Analytics for the Location Planning of Attention-Deficit Hyperactivity Disorder Monitoring Capacity in Adolescents

Elin Haf Williams
School of Mathematics
Cardiff University
Cardiff, UK
ORCID: 0009-0000-3062-5640

Elizabeth Williams
School of Mathematics
Cardiff University
Cardiff, UK
ORCID: 0000-0003-4515-441X

Daniel Gartner
School of Mathematics
Cardiff University
Cardiff, UK
ORCID: 0000-0003-4361-8559

Gemma Johns
Technology Enabled Care Cymru
Cardiff, UK
ORCID: 0000-0001-9823-4822

Alka Ahuja
Royal College of Psychiatrists (Wales)
Cardiff, UK
ORCID: 0000-0003-2658-2021

***Abstract*—Attention-deficit hyperactivity disorder (ADHD) is prevalent in children and adolescents, often treated with medication. Monitoring medication, however, strains healthcare resources, prompting exploration of remote monitoring. In this paper, we address the problem of locating hubs for healthcare assistants to travel to schools to cover the demand of a remote monitoring service for pupils with ADHD. We propose a facility location problem approach to decide on the number of hubs for healthcare assistants and where to locate them in order to cover the demand for remote monitoring in secondary schools in Wales, UK. The results provide insights into how many hub locations are needed to cover the demand. Thus, our mathematical modelling approach can help policy makers efficiently plan resources and help children and adolescents with ADHD to be monitored more effectively.**

***Index Terms*—mathematical modelling, linear programming, healthcare management**

I. Introduction

Attention-deficit hyperactivity disorder (ADHD) is considered to be one of the most prevalent neurodevelopmental/behavioural disorders amongst children and adolescents [1, 2] with prevalence commonly reported as 5% [1, 3, 4]. ADHD medication prescription prevalence has been increasing in the UK [4], possibly due to improved identification and recognition of ADHD. Common ADHD symptoms include the presence of pervasive, developmentally excessive, and impairing levels of overactivity, inattention, and impulsivity [4]. Furthermore, the diagnosis should also be considered in children and adolescents with poor attention, distractibility, hyperactivity, impulsiveness, poor academic performance, or behavioural problems [2].

Medication is part of the treatment in ADHD. It is usually tried if all non drug interventions are unsuccessful or if the condition is severe and has a significant impairment [5]. However, the medication options available to treat ADHD may cause side effects such as decreased appetite, reduction in height growth, sleeping problems, and changes in blood pressure and heart rate [2, 6]. Due to the aforementioned side effects, patients prescribed with ADHD medication need monitoring, requiring general practitioner (GP) or hospital appointments which add pressure onto the National Health Service (NHS). Frequent monitoring allows the optimal personalised dosage to be achieved [6].

Remote monitoring could reduce the number of in-person appointments required to achieve the necessary monitoring of ADHD patients, subsequently easing pressures on NHS services. Typically, remote monitoring involves capturing health-related data from patients in one location and transmitting the data to a clinician for review in another location [7, 8]. Data may be captured automatically by wearable technological equipment, or may be inputted manually into a system by patients [3, 7]. Health data that can be captured by remote monitoring includes blood pressure, heart rate, oxygen levels and other vital signs [7]. ADHD patients are ideal candidates for remote monitoring services because ADHD treatment does not require much physical interaction during their appointments. Therefore, remote appointments can be alternated with in-person appointments [9]. Additionally, patients with other conditions that call for medical supervision may also find remote monitoring services beneficial.

One challenge prevalent in the literature on remote monitoring is the inconsistent use of terminology and definitions. Many definitions exist referring to the concept of remote monitoring including telemedicine, telehealth, virtual ward, mHealth and wearable technologies. Dixon et al. [10] state that over 100 definitions of ‘telemedicine’ were found in a review in 2007. Mantena and Keshavjee [11] define remote

This work has been supported by the LEAP Digital Health Hub, which has been funded by EPSRC under grant number EP/X031349/1

monitoring to be a mode of digital health intervention allowing patients to be monitored away from a clinical setting. The World Health Organisation (WHO) defines telemedicine as "The delivery of health care services, where distance is a critical factor, by all health care professionals using information and communication technologies for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, research and evaluation, and for the continuing education of health care providers" [12]. Merritt [13] suggests "all health services provided using telecommunications technology" as a broad definition of telehealth. Research should be conducted to establish unanimous and universal definitions of the terminology used.

In this paper, we address the problem of finding the optimal number of hubs for healthcare assistants to deliver a remote monitoring service in secondary schools in Wales. Healthcare assistants would be located in hubs and would travel to secondary schools twice a year to support the delivery of remote monitoring. We specifically focus on secondary schools as these institutions typically have a higher number of pupils on medication or with chronic health conditions that require monitoring, compared to primary schools. To that extent, a mathematical model is developed with the aim of determining the number of hubs for healthcare assistants required to effectively administer the service. Using data from secondary schools across Wales, UK, we solve the problem using a metaheuristic optimisation approach and compare it with the optimal solution determined by an open source solver. The novelty of this paper lies in its application of the optimisation problem, offering a potential solution to support the implementation of a new remote monitoring service. Visualisations of solutions are provided to aid decision-makers in evaluating the allocation of healthcare assistants to schools and the corresponding demand coverage in each solution.

The remainder of this paper is structured as follows: Section II provides an overview of related work signifying the possible benefits of remote monitoring technology, and indicates some operational research (OR) techniques that could be utilised to approach the problem of this paper. In Section III, a formal problem description is provided followed by our mathematical model. Furthermore, the algorithm utilised to solve the problem is described. The experimental results are detailed in Section IV, with a discussion provided in Section V. Section VI concludes the paper and provides recommendations for future work.

II. Related Work

This section provides an overview of related literature organised into three themes. The first area explores the benefits, feasibility and acceptance of remote monitoring in schools. The second area focuses on OR methods applied in the context of remote monitoring. Lastly, the third area examines the literature on the facility location problem, particularly within the healthcare context.

A. *Benefits, feasibility and acceptance of remote monitoring in schools*

Reductions in travel time, travel distance, waiting time and cost are commonly cited benefits of remote monitoring services, portraying the burden that in-person monitoring appointments place on patients, families and caregivers [10, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24]. Another frequently mentioned benefit of remote monitoring services is the improved access to healthcare [14, 15, 16, 17].

An important consideration when implementing remote monitoring services is access to the required technology. Several articles have researched disparities in access to remote monitoring, and have consistently observed older age, rurality, race, ethnicity, language, internet access and insurance status to impact the level of interaction with remote monitoring services [19, 22, 25]. Implementing remote monitoring services in schools could minimise disparities in access to a stable internet connection and the required technology. Additionally, being absent from school to attend medical appointments is a common concern reported by patients and caregivers of the children receiving medications or treatments [15, 21, 26].

Implementing remote monitoring services in schools could enable medical appointment participation from everyone involved in a child's day-to-day life including teachers, caregivers, clinicians, and the patient themselves [10]. This could be advantageous to children receiving ADHD medication because both teachers and parents observe the child's behaviours and potential side effects of the medication at various times of the day, providing a more comprehensive understanding of the child's overall well-being.

Remote monitoring services can also improve feelings of empowerment, allowing children to take control of their condition and to feel greater involvement in their treatment [27]. Promoting feelings of empowerment and involvement early on in life is pivotal to maximise medication adherence and self-management skills, thus leading to an improved quality of life for the patient [27].

Lin et al. [26] explored the effectiveness of a school-based remote monitoring intervention aimed at enhancing asthma control, severity and monitoring adherence in participants aged 10 to 17 years old from economically deprived areas. The study utilised a remote monitoring device to track inhaler utilisation where the inhaler was linked to mobile device software via Bluetooth connection. Results indicated a significant improvement in asthma severity among participants diagnosed with severe asthma, while those with non-severe asthma experienced a smaller improvement. The authors underscored the potential of remote monitoring to enhance healthcare access for individuals from economically disadvantaged communities and highlighted the cost-reducing benefits of a school-based remote monitoring service.

B. *Operational research and remote monitoring*

The majority of research on remote monitoring focuses on the feasibility, utilisation, opinions and compliance of remote monitoring services [19, 22, 24]. This may be a consequence of remote monitoring being a relatively new service, as evidenced by the significant rise in remote monitoring-related literature that has occurred since the COVID-19 pandemic. The lack of research could also be attributed to inconsistent use of terminology concerning remote monitoring. Consequently, there exists a gap in the literature regarding the application of OR techniques to remote monitoring services, particularly in supporting its implementation through mathematical modelling.

A number of papers have conducted literature reviews on the application of OR to healthcare. More specifically, in a context similar to remote monitoring, Grieco et al. [28] carried out a literature review exploring the application of OR to home healthcare (HHC). The review focused on the use of OR to address strategic, tactical and operational planning decisions. The most common decisions examined were related to the allocation of staff, visit scheduling and routing of visits. Mixed-integer programming (MIP) emerged as the predominant OR method used to address these issues, often based on the vehicle routing problem. Consequently, the most common measure of system performance was staff travel distance, with the objective function typically focusing on minimising travel costs.

Markov models have been used to model patient disease progression and compare two patient groups: one group using a remote monitoring device and a control group. Padula et al. [29] analysed the cost-utility of Bluetooth-enabled pulse-oximetry monitors for COVID-19 patients employing a Markov model comprising six health states. Health outcomes improved for patients using remote pulse-oximetry monitors and costs were reduced. Yao et al. [30] utilised a constrained Markov decision process to model methods to optimise electrocardiography readings under a constrained energy consumption budget.

A variety of simulation models have been utilised to represent the advantages of remote monitoring. Faezipour and Faezipour [31] developed a system dynamics model to explore the effectiveness of a smart-phone based heart monitoring service, based on elctrocardiogram (ECG) signals. A feedback model was developed, based on factors such as patient well-being, care, cost, convenience, and user-friendliness, along with various embedded ECG system design and performance metrics. Gorelova et al. [32] utilised a discrete event simulation model to demonstrate changes to patient flow in infertility treatment when using a wearable device to gather hormone level data. When a concerning hormone level reading was observed, the patient would be prioritised for an online appointment. As a result of using a remote monitoring device, mean waiting times for appointments were reduced by 36.5% and there was an 88% increase in the number of patients that could be served by one physician. Finally, an agent-based simulation model was used by Montagna and Omicini [33] to model the changes to Type I diabetes patients' health when self-management interventions were introduced. Remote monitoring devices collected information including physical activity and vital signs. The model had two levels, where the high-level model characterised patients' utilisation of the tool, and the disease model depicted the disease physiopathology. Improvements to patients' health were recognised as a result of remote monitoring.

The majority of literature applying OR methods to remote monitoring has focused on the feasibility, benefits and acceptance of remote monitoring. Consequently, there is a significant lack of consideration of the implications of a remote monitoring service on the workforce.

C. Facility Location Problem (FLP)

The FLP is an optimisation problem in which a set of potential facilities with limited capacities are chosen to serve the demand at demand points. The FLP determines which facilities serve which demand points in a way to optimise the objective function, for example, minimising the total distance travelled or total costs [34]. The FLP has been applied to a variety of healthcare settings, for example, hospital location [35], HHC [36], medication delivery [37] and ward planning [38].

Grange et al. [38] applied the FLP solver to the virtual ward planning problem for frail and elderly patient monitoring. Their mixed-integer linear programming model jointly optimises virtual ward locations, staff allocation, and patient assignment while balancing coverage and workload. Through a case study using regional healthcare data, the authors demonstrated the FLP solver's effectiveness for virtual ward capacity planning by considering location, staffing, and patient decisions jointly.

Ahmadi-Javid [39] conducted a literature review to construct a framework to classify healthcare FLPs. The applications can be broadly separated into non-emergency or emergency facilities. Non-emergency facilities included blood banks and doctors' offices, whereas emergency facilities included permanent facilities such as emergency centres and temporary facilities including temporary medical centres.

Zhang et al. [35] applied the FLP to a hospital setting, aiming to minimise disparities in access to community hospitals while considering costs such as construction and travel, and simultaneously maximising demand point coverage. Zhang et al.'s model included a set of demand points and sets of potential community and general hospitals. The model integrates parameters such as distances between demand points and candidate hospital capacities. Additionally, it accounts for the proportion of the demand point population necessitating different levels of medical services.

A maximal covering location problem (MCLP) applied to emergency medical services was presented by Erkut et al. [40] where the model aimed to maximise the number of surviving patients in an ambulance location problem. Erkut et al. highlighted two weaknesses of the standard MCLP model. Firstly, it assumes the constant availability of an emergency vehicle, and secondly, it overlooks the variability in travel times.

Pourrezaie-Khaligh et al. [36] developed a two-stage HHC FLP in which base locations were needed for HHC staff to start their journeys. The model was constructed under uncertain demand, and transportation decisions were made following determining base locations. The objective was to maximise profits, comprised of revenue and capacity costs.

The aforementioned applications of the FLP demonstrate the feasibility of applying the model to a healthcare setting. Nevertheless, the literature has not yet applied the FLP to a remote monitoring setting, reiterating the lack of consideration of the implications of the service on the workforce.

D. Conclusion

The literature demonstrates the feasibility and general acceptability of remote monitoring services. It was highlighted that implementing a school-based remote monitoring service could improve access to healthcare [14, 15, 16, 17]. Additionally, a school-based remote monitoring service could reduce the burdens of time and cost on patients, parents and caregivers [15, 18, 21, 26]. Remote monitoring services could increase feelings of empowerment, consequently improving quality of life [27].

OR methods have been applied to remote monitoring settings, for example, to model disease progression and improvements in waiting times when using remote monitoring devices. Nevertheless, the literature lacks utilisation of OR methods to model the required workforce capacity adjustments and the demand and capacity planning for remote monitoring, reaffirming the incentive for this research.

Our search for related work revealed that the FLP has previously been utilised in healthcare settings, such as emergency service vehicle location planning [40] and HHC base location planning [36]. However, the model has not previously been used to model the demand and capacity of a remote monitoring service. Nevertheless, these previously developed FLP models could support the demand and capacity planning for remote monitoring of ADHD medication in secondary schools in Wales, facilitating the development of the models in this research.

III. Problem Description, Model Formulation and Solution Approach

The main objective of this paper is to determine the optimal location of hubs for healthcare assistants to travel to secondary schools to deliver a remote monitoring service to monitor ADHD medication. The objective is to minimise the total cost not only to set up the service but also when travelling from hubs to schools. Finally, we want to avoid long travel distances. A workshop conducted by TEC Cymru with stakeholders, including teachers and pupils, confirmed the feasibility of the proposed service. Satisfaction was expressed regarding the ability and portability of the remote monitoring equipment. Teachers expressed that they would prefer for a healthcare professional to bear the responsibility of remote monitoring rather than themselves.

A. Sets, indices and parameters

Let $\mathcal{I} := \{1, 2, 3, \ldots, n\}$ denote the set of schools and $\mathcal{J} := \{1, 2, 3, \ldots, m\}$ denote the set of healthcare assistant hub locations. Let $i \in \mathcal{I}$ be an index for a school and $j \in \mathcal{J}$ be an index for a potential healthcare assistant hub location. Furthermore, let b_i indicate the demand at school i. Let s_j denote the cost for setting up a hub for healthcare assistants at location j. Let k_j be the capacity of the healthcare assistant hub at location j, where capacity means the total number of appointments that can be administered by healthcare assistants. Let c_{ij} represent the travel cost between healthcare assistant hub location j and school i. Let d_{ij} be the distance between school i and healthcare assistant hub location j, with D being an upper limit on the travel distance.

B. Decision variables

We introduce the following three sets of decision variables. Firstly,

$$y_j = \begin{cases} 1, & \text{if location } j \text{ is used as a hub in locating} \\ & \text{healthcare assistants} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Secondly, our real-valued decision variables $x_{ij} \in \mathbb{R}_{\geq 0}$ count the demand that school i sends to hub j. Finally, our decision variables z_{ij} are denoted as:

$$z_{ij} = \begin{cases} 1, & \text{if the hub at location } j \text{ receives demand from} \\ & \text{school } i \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

C. Objective function and constraints

Since the aim is to minimise total cost, our objective function is comprised of two terms. The first term of the objective function (3) minimises the travelling costs of healthcare assistants to schools. The second term represents the setup costs of deploying healthcare assistant hubs.

$$\text{minimise} \quad \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} c_{ij} x_{ij} + \sum_{j \in \mathcal{J}} s_j y_j \tag{3}$$

subject to

$$\sum_{i \in \mathcal{I}} x_{ij} \leq k_j y_j \qquad \forall j \in \mathcal{J} \tag{4}$$

$$\sum_{j \in \mathcal{J}} x_{ij} \geq b_i \qquad \forall i \in \mathcal{I} \tag{5}$$

$$M \cdot z_{ij} - x_{ij} \geq 0 \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{6}$$

$$z_{ij} \cdot d_{ij} \leq D \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{7}$$

$$x_{ij} \in \mathbb{R}_{\geq 0} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{8}$$

$$y_j \in \{0, 1\} \qquad \forall j \in \mathcal{J} \tag{9}$$

$$z_{ij} \in \{0, 1\} \qquad \forall i \in \mathcal{I}, j \in \mathcal{J} \tag{10}$$

Constraint (4) ensures that the demand which healthcare assistant hubs are serving do not exceed their capacity. Constraint (5) establishes that the total demand that is looked after by the hubs are guaranteed. Constraint (6) links the flow variables x_{ij} with binary variables z_{ij} that denote whether hub j is taking care of location i. We use a big M formulation where M can be set to an upper bound on the demand. Constraint (7) guarantees that the maximum distance D to travel from the hub to the schools is not exceeded. The decision variables and their domains are provided by (8)–(10).

D. Solving the mathematical model

Since our model is a generalisation of the FLP, solving large instances with standard solvers to optimality is challenging. An alternative way is to use a metaheuristic approach, for example, based on the tabu search (TS) algorithm. The TS algorithm is a metaheuristic used to solve optimisation tasks. The algorithm enables solutions to escape local optimal solutions. The assignment of locations to facilities differs at each iteration, and the solution which gives the best objective function is selected. A list of previously visited solutions is kept, known as the tabu list, and the solution cannot return to the tabu list's solutions for a number of iterations, enabling the solution to escape local optima.

The algorithm differs in the case of the uncapacitated and capacitated FLP, as explained by Erdoğan et al. [34]. For the capacitated FLP, the FLP addressed in this paper, exceeding a facility's capacity results in a penalisation, in addition to penalisations for missing locations and violating a maximum distance constraint. The assignment of locations to facilities is stored in an ordered list, where the list's first location denotes the facility's location. The solution begins with an empty solution, and adds one location to one list at a time, either to the beginning or to the end of the list. The objective function is evaluated when exchanging a location and a facility in a list, and the best result is returned. Additionally, the objective function is evaluated when a location is re-assigned. The candidate solutions do not involve tabu list solutions, except for in the instance when the solution improves the current best known solution.

IV. Experimental Results

In what follows, we describe the data used in our experimental study followed by a presentation of the results broken down by various levels of detail.

A. Demand

Postcodes of secondary schools in Wales were obtained from a data set from the Welsh Government website [41] (Figure 1).

The same data set also included the number of pupils in each secondary school, which was used to calculate each school's demand. Although ADHD prevalence rates are commonly estimated to be 5% [1, 3, 4], ADHD medication administration rates are much lower in Wales at 0.96% [42]. For the healthcare assistant hub location problem (HAHLP) model, demand in each school was estimated by multiplying the number of pupils in the school by the ADHD medication administration rate of 0.96%.

Fig. 1. Location of secondary schools in Wales - Correct as of May 2023 [41].

B. Model assumptions

We make the following assumptions: all healthcare assistants work full-time and are homogeneous as no skill level is required. Each appointment is allocated 15 minutes with working hours between 09:00-14:00. Furthermore, we assume a 15 minute break for healthcare assistants, resulting in a maximum of 19 appointments per day.

Children require monitoring twice a year, based on standard practice guidelines [43], and considering the school year spans 39 weeks, models should be formulated for each 19 week period. With 19 appointments per day over 19 weeks, and each week comprising of five days, the maximum capacity for healthcare assistant appointments within each 19 week cycle totals 1,805 appointments as given by Equation (11).

$$
\begin{aligned}
\text{Max. appointment capacity} = {} & \text{no. of appointments per day} \\
& \times \text{no. of days in working week} \\
& \times \text{no. of weeks in cycle}
\end{aligned} \tag{11}
$$

The setup cost is assumed to be the cost to employ a healthcare assistant per 19 weeks, i.e. half of healthcare assistants' annual salary, and is assumed to be homogeneous across all healthcare assistants as all healthcare assistants are assumed to be homogeneous. The salary of a healthcare assistant is assumed to be £23,000 [44]. Hence, the setup cost is assumed to be £11,500. Additionally, the cost of travel is set to be £0.45 per unit distance [45].

C. Illustrative model

An illustrative model was constructed to test and understand the FLP spreadsheet solver's input parameters. For simplification, secondary school locations were restricted to those in Cardiff, presented in Figure 2.

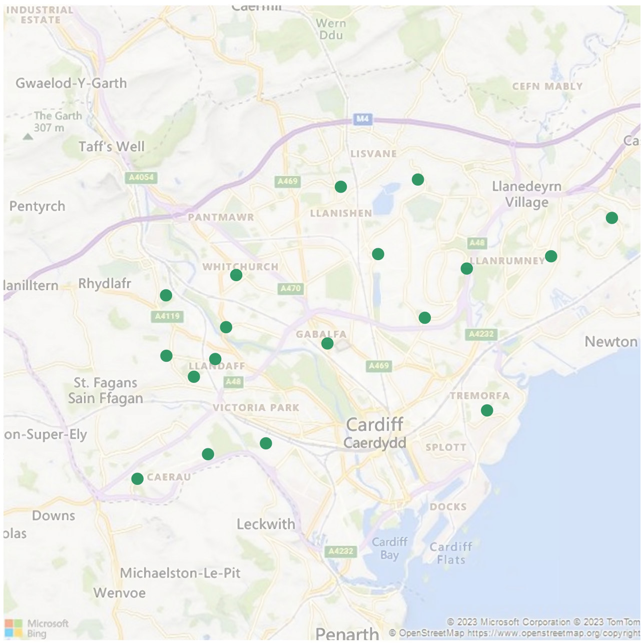


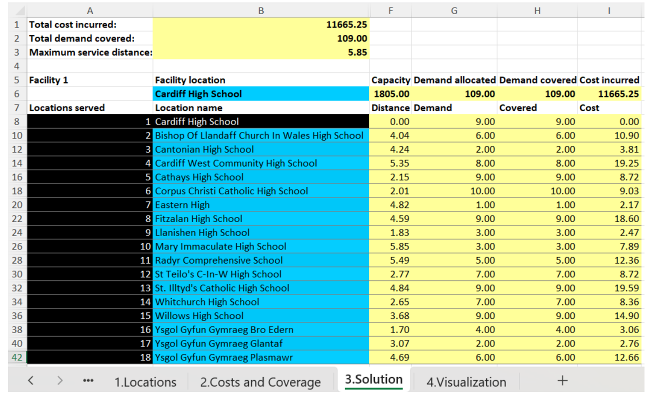
Fig. 2. Secondary schools in Cardiff.

Demand in each school was calculated by generating a random number between one and ten. A capacity of 1,805 was allocated to each possible healthcare assistant hub along with a setup cost of £11,500 and a cost of 0.45 per unit distance. The maximum number of healthcare assistant hubs to locate was set to 18, equal to the number of secondary schools in Cardiff. The objective of the solution was to minimise the total cost, comprised of setup and travelling costs. The solver function was run for 60 seconds to generate a solution, and a feasibility check was run on the solution to ensure that the demand allocated to each healthcare assistant hub did not exceed its capacity. The illustrative model was performed on a machine with an Intel Core i7-8665U processor running at 1.9GHz with 32GB of RAM.

One healthcare assistant hub was located at Cardiff High School which was allocated the total demand across all schools of 109 appointments, outlined in Figure 3. The solution was represented visually, illustrated in Figure 4, where the square represented the secondary school in which the hub for healthcare assistants would be based, dots represented the secondary schools, and lines connected each secondary school to the hub serving its demand.

D. Computational results comparing the tabu search heuristic and the mathematical model

Returning to the case of 178 secondary schools, we stopped the TS and the MIP after 60, 600, 3,600 and 36,000 seconds



A	B	F	G	H	I
Total cost incurred:	11665.25				
Total demand covered:	109.00				
Maximum service distance:	5.85				
Facility 1	Facility location	Capacity	Demand allocated	Demand covered	Cost incurred
	Cardiff High School	1805.00	109.00	109.00	11665.25
Locations served	Location name	Distance	Demand	Covered	Cost
1	Cardiff High School	0.00	9.00	9.00	0.00
2	Bishop Of Llandaff Church In Wales High School	4.04	6.00	6.00	10.90
3	Cantonian High School	4.24	2.00	2.00	3.81
4	Cardiff West Community High School	5.35	8.00	8.00	19.25
5	Cathays High School	2.15	9.00	9.00	8.72
6	Corpus Christi Catholic High School	2.01	10.00	10.00	9.03
7	Eastern High	4.82	1.00	1.00	2.17
8	Fitzalan High School	4.59	9.00	9.00	18.60
9	Llanishen High School	1.83	3.00	3.00	2.47
10	Mary Immaculate High School	5.85	3.00	3.00	7.89
11	Radyr Comprehensive School	5.49	5.00	5.00	12.36
12	St Teilo's C-In-W High School	2.77	7.00	7.00	8.72
13	St. Illtyd's Catholic High School	4.84	9.00	9.00	19.59
14	Whitchurch High School	2.65	7.00	7.00	8.36
15	Willows High School	3.68	9.00	9.00	14.90
16	Ysgol Gyfun Gymraeg Bro Edern	1.70	4.00	4.00	3.06
17	Ysgol Gyfun Gymraeg Glantaf	3.07	2.00	2.00	2.76
18	Ysgol Gyfun Gymraeg Plasmawr	4.69	6.00	6.00	12.66

1.Locations 2.Costs and Coverage 3.Solution 4.Visualization

Fig. 3. Illustrative model solution - demand allocated to the healthcare assistant hub located at Cardiff High School.

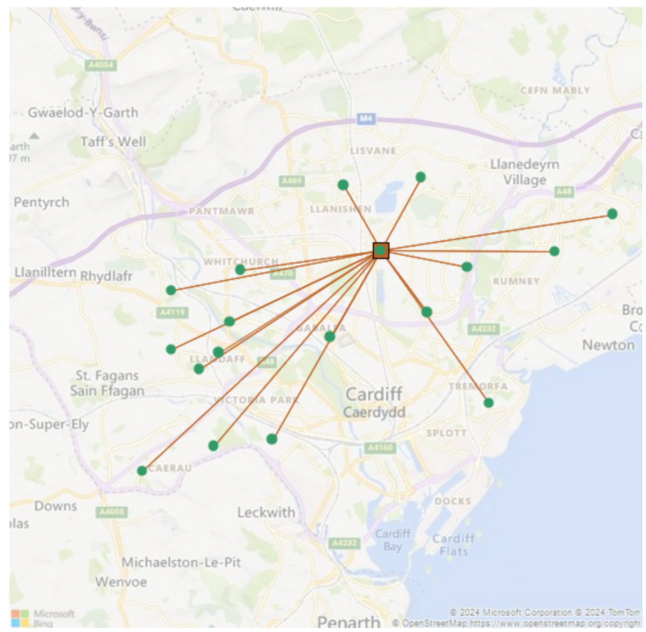


Fig. 4. Visualisation of the solution of the illustrative model.

runtime. Similar to Section IV-C, the computational experiments were performed on a machine with an Intel Core i7-8665U processor running at 1.9GHz with 32GB of RAM. The results displaying the objective function values and number of hubs are shown in Tables I and II, respectively.

TABLE I
OBJECTIVE FUNCTION VALUE FOR THE TABU SEARCH AND THE MIP.

	60s	600s	3,600s	36,000s
TS	79,502.19	79,166.65	79,166.65	79,166.65
MIP	69,953.89	69,942.32	69,942.32	69,942.32

Table I reveals that, after 10 hours of computation time the MIP achieves a cost which is 88.3% of the value of the TS model. Even after a relatively short computation time, the gap between the TS and the MIP is quite substantial.

TABLE II
NUMBER OF LOCATIONS FOR THE TABU SEARCH AND THE MIP.

	60s	600s	3,600s	36,000s
TS	6	6	6	6
MIP	5	5	5	5

The results from Table II shed more light into why this substantial difference between the objective function values occurs. The TS always produces a higher number of locations compared to the MIP, which finds a stable number of five locations to select as hubs for healthcare assistants monitoring children and adolescents with ADHD.

By deploying fewer hubs, the MIP model was able to reduce the overall setup costs, while still adequately covering the demand across the schools. In contrast, the TS algorithm over-provisioned the number of hubs, leading to higher setup costs without a commensurate improvement in the ability to serve the demand. This highlights the advantage of mathematical programming taken in the MIP model - it was able to more efficiently locate the optimal number and placement of hubs to minimise the total cost, both in terms of setup and travel expenses. The TS heuristic, while a useful approximate method, did not capture this tradeoff as effectively, resulting in the gap in objective function values between the two approaches.

E. Results for the Healthcare Assistant Hub Location Problem Model

As described in Section IV-B, healthcare assistant capacity was assumed to be 1,805 appointments per 19 weeks. In the HAHLP model, demand was assumed to be 0.96% [42]. Each school could be a hub for healthcare assistants. The setup cost per healthcare assistant was £11,500, and the cost per unit distance was 0.45. The number of locations was 178, equal to the number of secondary schools in Wales, and the maximum number of hubs to locate was set to 150. The solution's objective was to minimise the total cost, incorporating setup and travelling costs.

1) Initial solution of the Healthcare Assistant Hub Location Problem Model: The MIP solver was run using the Gurobi Solver, to enable optimality to be reached. This resulted in two healthcare assistant hubs being established. One hub was based in Whitchurch High School serving 122 schools, while the second was based at Ysgol Maes Garmon, serving 56 schools.

The solution's visualisation, shown in Figure 5, portrayed that one healthcare assistant hub would serve the schools in the south, and one would serve the schools in the north of Wales. The maximum distance travelled was 108 miles, which could be unrealistic and unacceptable for healthcare assistants to travel. Additionally, if the remote monitoring service were to be expanded to monitor additional health conditions, healthcare assistants might not have the capacity to travel long distances. These factors supported the inclusion of a maximum travel distance.

2) Healthcare Assistant Hub Location Problem Model with a travel distance limit results: A travel distance limit of 50

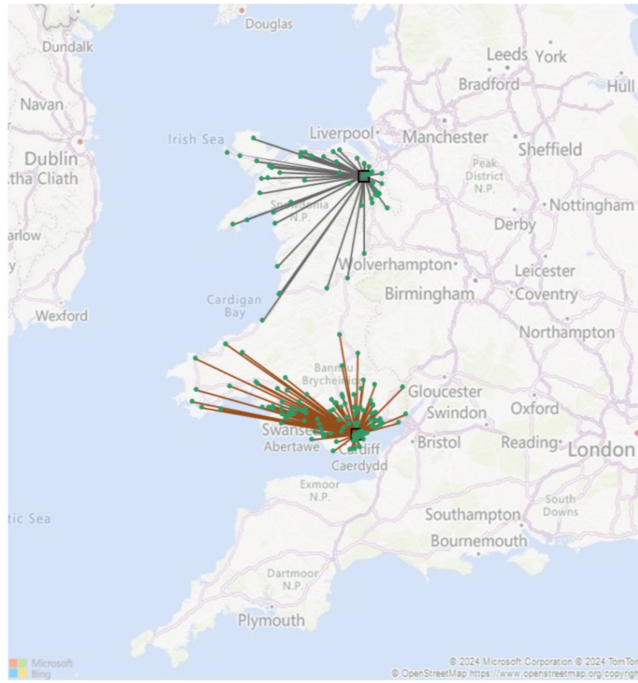


Fig. 5. Initial solution of the healthcare assistant hub location problem model.

miles was incorporated into the MIP (see Constraints (7) in Section III). This was deemed a reasonable distance to travel in one day. After running the solver to optimality, the updated solution, portrayed in Figure 6, resulted in five healthcare assistant hubs being located with a maximum distance travelled of 49.52 miles.

One healthcare assistant hub was stationed in the following Welsh local authorities: Cardiff, Carmarthenshire, Ceredigion, Denbighshire, and Gwynedd. It is important to note that healthcare assistants served demand beyond the local authority in which they were stationed. The highest demand was allocated to the hubs based in Cardiff and Denbighshire. The smallest demand was assigned to the hub based in Ceredigion.

The schools in which healthcare assistant hubs would be located, the number of schools served by each healthcare assistant hub, and the demand allocated to each healthcare assistant hub are presented in Tables III and IV within the Appendix.

V. DISCUSSION

This paper investigated the demand and capacity planning for remote monitoring of ADHD medication in secondary schools in Wales. The future intention is to extend the service to monitor additional health conditions, including eating disorders and diabetes.

A. Healthcare Assistant Hub Location Problem Model

The initial optimal solution of the HAHLP, displayed in Figure 5, resulted in only two healthcare assistant hubs being located, with one serving the north and one serving the south of Wales. Healthcare assistant utilisation was relatively high.

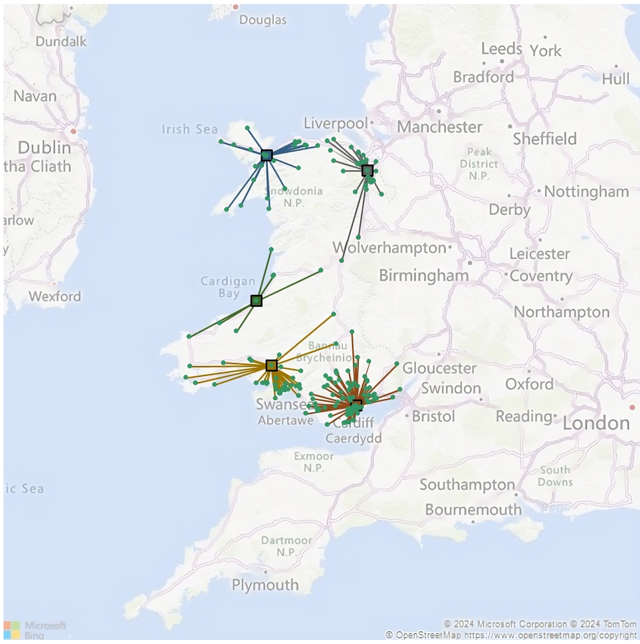


Fig. 6. Solution of the healthcare assistant location problem model with a travel distance limit.

The demand assigned to the hub in South Wales was significantly greater than the demand assigned to the hub in North Wales, consistent with the greater number of schools in South Wales, depicted in Figure 1. However, this solution resulted in large and unrealistic travel distances for healthcare assistants. The extensive travel distances resulted in this solution being unrealistic, and inspired the inclusion of a maximum travel distance limit.

The experimental results of the HAHLP indicated that incorporating a travel distance limit increased the number of required healthcare assistant hubs to five. Each hub served a smaller geographical area, leading to reduced travel distances. However, this approach resulted in decreased healthcare assistant utilisation. Our HAHLP demonstrated the importance of a balance between minimising travel distances and maximising healthcare assistant utilisation.

A disadvantage of the HAHLP model for the demand and capacity planning for remote monitoring of ADHD medication in secondary schools in Wales was its inability to incorporate randomness, for example, healthcare assistant absence or changes in demand. Furthermore, the HAHLP model's demand was unrealistic as it assumed that demand was directly proportional to the number of pupils in each school. Each school is likely to have a different prevalence of children being prescribed ADHD medication, therefore alternative factors such as local authorities' rate of ADHD diagnosis and medication administration should be considered. Nevertheless, when the service is implemented, the exact demand in each school could be determined, therefore the HAHLP model may become more realistic in the future.

B. Modelling approach

The MIP was chosen to model the demand and capacity planning for remote monitoring of ADHD medication in secondary schools in Wales, however, alternative OR modelling approaches could have been utilised. A simulation model developed to incorporate variation could enable an evaluation of both the proposed service and its implications on the NHS. Simulation models could support the forecasting of future demand and be utilised for strategic planning. Similarly to the MIP model, simulation models incorporate interactive elements to support investigations of the consequences of adjusting parameters.

C. Limitations

Solutions were generated by running the model once. Running the model multiple times would enable comparisons across all solutions to determine the optimal and most appropriate solution. Demand used in the model was based on assumptions, including assuming homogeneous demand across local authorities and assuming demand to be proportional to the number of pupils in each school, both of which could impact the realism of results. If data were available, future research could model demand by local authority. However, once the service is implemented, precise demand figures for each school could be determined, enabling the input of these numbers into the MIP and FLP spreadsheet solvers to obtain realistic results.

The estimated capacity of healthcare assistants did not include travel times to and from schools, thus assuming that travel was completed outside of the working hours of 09:00-14:00. However, this assumption may not be realistic or acceptable. It is important to model the implications of incorporating travel time into healthcare assistants' capacity. Doing so would likely reduce the maximum number of appointments that could be delivered, potentially necessitating an increase in the number of healthcare assistant hubs required. Furthermore, the model did not incorporate fairness in terms of the amount of travel required by the healthcare assistants, neither does is consider a trade off between the number of hubs located and the amount of travel required by healthcare assistants.

All healthcare assistants were assumed to work full time, however, demand assigned to healthcare assistants was rarely above half of their estimated capacity (Table IV within the Appendix). Employing some part-time healthcare assistants may be a better financial decision by reducing setup costs and increasing healthcare assistant utilisation.

This paper applies the proposed service to one geographic location and educational context. The model's generalisability could be improved by testing the model in other locations to see whether the proposed service would also be achievable elsewhere, and how rurality and urbanity may affect the practicality of the travel distance limit. Nevertheless, the model presented in this paper provides the concept of the service and a framework for its implementation in practice.

VI. Conclusion and Future Work

A. Conclusion

This research enhances the literature on remote monitoring by considering the demand and capacity planning for remote monitoring of ADHD medication in secondary schools in Wales. The analysis builds on existing knowledge of the implications of remote monitoring by considering its consequences on the workforce. The results support the administration of a remote monitoring service by investigating the number of healthcare assistant hubs required to implement an efficient service for ADHD medication monitoring, and provides a visual representation of the models' solution.

The literature review provides evidence of the feasibility and benefits of a school-based remote monitoring service, including reducing hospital admissions and increasing access to healthcare. The literature review suggests that demand and capacity planning for a school-based remote monitoring service has not previously been considered or conducted. However, OR techniques have previously been applied to remote monitoring contexts and the FLP has been applied to healthcare contexts, providing evidence of OR's ability to support the efficient implementation of remote monitoring. Previously developed FLP models applied to other healthcare settings provided a platform for the development of this research's models.

The initial HAHLP model inspired the inclusion of a travel distance limit to generate realistic travel distances for healthcare assistants. Five healthcare assistant hubs are needed to serve the demand modelled in the MIP model with a travel distance limit. Healthcare assistant hubs should be situated in each of the following local authorities in Wales: Cardiff, Carmarthenshire, Ceredigion, Denbighshire and Gwynedd. Whilst the HAHLP model's demand was based on many assumptions, the HAHLP model will become increasingly more useful as demand becomes more certain.

The visualisations of the model's solutions were critical to support conclusions because they enabled a visual evaluation of the solution's efficiency. The visual solutions are particularly valuable because they enable mathematical results to be presented clearly to non-technical audiences.

B. Future work

The eventual aim of the project is to deliver the remote monitoring service for numerous health conditions. Health conditions may need to be monitored at different frequencies therefore future work will need to consider how to best expand the model developed in this paper to incorporate additional health conditions.

To enhance and progress the work conducted in this research, following the determination of the number of healthcare assistant hubs required to implement the remote monitoring service for ADHD medication in secondary schools in Wales, it would be necessary to develop personalised schedules or routes for each healthcare assistant. These schedules should specify which schools they will visit each week. There is also potential for this work to be expanded to the remainder of the UK to determine remote monitoring services for ADHD medication across all secondary schools.

A nurse scheduling problem could be utilised to support the development of a schedule for the healthcare assistants delivering the service. Applying the nurse scheduling problem to this project will be less complex than a typical nurse scheduling problem because there will be no skill level requirements as healthcare assistants are assumed to be homogeneous. Additionally, there will be no weekend, overnight or days off requirements because the service will only be implemented during school hours.

The vehicle routing problem could also be a supporting model. An optimal route between the schools minimising travelling costs could be determined. The service could be modelled as a capacitated vehicle routing problem where healthcare assistants would have limited carrying capacities, where their carrying capacity would be the number of appointments that could be delivered each day. Once the routes are constructed, travelling costs could be calculated, facilitating an accurate cost analysis of the remote monitoring service for ADHD medication in secondary schools in Wales.

References

[1] D. Coghill et al. "The management of ADHD in children and adoelscents: Bringing evidence to the clinic: Perspective from the european ADHD guidelines group (EAGG)". In: *European Child and Adolescent Psychiatry* 32 (2021), pp. 337–1361. DOI: 10.1007/s00787-021-01871-x.

[2] B. T. Felt et al. "Diagnosis and management of ADHD in children". In: *American Family Physician* 90.7 (2014), pp. 456–464.

[3] L. Simons et al. "Developing mHealth remote monitoring technology for attention deficit hyperactivity disorder: A qualitative study eliciting user priorities and needs". In: *JMIR mHealth and uHealth* 4.1 (2016). DOI: 10.2196/mhealth.5009.

[4] K. Sayal et al. "ADHD in children and young people: prevalence, care pathways, and service provision". In: *The Lancet Psychiatry* 5.2 (2018), pp. 175–186. DOI: 10.1016/S2215-0366(17)30167-0.

[5] National Institute for Health and Care Excellence. *Attention deficit hyperactivity disorder: diagnosis and management*. Accessed: 8th April 2024. 2019. URL: https://www.nice.org.uk/guidance/ng87/chapter/Recommendations#managing-adhd.

[6] M. E. Feldman, A. Charach, and S. A. Bélanger. "ADHD in children and youth: Part 2-treatment". In: *Pediatrics and Child Health* 23.7 (2018), pp. 462–472. DOI: 10.1093/pch/pxy113.

[7] A. Vegesna et al. "Remote patient monitoring via non-invasive digital technologies: A systematic review". In: *Telemedicine and e-Health* 23.1 (2017), pp. 3–17. DOI: 10.1089/tmj.2016.0051.

[8] H. Walton et al. "Patients' experiences of, and engagement with, remote home monitoring services for COVID-19 patients: A rapid mixed-methods study". In: *Health Expectations* 25.5 (2022), pp. 2386–2404. DOI: 10.1111/hex.13548.

[9] N. S. Soares and D. L. Langkamp. "Telehealth in developmental-behavioral pediatrics". In: *Journal of Developmental and Behavioral Pediatrics* 22.8 (2012), pp. 656–665. DOI: 10.1097/DBP.0b013e3182690741.

[10] E. Dixon et al. “Telemedicine and cystic fibrosis: Do we still need face-to-face clinics?” In: *Pediatric Respiratory Reviews* 42 (2022), pp. 23–28. DOI: 10.1016/j.prrv.2021.05.002.

[11] S. Mantena and S. Keshavjee. “Strengthening healthcare delivery with remote patient monitoring in the time of COVID-19”. In: *BMJ Health & Care Informatics* 28.1 (2021). DOI: 10.1136/bmjhci-2020-100302.

[12] WHO Global Obervatory for eHealth. *Telemedicine: Opportunities and Developments in Member States: Report on the Second Global Survey on eHealth*. Geneva, Switzerland: World Health Organization, 2010. DOI: 10.4258/hir.2012.18.2.153.

[13] L. S. Merritt. “Preparing nurse practitioner students for virtual visits: An innovative computer-based text-messaging simulation”. In: *Clinical Simulation* 43 (2020), pp. 17–20. DOI: 10.1016/j.ecns.2020.02.006.

[14] Y. N. Evans et al. “Using telemedicine to reach adolescents during the COVID-19 pandemic”. In: *Journal of Adolescent Health* 67.4 (2020), pp. 469–471. DOI: 10.1016/j.jadohealth.2020.07.015.

[15] Z. Gan et al. “Single institution experience with telemedicine for pediatric urology outpatient visits: Adapting to COVID-19 restrictions, patient satisfaction, and future utilization”. In: *Journal of Pediatric Urology* 17.4 (2021). DOI: 10.1016/j.jpurol.2021.05.012.

[16] M. Jolstedt et al. “Long-term outcomes of internet-delivered cognitive behaviour therapy for pediatric anxiety disorders: Towards a stepped care model of health care delivery”. In: *European Child and Adolescent Psychiatry* 30.11 (2021), pp. 1723–1732. DOI: 10.1007/s00787-020-01645-x.

[17] C. S. McCrae et al. “Telehealth cognitive behavioral therapy for insomnia in children with autism spectrum disorder: A pilot examining feasibility, satisfaction, and preliminary findings”. In: *Autism* 25.3 (2021), pp. 667–680. DOI: 10.1177/1362361320949078.

[18] C. E. Mount, N. Elson, and S. Ahmad. “Multidisciplinary community paediatric video appointments during COVID-19 pandemic: Descriptive study”. In: *Archives of Disease in Childhood* 106.3 (2021). DOI: 10.1136/archdischild-2020-320011.

[19] E. M. Cahan et al. “The impact of telehealth adoption during COVID-19 pandemic on patterns of pediatric subspecialty care utilization”. In: *Academic Pediatrics* 8 (2022), pp. 1375–1383. DOI: 10.1016/j.acap.2022.03.010.

[20] M. A. Mahmoud et al. “Telemedicine (virtual clinic) effectively delivers the required healthcare service for pediatric ambulatory surgical patients during the current era of COVID-19 pandemic: A mixed descriptive study”. In: *Journal of Pediatric Surgery* 57.4 (2022), pp. 630–636. DOI: 10.1016/j.jpedsurg.2021.11.018.

[21] A. Ripp et al. “Telehealth utilization and follow-up visits in developmental-behavioral pediatrics during the COVID-19 pandemic in 2020”. In: *Journal of Developmental and Behavioral Pediatrics* 43.5 (2022), pp. 297–302. DOI: 10.1097/DBP.0000000000001040.

[22] A. Barwise et al. “Perceptions and use of telehealth among diverse communities: Multisite community-engaged mixed methods study”. In: *Journal of Medical Internet Research* 25 (2023). DOI: 10.2196/44242.

[23] A. Stagg et al. “Initial experience with telemedicine for interstage monitoring in infants with palliated congenital heart disease”. In: *Pediatric Cardiology* 44.1 (2023), pp. 196–203. DOI: 10.1007/s00246-022-02993-y.

[24] B. T. Villalobos et al. “Patient perceptions of trauma-focused telemental health services using the Telehealth Satisfaction Questionnaire (TSQ)”. In: *Psychological Services* 20.1 (2023), pp. 107–121. DOI: 10.1037/ser0000605.

[25] V. Hsiao et al. “Disparities in telemedicine access: A cross-sectional study of a newly established infrastructure during the COVID-19 pandemic”. In: *Applied Clinical Informatics* 12.3 (2021), pp. 445–458. DOI: 10.1055/s-0041-1730026.

[26] N. Y. Lin et al. “Telehealth delivery of adherence and medication management system improves outcomes in inner-city children with asthma”. In: *Pediatric Pulmonology* 55.4 (2020), pp. 858–865. DOI: 10.1002/ppul.24623.

[27] J. Edwards et al. “Digital technologies for children and parents sharing self-management in childhood chronic or long-term conditions: A scoping review”. In: *Children* 8.12 (2021), pp. 1203–1223. DOI: 10.3390/children8121203.

[28] L. Grieco, M. Utley, and S. Crowe. “Operational research applied to decisions in home health care: A systematic literature review”. In: *Journal of the Operational Research Society* 72.9 (2021), pp. 1960–1991. DOI: 10.1080/01605682.2020.1750311.

[29] W. V. Padula et al. “A cost-utility analysis of remote pulse-oximetry monitoring of patients with COVID-19”. In: *Value Health* 25.6 (2022), pp. 890–896. DOI: 10.1016/j.jval.2021.09.008.

[30] B. Yao, Y. Chen, and H. Yang. “Constrained Markov decision process modeling for optimal sensing of cardiac events in mobile health”. In: *IEEE Transactions on Automation Science and Engineering* 19.2 (2022), pp. 1017–1029. DOI: 10.1109/TASE.2021.3052483.

[31] M. Faezipour and M. Faezipour. “System dynamics modeling for smartphone-based healthcare tools: Case study on ECG monitoring”. In: *IEEE Systems Journal* 15.2 (2021), pp. 3036–3045. DOI: 10.1109/JSYST.2020.3009187.

[32] A. Gorelova et al. “Applying discrete event simulation on patient flow scenarios with health monitoring systems”. In: *Web Engineering. ICWE 2023. Lecture Notes in Computer Science*. Ed. by I Garrigós, J M Murillo Rodríguez, and M Wimmer. Cham: Springer, 2023. DOI: 10.1007/978-3-031-34444-2_8.

[33] S. Montagna and A. Omicini. “Agent-based modeling for the self-management of chronic diseases: An exploratory study”. In: *Simulation* 93.9 (2017), pp. 781–793. DOI: 10.1177/0037549717712605.

[34] G. Erdoğan, N. Stylianou, and C. Vasilakis. “An open source decision support system for facility location analysis”. In: *Decision Support Systems* 125 (2019), pp. 1–12. DOI: 10.1016/j.dss.2019.113116.

[35] H. Zhang et al. “Multi-objective two-level medical facility location problem and tabu search algorithm”. In: *Information Sciences* 608 (2022), pp. 734–756. DOI: 10.1016/j.ins.2022.06.083.

[36] P. Pourrezaie-Khaligh, A. Ardestani-Jaafari, and B. M. Tosarkani. “Home health care facility location problem under demand uncertainty”. In: *INFOR: Information Systems and Operational Research* (2024). DOI: 10.1080/03155986.2023.2286889.

[37] M. Veenstra et al. “A simultaneous facility location and vehicle routing problem arising in health care logistics in the Netherlands”. In: *European Journal of Operational Research* 268.2 (2018), pp. 703–715. DOI: 10.1016/j.ejor.2018.01.043.

[38] H. Grange et al. “Capacity Planning of Virtual Wards for Frail and Elderly Patients”. In: *Healthcare* 15.5 (2024), p. 533.

[39] A. Ahmadi-Javid, P. Seyedi, and S. S. Syam. “A Survey of Healthcare Facility Location”. In: *Computers and Operations Research* 79 (2017), pp. 223–263. DOI: 10.1016/j.cor.2016.05.018.

[40] E. Erkit, A. Ingolfsson, and G. Erdoğan. “Ambulance location for maximum survival”. In: *Naval Research Logistics* 55 (1 2007), pp. 42–58. DOI: 10.1002/nav.20267.

[41] Welsh Government. *Address list of schools*. Accessed: 11 July 2023. 2023. URL: https://www.gov.%20wales/address-list-schools.
[42] M. Fleming et al. “Age within schoolyear and attention-deficit hyperactivity disorder in Scotland and Wales”. In: *BMC Public Health* 22 (2022). DOI: 10.1186/s12889-022-13453-w.
[43] NHS. *Methylphenidate for children*. Accessed: 25 November 2024. 2021. URL: https://www.nhs.uk/medicines/methylphenidate-children/.
[44] Careers Wales. *Healthcare assistant*. Accessed: 31 July 2023. 2023. URL: https://careerswales.gov.wales/job-information/healthcare-assistant.
[45] GOV.UK. *Claim tax relief for your job expenses*. Accessed: 13 August 2023. 2023. URL: https://www.gov.uk/tax-relief-for-employees/vehicles-you-use-for-work.

Appendix

TABLE III
INITIAL DETERMINISTIC HEALTHCARE ASSISTANT LOCATION PROBLEM MODEL.

Healthcare Assistant Location	Number of Schools Served	Demand Allocated
Whitchurch High School	122	1235
Ysgol Maes Garmon	56	430

TABLE IV
MIP MODEL WITH A TRAVEL DISTANCE LIMIT.

Healthcare Assistant Hub Location	Number of Schools Served	Demand Allocated
Corpus Christi Catholic High School	82	864
Castell Alun High School	28	235
Ysgol Maes y Gwendraeth	37	356
Ysgol Tryfan	23	162
Gyfun Aberaeron Comprehensive	8	48