_{c\in C}Y_{cls}\le 1\quad \forall l\in L,\forall s\in S \tag{7}$$

$$\sum_{l\in L}Y_{cls}\le 1\quad \forall c\in C,\forall d\in D,\forall s\in S_d \tag{8}$$

$$\sum_{s\in S_d}\sum_{l\in L}Y_{cls}\le S_{\max}\quad \forall c\in C,\forall d\in D \tag{9}$$

$$Y_{cls}\ +Y_{cl's'}\le 1$$
$$\forall c\in C,,\forall l,l'\in L: l!\ne l'\&\&T_{ll'}>T_{\max},\forall d \tag{10}$$
$$\in D,\forall s,s'\in S_d: s<s'$$

$$Y_{cls}\le W_{cl}\quad \forall c\in C,\forall l\in L,\forall s\in S \tag{11}$$

$$\sum_{c\in C}W_{cl}\le N_l\quad \forall l\in L \tag{12}$$

$$\sum_{l\in L}W_{cl}\le N_c\quad \forall c\in C \tag{13}$$

$$W_{cl}\le P_{cl}\quad \forall c\in C,\forall l\in L \tag{14}$$

$$Y_{cls}\le H_{cs}\quad \forall c\in C,\forall l\in L,\forall s\in S \tag{15}$$

$$X_{cls}^a\le M\ B_{ca}\quad \forall c\in C,\forall l\in L,\forall s\in S,\forall a\in A \tag{16}$$

$$MaxZ\ge Z_c^-/H_c\quad \forall c\in C \tag{17}$$

$$Y_{cls}\ \in\{0,1\}S\quad \forall c\in C,\forall l\in L,\forall s\in S \tag{18}$$

$$X_{cls}^a\in\mathbb{Z}\quad \forall c\in C,\forall l\in L,\forall s\in S,\forall a\in A \tag{19}$$

$$W_{cl}\ \in\{0,1\}\quad \forall c\in C,\forall l\in L \tag{20}$$

$$Z_c^-\in\mathbb{Z}\quad \forall c\in C \tag{21}$$

The objective of the model (1) is twofold. The primary objective is to minimize the number of unassigned appointments, effectively minimizing unmet demand. The secondary objective is to minimize the maximum percentage of unassigned hours across all clinicians. The fact that the second objective is a percentage (always less or equal one) while the first objective is a positive integer number ensures that minimizing unmet demand is the primary objective. Only in the case of alternative optimal solutions with respect to the first objective, the second objective is minimized. Constraints (2) ensure that for each clinic location and appointment type, the total number of appointments assigned to all clinicians in all shifts does not exceed the appointment demand for that type in that clinic location. Constraints (3) limit the duration of appointments assigned to each shift, ensuring that for each clinician, shift, and clinic location, the total duration of all assigned appointments does not exceed the length of the shift. Constraints (4) ensures that the total duration of appointments assigned to each clinician across all clinic locations and shifts does not exceed the clinician's availability. They also capture the unassigned hours for each clinician through the variables Z_c^- .

Constraints (5) ensure that appointments can be assigned to a clinician in a clinic location during a shift only if the clinician has been assigned to that clinic location in that shift ($Y_{cls}=1$). To ensure that these constraints work as intended, M can be set equal to $\lfloor L_s/R_a\rfloor$ (ie, the maximum number of appointments of type a that can be carried out in shift s). Constraints (6) ensure that if a clinic location is assigned to a clinician in a shift, then at least one appointment must be assigned to that clinician in the shift. Constraints (7) ensure that at most one clinician is assigned to each clinic location in each shift. Constraints (8) ensure that each clinician can be assigned to at most one clinic location in each shift within a day.

Constraints (9) limit the maximum number of shifts per day for each clinician to a predefined value $S_{\max}$. Constraints (10) impose travel time constraints for shifts within a day, preventing a clinician from being assigned to clinic locations that are too far apart ($T_{ll'}>T_{\max}$) in consecutive shifts. Constraints (11) link the variables Y and W, ensuring that a clinician can be assigned to a clinic location in a given shift ($Y_{cls}=1$), only if the clinician is assigned to that clinic location. Constraints (12) limit the number of clinicians assigned to each clinic location to a maximum of N_l. Constraints

(13) limit the number of clinic locations assigned to each clinician to a maximum of N_c.

Constraints (14) enforce clinic location preferences, ensuring that a clinician can only be assigned to a clinic location if the clinician has a preference for that clinic location. Similarly, constraints (15) enforce shift assignment feasibility, ensuring that a clinician can only be assigned to a shift if the clinician is available for that shift. Constraints (16) ensure that clinician can only be assigned appointments of a specific type if they have the required skill for that appointment type. M can be set to the same value as in constraints (5). Constraint (17) ensures that the variable MaxZ is greater than or equal to a percentage of unassigned hours (Z_c^-/H_c) for each clinician, effectively capturing the maximum percentage of unassigned hours across all clinicians. This constraint allows for a fair comparison between clinicians with different total available hours, as it considers the proportion of unassigned time relative to each clinician's capacity. Finally, constraints (18)—(21) define the domain of the variables.

5.2. Model validation

The verification and validation of the model with the stakeholders took place during the COVID-19 pandemic, which brought about wide-ranging changes in the organization of mental health services. These changes included pausing "non-essential" services, deploying staff to new and unfamiliar roles, and transitioning to remote working (Liberati et al., 2021). Due to the unprecedented nature of the pandemic and the complete lack of face-to-face appointments, the service decided to offer longer appointments to patients to counteract the absence of in-person contact. The operational policy was modified to adapt to a potential surge in demand, necessitating the assessment of resource utilization and service capacity. As a result, a COVID model variant was developed to aid in planning operations during the pandemic.

The initial "Non-COVID" model assumed that clinicians deliver the service as usual, while the COVID variant assumed that all appointments were telephone-based and removed constraints on clinician travel and clinician skill requitement. Constraints (10) and (16) were removed, and constraints (2)—(5) were simplified to reflect the existence of only telephone appointments. This adaptation of the model to the unique circumstances of the pandemic demonstrates its flexibility and responsiveness to changing operational requirements, further validating its usefulness as a decision-support tool for the PCMH service.

6. Computational results

To evaluate the model's performance and assess the impact of various operational strategies, we conducted a comprehensive scenario analysis using real-world data from the PCMH service. By comparing the model's outputs across these scenarios, we aimed to identify potential areas for improvement and provide actionable insights to support decision-making and enhance service efficiency.

6.1. Inputs and scenario generation

Based on discussion with stakeholders, several alternative service design options were derived for scenario analysis. In the descriptive stage of the methodology, we identified problems relating to clinic shift duration, appointment duration, and clinician hours. We were guided by stakeholders to explore these issues as well as an increase in demand. Scenarios were generated using experimental model input values derived from the prescriptive and descriptive analytics stages. For the analysis, data from the service for a specific planning period of 4 wk (1st to 30th of May 2021) was extracted to compare service improvements and model performance.

This period was considered for its high demand values. For appointment durations, two profiles (Pa and Pb) discussed in Section 4.1, Table 3 were used. For clinician availability over a 4-week planning period, stakeholders supplied shift durations of 2.5 h for the Non-COVID and COVID scenarios, and weekly shifts for clinicians grouped by band were based on the discussion in Section 4.1, Figure 4. Table 6 depicts the standardization strategy for clinician availability. In practice, the service did not have standardized specifications for appointment durations and clinician availability, and appointments were scheduled on an ad-hoc basis by each clinician.

6.1.1. The scenarios

We developed 16 scenarios to systematically evaluate the impact of various operational strategies. Table 7 summarizes these scenarios. Scenarios 1–4 used the perceived clinician availability, while scenarios 5–8

Table 6. Standardised clinician availability.

	Standardised availability		
Clinician Band	Available Shifts (4 Weeks)	Weekly Shifts	Available Hours (2.5 hr shift)
8a	20	5	50
7	28	7	70
6a	32	8	80
6b	12	3	30
6c	16	4	40

used standardized availability depicted in Table 6. In scenarios 1, 2, 5 and 6 we used current appointment demand, whereas scenarios 3, 4, 7, and 8 utilised an increase demand of about 15% which was the result of the forecasting and stakeholders' intuition.

For COVID scenarios, each of the previous combinations were further combined with two appointment duration profiles (Pa and Pb, Table 3). Scenarios 9–16 in the table were COVID-variant counterparts of scenarios 1–8. Note that in these scenarios, only one appointment type was offered *via* the telephone. Therefore, the appointment duration for profile Pa was taken to be 45 min, while profile Pb was 60 min. These values were supplied by stakeholders. Table 8 depicts scenario specification for the non-COVID model variant. The second column has clinician available hours, the third has the number of appointments for each type across all locations and the last has the appointment duration with a total duration of all appointments.

Likewise, Table 9 displays scenario specifications for the COVID model variant.

Table 7. Summary of scenario options.

Scenarios		Clinician available hours (H_c)	Appointment demand (F_l^a)	Appointment duration (R_a)
Non-COVID	COVID			
1	9	Perceived	Current	Pa
2	10	Perceived	Current	Pb
3	11	Perceived	Increased	Pa
4	12	Perceived	Increased	Pb
5	13	Standardised	Current	Pa
6	14	Standardised	Current	Pb
7	15	Standardised	Increased	Pa
8	16	Standardised	Increased	Pb

6.2. Non-COVID model scenarios results

We evaluated the proposed optimization model's efficacy in scheduling clinicians by comparing its outputs against the historical appointment data from a four-week planning period (1st to 30th of May 2021).

6.2.1. Unmet demand and clinician utilization

Table 10 is a summary of the scenario results, focusing on unmet demand and clinician utilization in terms of unassigned hours. Specifically, the table

Table 8. Non-COVID scenario specifications.

	Clinician available hours													Appointment demand					Appointment duration				
Scenario	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Total	A	F	T	C	Total	A	F	T	C	Total Hrs
1	48	50	48	50	63	60	45	73	73	35	43	30	615	53	264	269	6	592	60	45	30	45	390
2	48	50	48	50	63	60	45	73	73	35	43	30	615	53	264	269	6	592	60	60	45	60	525
3	48	50	48	50	63	60	45	73	73	35	43	30	615	137	425	96	41	699	60	45	30	45	535
4	48	50	48	50	63	60	45	73	73	35	43	30	615	137	425	96	41	699	60	60	45	60	675
5	50	50	50	70	70	70	70	80	80	40	30	30	690	53	264	269	6	592	60	45	30	45	390
6	50	50	50	70	70	70	70	80	80	40	30	30	690	53	264	269	6	592	60	60	45	60	525
7	50	50	50	70	70	70	70	80	80	40	30	30	690	137	425	96	41	699	60	45	30	45	535
8	50	50	50	70	70	70	70	80	80	40	30	30	690	137	425	96	41	699	60	60	45	60	675

Table 9. COVID scenario specifications.

	Clinician available hours															
Scenario	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Total	Total appointment demand	Appointment duration	Total appointment hours
9	48	50	48	50	63	60	45	73	73	35	43	30	615	592	45	444
10	48	50	48	50	63	60	45	73	73	35	43	30	615	592	60	592
11	48	50	48	50	63	60	45	73	73	35	43	30	615	699	45	524
12	48	50	48	50	63	60	45	73	73	35	43	30	615	699	60	699
13	50	50	50	70	70	70	70	80	80	40	30	30	690	592	45	444
14	50	50	50	70	70	70	70	80	80	40	30	30	690	592	60	592
15	50	50	50	70	70	70	70	80	80	40	30	30	690	699	45	524
16	50	50	50	70	70	70	70	80	80	40	30	30	690	699	60	699

Table 10. Non-COVID scenario outputs.

	Unassigned hours per clinician													Unmet demand per appointment type				
Scenario	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Total	*A*	*F*	*T*	*C*	Total unmet demand
1	17	18	18	18	23	22	17	27	27	13	16	11	225	0	0	0	0	0
2	7	8	7	7	10	9	7	11	11	5	7	4	90	0	0	0	0	0
3	7	6	6	6	8	8	6	10	10	5	6	4	81	0	0	0	0	0
4	1	1	0	0	0	0	0	1	0	0	0	0	3	19	39	1	4	63
5	22	22	22	31	30	31	30	35	35	17	13	13	300	0	0	0	0	0
6	12	12	12	16	17	17	17	19	20	10	7	7	165	0	0	0	0	0
7	12	11	12	16	16	16	15	18	18	9	7	7	156	0	0	0	0	0
8	1.3	1	0.8	1.3	1.3	1.8	1.5	2	2	1	0.5	0.8	15	0	0	0	0	0

shows the number of unassigned hours for each clinician (C1–C12) across all scenarios, as well as the total unassigned hours for each scenario. It also presents the unmet demand for each appointment type (A: Assessment, F: Follow-up, T: Telephone, C: Community) and the total unmet demand per scenario. The model demonstrated strong performance in meeting demand across most scenarios. All scenarios except 4 showed zero unmet demand, indicating that the model could allocate appointments efficiently to meet all service needs under various conditions. This suggests that when optimally scheduled, the current workforce could generally meet service demand without accumulating significant waiting lists.

Scenario 4 revealed potential capacity limitations under high-demand situations combined with longer appointment durations. It showed 63 unmet appointments, the majority of which (39) were follow up appointments. However, scenario 8, despite facing high demand and longer appointment durations, successfully met all appointment demands with zero unmet appointments when standardized availability was implemented.

In terms of clinician utilization, the model effectively allocated available hours across all scenarios. In scenarios with perceived availability (1–4), the total unassigned hours ranged from 3 to 225 h, representing between 0.5% and 36.6% of total available hours. Scenarios with standardized availability (5–8) showed a range of 15–300 unassigned hours, or 2.2%–43.5% of total available hours. This higher upper range in standardized scenarios reflects a more structured approach to clinician time management, providing buffer capacity for unforeseen circumstances or additional tasks.

Notably, scenario 8 achieved the highest clinician utilization, with only 15 unassigned hours (2.2% of total available hours) while still meeting all appointment demands. This scenario demonstrated the model's capability to efficiently utilize clinician time when faced with high demand and longer appointment durations, provided standardized availability was implemented.

6.2.2. Appointment distribution and fairness

To evaluate the model's effectiveness in improving demand allocation, we compared the recorded appointment distribution data from the four-week planning period against the model's outputs for scenarios 1, 2, 5, and 6. These specific scenarios were chosen as they consider the same demand for appointments as the recorded data, allowing for a direct comparison.

Table 11 reveals substantial disparities in the percentage of demand met by each clinician under the current practice, ranging from 2% to 15%. This wide range indicated significant imbalances in workload distribution and resource utilization inefficiencies. In contrast, the optimized model outputs demonstrated a more balanced distribution of demand fulfillment across all clinicians, even without standardizing availabilities.

Table 11. Recorded versus model assigned appointment distribution.

Clinician	Recorded	Scenario 1	Scenario 2	Scenario 5	Scenario 6
1	6%	7%	8%	7%	7%
2	8%	8%	8%	8%	7%
3	5%	7%	8%	8%	7%
4	10%	9%	8%	11%	10%
5	2%	10%	10%	9%	10%
6	13%	9%	10%	9%	10%
7	15%	7%	7%	10%	11%
8	13%	11%	11%	11%	11%
9	12%	12%	12%	11%	12%
10	6%	7%	6%	6%	6%
11	4%	8%	7%	5%	4%
12	5%	5%	5%	4%	4%

For instance, in Scenario 1, the demand met by Clinicians C4-C7 in Band 7 ranged from 7% to 10%, a notable improvement from the recorded range of 2%–15%. Standardizing clinician availabilities (Scenarios 5 and 6) further enhanced equity within each band, as exemplified by clinicians in Band 7, all being assigned 9%–11% of the demand, minimizing the 2%–15% gap in the recorded data.

6.2.3. Impact of standardization and secondary objective

Figure 17 illustrates the impact of standardization and the secondary objective across different scenarios. Each subplot represents a scenario, with clinicians (C1–C12) on the x-axis and hours on the y-axis. The blue bar represents the total availability for each clinician, with the orange portion showing model-assigned hours and the gap between the bars representing unassigned hours. The percentage indicates the proportion of available hours that remained unassigned.

In scenarios with perceived availability (1–4), we observed varying total availabilities across clinicians, even within the same band. Scenario 1 showed unassigned hours ranging from 36% to 38%, while Scenario 2 demonstrated an expected increase in utilization (14%–16% unassigned) due to longer appointment durations. Despite similar percentages within scenarios, the actual unassigned hours differed due to varying availabilities. Scenarios with standardized availability (5-8) showed more consistent total availability within bands and more uniform percentages of unassigned hours. For instance, Scenario 5 show 43%–44% unassigned hours for all clinicians, with consistent total availability within each band. Scenario 8 achieved the highest

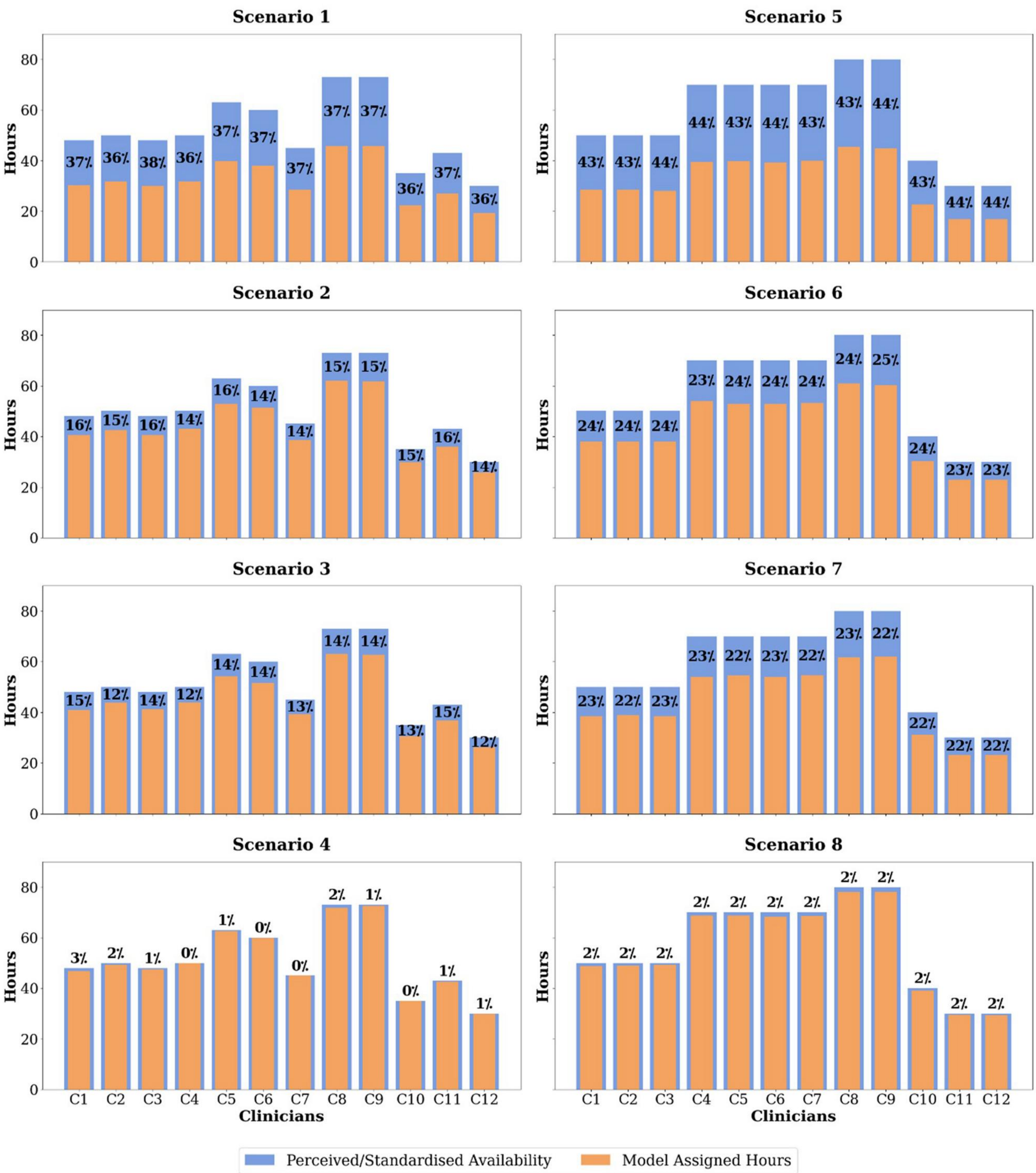


Figure 17. Appointment hours vs available clinician hours.

utilization, with only 2% unassigned hours across all clinicians. The comparison between scenarios 1–4 and 5–8 clearly illustrates how standardized availability lead to more consistent total hours within bands and a more balanced distribution of unassigned hours across clinicians. This standardization addressed the issue of some clinicians potentially having disproportionately more or fewer unassigned hours relative to their peers, as seen in the scenarios with perceived availability.

6.2.4. Optimised clinician allocation schedule

Figure 18 provides a sample optimised allocation schedule (scenario 8) generated by the model.

The full schedule can also be viewed Appendix Figure A1. This schedule offers a clear and concise view of the optimized resource allocation, ensuring that the right clinician is assigned to the right location at the right time to meet the specific appointment needs of the patients. The schedule specifies which clinician (represented by different colours)

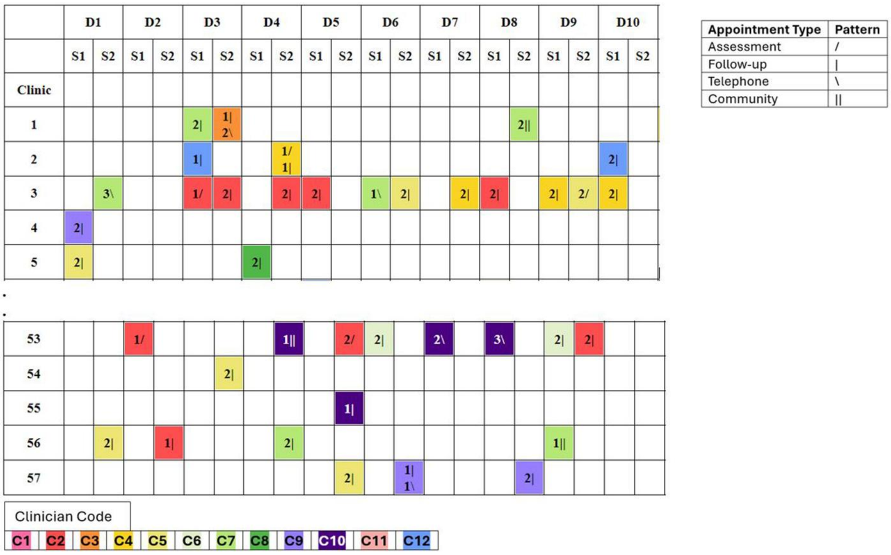


Figure 18. Sample optimized clinician allocation schedule.

Table 12. Covid model output summary.

	Unassigned hours per clinician (Hours)													
Scenario	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Total	Total unmet demand
9	13	14	13	14	18	17	13	20	20	10	12	8	171	0
10	3	2	2	2	3	2	2	3	3	1	2	1	23	0
11	7	7	7	7	9	9	7	11	11	5	6	5	91	0
12	1.5	0	0.5	0	0.5	0	0	1.5	0.5	0	0.5	0	5	89
13	18	18	18	25	25	25	25	29	28	15	11	11	246	0
14	7	7	7	10	10	10	10	11	12	6	4	4	98	0
15	13	12	13	17	17	15	17	19	20	10	7	8	166	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	9

should be assigned to each clinic location on a particular day and shift (S1 for AM shift and S2 for the PM shift). Furthermore, the type of appointment (assessment, follow-up, telephone, or community) to be conducted by the assigned clinician is indicated using specific patterns (/, |,\, or ||).

In conclusion, the model's dual focus on minimizing unmet demand and balancing unassigned hours, coupled with standardized availability, resulted in a more equitable and efficient resource allocation. While the model generally met demand effectively, the results from scenarios 4 highlighted the need for careful capacity planning when faced with increased demand or extended appointment durations. This demonstrated the practical value of the optimization approach in healthcare resource management and offered a robust tool for service planners to maximize efficiency while maintaining fairness among clinicians of varying skill levels and employment status.

6.3. COVID-19 model scenarios results

The COVID-19 model scenarios, summarized in Table 12, demonstrated the service's adaptability under unprecedented conditions. Table 12 presents the unassigned hours for each clinician, along with the total unmet demand for each scenario.

The model's performance across these scenarios highlighted its ability to optimize resource allocation even under challenging circumstances. For instance, scenario 16 shows the power of the optimization model in identifying a solution that utilized all available capacity. Despite the model assigning 100% of available hours across all clinicians, there remained 9 unmet appointments. This result underscores that the model had exhausted all possible efficient allocations, providing assurance that resources had been used to their maximum potential.

In contrast, scenarios like 13 and 14 demonstrated how the model balanced workload when there's less pressure on capacity. For instance, in scenario 13, with standardized availability and current demand, unassigned hours across clinicians were in the range 11–29. These values followed a similar pattern to those seen in Table 10 for the non-COVID scenarios, reflecting a fair distribution of workload.

These results illustrate the model's flexibility in adapting to various demand and capacity scenarios while maintaining equity in clinician utilization. Such insights were particularly valuable for contingency planning, allowing service managers to understand potential trade-offs and make informed decisions about resource allocation under different circumstances.

7. Discussion

In this section, we discuss the key contributions of our study, including a reflection on our multi-skill multi-location optimization model and the value of our integrated analytics approach. We also reflect on the implementation challenges encountered, the lessons learned, and the potential for future research.

7.1. Reflecting on the optimization model

Our study advances optimization modelling in mental healthcare by developing a novel multi-skill, multi-location scheduling approach that addresses fundamental service delivery challenges in a primary care setting (Bradley et al., 2017; Howells et al., 2022; Long & Meadows, 2018; Noorain et al., 2019; 2023). Unlike previous mental health optimization studies focused on narrow scheduling problems or simplified assumptions (Noorain et al., 2023), our model comprehensively tackles the complex interplay between geographical coverage, skill distribution, and continuity of care. The model uniquely addresses these challenges through several key mechanisms: balancing geographical coverage with skill-appropriate care delivery, maintaining consistent service presence while optimizing resource utilization, and effectively handling the complexity of hierarchical nursing bands combined with varied intervention types.

While sharing characteristics with other healthcare scheduling applications - such as resource coordination from multi-appointment scheduling (Marynissen & Demeulemeester, 2019), staff routing from home healthcare (Goodarzian et al., 2023), and resource utilization optimization from outpatient scheduling (Ahmadi-Javid et al., 2017) – our model addresses a distinct combination of requirements that sets it apart from existing approaches. Unlike home healthcare where travel time optimization is paramount, or outpatient scheduling focused on single-location resource utilization, our model prioritizes maintaining continuity of care while ensuring appropriate skill distribution across a network of primary care locations. This distinctive approach proved effective in our case study, achieving more equitable workload distribution across clinicians while maintaining appropriate skill coverage, with the model's adaptation during COVID-19 further demonstrating its flexibility in supporting service delivery.

While developed specifically for mental health services, elements of our model could be adapted for other community healthcare services that need to maintain a regular presence across multiple locations (Palmer et al., 2018). The skill hierarchies and intervention types would need to be redefined to match specific service requirements, but the core approach of balancing geographical coverage with specialized skill requirements has potential broader applications in community healthcare service planning.

7.2. The value of analytics-driven optimization modelling

Our study advances healthcare analytics by explicitly demonstrating how data analysis shapes optimization model development (Noorain et al., 2023). While integrated approaches exist (Galetsi & Katsaliaki, 2020; Lepenioti et al., 2020), we detail a systematic process that moves beyond parameter estimation (Bernardelli et al., 2024; Ordu et al., 2021) to fundamentally inform model formulation through visualization, statistical analysis, time series forecasting, and simulation.

The analytics process showed several insights that directly shaped our model development. Historical data analysis showed most appointments were completed within 45 min, contradicting perceived durations of over 60 min. This finding led to the implementation of standardized appointment duration parameters in the model. Additionally, clinician utilization analysis uncovered significant workload imbalances within the same skill bands, informing our model's fairness constraints and the development of standardized availability templates.

In our location-specific demand analysis, we found inefficient but strategically important staffing patterns. While some locations appeared overstaffed relative to current demand, this arrangement served important purposes: maintaining continuity of care, preserving established GP practice relationships, and retaining capacity for managing demand fluctuations. This insight significantly influenced how we modelled clinician-location assignments, demonstrating the value of combining quantitative analysis with operational context. What initially appeared as an inefficient resource allocation was revealed through analytics to be a deliberate strategy supporting long-term service stability and relationships.

These findings illustrate how analytics can systematically inform optimization model development. Our approach enabled us to develop a robust model despite data limitations, similar to recent work using nonlinear models for scheduling constraints (Wang et al., 2021) and classification trees for threshold identification (Sir et al., 2017).

7.3. Implementation challenges and lessons learned

In the optimization community, implementation encompasses computational aspects that focus on developing efficient solution procedures balancing solution quality and computational speed, often involving mathematical algorithms and software prototypes (Humagain et al., 2020). It also includes practical implementation, where models are tested and applied in real operational environments to closely reflect real-world conditions (Ahmadi-Javid et al., 2017).

While our model provided valuable short-term insights for service improvement and workforce planning through real data utilization (Fajemisin et al., 2024), it was not implemented for ongoing use by the service due to several concurrent organizational changes. The service's distributed structure across multiple GP practices, each using different electronic health record systems (RiO and EMIS), created information governance challenges for data integration. The transition was further affected by the departure of the project champion (transformation lead). Most significantly, the introduction of the NHS Long Term Plan's Community Mental Health Framework (CMHF) mandated fundamental changes to mental health service delivery, including a shift from primary care-based to location-based community mental health services (NCCMH, 2021). For KMPT, this meant the dissolution of the PCMH service that was the focus of our study. Following the ratification of operational policies in early 2022 (KMPT, 2022), the trust began implementing these transformational changes, with full implementation planned between 2023 and 2026. These barriers to long-term deployment mirror challenges identified in other recent studies (Abuabara et al., 2022).

However, in other hard OR approaches such as simulation modelling, implementation takes on a broader meaning, including stakeholder learning about complex situations (Brailsford et al., 2019; Harper & Mustafee, 2023; Kotiadis & Tako, 2010; Long et al., 2020). From this view, our work led to valuable organizational learning and practical changes. As noted by Stakeholder D: "I think to answer your question of anything that has directly changed since we started the study. The data that you have explored and presented to us, we went back to the Business Intelligence (BI) team and said to them that these aspects are not being reported on and should be included in the report." The Project Champion further emphasized the practical impact: And also, raising our awareness about areas where we can do some efficiency savings in clinical time and that is a direct impact of this work. This was complemented by Stakeholder J's observation: "We also saw that there are certain things we are not capturing in the database that we should capture." Through the analysis, stakeholders recognized several data collection gaps, including that patient-related consultations with GPs conducted by band 8 clinicians were not recorded in their database system, and using individual clinician "Job Plans" to better understand working patterns.

The stakeholders clearly recognized the value of the analytics-driven optimization approach. The Project Champion noted: "So, I have connected with the director of performance, and I am trying to facilitate wider conversations. To make a recommendation to the wider trust about the work that this study has conducted." This led to interest in wider application, as evidenced by Stakeholder G: "Personally, I would like to use the optimization model with other services that I am working with, but I realise this is outside the scope of this work, but I would put it down as an aspiration."

As ongoing collaborators with the healthcare trust, we hope to go back and adapt and apply our analytics-driven approach to the new service model once the system has settled into its transformed state, reflecting our commitment to developing flexible models that can evolve with changing healthcare delivery frameworks (Long et al., 2022).

7.4. Future research

Future research could address several promising methodological directions. Researchers could explore strategies for increasing workforce flexibility through substitution and cross-training techniques (Afshar-Nadjafi, 2021; De Bruecker et al., 2015), incorporate stochastic demand elements using methods such as stochastic, robust or fuzzy optimization (Dai & Wang, 2024; Gökalp et al., 2024), and develop queuing models that account for uncertain treatment durations (Kim & Lee, 2021). For larger problem instances, development of efficient solution method including multi-objective genetic algorithms (Farughi et al., 2020), or hybrid approaches like Variable Neighbourhood Search-Dynamic Programming (Lan et al., 2022) would enable the extension to more complex scheduling scenario. In our model, fairness in addressed by choosing the "fairest" among multiple optimal solutions based on the secondary objective. Future research could explore alternative approaches to fairness such as minimizing differences between individual penalties (Wolbeck et al., 2020). The model could also be enhanced by utilising strategic approaches such as location-allocation criteria to improve continuity of care (Mitropoulos et al., 2023), leading to better patient outcomes and more efficient use of healthcare resources.

8. Conclusion

This article presents an integrated descriptive, predictive, and prescriptive analytics approach to develop an optimization model for planning mental healthcare services. Through a case study with a Primary Care Mental Health service in the UK, we demonstrate how analytics and optimization can work together to address real-world healthcare planning challenges. Our study provides valuable insights into the practical challenges of healthcare optimization while offering a robust foundation for decision-support tools that can enhance efficiency, access, and equity. The case findings suggest opportunities for future research to explore workforce flexibility, stochastic demand modeling, fairness mechanisms and continuity of care.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

No funding was received.

ORCID

Sheema Noorain http://orcid.org/0000-0003-3693-289X
Maria Paola Scaparra http://orcid.org/0000-0002-2725-5439
Kathy Kotiadis http://orcid.org/0000-0001-8004-5708

References

Abuabara, L., Werner-Masters, K., & Paucar-Caceres, A. (2022). Daily food planning for families under Covid-19: Combining analytic hierarchy processes and linear optimisation. *Health Systems*, *11*(3), 232–250. https://doi.org/10.1080/20476965.2022.2080006

Afshar-Nadjafi, B. (2021). Multi-skilling in scheduling problems: A review on models, methods and applications. *Computers & Industrial Engineering*, *151*, 107004. https://doi.org/10.1016/j.cie.2020.107004

Ahmadi-Javid, A., Jalali, Z., & Klassen, K. J. (2017). Outpatient appointment systems in healthcare: A review of optimization studies. *European Journal of Operational Research*, *258*(1), 3–34. https://doi.org/10.1016/j.ejor.2016.06.064

Ahmed, A., & Frohn, E. (2021). A predictive and prescriptive analytical framework for scheduling language medical interpreters. *Health Care Management Science*, *24*(3), 531–550. https://doi.org/10.1007/s10729-020-09536-y

Al-Yakoob, S. M., & Sherali, H. D. (2007). Multiple shift scheduling of hierarchical workforce with multiple work centers. *Informatica*, *18*(3), 325–342. https://doi.org/10.15388/Informatica.2007.180

Al-Yakoob, S. M., & Sherali, H. D. (2008). A column generation approach for an employee scheduling problem with multiple shifts and work locations. *Journal of the Operational Research Society*, *59*(1), 34–43. https://doi.org/10.1057/palgrave.jors.2602294

Andersen, A. R., Nielsen, B. F., Reinhardt, L. B., & Stidsen, T. R. (2019). Staff optimization for time-dependent acute patient flow. *European Journal of Operational Research*, *272*(1), 94–105. https://doi.org/10.1016/j.ejor.2018.06.015

Attia, D., Bürgy, R., Desaulniers, G., & Soumis, F. (2019). A decomposition-based heuristic for large employee scheduling problems with inter-department transfers. *EURO Journal on Computational Optimization*, *7*(4), 325–357. https://doi.org/10.1007/s13675-019-00119-3

Aurizki, G. E., & Wilson, I. (2022). Nurse-led task-shifting strategies to substitute for mental health specialists in primary care: A systematic review. *International Journal of Nursing Practice*, *28*(5), e13046. https://doi.org/10.1111/ijn.13046

Bard, J. F., & Wan, L. (2008). Workforce design with movement restrictions between workstation groups. *Manufacturing & Service Operations Management*, *10*(1), 24–42. https://doi.org/10.1287/msom.1060.0148

Bernardelli, A. M., Bonasera, L., Duma, D., & Vercesi, E. (2024). Multi-objective stochastic scheduling of inpatient and outpatient surgeries. *Flexible Services and Manufacturing Journal*, 1–55. https://doi.org/10.1007/s10696-024-09542-0

Bester, M. J., Nieuwoudt, I., & Van Vuuren, J. H. (2007). Finding good nurse duty schedules: A case study. *Journal of Scheduling*, *10*(6), 387–405. https://doi.org/10.1007/s10951-007-0035-7

Bradley, B. D., Jung, T., Tandon-Verma, A., Khoury, B., Chan, T. C. Y., & Cheng, Y. L. (2017). Operations research in global health: A scoping review with a focus on the themes of health equity and impact. *Health Research Policy and Systems*, *15*(1), 32. https://doi.org/10.1186/s12961-017-0187-7

Brailsford, S. C., Eldabi, T., Kunc, M., Mustafee, N., & Osorio, A. F. (2019). Hybrid simulation modelling in operational research: A state-of-the-art review. *European Journal of Operational Research*, 278(3), 25. https://doi.org/10.1016/j.ejor.2018.10.025

British Medical Association. (2020). *Beyond parity of esteem – Achieving parity of resource, access and outcome for mental health in England*. https://www.bma.org.uk/media/2099/mental-health-parity-of-esteem-report-jan-2020-2.pdf

Brunner, J. O., Bard, J. F., & Kolisch, R. (2009). Flexible shift scheduling of physicians. *Health Care Management Science*, *12*(3), 285–305. https://doi.org/10.1007/s10729-008-9095-2

Brunner, J. O., & Edenharter, G. M. (2011). Long term staff scheduling of physicians with different experience levels in hospitals using column generation. *Health Care Management Science*, *14*(2), 189–202. https://doi.org/10.1007/s10729-011-9155-x

Burke, E. K., De Causmaecker, P., Berghe, G. V., & Van Landeghem, H. (2004). The state of the art of nurse rostering. *Journal of Scheduling*, *7*(6), 441–499. https://doi.org/10.1023/B:JOSH.0000046076.75950.0b

Cardoen, B., Demeulemeester, E., & Beliën, J. (2010). Operating room planning and scheduling: A literature review. *European Journal of Operational Research*, *201*(3), 921–932. https://doi.org/10.1016/j.ejor.2009.04.011

Carter, M. W., & Busby, C. R. (2023). How can operational research make a real difference in healthcare? Challenges of implementation. *European Journal of Operational Research*, *306*(3), 1059–1068. https://doi.org/10.1016/j.ejor.2022.04.022

Cayirli, T., & Veral, E. (2003). Outpatient scheduling in health care: A review of literature. *Production and Operations Management*, *12*(4), 519–549. https://doi.org/10.1111/j.1937-5956.2003.tb00218.x

Cheng, C., & Kuo, Y. (2016). A dissimilarities balance model for a multi-skilled multi-location food safety inspector scheduling problem. *IIE Transactions*, *48*(3), 235–251. https://doi.org/10.1080/0740817X.2015.1057303

Cissé, M., Yalçındağ, S., Kergosien, Y., Şahin, E., Lenté, C., & Matta, A. (2017). OR problems related to Home Health Care: A review of relevant routing and scheduling problems. *Operations Research for Health Care*, *13-14*, 1–22. https://doi.org/10.1016/j.orhc.2017.06.001

Cohn, A., Root, S., Kymissis, C., Esses, J., & Westmoreland, N. (2009). Scheduling medical residents at boston university school of medicine. *Interfaces*, *39*(3), 186–195. https://doi.org/10.1287/inte.1080.0369

Conboy, K., Mikalef, P., Dennehy, D., & Krogstie, J. (2020). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. *European Journal of Operational Research*, *281*(3), 656–672. https://doi.org/10.1016/j.ejor.2019.06.051

Dahmen, S., Rekik, M., & Soumis, F. (2018). An implicit model for multi-activity shift scheduling problems. *Journal of Scheduling*, *21*(3), 285–304. https://doi.org/10.1007/s10951-017-0544-y

Dahmen, S., Rekik, M., Soumis, F., & Desaulniers, G. (2020). A two-stage solution approach for personalized multi-department multi-day shift scheduling. *European Journal of Operational Research*, *280*(3), 1051–1063. https://doi.org/10.1016/j.ejor.2019.07.068

Dai, Z., & Wang, J. J. (2024). Elective surgery scheduling considering transfer risk in hierarchical diagnosis and treatment system. *Journal of the Operational Research Society*, *75*(4), 660–672. https://doi.org/10.1080/01605682.2023.2198557

De Bruecker, P., Van den Bergh, J., Beliën, J., & Demeulemeester, E. (2015). Workforce planning incorporating skills: State of the art. *European Journal of Operational Research*, *243*(1), 1–16. https://doi.org/10.1016/j.ejor.2014.10.038

De Causmaecker, P., & Berghe, G. V. (2011). A categorisation of nurse rostering problems. *Journal of Scheduling*, *14*(1), 3–16. https://doi.org/10.1007/s10951-010-0211-z

Duan, Y., Cao, G., & Edwards, J. S. (2020). Understanding the impact of business analytics on innovation. *European Journal of Operational Research*, *281*(3), 673–686. https://doi.org/10.1016/j.ejor.2018.06.021

Elleuch, M. A., Hassena, A. B., Abdelhedi, M. and., & Pinto, F. S. (2021). Real-time prediction of COVID-19 patients health situations using Artificial Neural Networks and Fuzzy Interval Mathematical modeling. *Applied Soft Computing*, *110*, 107643. https://doi.org/10.1016/j.asoc.2021.107643

Erhard, M., Schoenfelder, J., Fügener, A., & Brunner, J. O. (2018). State of the art in physician scheduling. *European Journal of Operational Research*, *265*(1), 1–18. https://doi.org/10.1016/j.ejor.2017.06.037

Fajemisin, A. O., Maragno, D., & den Hertog, D. (2024). Optimization with constraint learning: A framework and survey. *European Journal of Operational Research*, *314*(1), 1–14. https://doi.org/10.1016/j.ejor.2023.04.041

Farughi, H., Tavana, M., Mostafayi, S., & Santos Arteaga, F. J. (2020). A novel optimization model for designing compact, balanced, and contiguous healthcare districts. *Journal of the Operational Research Society*, *71*(11), 1740–1759. https://doi.org/10.1080/01605682.2019.1621217

Fikar, C., & Hirsch, P. (2017). Home health care routing and scheduling: A review. *Computers & Operations Research*, *77*, 86–95. https://doi.org/10.1016/j.cor.2016.07.019

Franz, L. S., Baker, H. M., Leong, G. K., & Rakes, T. R. (1989). A mathematical model for scheduling and staffing multiclinic health regions. *European Journal of Operational Research*, *41*(3), 277–289. https://doi.org/10.1016/0377-2217(89)90249-X

Galetsi, P., & Katsaliaki, K. (2020). A review of the literature on big data analytics in healthcare. *Journal of the Operational Research Society*, *71*(10), 1511–1529. https://doi.org/10.1080/01605682.2019.1630328

Gask, L. (2005). Overt and covert barriers to the integration of primary and specialist mental health care. *Social Science & Medicine (1982)*, *61*(8), 1785–1794. https://doi.org/10.1016/j.socscimed.2005.03.038

Gökalp, E., Cakir, M. S., & Satis, H. (2024). Dynamic capacity planning of hospital resources under COVID-19 uncertainty using approximate dynamic programming. *Journal of the Operational Research Society*, *75*(1), 13–25. https://doi.org/10.1080/01605682.2023.2168570

Goodarzian, F., Garjan, H. S., & Ghasemi, P. (2023). A state-of-the-art review of operation research models and applications in home healthcare. *Healthcare Analytics*, *4*, 100228. https://doi.org/10.1016/j.health.2023.100228

Grieco, L., Utley, M., & Crowe, S. (2021). Operational research applied to decisions in home health care: A systematic literature review. *Journal of the Operational Research Society*, *72*(9), 1960–1991. https://doi.org/10.1080/01605682.2020.1750311

Gupta, N., Bhalla, I. P., & Rosenheck, R. A. (2019). Treatment of veterans with psychiatric diagnoses nationally in the veterans health administration: A comparison of service delivery by mental health specialists and other providers. *Administration and Policy in Mental Health*, *46*(3), 380–390. https://doi.org/10.1007/s10488-018-00920-z

Harper, A., & Mustafee, N. (2023). Participatory design research for the development of real-time simulation models in healthcare. *Health Systems*, *12*(4), 375–386. https://doi.org/10.1080/20476965.2023.2175730

Hertz, A., & Lahrichi, N. (2009). A patient assignment algorithm for home care services. *Journal of the Operational Research Society*, *60*(4), 481–495. https://doi.org/10.1057/palgrave.jors.2602574

Hindle, G., Kunc, M., Mortensen, M., Oztekin, A., & Vidgen, R. (2020). Business analytics: Defining the field and identifying a research agenda. *European Journal of Operational Research*, *281*(3), 483–490. https://doi.org/10.1016/j.ejor.2019.10.001

Hindle, G. A., & Vidgen, R. (2018). Developing a business analytics methodology: A case study in the foodbank sector. *European Journal of Operational Research*, *268*(3), 836–851. https://doi.org/10.1016/j.ejor.2017.06.031

HM Government (2021). *COVID-19 mental health and wellbeing recovery action plan*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/973936/covid-19-mental-health-and-wellbeing-recovery-action-plan.pdf

Howells, M., Andrew, L., & Gartner, D. (2022). Modelling the accessibility of adult psychology services using discrete event simulation. Presented at Hawai'i International Conference on System Sciences (HICSS), Maui, Hawaii, USA, 3-7 January 2022.

Hulshof, P. J., Kortbeek, N., Boucherie, R. J., Hans, E. W., & Bakker, P. J. (2012). Taxonomic classification of planning decisions in health care: A structured review of the state of the art in OR/MS. *Health Systems*, *1*(2), 129–175. https://doi.org/10.1057/hs.2012.18

Humagain, S., Sinha, R., Lai, E., & Ranjitkar, P. (2020). A systematic review of route optimisation and preemption methods for emergency vehicles. *Transport Reviews*, *40*(1), 35–53. https://doi.org/10.1080/01441647.2019.1649319

Jang, H. (2019). A decision support framework for robust R&D budget allocation using machine learning and optimization. *Decision Support Systems*, *121*, 1–12. https://doi.org/10.1016/j.dss.2019.03.010

Kahraman, C. and Topcu, Y. I. (Eds.). (2018). *Operations research applications in health care management*. Springer International Publishing.

Kakuma, R., Minas, H., Van Ginneken, N., Dal Poz, M. R., Desiraju, K., Morris, J. E., Saxena, S., & Scheffler, R. M. (2011). Human resources for mental health care: Current situation and strategies for action. *Lancet*, *378*(9803), 1654–1663. https://doi.org/10.1016/S0140-6736(11)61093-3

Kellogg, D. L., & Walczak, S. (2007). Nurse scheduling: From academia to implementation or not? *Interfaces*, *37*(4), 355–369. https://doi.org/10.1287/inte.1070.0291

Kent and Medway NHS and Social Care Partnership Trust (KMPT). (2022). *Community mental health teams operational policy*. https://www.kmpt.nhs.uk/media/3756/foi-id-34285-1.pdf

Kenwright, M., Fairclough, P., McDonald, J., & Pickford, L. (2024). Effectiveness of community mental health nurses in an integrated primary care service: An observational cohort study. *International Journal of Nursing Studies Advances*, *6*, 100182. https://doi.org/10.1016/j.ijnsa.2024.100182

Kim, S., & Lee, C. (2021). A branch and price approach for the robust bandwidth packing problem with queuing delays. *Annals of Operations Research*, *307*(1 – 2), 251–275. https://doi.org/10.1007/s10479-021-04292-w

Kotiadis, K. (2007). Using soft systems methodology to determine the simulation study objectives. *Journal of Simulation*, *1*(3), 215–222. https://doi.org/10.1057/palgrave.jos.4250025

Kotiadis, K., & Tako, A. A. (2010). *PartiSim user guide to facilitation*. ResearchGate. DOI: https://doi.org/10.13140/RG.2.1.3659.1201.

Kotiadis, K., Tako, A. A., & Vasilakis, C. (2014). A participative and facilitative conceptual modelling framework for discrete event simulation studies in healthcare. *Journal of the Operational Research Society*, *65*(2), 197–213. https://doi.org/10.1057/jors.2012.176

Kotiadis, K., & Robinson, S. (2008). Conceptual modelling: Knowledge acquisition and model abstraction. Paper presented at the *2008 Winter Simulation Conference*, 951–958.

Kraus, M., Feuerriegel, S., & Oztekin, A. (2020). Deep learning in business analytics and operations research: Models, applications and managerial implications. *European Journal of Operational Research*, *281*(3), 628–641. https://doi.org/10.1016/j.ejor.2019.09.018

Kuo, Y., Leung, J. M., & Yano, C. A. (2014). Scheduling of multi-skilled staff across multiple locations. *Production and Operations Management*, *23*(4), 626–644. https://doi.org/10.1111/poms.12184

Lamé, G., Crowe, S., & Barclay, M. (2022). "What's the evidence?"—Towards more empirical evaluations of the impact of OR interventions in healthcare. *Health Systems*, *11*(1), 59–67. https://doi.org/10.1080/20476965.2020.1857663

Lan, S., Fan, W., Yang, S., Mladenović, N., & Pardalos, P. M. (2022). Solving a multiple-qualifications physician scheduling problem with multiple types of tasks by dynamic programming and variable neighborhood search. *Journal of the Operational Research Society*, *73*(9), 2043–2058. https://doi.org/10.1080/01605682.2021.1954485

Le, L. K. D., Esturas, A. C., Mihalopoulos, C., Chiotelis, O., Bucholc, J., Chatterton, M. L., & Engel, L. (2021). Cost-effectiveness evidence of mental health prevention and promotion interventions: A systematic review of economic evaluations. *PLOS Medicine*, *18*(5), e1003606. https://doi.org/10.1371/journal.pmed.1003606

Lee, E. K., Atallah, H. Y., Wright, M. D., Post, E. T., Thomas, C., Wu, D. T., & Haley, L. L. (2015). Transforming hospital emergency department workflow and patient care. *Interfaces*, *45*(1), 58–82. https://doi.org/10.1287/inte.2014.0788

Leeftink, A. G., Bikker, I. A., Vliegen, I., & Boucherie, R. J. (2018). Multi-disciplinary planning in health care: A review. *Health Systems*, *9*(2), 95–118. https://doi.org/10.1080/20476965.2018.1436909

Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, *50*, 57–70. https://doi.org/10.1016/j.ijinfomgt.2019.04.003

Li, Y., Kong, N., Chen, M., & Zheng, Q. P. (2016). Optimal physician assignment and patient demand allocation in an outpatient care network. *Computers & Operations Research*, *72*, 107–117. https://doi.org/10.1016/j.cor.2016.02.013

Liberati, E., Richards, N., Willars, J., Scott, D., Boydell, N., Parker, J., Pinfold, V., Martin, G., Dixon-Woods, M., & Jones, P. B. (2021). A qualitative study of experiences of NHS mental healthcare workers during the Covid-19 pandemic. *BMC Psychiatry*, *21*(1), 250. https://doi.org/10.1186/s12888-021-03261-8

Long, K. M., McDermott, F., & Meadows, G. N. (2020). Factors affecting the implementation of simulation modelling in healthcare: A longitudinal case study evaluation. *Journal of the Operational Research Society*, *71*(12), 1927–1939. https://doi.org/10.1080/01605682.2019.1650624

Long, K. M., & Meadows, G. N. (2018). Simulation modelling in mental health: A systematic review. *Journal of Simulation*, *12*(1), 76–85. https://doi.org/10.1057/s41273-017-0062-0

Long, E. F., Montibeller, G., & Zhuang, J. (2022). Health decision analysis: evolution, trends, and emerging

topics. *Decision Analysis*, *19*(4), 255–264. https://doi.org/10.1287/deca.2022.0460
Maenhout, B., & Vanhoucke, M. (2013). An integrated nurse staffing and scheduling analysis for longer-term nursing staff allocation problems. *Omega*, *41*(2), 485–499. https://doi.org/10.1016/j.omega.2012.01.002
Marynissen, J., & Demeulemeester, E. (2019). Literature review on multi-appointment scheduling problems in hospitals. *European Journal of Operational Research*, *272*(2), 407–419. https://doi.org/10.1016/j.ejor.2018.03.001
McCartan, C., Adell, T., Cameron, J., Davidson, G., Knifton, L., McDaid, S., & Mulholland, C. (2021). A scoping review of international policy responses to mental health recovery during the COVID-19 pandemic. *Health Research Policy and Systems*, *19*(1), 58. https://doi.org/10.1186/s12961-020-00652-3
McLeod, K., & Simpson, A. (2017). Exploring the value of mental health nurses working in primary care in England: A qualitative study. *Journal of Psychiatric and Mental Health Nursing*, *24*(6), 387–395. https://doi.org/10.1111/jpm.12400
Mitropoulos, P., Adamides, E., & Mitropoulos, I. (2023). Redesigning a network of primary healthcare centres using system dynamics simulation and optimisation. *Journal of the Operational Research Society*, *74*(2), 574–589. https://doi.org/10.1080/01605682.2022.2096499
Mizan, T., & Taghipour, S. (2022). Medical resource allocation planning by integrating machine learning and optimization models. *Artificial Intelligence in Medicine*, *134*, 102430. https://doi.org/10.1016/j.artmed.2022.102430
Moradi, S., Najafi, M., Mesgari, S., & Zolfagharinia, H. (2022). The utilization of patients' information to improve the performance of radiotherapy centers: A data-driven approach. *Computers & Industrial Engineering*, *172*, 108547. https://doi.org/10.1016/j.cie.2022.108547
National Collaborating Centre for Mental Health (NCCMH). (2021). The Community Mental Health Framework for adults and older adults: Royal College of Psychiatrists. www.rcpsych.ac.uk. https://www.rcpsych.ac.uk/improving-care/nccmh/service-design-and-development/community-framework
Naylor, C., Bell, A., Baird, B., Heller, A., & Gilburt, H. (2020). *Mental health and primary care networks: Understanding the opportunities*. The King's Fund.
Nearchou, A. C., Giannikos, I. C., & Lagodimos, A. G. (2020). Multisite and multishift personnel planning with set-up costs. *IMA Journal of Management Mathematics*, *31*(1), 5–31. https://doi.org/10.1093/imaman/dpy017
NHS Confederation. (2022). *Running hot: the impact of the pandemic on mental health services. ()*. https://www.nhsconfed.org/publications/running-hot
NHS Digital. (2022). *Mental health services monthly statistics, performance December 2021, provisional January 2022*. NHS Digital. Retrieved May 25, 2022, from https://digital.nhs.uk/data-and-information/publications/statistical/mental-health-services-monthly-statistics/performance-december-2021-provisional-january-2022
NHS England. (2020). *The five year forward view for mental health*. https://www.England.Nhs.Uk/Wp-Content/Uploads/2014/10/5yfv-Web.Pdf,
Ninh, A., Bao, Y., McGibney, D., & Nguyen, T. (2024). Clinical site selection problems with probabilistic constraints. *European Journal of Operational Research*, *316*(2), 779–791. https://doi.org/10.1016/j.ejor.2024.03.013
Noorain, S. (2024). *Towards facilitated optimisation*. Doctoral dissertation, University of Kent.
Noorain, S., Paola Scaparra, M., & Kotiadis, K. (2023). Mind the gap: A review of optimisation in mental healthcare service delivery. *Health Systems*, *12*(2), 133–166. https://doi.org/10.1080/20476965.2022.2035260
Noorain, S., Kotiadis, K., & Scaparra, M. P. (2019). *Application of discrete-event simulation for planning and operations issues in mental healthcare*. 2019 Winter Simulation Conference (WSC), 1184–1195. https://doi.org/10.1109/WSC40007.2019.9004749
Olya, M. H., Badri, H., Teimoori, S., & Yang, K. (2022). An integrated deep learning and stochastic optimization approach for resource management in team-based healthcare systems. *Expert Systems with Applications*, *187*, 115924. https://doi.org/10.1016/j.eswa.2021.115924
Omboni, S., Padwal, R. S., Alessa, T., Benczúr, B., Green, B. B., Hubbard, I., Kario, K., Khan, N. A., Konradi, A., Logan, A. G., Lu, Y., Mars, M., McManus, R. J., Melville, S., Neumann, C. L., Parati, G., Renna, N. F., Ryvlin, P., Saner, H., Schutte, A. E., & Wang, J. (2022). The worldwide impact of telemedicine during COVID-19: Current evidence and recommendations for the future. *Connected Health*, *1*, 7–35. https://doi.org/10.20517/ch.2021.03
Ordu, M., Demir, E., Tofallis, C., & Gunal, M. M. (2021). A novel healthcare resource allocation decision support tool: A forecasting-simulation-optimization approach. *Journal of the Operational Research Society*, *72*(3), 485–500. https://doi.org/10.1080/01605682.2019.1700186
Ortíz-Barrios, M. A., & Alfaro-Saíz, J. J. (2020). Methodological approaches to support process improvement in emergency departments: A systematic review. *International Journal of Environmental Research and Public Health*, *17*(8), 2664. https://doi.org/10.3390/ijerph17082664
Pagel, C., Richards, D. A., & Utley, M. (2012). A mathematical modelling approach for systems where the servers are almost always busy. *Computational and Mathematical Methods in Medicine*, *2012*, 290360–290366. https://doi.org/10.1155/2012/290360
Palmer, R., Fulop, N. J., & Utley, M. (2018). A systematic literature review of operational research methods for modelling patient flow and outcomes within community healthcare and other settings. *Health Systems*, *7*(1), 29–50. https://doi.org/10.1057/s41306-017-0024-9
Park, S., Elliott, J., Berlin, A., Hamer-Hunt, J., & Haines, A. (2020). Strengthening the UK primary care response to Covid-19. *BMJ*, *370*, m3691. https://doi.org/10.1136/bmj.m3691
Petropoulos, F., Laporte, G., Aktas, E., Alumur, S. A., Archetti, C., Ayhan, H., Battarra, M., Bennell, J. A., Bourjolly, J.-M., Boylan, J. E., Breton, M., Canca, D., Charlin, L., Chen, B., Cicek, C. T., Cox, L. A., Currie, C. S. M., Demeulemeester, E., Ding, L., Disney, S. M., Ehrgott, M., … Zhao, X. (2024). Operational research: Methods and applications. *Journal of the Operational Research Society*, *75*(3), 423–617. https://doi.org/10.1080/01605682.2023.2253852
Pierce, M., McManus, S., Hope, H., Hotopf, M., Ford, T., Hatch, S. L., John, A., Kontopantelis, E., Webb, R. T., Wessely, S., & Abel, K. M. (2021). Mental health responses to the COVID-19 pandemic: A latent class trajectory analysis using longitudinal UK data. *The*

Lancet. Psychiatry, *8*(7), 610–619. https://doi.org/10.1016/S2215-0366(21)00151-6

Pomerantz, A., Cole, B. H., Watts, B. V., & Weeks, W. B. (2008). Improving efficiency and access to mental health care: Combining integrated care and advanced access. *General Hospital Psychiatry*, *30*(6), 546–551. https://doi.org/10.1016/j.genhosppsych.2008.09.004

Price, M. K. (2024). *Mental Health Nurses in primary care 'critical but under recognised'*. Nursing in Practice. https://www.nursinginpractice.com/latest-news/mental-health-nurses-in-primary-care-critical-but-under-recognised/

Rais, A., & Viana, A. (2011). Operations research in healthcare: A survey. *International Transactions in Operational Research*, *18*(1), 1–31. https://doi.org/10.1111/j.1475-3995.2010.00767.x

Respicio, A., Moz, M., Pato, M. V., Somensi, R., & Flores, C. D. (2018). A computational application for multi-skill nurse staffing in hospital units. *BMC Medical Informatics and Decision Making*, *18*(1), 53. https://doi.org/10.1186/s12911-018-0638-2

Restrepo, M. I., Gendron, B., & Rousseau, L. (2017). A two-stage stochastic programming approach for multi-activity tour scheduling. *European Journal of Operational Research*, *262*(2), 620–635. https://doi.org/10.1016/j.ejor.2017.04.055

Samorani, M., & LaGanga, L. R. (2015). Outpatient appointment scheduling given individual day-dependent no-show predictions. *European Journal of Operational Research*, *240*(1), 245–257. https://doi.org/10.1016/j.ejor.2014.06.034

Samudra, M., Van Riet, C., Demeulemeester, E., Cardoen, B., Vansteenkiste, N., & Rademakers, F. E. (2016). Scheduling operating rooms: Achievements, challenges and pitfalls. *Journal of Scheduling*, *19*(5), 493–525. https://doi.org/10.1007/s10951-016-0489-6

Sir, M. Y., Nestler, D., Hellmich, T., Das, D., Laughlin, M. J., Dohlman, M. C., & Pasupathy, K. (2017). Optimization of multidisciplinary staffing improves patient experiences at the Mayo Clinic. *Interfaces*, *47*(5), 425–441. https://doi.org/10.1287/inte.2017.0912

Tako, A. A., & Kotiadis, K. (2015). PartiSim: A multi-methodology framework to support facilitated simulation modelling in healthcare. *European Journal of Operational Research*, *244*(2), 555–564. https://doi.org/10.1016/j.ejor.2015.01.046

Tako, A. A., & Kotiadis, K. (2018). PartiSim Toolkit V2. https://repository.lboro.ac.uk/articles/PartiSim_Toolkit_V2/9496868/files/17123519.pdf

Tako, A. A., Kotiadis, K. (2012). Facilitated conceptual modelling: Practical issues and reflections. *Paper Presented at the Proceedings of the 2012 Winter Simulation Conference (WSC)*, 1–12.

Thielen, C. (2018). Duty rostering for physicians at a department of orthopedics and trauma surgery. *Operations Research for Health Care*, *19*, 80–91. https://doi.org/10.1016/j.orhc.2018.03.004

Uriarte, A. G., Zúñiga, E. R., Moris, M. U., & Ng, A. H. (2017). How can decision makers be supported in the improvement of an emergency department? A simulation, optimization and data mining approach. *Operations Research for Health Care*, *15*, 102–122. https://doi.org/10.1016/j.orhc.2017.10.003

Valentine, A. Z., Hall, S. S., Sayal, K., & Hall, C. L. (2024). Waiting-list interventions for children and young people using child and adolescent mental health services: A systematic review. *BMJ Mental Health*, *27*(1), e300844. https://doi.org/10.1136/bmjment-2023-300844

Van den Bergh, J., Beliën, J., De Bruecker, P., Demeulemeester, E., & De Boeck, L. (2013). Personnel scheduling: A literature review. *European Journal of Operational Research*, *226*(3), 367–385. https://doi.org/10.1016/j.ejor.2012.11.029

Van Der Heijde, C. M., De Bruijn-De Goffau, C. E., & Vonk, P. (2024). The potential of non-clinical guidance alongside e-mental Health to overcome non adherence. *European Journal of Public Health*, *34*(Suppl 3), ckae144-1602. https://doi.org/10.1093/eurpub/ckae144.1602

Van't Veer-Tazelaar, P., Smit, F., van Hout, H., van Oppen, P., van der Horst, H., Beekman, A., & van Marwijk, H. (2010). Cost-effectiveness of a stepped care intervention to prevent depression and anxiety in late life: Randomised trial. *The British Journal of Psychiatry*, *196*(4), 319–325. https://doi.org/10.1192/bjp.bp.109.069617

Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas-Barrón, L. E. (2021). Discrete-event simulation modeling in healthcare: A comprehensive review. *International Journal of Environmental Research and Public Health*, *18*(22), 12262. https://doi.org/10.3390/ijerph182212262

Vermuyten, H., Namorado Rosa, J., Marques, I., Beliën, J., & Barbosa-Póvoa, A. (2018). Integrated staff scheduling at a medical emergency service: An optimisation approach. *Expert Systems with Applications*, *112*, 62–76. https://doi.org/10.1016/j.eswa.2018.06.017

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Vishwakarma, L. P., Singh, R. K., Mishra, R., & Kumari, A. (2025). Application of artificial intelligence for resilient and sustainable healthcare system: Systematic literature review and future research directions. *International Journal of Production Research*, *63*(2), 822–844. https://doi.org/10.1080/00207543.2023.2188101

Wang, L., & Demeulemeester, E. (2023). Simulation optimization in healthcare resource planning: A literature review. *IISE Transactions*, *55*(10), 985–1007. https://doi.org/10.1080/24725854.2022.2147606

Wang, F., Zhang, C., Zhang, H., & Xu, L. (2021). Short-term physician rescheduling model with feature-driven demand for mental disorders outpatients. *Omega*, *105*, 102519. https://doi.org/10.1016/j.omega.2021.102519

Wolbeck, L., Kliewer, N., & Marques, I. (2020). Fair shift change penalization scheme for nurse rescheduling problems. *European Journal of Operational Research*, *284*(3), 1121–1135. https://doi.org/10.1016/j.ejor.2020.01.042

Wright, P. D., & Mahar, S. (2013). Centralized nurse scheduling to simultaneously improve schedule cost and nurse satisfaction. *Omega*, *41*(6), 1042–1052. https://doi.org/10.1016/j.omega.2012.08.004

Yaspal, B., Jauhar, S. K., Kamble, S., Belhadi, A., & Tiwari, S. (2023). A data-driven digital transformation approach for reverse logistics optimization in a medical waste management system. *Journal of Cleaner*

Production, *430*, 139703. https://doi.org/10.1016/j.jclepro.2023.139703

Yousefi, M., Yousefi, M., & Fogliatto, F. S. (2020). Simulation-based optimization methods applied in hospital emergency departments: A systematic review. *Simulation*, *96*(10), 791–806. https://doi.org/10.1177/0037549720944483

Zhou, C., Hao, Y., Lan, Y., & Li, W. (2023). To introduce or not? Strategic analysis of hospital operations with telemedicine. *European Journal of Operational Research*, *304*(1), 292–307. https://doi.org/10.1016/j.ejor.2021.12.020

Zhu, S., Fan, W., Yang, S., Pei, J., & Pardalos, P. M. (2019). Operating room planning and surgical case scheduling: A review of literature. *Journal of Combinatorial Optimization*, *37*(3), 757–805. https://doi.org/10.1007/s10878-018-0322-6

Zimmerman, S. L., Bi, A., Dallow, T., Rutherford, A. R., Stephen, T., Bye, C., Hall, D., Day, A., Latham, N., & Vasarhelyi, K. (2021). Optimising nurse schedules at a community health centre. *Operations Research for Health Care*, *30*, 100308. https://doi.org/10.1016/j.orhc.2021.100308

Appendix A

Table A1. Model notation table.

	Notation	Description
Sets	A	Set of appointment types, each with a skill requirement, indexed by a
	C	Set of clinicians, indexed by c
	L	Set of clinic locations, indexed by l
	D	Set of days in the planning horizon, indexed by d
	S	Set of shifts across all days in the planning horizon, indexed by s
	S_d	Set of shifts $s \in S$ for each day $d \in D$ (typically two shifts per day : AM&PM)
Parameters	L_s	Length of shift s
	F_l^a	Demand for appointment type $a \in A$ in clinic location $l \in L$
	B_{ca}	1, if clinician $c \in C$ is skilled for appointment type $a \in A$, 0 otherwise
	$T_{l_1 l_2}$	Distance between clinic locations $l_1, l_2 \in L : l_1 \neq l_2$
	R_a	Duration of appointment type $a \in A$
	P_{cl}	1, if clinician $c \in C$ can be assigned to clinic location $l \in L$, 0 otherwise
	T_{max}	Maximum travel distance between clinics
	S_{max}	Maximum number of shifts per day
	N_c	Maximum number of clinic locations that can be assigned to a clinician
	N_l	Maximum number of clinicians that can be assigned to a clinic location
	H_c	Total available hours per clinician $c \in C$
	H_{cs}	1, if clinician $c \in C$ is available in shift $s \in S$, 0 otherwise
	M	A sufficiently large constant
Decision Variables	Y_{cls}	1, if clinician $c \in C$ is assigned to clinic location $l \in L$ in shift $s \in S$ 0, otherwise
	X_{cls}^a	number of appointments of type $a \in A$ assigned to clinicia $\in C$ at clinic location $l \in L$ in shift $s \in S$
	W_{cl}	1, if clinic location $l \in L$ is assigned to clinician $c \in C$ 0, otherwise
	Z_c^-	Unassigned hours for each clinician $c \in C$
	$MaxZ$	maximum percentage of unassigned hours across all clinicians $c \in C$

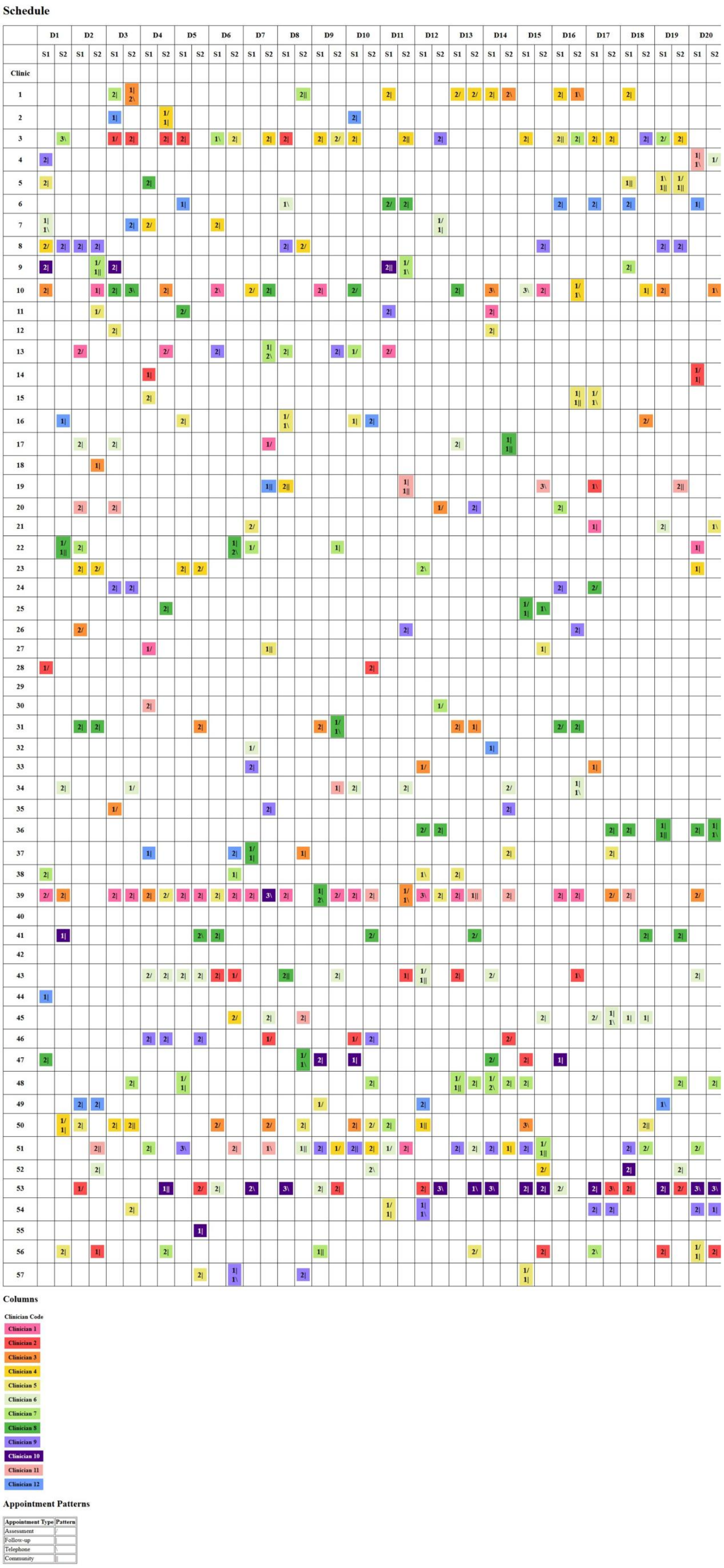


Figure A1. Model generated clinician assignment schedule.

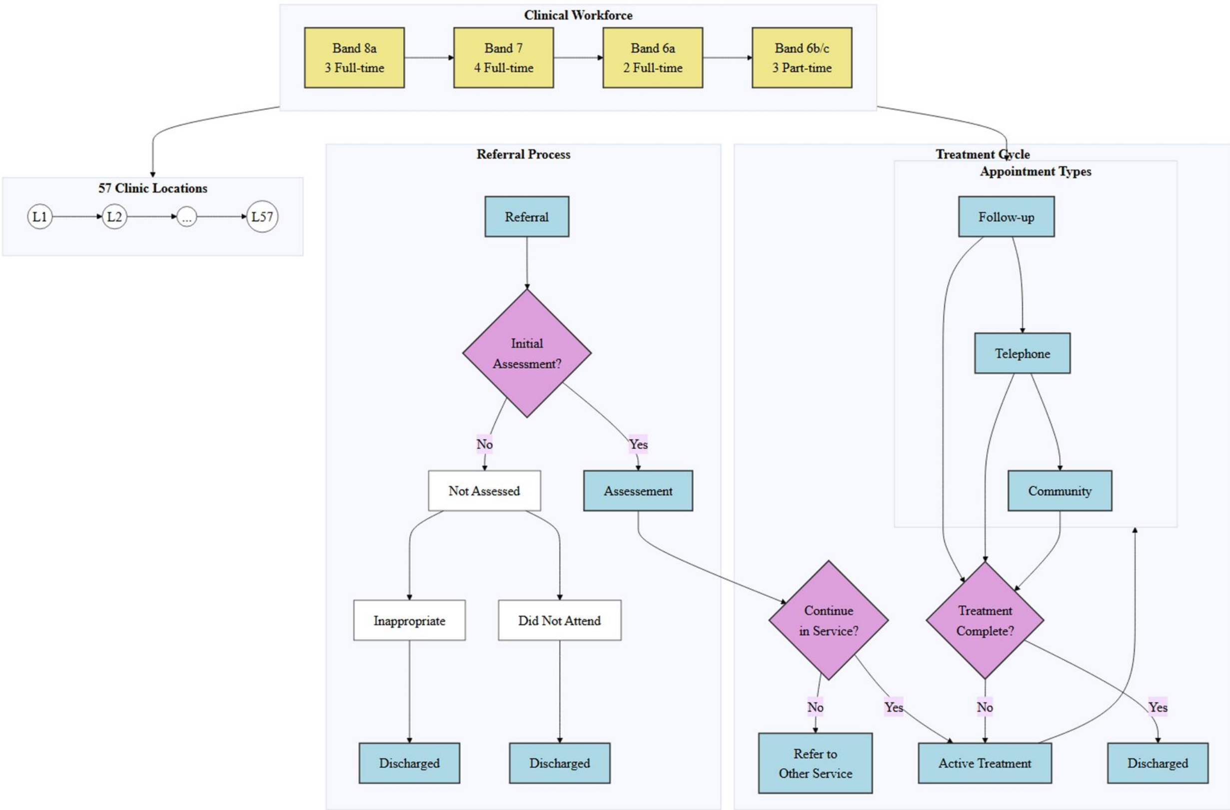
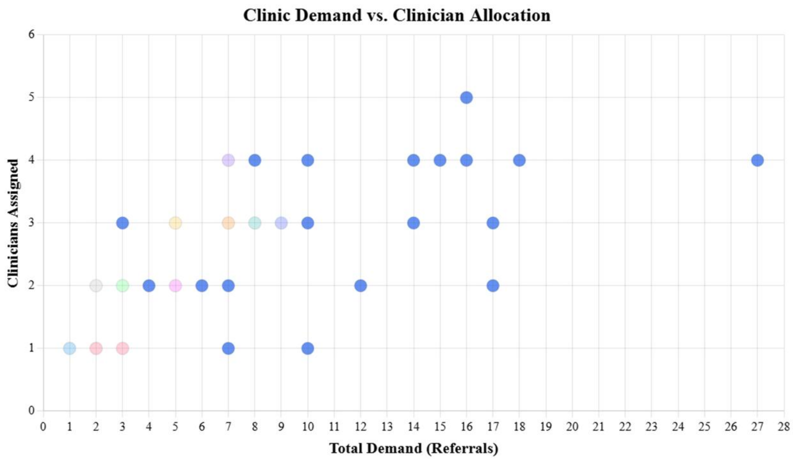


Figure A2. PCMHS patient pathway.



Reference Table: Locations Sharing Coordinates

Demand	Clinicians	Locations
1	1	L15, L19, L32, L4, L40, L42, L45, L46, L53, L56
2	1	L24, L28, L35, L38
2	2	L11, L18, L22, L41
3	1	L1, L29
3	2	L23, L57
5	2	L21, L33, L50
5	3	L43, L5
7	3	L54, L9
7	4	L17, L7
8	3	L26, L30, L48, L6
9	3	L12, L27, L51

Figure A3. Clinicic demand Vs. clinician allocation plot with reference table.