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ORIGINAL RESEARCH

Towards a Comprehensive Framework for Health Workforce Modelling: Addressing Gaps and Enhancing Decision-Making

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Introduction: This study addresses critical gaps in healthcare workforce planning by developing an adaptable workforce modelling framework implemented as a user-friendly decision support tool (DST). Current approaches often lack the flexibility to accommodate real-world healthcare settings and fail to address detailed granular-level workforce requirements.

Methods: Our framework offers a standardised methodology for comprehensive workforce modelling, enhancing comparability and reliability across healthcare systems using a proposed data-driven continuous dynamic constrained optimisation (CDCO) modelling approach. It bridges the theoretical approach with practical application while incorporating granular-level factors and workforce dynamics to meet patient demand, ensure the quality of care, and enhance accessibility for timely decision-making.

Results: The framework's applicability and reliability were demonstrated through collaboration with a high-demand NHS Trust in England, where substantial allied health professional services face persistent staffing shortages and pressing budgetary needs, with a focus on physiotherapist workforce planning. Model validation included benchmark comparisons against real-world data and the Trust's internal results, as well as expert face validation. Sensitivity analysis was also conducted to assess the robustness of the model outputs. Under 5.8% annual demand growth and the proposed skill-mix upgrade, maintaining an 81% demand met rate would require 8.99 additional WTE and increase the monthly full-establishment budget by $33,123. In comparison, achieving a 91% met rate would require 14.70 additional WTE and increase the monthly budget by $47,976.

Discussion: This study advances healthcare workforce planning by integrating fragmented modelling components into an adaptable framework and operationalising it through a user-friendly DST that accommodates multi-skilled workforce structures and supports more equitable access to healthcare services, subject to appropriate service-level data and stakeholder engagement.

Keywords: health workforce planning, modelling framework, dynamic optimisation, decision support systems, human resource management

Introduction

Effective health workforce planning is instrumental in ensuring the right care is delivered at the right time and place, achieving core objectives such as better health outcomes, timely access to services, and equitable distribution of healthcare resources.[1] The ramifications of lacking a robust workforce plan are severe, impacting staff shortages and economic costs.[2] Health workforce expenditures constitute the largest share of healthcare costs globally, ranging from roughly 45–55% in high-income health systems such as the NHS in England,[3] Germany,[4] and the USA,[5] to 40–70% in low- and middle-income countries.[6,7]

Global staff shortages are already translating into measurable harm to patients across health systems. In England, the elective care waiting list stood at 7.7 million procedures in July 2024, affecting around 6.4 million individuals and contributing to deteriorating health in an estimated 10% of this population,[8] consistent with earlier evidence linking NHS staff shortages to longer waits and poorer outcomes.[9,10] Comparable pressures are reported elsewhere in Europe and North America: Germany is projected to need 500,000 additional nurses by 2030,[11] and the USA faces a projected

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shortfall of up to 124,000 physicians by 2034.[12] These pressures are compounded by ageing populations and rising demand,[13] and by a long-standing pattern of poor or absent workforce planning that has itself been identified as a driver of current shortages,[14,15] reinforcing already inadequate funding.

Health workforce modelling has therefore become essential to workforce planning, offering a quantitative means of achieving the "six rights" of the health workforce: the right number of professionals, with the right skills, in the right place, at the right time, and within the right financial resources.[2,16,17] Despite its importance, our review of the literature (Literature Review) identifies several persistent limitations in current workforce projection methods, summarised below.

1) There is no standardised, universally applicable modelling framework that can be flexibly adapted across healthcare contexts, services, and providers,[18,19] which limits the comparability and reliability of workforce planning across systems.
2) Existing approaches typically fail to model workforce requirements at the granular, service-level skill-mix required in practice,[20,21] eg, specifying "X doctors and Y nurses" for a department is inadequate where, as in the NHS, nursing staff span multiple bands (2–8) with materially different roles and responsibilities. Any credible framework must therefore operate at this micro level rather than relying on high-level, population-based estimates.
3) User-friendly decision support tools (DSTs) for non-specialist end-users such as service managers and policymakers remain scarce, as existing simulation-based models tend to be robust but resource-intensive and to demand substantial modelling expertise.[22]
4) Most models address either current workforce optimisation or future demand prediction in isolation, whereas Bosak et al[18] and Lee et al[19] argue that robust workforce planning requires all three components (current need, future demand, and supply) to be integrated together.
5) Workforce requirements are inherently dynamic, shifting with patient demand and staff turnover,[19,23] yet existing models rarely accommodate this dynamism alongside demand projections and staffing establishment.
6) Mathematically formulated workforce models are rarely validated against real-world implementation, which is essential to establish their robustness for policy use.[19,24]

Taken together, these gaps point to a common shortfall in prior frameworks: existing approaches tend to address these components separately, hence the need for a standardised structure, granular skill-mix, integrated demand-supply-need modelling, dynamic responsiveness, accessibility for non-specialists, and real-world validation, rather than as a single, coherent methodology. No published framework to date combines all of these elements within one, transferable, and practically validated approach. This study addresses that gap directly: we propose a data-driven continuous dynamic constrained optimisation (CDCO) framework that, unlike prior models, (i) is applicable across healthcare contexts and services rather than context-specific; (ii) operates at the granular, band and skill-level required for practical staffing decisions rather than high-level workforce aggregates; (iii) integrates current need, future demand, and supply within a single dynamic optimisation rather than treating them separately; and (iv) is operationalised through an accessible DST and validated through real-world deployment, rather than remaining a theoretical or simulation-only construct.

The objective of this study is to develop and validate a health workforce modelling framework that integrates these previously fragmented components and translates them into an accessible, practically deployable DST. Specifically, the study addresses three research questions: (1) how can the workforce components of current need, future demand, and supply be integrated within a single modelling framework; (2) how can dynamic optimisation translate changing demand and service targets into band-specific staffing, skill-mix, and budget requirements; and (3) how can the framework be operationalised through an accessible DST to support practical workforce-planning decisions?

This study makes three contributions: (1) It integrates previously fragmented workforce planning components into a single generic framework applicable across healthcare contexts and advances service-level dynamic workforce modelling. (2) It operationalises this framework through a user-oriented DST that enhances operational usability and supports use by non-specialist service managers and policymakers. (3) It demonstrates the framework's practical application and validity through a real-world case study of granular-level physiotherapist staffing and budget planning within a complex NHS setting, while supporting evidence-informed decision-making.

The remainder of the article is structured as follows. Literature Review provides a comprehensive literature review. Healthcare Workforce Modelling Framework introduces the workforce modelling framework, applicable to any setting and service globally, detailing the necessary steps for decision-makers to follow in establishing their specific workforce needs. Proposed Workforce Model outlines the methodology, focusing on the optimisation model. Case Study presents a case study demonstrating the framework's practical application, developed in collaboration with Allied Health Professionals (AHPs) at a major NHS Trust in England to optimise physiotherapist (PT) allocations within a DST. Results presents and analyses the results of the case study to validate the framework, and Discussion discusses the findings and their implications.

Literature Review

In this section, we examine the key frameworks and models used to address complex workforce issues, building on previous reviews and studies.[18,19,22,25] We also identify the strengths and limitations of these approaches and emphasise the need for further development and innovation to enhance the effectiveness of workforce planning. Existing healthcare workforce modelling methods primarily include mathematical methods and computer simulation methods. These methods serve different purposes in coping with the complexities of healthcare workforce planning.

Existing Concepts and Frameworks

The conceptual foundations for healthcare workforce planning span several methodological domains. Lee et al[19] and Bosak et al[18] conducted systematic reviews of health workforce projection modelling concepts using the PRISMA approach. They categorised the models into eight types, including population-to-provider ratio models, utilisation models, needs-based models, skill-mix models, stock-and-flow models, agent-based simulation models, system dynamic models, and budgetary models. Each of these models is designed to address specific objectives within workforce planning, with various methodologies offering distinct strengths and limitations. These reviews emphasise the need for an integrated approach that incorporates both supply-side and demand-side analyses, as suggested Safarishahrbijari.[22] It shows that recent advancements in workforce planning have increasingly moved toward complex systems approaches, combining multiple models to provide a comprehensive view of the workforce landscape. Skill-mix has been identified as a particularly critical dimension of workforce design. Dubois et al[20] emphasise that incorporating appropriate skill-mix configurations into modelling frameworks is essential for capturing real-world workforce flexibility and productivity.

A robust workforce planning framework proposed by Willis,[26] comprising four core components: horizon scanning, scenario generation, workforce modelling, and policy analysis. This framework has since been further examined and applied across multiple studies. Willis et al[23] applied the framework using a system dynamics approach to capture long-term workforce behaviour. Amorim-Lopes et al[24] extended the framework by incorporating broader stakeholder and expert insights through morphological analysis and by integrating mathematical programming to support scenario evaluation. More recently, Benahmed et al[27] applied the framework within a complex healthcare setting, emphasising the importance of multi-actor engagement and context-specific workforce parameters. The adaptations enhanced the framework's ability to accommodate the inherent uncertainty and complexity of workforce systems. While these frameworks provided a conceptual foundation, the literature points to the need for further elaboration of health workforce considerations. Building on these insights, the present study extends existing frameworks by integrating granular clinical, operational, and workforce definitions, thereby supporting a more comprehensive and evidence-informed framework.

Mathematical Methods for Healthcare Workforce Modelling

Current mathematical methods are utilised to find optimal workforce establishments under certain circumstances. For example, an integer programming model was developed to cope with medical staff scheduling problems for the emergency medical service system by minimising the total cost and workforce supply.[28] Two scenarios were implemented to compare the staff employment and training. The model improved the staff scheduling efficiency and flexibility. In another example, a linear programming model was developed to maximise the population health benefits in Uganda.[29] This model examined two scenarios: a base scenario and task-shifting scenarios with different numbers of interventions. The required workforce was optimised to enhance public health outcomes. In addition, mathematical models can

optimise multiple workforce objectives. An optimal nurse staffing model was developed using a linear programming approach to optimize the workforce with respect to quality of care, nurse staffing levels, and costs.[30] Additionally, a multi-objective optimization model was introduced to optimize both the size and skill mix of nurses for scheduling in nursing homes. The model reduced the total overtime hours and increased the nurse-to-resident ratios.[31]

Multiperiod linear programming (MLP) is a mathematical method used to optimise decision-making over multiple time periods. Nezamoddini et al[32] employed an MLP model across various daytime periods for non-emergency patient transfer between hospitals to minimise patient wait times. Additionally, their study investigated the impact of several parameters, including transfer time, cost, and the maximum number of patients. Ordu et al[33] presented a hybrid analytical model that combines DES and multi-period integer linear programming approach to optimise hospital resources, specifically beds, physicians, and nurses, in response to future patient demand and activities. The MLP approach supported the optimisation of resource allocation over multiple periods.

One notable advantage of conventional mathematical methods is their ease of formulation. These methods utilise well-established mathematical techniques to address workforce challenges, yielding precise and quantifiable results. However, they typically focus on optimising the current workforce configuration, without accounting for the dynamic nature of the system. As a result, fluctuations in demand and changes in supply are not adequately analysed. The MLP approach is formulated and solved as one large linear programming problem model, considering all time periods simultaneously, which leads to a loss of insight into workforce dynamics between periods. In contrast, dynamic optimisation models are designed to address sequential decision problems, such as staff turnover, recruitment, and training, allowing for a more comprehensive analysis of workforce evolution over time.

Computer Simulation Methods for Healthcare Workforce Modelling

In comparison, computer simulation methods can incorporate uncertainties within complex healthcare systems and explore the what-if scenarios. The methods applied to healthcare workforce modelling include discrete-event simulation (DES), agent-based simulation (ABS) and system dynamics (SD).

DES has been widely used to model hospital operations and patient pathways.[34] In these simulations, the workforce is represented as a key resource, allowing for the analysis of how staff availability impacts the overall efficiency and effectiveness of hospital processes. A discrete-event simulation model was developed to simulate elective surgery, and emergency surgery patient flows and run resource allocation scenarios.[35] The staff of consultants and registered nurses for different patient flows were included. The ratios of day and night staff were applied accordingly. DES can be combined with mathematical models to optimise the healthcare workforce. For example, a linear programming model that was integrated with a DES model to address stochastic constraints on medical staff allocation for an emergency department in Hong Kong.[36] Another example, Ordu et al[37] presents a novel decision support tool for healthcare resource allocation that integrates DES and integer linear programming. This hybrid model addresses the increasing pressures on the UK healthcare system by optimising the use of existing resources in response to rising demand and capacity shortages. Staffing levels of consultants and nurses were optimised for each specialty.

ABS simulates interactions of agents such as doctors and nurses by predefined rules. Therefore, it is primarily employed to analyse uncertainties in the workforce itself. A healthcare workforce planning model was developed by employing the ABS method to predict the supply of physicians and modelling the physician lifecycle.[17] The stochastic simulation was run with uncertainties of training time and physician number. The model enabled the exploration of different scenarios, such as changes to the retirement age and adjustments to staffing quotas. ABS can be used to manage staffing levels accordingly. Griffiths et al[38] developed an ABS model to determine the nurse staffing levels. The probability distributions of patients and staff were applied to support the staffing decision by running the Monte Carlo simulation. The model focuses on wards and simulates staff shifts. The simulation calculates staffing costs and assesses whether each ward is understaffed, adequately staffed or overstaffed. The study highlights the need to consider factors beyond patient acuity and dependency, such as ward type and patient turnover, which also influence staffing requirements.

SD simulates the nonlinear behaviour of systems with continuous time and internal feedback loops. Therefore, the SD was mainly applied to estimate the relationship between the demand and the workforce supply. Abas et al[39] developed

a system dynamics model to predict the future workforce supply. The workforce life cycle flow was analysed with interactions between the training model, the population model, and the full-time equivalent staff model. In addition, Willis et al[23] proposed a framework for strategic healthcare workforce planning by using SD. The model shows the stock and flow behaviour of medical training. The paper highlights the challenges of accurately forecasting workforce requirements due to the long training periods and rapidly changing healthcare needs and technologies. SD can also be used to analyse macro-level system behaviours. An SD model was developed to evaluate the mismatch between the supply and demand of healthcare workers.[40] The ageing population, prevalent chronic illness, and the staff skill-mix were incorporated into the model. Masnick and McDonnell[41,42] developed a clinical workforce SD model to determine the appropriate mix of health service skills. The model analysed interactions, delays and feedback of supply and demand.

Simulation methods can analyse different workforce categories, addressing the varied roles within a healthcare setting, including doctors and nurses. These models can simulate stochastic demands, which are characterised by random and unpredictable variations in patient arrivals and healthcare needs. Nonetheless, they model healthcare systems from the macro-level, so the simulation models applied certain simplifications regarding staffing and did not take into account the specific staff establishment.

Applications of Dynamic Constrained Optimisation Problems (DCOPs)

Unlike conventional mathematical optimisation problems, dynamic constrained optimisation problems (DCOPs) have recently emerged as an approach to tackle more complex real-world challenges, because dynamic constraints and objective function are widely used in the real-world problems.[42] These dynamic constraints can reshape the feasible solution space, while changes in the objective function may alter the global optima. DCOPs are characterised by two key features:[43] (1) the objective function or constraints change over time, and (2) the optimisation process adapts to these changes. DCOPs have been successfully applied in diverse fields, including supply chain management,[44] hybrid power dispatch,[45] and financial portfolio selection.[46]

Recent developments have seen the application of DCOPs to workforce scheduling. A dynamic workforce scheduling optimisation model was introduced to assign tasks to telecommunications technicians.[47] To mitigate the challenges posed by variable demand, the potential for noncompliance, and uncertainties in task durations, the researchers implemented dynamic optimisation as a practical approximation for these complex scheduling processes. Similarly, Punyakum et al[48] formulated a dynamic workforce scheduling and routing model designed to optimise the performance of sugarcane harvesters. The model was used to determine routes for each individual technician team to minimise the total cost. Dynamic optimisation has also been applied to healthcare workforce training. Özdemir-Akyıldırım et al[49] proposed a continuous dynamic optimisation model with uncertain attrition rates to optimise medical staff training for service industries. The annual admission numbers were optimised by running the iterative algorithm.

However, despite the successful application of DCOPs in various domains including healthcare workforce training, they have not yet been widely explored in the context of healthcare workforce planning. Given the dynamic nature of healthcare environments—characterised by fluctuating patient demands, diverse team establishment, and varying staff turnovers. DCOPs could provide significant advantages in addressing these complexities of healthcare workforce planning. For example, Hu et al[50] developed a DCOP model for nurse planning. The model took into account staff training, hiring, and promotion processes in response to changing demand.

In summary, while computer simulations can model processes in great detail at the micro level—often requiring extensive data and expertise—most existing models focus on analysis at the macro level. They are usually scenario-based and aim to predict future needs, which simplifies the process of establishing workforce requirements. While conventional mathematical models can optimise the workforce in response to present demands, they are constrained in their capacity to forecast future transformations. DCOPs can incorporate such dynamic attributes and have not yet been applied to healthcare workforce planning. Accordingly, one of the main contributions of this paper is the development of a DCOPs model for healthcare workforce planning.

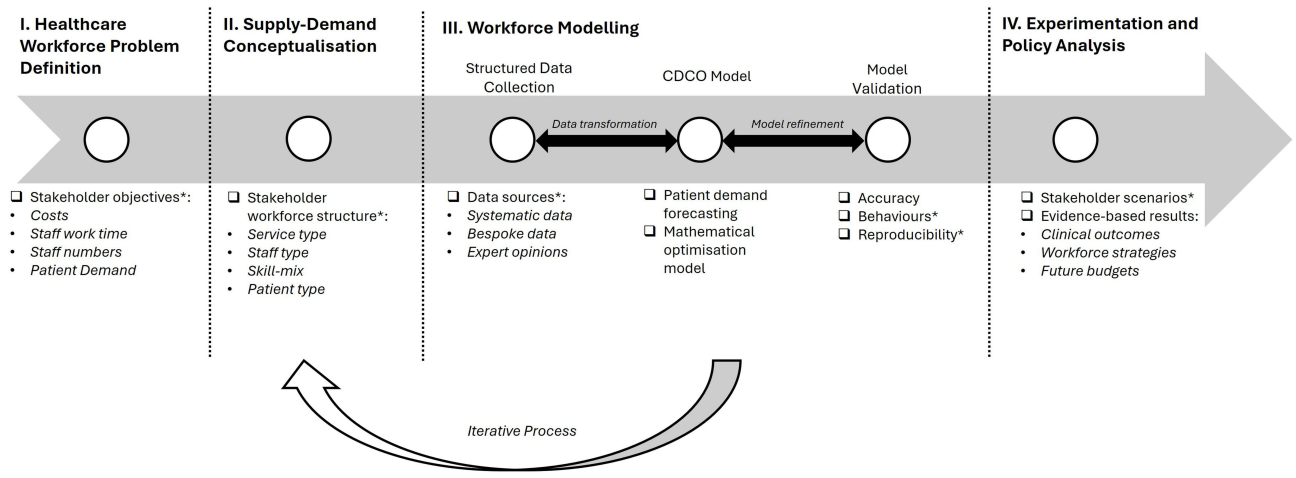


Figure 1 Healthcare workforce modelling framework (* Stakeholder-engaged activities).

Healthcare Workforce Modelling Framework

The developed framework comprises four stages: (1) healthcare workforce problem definition, (2) supply-demand conceptualisation, (3) workforce modelling, and (4) experimentation and policy analysis, see Figure 1. Stakeholders may be engaged at multiple stages with iterative processes.

Healthcare Workforce Problem Definition

The framework begins with a clear definition of the healthcare workforce problem, grounded in stakeholder priorities and operational realities. The challenges span institutional, organisational, and human resources management contexts within healthcare systems.[20] This stage synthesises clinical, managerial, and strategic requirements to establish an appropriate foundation for mathematical optimisation. It includes the systematic identification of service pressures, operational bottlenecks, and key performance indicators, such as cost constraints, reliance on temporary staff, student intake and training needs, and requirements for team expansion or skill-mix upgrades.[19,23,24] In developing the mathematical optimisation model, this phase involves specifying the objective functions, defining relevant decision scenarios, and determining the structure and format of the model outputs. Table 1 summarises the range of healthcare workforce optimisation problems commonly considered across the dimensions of cost, time, staffing levels, and patient demand.

Supply-Demand Conceptualisation

Comprehensive mapping of the healthcare workforce system requires structured engagement with a broad range of stakeholders across the healthcare setting. The consultations are essential for eliciting operational realities, clarifying

Table 1 Healthcare Workforce Optimisation Problems

Dimensions	Problem Description	References
Cost	Minimise staff costs with training and promotion	[50]
	Minimise the total staffing costs of regular and temporary staff	[31]
	Minimise the total cost of regular physicians	[51]
	Minimise the combined cost of staffing, patient queueing, and care management	[52]
Staff Work Time	Minimise staff unproductive time for solving staff shortage due to insufficient working time	[28]
	Minimise the expectation of patient waiting time	[36]
Staff Numbers	Minimise staff numbers to meet Resource requirements, such as the nurse-to-bed ratios	[33]
	Minimise staff over-supply and shortages to improve workforce balance	[24]
Patient Demand	Maximum treated patient numbers within available workforce capacity	[53]

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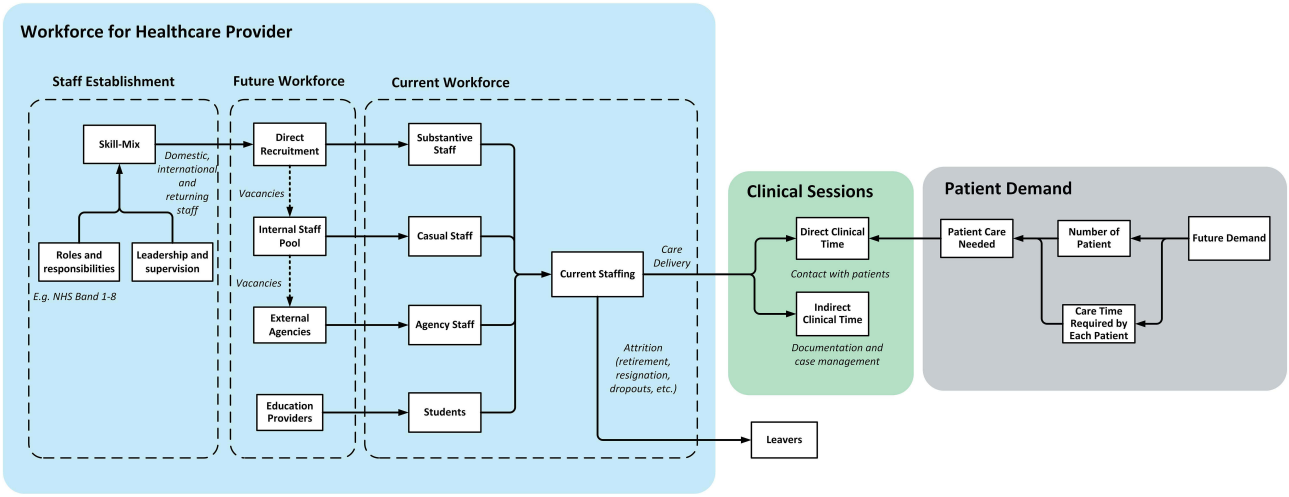


Figure 2 Proposed generic healthcare workforce structure.

system interdependencies, and capturing the complex dynamics underpinning service delivery. This process enables a detailed understanding of the system's complex dynamics and the inter-component interactions. Healthcare workforce models can be developed from either a supply-side[39,54] or demand-side.[21,55] However, recent research recommends integrating both sides to achieve a more comprehensive and realistic assessment of workforce needs.[18,19] The proposed conceptual structure synthesises both supply and demand dimensions, offering a comprehensive perspective to inform evidence-based workforce planning and policy decisions. Figure 2 illustrates the generic healthcare workforce concept we proposed and applied in the framework.

Workforce for Healthcare Provider

The supply side of the workforce comprises the staff establishment, the current workforce, and the future workforce. The staff establishment represents the planned staffing configuration required to meet future dynamic demand, specifying the number of staff across different grades (eg, NHS Bands 1–8) and the appropriate skill-mix needed to deliver safe and effective care.[56] The skill-mix encompasses the following considerations:[20,41,57] (1) Appropriate staff numbers and WTE (Whole-Time Equivalent) across grades; (2) A balance of qualifications; (3) The mix of junior and senior staff; (4) The composition of multidisciplinary teams; (5) The ratio of trainers to trainees.

However, due to global shortages of healthcare professionals, the current workforce often falls short of the established staffing requirement, so the future workforce is necessary to address the gaps.[58–60] The current workforce typically comprises permanent (substantive) staff recruited through domestic, international, and returning pathways, temporary staff drawn from internal staff banks and external agencies, and students on clinical placement from education providers (eg, universities).[18,50,54] Temporary staff are frequently used to fill short-term vacancies and provide surge capacity; however, evidence suggests that reliance on temporary staffing is associated with higher cost, variability in skill-mix, and reduced continuity of care.[61,62] Consequently, while temporary staff offer operational flexibility, temporary staff are incorporated conservatively within long-term workforce planning due to concerns regarding cost, stability, and sustainability.[14]

Patient Demand and Clinical Sessions

On the demand side, the patient numbers, patient type, care time per patient, interventions, severity and urgency (immediate, urgent, intermediate, or delayed care).[18,19] Patient demand can be translated into the required clinical time using established workload and time-allocation methods.[63] Clinical activities include both direct clinical (contact with patients) and indirect clinical time (eg, documentation and case management). The patient demand and clinical activities need to be elaborated upon and modified according to the healthcare provider's system or the specific context of the country.

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Workforce Modelling

Given the data-driven nature of the modelling approach, a comprehensive and structured data collection process is essential prior to developing the digital model. Drawing on established workforce-modelling frameworks and empirical case studies,[23,24,31,40,53,63,64] we adapted and proposed a set of core input parameters and their potential data sources for the healthcare workforce model, see Table S1 in the Supplementary Materials.

The input data collection process may require bespoke and supplementary data-gathering activities, as existing electronic health record (EHR) systems frequently lack the granularity needed to fully populate the modelling framework. In practice, additional data must often be elicited directly from healthcare stakeholders through structured meetings, interviews, or targeted data extraction requests. Importantly, as highlighted by Asplund et al,[65] securing ethical approval and establishing data-sharing agreements can be time-consuming processes. These steps are essential for ensuring compliance and data integrity but may introduce significant delays to data collection and subsequent analytical work.

Developing the workforce model is a key component of the framework and the main contribution of this study. The framework outlines how to develop a data-driven CDCO model. Figure 3 presents the structure of the optimisation model, which determines the optimal workforce configuration required to meet predicted future demand and associated clinical activities. Activities represent the demand side of the supply-demand equilibrium, necessitating accurate future demand forecasting. The number of activities is estimated based on the forecasted demand and required sessions per patient type. Demand can be forecasted using quantitative forecasting methods, such as multiple linear regression, exponential smoothing, and autoregressive integrated moving average (ARIMA). The optimisation model can be

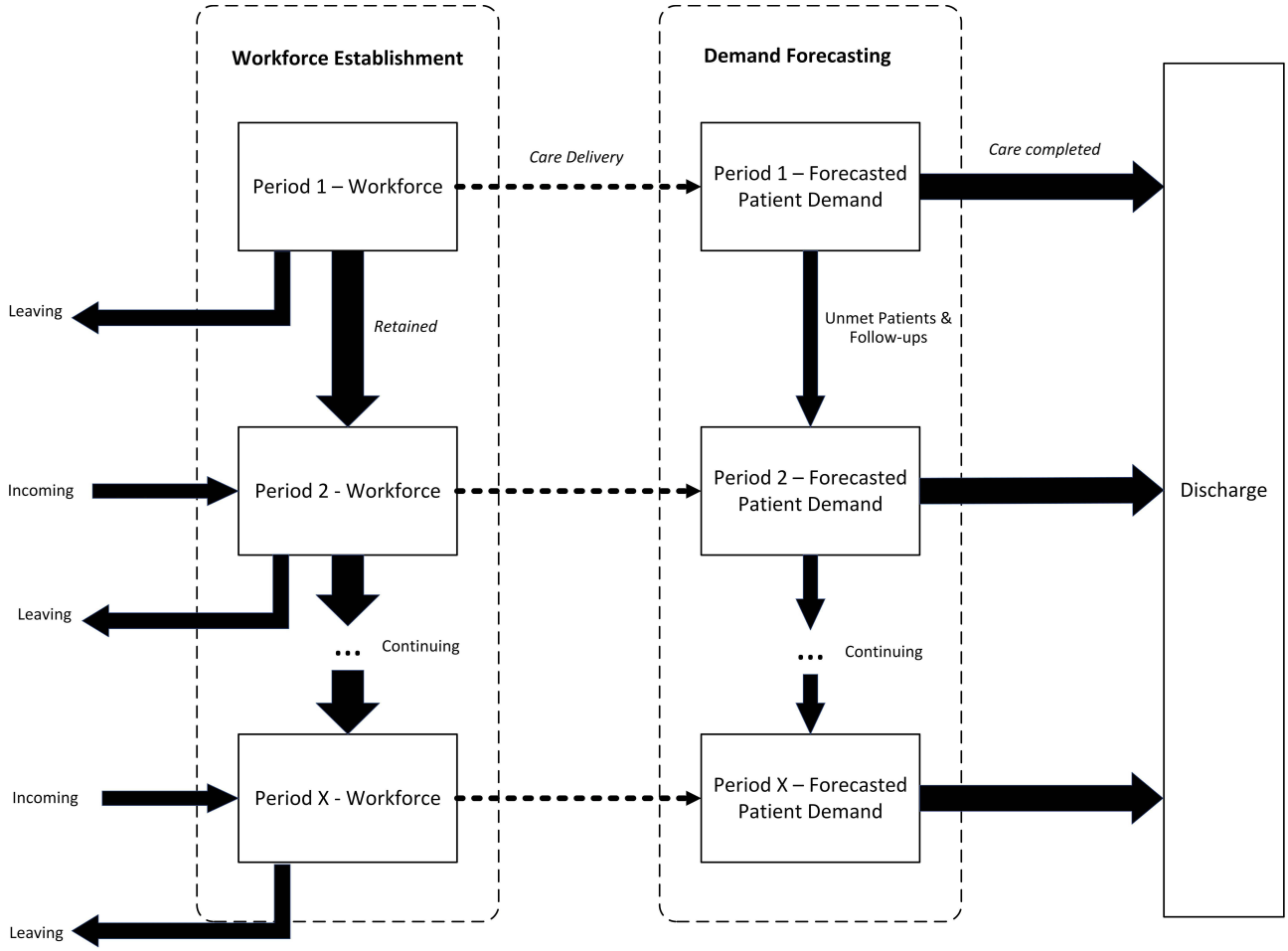


Figure 3 Healthcare workforce CDCO model structure.

implemented using various computational tools. These include spreadsheet applications such as Microsoft Excel and VBA,[53] high-level programming languages such as R, Python and Java[31], or specialised linear programming software such as GAMS, LINDO, CPLEX.[28,37] The choice of implementation platform depends on the complexity of the optimisation problems and the convenience for stakeholder implementation. Constraints are defined through stakeholder consultation, reflecting workforce planning, staff composition, and operational procedures. The mathematical formulation and the model structure are detailed in the methodology section, ensuring a rigorous optimisation framework that balances healthcare setting goals with operational realities. The optimisation model is run periodically (eg, weekly, monthly) over a simulation period (eg, a year), as seen in Figure 3. It accounts for dynamic factors such as patient demand fluctuations, staff attrition (due to resignations and retirements), and recruitment needs per period.

The workforce model can be validated from the following aspects:

Accuracy: The accuracy of the forecasting results was assessed using established performance metrics such as the Root Mean Square Error (RMSE) and Mean Absolute Scaled Error (MASE), which are widely recognised for evaluating forecasting performance in healthcare settings.[37] For robustness, the model is run under a baseline (current state) configuration, and key outputs, such as activities, demand levels, and total clinical hours, are compared against observed historical data. Deviations within an acceptable tolerance (eg, ±5%) indicate that the model provides an accurate and reliable representation of the real system. Additional robustness testing is conducted through sensitivity analysis, whereby key input parameters are systematically varied to observe the stability of outputs.[51] The constraint-level verification is performed by selectively activating and deactivating constraints to ensure that both the optimisation logic and the constraint set behave as intended.[66]

Behavioural Validity: Behavioural validity examines whether the model's outputs and dynamics reflect the expected behaviour of the real-world workforce system.[67] The conceptualised workforce structure and planning results could undergo stakeholder face validation, including healthcare providers, such as doctors, nurses, and managers, to ensure accurate representation of actual workforce dynamics, patient demand, and activities through semi-structured interviews, group meetings, workshops and interpreted results.[23,24] In the event of any errors or misrepresentations, the conceptualisation stage needs to be revisited to maintain its model validity. Subsequently, the model is evaluated for logical behaviour and accuracy.

Reproducibility: Reproducibility refers to the ability of independent users to replicate model results when applying the same data, parameter settings, and procedures.[68,69] Ensuring reproducibility is essential for model credibility and practical implementation, particularly when the model forms part of a DST intended for use by healthcare stakeholders. Reproducible modelling enhances transparency and strengthens evidence-based decision-making, thereby supporting wider adoption and sustained use within workforce planning processes.[53]

Experimentation for Policy Analysis

The design of scenarios and experimental conditions is intrinsically guided by the problem context and the strategic objectives of the study. Importantly, the scenarios should support both medium- and long-term workforce planning by enabling the projection of future workforce requirements under a range of policy and operational assumptions. Well-designed experiments allow decision-makers to examine the effects of varying workforce strategies and clinical outcomes, thereby evaluating the trade-offs between service quality and cost-effectiveness.[70,71] In practice, scenario development should reflect the priority areas identified by service managers, workforce leaders, and healthcare professionals, who may focus on strategic themes such as:

- Institutional and organisational future staff establishment;[20,37,52,64]
- Team composition across grades, roles, and qualifications;[57,63]
- Reallocation between permanent and temporary staff;[62]
- Staffing level adjustments;[20,31]
- Staff-to-patient or staff-to-population ratios;[40,61]
- Workforce supply and pipeline analysis;[24]
- Student intake planning;[23,72]
- Sensitivity and impact of policy uncertainties.[19]

Scenarios for key parameters, such as a sudden increase in patient demand or a national strike action by doctors and nurses can be informed by historical data, forecasting models, and expert judgement and subsequently evaluated within the workforce model. In practical health-system governance, particularly during periods of acute systemic stress or crisis, historical data alone may not adequately capture sudden shocks. Under such conditions, scenarios can be generated and iteratively updated as new operational information becomes available, enabling decision-makers to compare emerging conditions with the baseline estimation and revise workforce plans when historical patterns are no longer representative.

Proposed Workforce Model

This section outlines the proposed healthcare workforce model and explains how the formulations and rules are connected to real-world practices. A data-driven CDCO method was employed to optimise staff requirements in order to address current and future demand while ensuring the quality of care. Future demand can be projected using historical data, and current staffing levels are integrated to support ongoing operations. The model builds on the workforce-planning framework presented in Healthcare Workforce Modelling Framework, with its principal assumptions summarised previously in Table S1 of the Supplementary Material.

Problem Statement

The model is developed based on the following assumptions: (1) in each period, workforce capacity is determined to meet a specified service-demand target while maintaining the required skill mix and team structure across staff grades and minimising total staffing costs; (2) the permanent workforce in each period is linked to the previous period to ensure workforce continuity across the planning horizon; (3) effective workforce capacity reflects regulated clinical availability, sickness absence, and other leave; (4) where permanent workforce capacity is insufficient, shift-based and hourly temporary staff may be deployed, subject to predefined operational limits; and (5) permanent staffing decisions are modelled as integer headcounts to ensure realistic and implementable recommendations.

CDCO Workforce Model Formulation

Arriving Patient Demand

The demand clinical time demand d_t^{new} required by new patients in each period t is calculated as

$$d_t^{new} = f_t^{new}(\tau_1 + \tau_2)y\rho, \forall t \in T \tag{1}$$

where f_t^a denotes the forecasted number of arriving patients based on historical data. The clinical session time for each patient comprises τ_1 face-to-face time and τ_2 on-face-to-face time. Each patient requires y number of sessions with ρ staff involved per session. The value of ρ may exceed 1 in cases requiring special considerations, such as double-handed care or additional support commonly observed in services including PT.[73,74]

Model Parameters and Variables

Table 2 outlines the notations used in the optimisation model.

The decision variable set is defined as $x = \{n^1_{b,sub,t}, n^2_{b,bk,t}, n^3_{b,ag,t} | b \in B, t \in T\}$. The total clinical time provided by each grade b in period t is defined as

$$P_{b,sub,t}(x) = n^1_{b,sub,t}\omega_b\sigma\gamma\alpha_{b,sub}(1-\varepsilon_{b,sub})\left(1-\varphi_{b,sub}\right), \forall b \in B, \forall t \in T \tag{2}$$

$$P_{b,bk,t}(x) = n^2_{b,bk,t}\alpha_{b,bk}(1-\varepsilon_{b,bk})\left(1-\varphi_{b,bk}\right), \forall b \in B, \forall t \in T \tag{3}$$

$$P_{b,ag,t}(x) = n^3_{b,ag,t}\vartheta\alpha_{b,ag}(1-\varepsilon_{b,ag})\left(1-\varphi_{b,ag}\right), \forall b \in B, \forall t \in T \tag{4}$$

$$P_{bt}(x) = P_{b,sub,t}(x) + P_{b,bk,t}(x) + P_{b,ag,t}(x), \forall b \in B, \forall t \in T \tag{5}$$

Equations (2)–(4) define the clinical time provided by each staff type: substantive staff on a headcount basis, bank staff on an hourly basis, and agency staff on a shift basis, respectively. These equations convert staffing inputs into available

Table 2 Definitions of Notations

Notations	Definitions
Sets	
$t \in T$	The set of planning periods
$b \in B$	The set of healthcare staff grades
$s \in S$	The set of all staff types, $S = \{sub, bk, ag\}$ representing substantive staff, bank staff, and agency staff in the NHS, respectively. Substantive staff are modelled on a headcount basis, bank staff on an hourly basis, and agency staff on a shift basis
Subsets	
$S_{temp} \subseteq S$	The subset of temporary staff types, $S_{temp} = \{bk, ag\}$
$B_{sn} \subseteq B$	The subset of senior grade(s) responsible for supervision
$B_{jn} \subseteq B$	The subset of junior grade(s) required to work under supervision
$B_{hp} \subseteq B$	The subset of grade(s) considered high-priority due to grade upgrading
$B_{lp} \subseteq B$	The subset of grade(s) considered low-priority due to team upgrades
Parameters	
d_t^{new}	Forecast clinical time demand by new patients arrived in period $t \in T$
d_0	Initial clinical time demand
c_{bt}^1	Fixed pay rate for grade $b \in B$ in period $t \in T$
c_{bt}^2	Hourly pay rate for grade $b \in B$ in period $t \in T$
c_{bt}^3	Shift pay rate for grade $b \in B$ in period $t \in T$
ω_b	Staff WTE factor for grade $b \in B$
σ	Number of working weeks per planning period
γ	Number of working hours per WTE
ϑ	Number of working hours per shift
α_{bs}	Proportion of working time available for clinical activity for grade $b \in B$ and staff type $s \in S$
ε_{bs}	Proportion of working time absent due to sickness for grade $b \in B$ and staff type $s \in S$
φ_{bs}	Proportion of working time absent due to annual leave and holidays for grade $b \in B$ and staff type $s \in S$
k	Target demand completion rate
m_b^{max}	Maximum proportion of total clinical time that may be allocated to grade $b \in B$
m_b^{min}	Minimum proportion of total clinical time that may be allocated to grade $b \in B$
$\delta_{b,sub,t}$	Substantive staff retention rate for grade $b \in B$ at period $t \in T$
ξ	Required supervision ratio between senior and junior grades
ν	Staff grade for leadership $\nu \in B$
l	Proportion of leadership staff grade within the team
μ_{bs^*}	Maximum proportion of clinical time allocated to grade $b \in B$ and temporary staff type $s^* \in S_{temp}$
$\theta_{b,sub}$	Initial number of substantive staff for grade $b \in B$
Variables	
$P_{bst}(x)$	Clinical time provided by all staff in grade $b \in B$ and staff type $s \in S$ in period $t \in T$
$D_t^u(x)$	Unmet clinical time demand in period $t \in T$
$D_t^r(x)$	Required clinical time demand in period $t \in T$
Decision variables	
$n_{b,sub,t}^1$	Number of substantive staff required for grade $b \in B$ in period $t \in T$, measured on a headcount basis
$n_{b,bk,t}^2$	Number of bank staff hours required for grade $b \in B$ in period $t \in T$, measured on an hourly basis
$n_{b,ag,t}^3$	Number of agency staff shifts required for grade $b \in B$ in period $t \in T$, measured on a shift basis

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clinical time while accounting for clinical availability, sickness absence, and annual leave or public holidays. Equation (5) then aggregates the clinical time across all staff types to obtain the total clinical time provided by grade b in period t. The required demand and the unmet demand in period t are defined by

$$D_t^r(x) = k\left(d_t^{new} + D_{t-1}^u(x)\right), \forall t \in T \tag{6}$$

$$D_0^u(x) = d_0 \tag{7}$$

$$D_t^u(x) = max\left\{d_t^{new} + D_{t-1}^u(x) - \sum_{b\in B} P_{bt}(x), 0\right\}, t>1 \tag{8}$$

The required clinical demand time $D_t^r(x)$ combines forecasted new demand d_t^{new} and unmet demand $D_{t-1}^u(x)$ from the previous period $t-1$ with the target completion rate k. This definition accounts for both new and outstanding patient demand and ensures that total service requirements are incorporated.

Objective Function and Constraints

The healthcare workforce CDCO model can be formulated as follows:

$$minC_t = \sum_{b\in B}(n_{b,sub,t}^1 c_{bt}^1 + n_{b,bk,t}^2 c_{bt}^2 + n_{b,ag,t}^3 c_{bt}^3), \forall t \in T \tag{9}$$

$$\sum_{b\in B} P_{bt}(x) \geq D_t^r(x), \forall t \in T \tag{10}$$

$$\sum_{b\in B} P_{bt}(x) m_b^{max} \geq P_{bt}(x), \forall b \in B, \forall t \in T \tag{11}$$

$$\sum_{b\in B} P_{bt}(x) m_b^{min} \leq P_{bt}(x), \forall b \in B, \forall t \in T \tag{12}$$

$$\xi \sum_{b\in B_{sn}} n_{b,sub,t}^1 \geq \sum_{b\in B_{jn}} n_{b,sub,t}^1, \forall t \in T \tag{13}$$

$$\sum_{b\in B_{hp}} n_{b,sub,t}^1 \geq \sum_{b\in B_{lp}} n_{b,sub,t}^1, \forall t \in T \tag{14}$$

$$n_{v,sub,t}^1 \geq l \sum_{b\in B} n_{b,sub,t}^1 \forall \nu \in B, \forall t \in T \tag{15}$$

$$n_{b,sub,t}^1 \geq n_{b,sub,t-1}^1 \delta_{b,sub,t}, \forall t \in T, t>1 \tag{16}$$

$$P_{bs^*t}(x) \leq \mu_{bs^*} \sum_{s\in S} P_{bst}(x), \forall b \in B, \forall s^* \in S_{temp}, \forall t \in T \tag{17}$$

$$n_{b,sub,t}^1 \geq \theta_{b,sub}, \forall b \in B, t = 1 \tag{18}$$

$$n_{b,sub,t}^1 \in \mathbb{Z}^+, \forall b \in B, \forall t \in T \tag{19}$$

$$n_{b,bk,t}^2 \in \mathbb{R}^+, \forall b \in B, \forall t \in T \tag{20}$$

$$n_{b,ag,t}^3 \in \mathbb{Z}^+, \forall b \in B, \forall t \in T \tag{21}$$

The objective function (9) minimises the total staff cost in each period with different time measurements used across staff types, including WTE-based, hour-based, and shift-based deployments. The constraints (10) – (18) are described below to clarify their purposes and operational implications within the optimisation model.

Demand Coverage

Constraint (10) ensures that the total deployed clinical time is sufficient to meet the corresponding service demand in each period t. This constraint links workforce capacity directly to patient activity.

Skill-Mix Requirements: Staffing Grades, Supervision, Upgrading, and Leadership

Constraints (11) and (12) regulate the skill-mix composition of the workforce by defining upper and lower bounds on the proportion of clinical time contributed by each staff grade. These bounds preserve an appropriate balance between junior, senior and specialist staff and prevent the model from concentrating activity disproportionately within lower-cost grades. The constraints therefore ensure that the optimised workforce remains clinically feasible and consistent with the competencies, responsibilities and scope of practice associated with each grade.

Constraint (13) ensures that the supervision capacity provided by senior staff is sufficient to meet the supervisory requirements of all junior staff in each period. This reflects the operational need for clinical oversight, professional development, delegation and quality assurance. Without this constraint, the model could recommend an excessive number of junior staff without the senior capacity required to supervise them safely and effectively.

Constraint (14) represents the relationship between staff numbers within the team in each period t, which may result from team upgrading. Team upgrades occur when senior staff are introduced or promoted to strengthen the supervisory structure, enhance team capability, and improve service efficiency.

Constraint (15) establishes the minimum proportion of staff in leadership roles required to maintain effective management and clinical governance. Leadership staff, typically those in higher grades, are responsible for strategic planning, team management and service coordination.[14] Because these staff generally incur higher costs, the constraint prevents the optimisation model from disproportionately reducing leadership capacity in favour of lower-cost staffing configurations.

Staff Retention and Consistency

Constraint (16) specifies staff consistency and retention between consecutive periods, linking current workforce levels to the number of retained staff from the previous period $t-1$. The inclusion of monthly staff retention activity highlights the dynamic nature of the workforce. By tracking staff retention, it is possible to monitor fluctuations in turnover, identify emerging patterns or trends, and evaluate the effectiveness of retention strategies.

Temporary Staff Proportions

Constraint (17) limits the proportion of all types of temporary staff within each staff grade. Controlling the proportion of temporary staff in the workforce is essential to maintain service quality, continuity of care, and operational efficiency. Excessive reliance on temporary staff can undermine workforce stability and increase variability in service delivery.[14,62] The constraint therefore allows temporary staff to provide operational flexibility while preventing the model from relying excessively on them, as their greater flexibility could otherwise make them disproportionately attractive within the optimisation model.

Existing Staffing Configurations

Constraint (18) incorporates the current staff numbers within the team for the initial period $t=1$. This constraint ensures that the optimised workforce does not fall unrealistically below the existing establishment. By incorporating current staffing levels, the model produces a feasible workforce configuration that reflects operational conditions and supports a manageable transition towards future staffing requirements.

Case Study

The workforce modelling framework was applied in practice to validate and show its effectiveness in decision-making within a real-work setting. To achieve this, we collaborated with an NHS Trust which provides a full range of general acute, outpatient and diagnostic services to a local population of around 350,000 people, employing more than 4000 staff in England, to provide operational advice and evidence for their workforce planning of allied health professionals (AHPs). The healthcare provider has a variety of AHP roles, including physiotherapist, occupational therapist, and speech and language therapist, among others. The AHPs play a crucial role in treating, rehabilitating, and supporting patients.

In this study, we focused on the case of physiotherapists (PTs) as suggested by the Trust. PTs are one of the key components of the workforce, and there is a national shortage of PTs.[75] The stakeholder faces similar challenges that persist across the country, particularly staff shortages and low retention rates. In NHS England, healthcare staff are classified into nine Bands based on their level of responsibility and expertise. The organisation employs Band 2 to Band 4 PT staff, who are support workers, and Band 5 to Band 8 PT staff, who are qualified professionals and senior specialists. Due to staff turnover and sickness, temporary staff are required, sourced through the staff bank or external agencies, primarily for Bands 5, 6, and 7 roles. Several input parameters were estimated for the study, including patient demand, PT staff parameters (eg, retention, availability, skill-mix, pay rates) and clinical session parameters (eg number of sessions, session times). Where data was unavailable, we relied on data from the literature and stakeholder insights. The full lists of input parameters are provided in Table S2 (substantive staff parameters), Table S3 (temporary staff parameters) and Table S4 (clinical parameters) in the Supplementary Materials.

To estimate future activity levels, simple moving average, exponential smoothing and autoregressive integrated moving average (ARIMA) were compared using the mean absolute scaled error (MASE). Exponential smoothing achieved the lowest MASE value of 0.52, compared with 1.01 for the simple moving average and 1.67 for ARIMA, and was therefore selected for the analysis. Exponential smoothing is well suited to monthly patient-demand forecasting because it captures underlying level and trend patterns while assigning greater weight to recent observations, enabling forecasts to respond to changes in service demand.[76] It is also computationally efficient, requires relatively limited historical data, and produces transparent and interpretable forecasts suitable for operational workforce planning. After discussions with the team, the forecasting interval and the period for the optimisation model were set at one month. Figure 4 presents the forecasted monthly patient demand for the planning year. The forecasting model had a MASE value of 0.52, indicating a low error rate, which suggests that the model is reliable and effective in forecasting monthly patient demand.

The forecasted results indicate an increase in demand for the upcoming year, starting in May 2024, which aligns with the expectations of the healthcare provider. The forecasted patient demand indicates a 5.8% increase in the total annual number compared with the previous year, and this estimate was validated against stakeholder expectations. This projected growth is also consistent with national trends, due to rising demographic pressures and an ageing

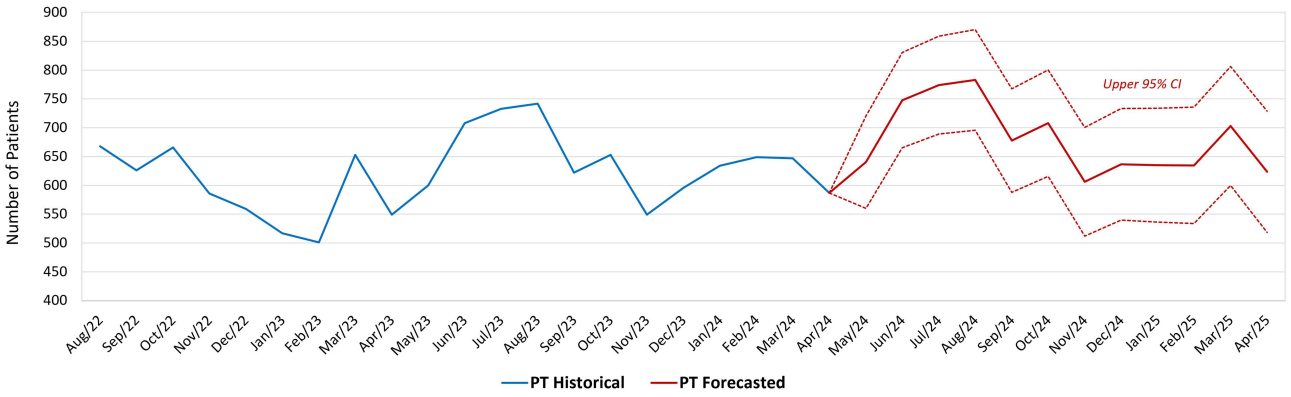


Figure 4 Forecasted patient demand for the planning year.

population.[14] The stakeholder's workforce structure and specific requirements were incorporated into the constraints outlined in the formulas from the previous section. For example, the provider wanted to upgrade skill sets and exclude Band 2 staff whose roles and responsibilities can be performed by Band 3 staff. Therefore, Band 2 staff, who are typically in entry-level or support roles, are not preferred in workforce planning. Additionally, the provider aims to maintain a workforce comprised solely of permanent staff to ensure workforce stability and avoid the higher costs associated with temporary staff. Key Stakeholder engagement in framework stages is presented in the Supplementary Materials Table S5.

To demonstrate how the proposed framework translates alternative service targets into changes in band-specific WTE requirements, workforce composition, staffing gaps, and establishment expenditure, three workforce-planning scenarios were evaluated for the planning year. OS-1 (Optimised Scenario 1) represents an optimised substantive-staff-only configuration under the current target demand-met rate (81%), while OS-2 (Optimised Scenario 2) applies a higher target demand-met rate (91%). OS-T (Optimised Scenario Temporary Staff Included) represents an optimised configuration in which temporary staffing is permitted under the current target demand-met rate (81%). The Baseline Situation (BS) reflects the provider's current workforce position, based on data from the preceding year, and serves as the benchmark for comparison with the optimised scenarios. In line with stakeholder priorities, the detailed analysis focused primarily on the optimised scenarios most relevant to workforce-planning decisions.

Results

Overall Results and Staff Establishment

Table 3 summarises the results for all scenarios designed to meet the target completion rate. The OS-T scenario demonstrates the model's capacity to integrate and optimise temporary staffing where required. Nevertheless, because stakeholder priorities centre on enhancing care quality and building a resilient substantive workforce, the role of temporary staff is not examined in depth. Accordingly, the discussion that follows focuses on OS-1, which applies an 81% target demand-met rate, and OS-2, which applies an increased target demand-met rate of 91%.

Table 4 presents the staff establishment results in WTE and proportions across all bands. The staff establishment for the optimised scenarios was determined based on the month with the highest forecast patient demand, which serves as a key reference point for the provider's workforce planning and budget allocation. In line with the provider's preference, Band 2 staff were excluded from the optimisation to facilitate an upgrade in the workforce skill mix. As a result of increased patient demand, both the total WTE and the band-specific WTE requirements in OS-1 and OS-2 were higher than those in the BS.

The results were validated against the provider's internal results and outputs from their existing workforce planning method. The model results showed agreement within a 5% deviation and were also assessed through expert face

Table 3 Summary of Scenario Results

	BS	OS-1	OS-2	OS-T
Total patient number	7720	8170 (+450)	8170 (+450)	8170 (+450)
Met patient number	6244	6687 (+443)	7410 (+1166)	6621 (+377)
Unmet patient number	1476	1483 (+7)	760 (−716)	1549 (+73)
Substantive staff WTE proportion	82.22%	100.00% (+17.78%)	100.00% (+17.78%)	94.77% (+12.55%)
Temporary staff WTE proportion	17.78%	0.00% (−17.78%)	0.00% (−17.78%)	5.23% (−12.55%)
Average agency staff shifts per month	37	0 (−37)	0 (−37)	34 (−3)
Average bank staff hours per month	318	0 (−318)	0 (−318)	90 (−228)

Notes: The numbers in brackets indicate the difference from the Baseline Situation. BS: Baseline Situation; OS-1: Optimised Scenario 1 with substantive staff only under the current target demand-met rate; OS-2: Optimised Scenario 2 with substantive staff only under an increased target demand-met rate; OS-T: Optimised Scenario with temporary staff included.

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Table 4 Staff Establishment Results in WTE

	BS	OS-1	OS-2	BS %	OS-1%	OS-2%
Band 2	2.50	0.00 (−2.50)	0.00 (−2.50)	6.03%	0.00% (−6.03%)	0.00% (−6.03%)
Band 3	4.60	6.44 (+1.84)	8.28 (+3.68)	11.09%	12.76% (+1.67%)	14.74% (+3.65%)
Band 4	5.00	8.00 (+3.00)	9.00 (+4.00)	12.05%	15.85% (+3.80%)	16.02% (+3.97%)
Band 5	11.10	12.03 (+0.93)	12.95 (+1.85)	26.76%	23.84% (−2.92%)	23.05% (−3.71%)
Band 6	10.46	14.26 (+3.80)	15.21 (+4.75)	25.22%	28.25% (+3.04%)	27.07% (+1.86%)
Band 7	5.96	6.95 (+0.99)	7.95 (+1.99)	14.37%	13.77% (−0.60%)	14.15% (−0.22%)
Band 8	1.86	2.79 (+0.93)	2.79 (+0.93)	4.48%	5.53% (+1.04%)	4.97% (+0.48%)
Total	41.48	50.47 (+8.99)	56.18 (+14.70)	100.00%	100.00%	100.00%

Notes: The numbers in brackets indicate the difference from the Baseline Situation. BS: Baseline Situation; OS-1: Optimised Scenario 1 with substantive staff only under the current target demand-met rate; OS-2: Optimised Scenario 2 with substantive staff only under an increased target demand-met rate.

validation, as shown in Table S5 - Key Stakeholder Engagement Across the Framework Stages in the Supplementary Material.

Workforce Dynamics

Staff numbers are an important metric for recruitment and healthcare resource planning. Understanding staff numbers helps the healthcare provider make decisions on staff training, retention strategies, and improving workforce resilience to ensure that it can adapt to evolving healthcare needs. Figure 5 presents the required and current substantive staff numbers by band for each month under the OS-1 and OS-2 scenarios. In particular, Band 3 and Band 4 staff perform complementary roles within the workforce. Therefore, increasing the target demand-met rate does not necessarily increase the required staff numbers in both bands, provided that the skill-mix requirements are satisfied. This enables the optimisation model to identify the most cost-effective workforce configuration.

Budget Analysis

In response to rising patient demand and the need to optimise workforce composition, the overall staff establishment budget is projected to increase, as shown in Table 5. These estimates were calculated using the standard NHS pay rates for each band. The increases are particularly notable for Bands 4 and 6. Under OS-1, with an 81% target demand-met rate, the respective monthly budget increases are £7278 and £14,988. Under OS-2, with a 91% target demand-met rate, the corresponding increases are £9705 and £18,734. Bands 5 and 6 account for the largest proportions of the total establishment budget. As these bands play core roles in the delivery of physiotherapy care, the increased budget allocation is important for supporting service provision in the context of rising patient demand.

Sensitivity Analysis

A sensitivity analysis was conducted to investigate the impact of key clinical parameters on the total WTE in staff establishment and the associated budget (see Supplementary Materials Table S6). The input parameters, including face-to-face time, non-face-to-face time, and number of sessions per patient, were varied by ±30% from the baseline value. The target met session rate was adjusted by ±20%, as it should remain above 1. The number of sessions per patient was identified as the most sensitive parameter, and the changes generated the largest and nearly proportional impact on WTE (+29%/−30%) and budget (+27%/−31%). This suggests that stakeholders should pay particular attention to the influence of this parameter. Variations in face-to-face and non-face-to-face time reflected their proportional contributions to clinical workload and then staff establishment and the budget. Overall, the outputs were more sensitive to decreases than

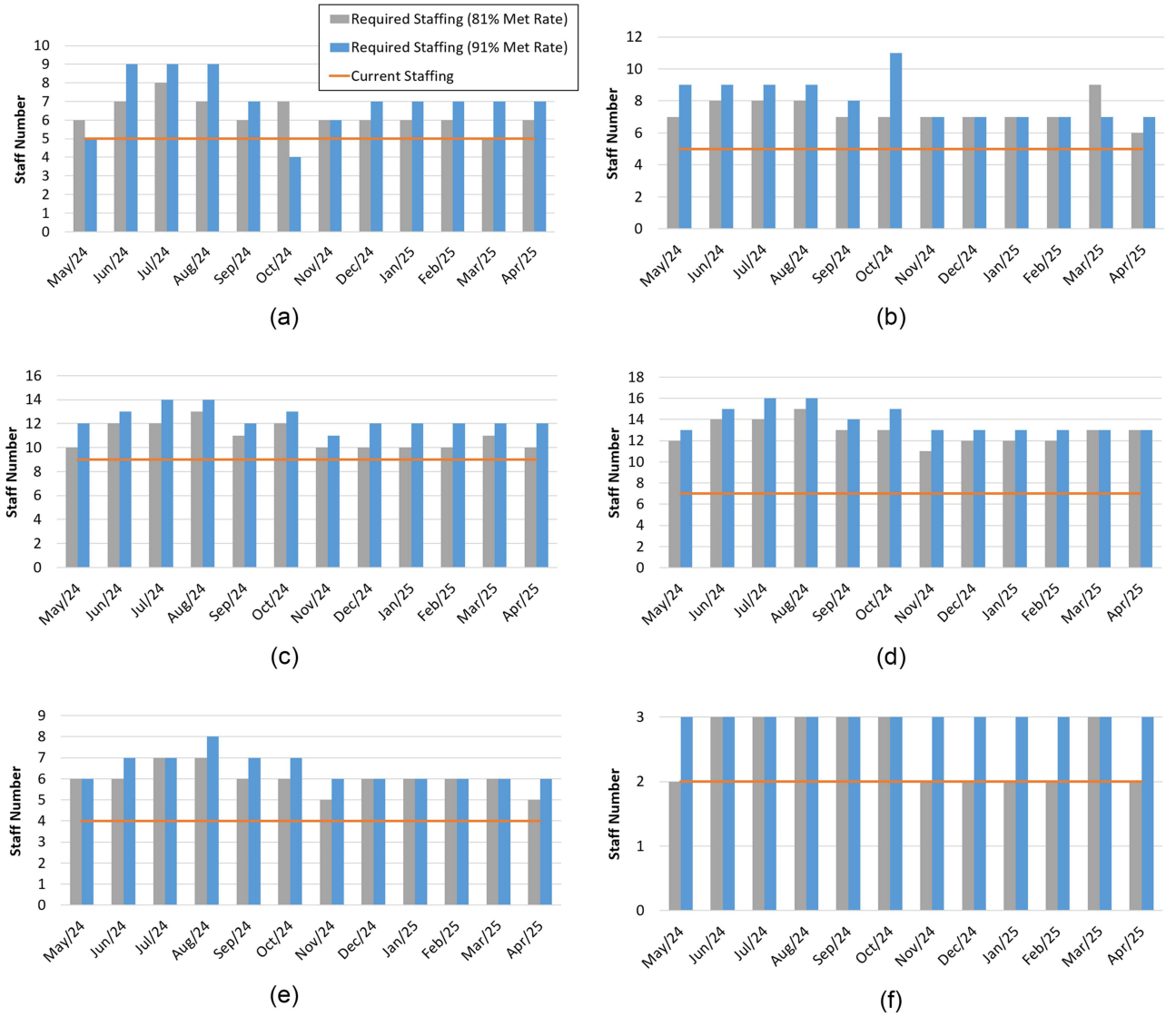


Figure 5 Current and required substantive staffing levels under optimisation scenarios OS-1 and OS-2, by NHS staff band: (**a**) Band 3, (**b**) Band 4, (**c**) Band 5, (**d**) Band 6, (**e**) Band 7 and (**f**) Band 8.

increases in these parameters, which suggests that reductions in clinical parameters have more effects on staff establishment and budget.

Discussion

Principal Findings

Persistent gaps in the healthcare workforce-planning literature, together with the needs identified by practitioners and key opinion leaders, indicate a continuing requirement for comprehensive and practically accessible modelling approaches. In response, this study developed a workforce-modelling framework designed to be adaptable to different healthcare services and settings, subject to the availability of relevant workforce and service data and the involvement of appropriate domain expertise in model calibration and validation as outlined in Table S5 in the Supplementary Materials. The framework is underpinned by an optimisation-based operations research approach and implemented as an Excel-based decision-support tool using Visual Basic for Applications. This implementation was intended to facilitate transparent and accessible use by healthcare stakeholders with varying levels of technical expertise.

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Table 5 Monthly Staff Establishment Budgets by Bands

	BS	OS-1	OS-2	BS %	OS-1%	OS-2%
Band 2	£5904	£0 (−£5904)	£0 (−£5904)	4%	0% (−4%)	0% (−4%)
Band 3	£10,698	£14,977 (+£4279)	£19,256 (+£8558)	7%	9% (+2%)	10% (+3%)
Band 4	£12,131	£19,409 (+£7278)	£21,836 (+£9705)	8%	11% (+3%)	11% (+3%)
Band 5	£36,483	£39,523 (+£3040)	£39,523 (+£3040)	26%	22% (−4%)	21% (−5%)
Band 6	£41,215	£56,203 (+£14,988)	£59,949 (+£18,734)	29%	32% (+3%)	31% (+2%)
Band 7	£26,405	£30,805 (+£4400)	£35,206 (+£8801)	18%	17% (−1%)	18% (0%)
Band 8	£10,084	£15,126 (+£5042)	£15,126 (+£5042)	7%	9% (+2%)	8% (+1%)
Total	£142,920	£176,043 (+£33,123)	£190,896 (+£47,976)	100%	100%	100%

Notes: The numbers in brackets indicate the difference from the Baseline Situation. BS: Baseline Situation; OS-1: Optimised Scenario 1 with substantive staff only under the current target demand-met rate; OS-2: Optimised Scenario 2 with substantive staff only under an increased target demand-met rate.

The application of this framework in collaboration with a high-demand NHS Trust in England, working closely with the AHP team. The tool was used to predict and optimise the staff establishment and staffing levels of PTs, and it is currently being utilised by the Trust for informed decision-making. The Associate Director of Allied Health Professionals praised the DST, stating:

> It has been incredible working with the team on this study. I have been unable to robustly explain and justify the workforce that we require in order for our AHP's to deliver safe and effective care. It is well recognised that there are no national tools specifically for AHP's, and I am increasingly excited at the detail and opportunity the DST will bring to our trust, but also generally to AHP's and indeed other staffing groups on a wider scale in the future.

Our collaboration with the NHS Trust validated the tool's effectiveness, and the results suggest that an increase in staff establishment is necessary to meet future patient demand, along with structural changes to improve the quality of care. The integration of demand-side and supply-side enhances the credibility and decision-usefulness of the model for service managers and policymakers, as advocated by Lee et al[19] and Bosak et al.[18] These outcomes further emphasise the importance of an optimised skill-mix within the team, aligning with the observations of workforce dynamics, as emphasised by Dubois et al.[20]

Under 5.8% annual demand growth and the proposed skill-mix upgrade, maintaining an 81% demand-met rate would require an additional 8.99 WTE and increase the monthly full-establishment budget by $33,123. Achieving a 91% demand-met rate would require 14.70 additional WTE and increase the monthly budget by $47,976. These findings indicate a projected shortage of substantive staff across most bands, driven by rising patient demand, the planned skill-mix changes, and the current reliance on temporary staff. Staffing requirements increased particularly in Bands 3, 4, and 6 under both optimised scenarios, suggesting that the current establishment may underestimate the capacity needed in these bands to meet future demand. The provider may therefore need to prioritise recruitment, retention, and workforce capacity in these areas, while recognising the associated increase in budget requirements and changes in the staffing cost structure. The number of clinical sessions required per patient was identified as the most sensitive parameter, indicating that relatively small changes in treatment intensity can substantially affect projected staffing requirements and costs. These findings are consistent with the priorities outlined in the NHS Long Term Workforce Plan.[14]

It is important to achieve a balance between complexity and usability in workforce modelling.[22,23] Current approaches require extensive expertise and resources to develop, making them less accessible for timely and informed decision-making. While simulation-based models using systems dynamics and discrete event simulations can capture intricate details and provide superior insights, they are often challenging to develop, costly, and difficult to implement. In contrast, our DST is cost-effective, comprehensive, and easy to develop with the support of an OR specialist, making it

highly suitable for practical decision-making. Importantly, the engagement of policymakers throughout the process strengthened the relevance and applicability of the results for strategic decision-making, consistent with the evidence reported by Rees et al.[77] Furthermore, the step-by-step structure of our modelling framework, accompanied by healthcare-specific definitions and parameter guidance, enables workforce planning teams to independently construct and refine their internal workforce plans. This represents a practical extension of earlier frameworks proposed by Willis[26] and Amorim-Lopes et al.[24]

Recommendations for Practitioners and Key Opinion Leaders

Based on the development of the workforce modelling framework within a DST environment, there are a few recommendations that emerge.

Standardising Decision-Making Tools and Minimising Health Inequality

As the size and complexity of the health workforce expand, it becomes imperative for services and planners—acting as KOLs, to embrace standardised reporting systems and tools that ensure quality, robustness, and transparency. Consistent use of such a system across services, departments, and specialties is essential to ensure accuracy and accountability for institutional or organisational purposes.[20] Excel's widespread use and acceptance in the industry ensure that our solution can be adopted globally at minimal cost, especially by services based in low- and middle-income countries (LMICs). As highlighted by Hosseinpoor et al,[78] improving the accessibility of decision-support tools is essential for reducing health inequalities in countries. The extensive use of Excel-based tools by organisations such as the WHO demonstrates the value of accessible, low-cost platforms in supporting equitable health systems.[79]

Our localised, user-friendly DST may be particularly valuable in LMICs and fragile or emerging health systems, where workforce shortages, limited analytical capacity, and constrained budgets can impede progress towards Universal Health Coverage (UHC).[80] By translating locally available workforce, demand, and cost data into context-specific staffing and demand scenarios, the DST can support transparent resource allocation, healthcare investment, and broader health-system transformation and digitalisation through the use of widely available, low-cost spreadsheet software such as Microsoft Excel.

Adapting of Multi-Skill Structures and Workforce Dynamics

Effective adaptation of the health workforce framework should prioritise a multi-professional, skill-mixed approach to service delivery.[20] Additionally, projections of future service demands should integrate factors such as chronic diseases, patients with multiple conditions, population growth and ageing.[27,81,82] As the demand for patient-centred care delivered by multi-professional teams rises, there arises a methodological challenge in accurately modelling team-based care. Hence, it is crucial to transition from group-clustered approaches to multiple-skill-based frameworks to effectively address the evolving demands and complexities of workforce planning.

Integrating Financial and Budgetary Analysis for Future Uncertainties

Integrating financial factors into workforce planning ensures that healthcare organisations align projected workforce needs with available resources and remain resilient to future uncertainties as remarked by Willis et al[23] and Amorim-Lopes et al.[24] This approach helps decision-makers allocate budgets wisely, optimise resource use, and manage financial risks related to staffing shortages or surpluses. It also supports fiscal sustainability by pinpointing cost-effective ways to meet healthcare demands while maintaining quality care. Connecting workforce efficiency and budget analysis allows organisations to proactively manage financial constraints, improve operational efficiency, and enhance overall healthcare delivery and patient outcomes.[77,83] Our comprehensive framework not only aids strategic decision-making but also builds a stronger, adaptable healthcare workforce ready to tackle present and future challenges effectively.

Enhancing Data Integration for Comprehensive Workforce Planning in Healthcare

In many healthcare settings, granular longitudinal data on patients and the workforce are either unavailable or collected but not systematically integrated within electronic health record systems.[25] Strengthening data collection and integration processes is therefore essential for robust workforce planning. For example, various work patterns, including part-time,

agency, temporary, and full-time roles, should be systematically captured and incorporated into e-rostering systems to ensure that variations in clinical time allocation and availability are accurately reflected in workforce models. Stakeholder engagement is also critical, as their insights provide the context-specific information needed for modelling.[23,77] Inputs from clinicians, service managers, and policymakers should be incorporated to reflect factors such as required skill-mix, specialised patient needs, and team management.

Closing the Gap: Advancing Practical Application of Innovative Health Systems Models Through User-Friendly Decision Support Tools

Evidence accumulated over more than two decades of implementation science indicates a persistent gap between research findings and their practical application.[19,26,83] Researchers excel in developing innovative models for health systems management, including workforce planning methodologies, as outlined in our review of the literature. However, these models often remain confined to academic outputs and frequently encounter the implementation pitfalls in decision-making highlighted by Dubois and Singh[20] and Lee et al.[19] Although several frameworks, such as robust workforce planning frameworks, have been developed for this reason and applied in studies by Willis et al,[23] Benahmed et al[27] and Amorim-Lopes et al[24] through the integration of mathematical modelling and structured stakeholder engagement. The challenges still remain for health KOLs when attempting to implement these approaches. One of the primary reasons for this gap is the complexity of these models, making them challenging to use and understand. To bridge this divide, we advocate for the development of user-friendly DST like the one in this article, accompanied by training and user manuals. This approach ensures that teams receive the necessary support precisely when they need it, facilitating the practical application of research insights in real-world healthcare settings. Moreover, the proposed standardised DST can support rapid scenario planning during periods of acute systemic stress or crisis, as the model is parameterised and responsive to changes in key assumptions and operational inputs.

The adaptable structure of the proposed framework and CDCO model suggest potential transferability to other healthcare services, professional groups, and organisational settings, provided that appropriate local data and contextual information are available. Although the framework includes some standardised components for workforce modelling and decision support, its assumptions and parameters need to be adapted and validated to reflect local service requirements.

Limitations

Although Recommendation 4 emphasises the importance of robust data-collection processes, some health systems, including those in high-income countries, may lack the granular workforce and activity data required to implement the proposed framework. This challenge may be particularly pronounced outside the NHS and in LMIC settings, as discussed in the Introduction, where workforce information systems and data-integration capabilities may be less developed. Consequently, additional data collection, proxy estimates or model adaptation may be required, which could affect the precision and reliability of the resulting workforce plans.

Additionally, implementation also required close collaboration with AHP service managers to define assumptions, interpret model outputs and translate the findings into feasible staffing decisions, as summarised in Table S5 of the Supplementary Material. The time, expertise, stakeholder engagement and organisational commitment required for this process may not be readily available in every service or setting. Workforce structures can be shaped by local policies, professional judgement and accumulated operational experience, making the standardisation and transfer of establishment rules across settings challenging.

Finally, validation was conducted within a single NHS Trust and professional service. Although the framework is designed to be structurally adaptable to other settings, subject to appropriate data, calibration and domain expertise, empirical evidence of its performance in other professions, services and health systems is not yet available. External validation across multiple settings is therefore a natural next step for future research.

Future Research

Future research will focus on refining the methodology to ensure precise and reliable estimation of the workforce. For example, staff establishment could be further refined by dividing the workforce into specialty-based teams. This would

enable the inclusion of additional factors, such as staff and student training, and specific team requirements of specialties. On the other hand, the model could be further improved by incorporating a behavioural modelling approach which surely would undoubtedly require a distinct data collection. This addition would help to better capture the drivers of staff retention and turnover. We are currently expanding our DST to become web-based and hosted on the cloud, making it accessible from any device. This enhancement aims to improve the tool's usability and user experience, enabling workforce projections to be generated with a single click. Additionally, we will integrate it with local electronic health record systems to ensure real-time cleaning, preparation, and analysis of activity-related data (such as elective and non-elective procedures). This integration will allow input parameters to be updated instantly, adjusting workforce requirements based on service demand. It will also facilitate real-time updates for workforce-related inputs, such as adding new staff or accounting for retirements.

Conclusion

Workforce modelling and projections pose a significant challenge for health service planners. This study addresses this gap by developing a novel framework that can be adapted to any setting and services globally, provided the necessary data is available. The framework emphasises the theoretical approach with practical application while incorporating granular-level factors and workforce dynamics to meet patient demand, ensure the quality of care, and enhance accessibility for timely decision-making. This is supported by the proposed data-driven CDCO modelling approach and robust health workforce data intelligence, all within an easy-to-use Excel environment. It is crucial to use software accessible to staff in low- and middle-income countries (LMICs), as more expensive options may be inaccessible for services and organisations in these regions. Currently, an NHS Trust in England is effectively using this tool for AHP services, with plans to extend its application to other services within the Trust and other providers nationally.

While the DST may be accessible for LMICs and other resource-constrained settings, its effectiveness depends on the availability of sufficiently detailed longitudinal data on workforce capacity and service demand. Limited data infrastructure, poor data quality, and fragmented information systems may constrain model calibration and reduce the reliability of its outputs, highlighting the need to strengthen routine data collection, standardisation, and integration.

Data Sharing Statement

Data available within the article and its Supplementary Materials.

Ethics Approval

This study received ethics approval from the University of Hertfordshire, approved by the Social Sciences, Arts and Humanities Ethics Committee with Delegated Authority, under protocol number cBUS/SF/UH/06109. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and relevant institutional research ethics requirements. The research used anonymised and/or aggregated workforce and service-level data, and no identifiable patient-level data were used. Stakeholder interactions undertaken to inform the modelling process were conducted in accordance with the approved protocol, with information handled confidentially.

Consent to Participate

Informed written consent was obtained from participants involved in the stakeholder engagement activities. These activities were conducted in accordance with the ethics protocol.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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