Dissertation overview:

* Problem and motivation:  
    
  We all know the current state of the NHS, which has an extremely long waiting list. Even for a small procedure, a patient has to wait for a long time, especially for planned procedures like cataract surgeries, etc.. The reason behind it is basically the way the NHS treats its patients. There is a limited number of NHS hospitals and providers and most of them are teaching hospitals which can only take in a limited number of cases and most of them are overloaded with a lot of patients, especially after COVID-19 which added to the burden on the healthcare system where all the non-critical surgeries were pushed to a later date and added to the patient load. So to avoid this kind of situation, the NHS outsources its patients to private providers, which perform the surgeries for the NHS, and the NHS pays these private providers an agreed amount per surgery based on the complexity and the procedure. The patient has the right to choose which provider they want to choose which provider they want their surgery to be done, which also includes the private providers based. The problem here is that all the providers be it NHS or the private providers all of them have their individual waiting lists, leading to unequal utilization and waiting time. There can be cases where one of the provider has a waiting time of beyond 18 weeks and the other provider has the waiting time of not more than 2 weeks. So the basic solution to the problem was to try, simulate and implement a strategy where the waiting lists of all the different providers into a common waiting list and suggest new patients to the provider with the least waiting time. The final decision is to be made by the patient on which provider they want to take. Along with that we also evaluated the scenario where we shifted the triage point from the optometrist to NHS level. We wanted to simulate the scenarios and evaluated the impact of merging the waiting lists and shifting the triage point to NHS on reducing waiting time, increasing optimization of the providers and eventually costs to the NHS.  
    
  Introduction:  
    
  The NHS is under increasing pressure to deliver healthcare in a post-COVID-19 world, facing growing patient demand and limited resources. Elective care backlogs have further intensified this challenge, making the efficient use of existing capacity more critical than ever. Patient Treatment Lists (PTLs) are currently maintained separately by different providers; however, this fragmented approach often results in inefficient resource utilisation. In the Cambridgeshire and Peterborough Integrated Care Board (ICB), independently managed PTLs lead to unequal waiting times, underutilised clinical capacity, and disparities in access to care. Given that surgical services account for 10–30% of hospital expenditures, optimising surgery scheduling and resource allocation could result in significant cost savings (Cardoen, Demeulemeester, & Beliën, 2010). The NHS Long Term Plan and local ICB strategies call for more integrated models of care. A single PTL approach—where referrals are pooled and dynamically allocated across the system—offers the potential to enhance equity, reduce delays, and balance workloads more effectively. Lessons from other domains reinforce this approach. For example, airports manage unpredictable passenger flow using centralised queueing systems (Wu & Mengersen, 2013), while traffic engineering applies mathematical models to optimise capacity usage in complex, distributed networks (Helbing, 2001). This research leverages such parallels to propose a data-driven strategy for NHS patient flow optimisation.

Few important points that can be added to the introduction and problem motivation:

* We have got the data from the Cambridgeshire and Peterborough ICB which has 2 datasets:
  + Patient treatment details of cataract surgery of the last 3 financial years, having the columns (take it from the old data) but not having the waiting time
  + New patient treatment details of cataract surgery of the last financial year having the actual waiting time for the patients along with the patient urgency list.
* The general way of treating patients is based on the patient comes in, the tests are dine then the diagnosis is done and finally the treatment.
* We have 2 kind of providers NHS and independent providers.
* The aim is to model the whole system and evaluate the impacts of merging the single patient treatment lists into 1
* Note this is the waiting list that is the patient waiting for the surgery to be done not the waiting on the reception/doctors, etc.
* The current flow is patient visits the optometrist and then if surgery is needed the optometrist suggests the patient with a provider( which may be biased as the optometrist might be getting a commission or some benefit from the providers which might benefit both the parties) and eventually the patient has the right to choose where they need their treatment to be done. After that the patient is added to the waiting list and then the procedure is done.
* WE have 3 types of patient priorities that we can model:
  + Urgent
  + 2 week waiting
  + Routine
* The waiting time in the second dataset is calculated based on the day they patient was added to the list to the day of treatment
* We have data with different cases of cataract which are categorized by several categories(HRG’s) which have been detailed below:
  + Least to Most Complex

1. Minor, Cataract or Lens Procedures

2. Intermediate, Cataract or Lens Procedures, with CC Score 0-1 3. Intermediate, Cataract or Lens Procedures, with CC Score 2+

4. Phacoemulsification Cataract Extraction and Lens Implant, with CC Score 0-1

5. Phacoemulsification Cataract Extraction and Lens Implant, with CC Score 2-3

6. Phacoemulsification Cataract Extraction and Lens Implant, with CC Score 4+

7. Complex, Cataract or Lens Procedures, with CC Score 2+

8. Very Major, Cataract or Lens Procedures, with CC Score 0-1

9. Very Major, Cataract or Lens Procedures, with CC Score 2+

* + The ranking reflects both the technical demands of the procedure (Minor < Intermediate < Phaco < Complex < Very Major) and the patient risk level (CC score).
  + The CC score is the comorbidities index of the patient
* We also have the LSOA(Lower layer Super Output Areas) which can be used to recommend patients providers.
* WE also have a variable time of each HRG on complexity and also the providers where the generally the same procedure at a private provider is done more swiftly than the NHS as NHS is a teaching hospital and the students also perform the surgeries.
* **Cataract Surgery Operating Times and Trainee Experience**
  + From 11,067 cases, **9,552 (86.3%)** had a recorded operating time.
  + The mean ± SD operating times in minutes were as follows:
    - **Consultants:** 19±10
    - **Junior:** 30±11
    - **Intermediate:** 27±12
    - **Senior Trainees:** 24±10
    - **Fellows:** 31±11
  + **Source:** Nderitu, P. & Ursell, P. Factors affecting cataract surgery operating time among trainees and consultants. *J. Cataract Refract. Surg.* 45, 816–822 (2019). **Source:** Park, D. Y., Walkden, A. & Klerk, T. A. D. Effect of cataract surgery training on operating room productivity: How long trainees take. *J. Cataract Refract. Surg.* 42, 1297–1301 (2016).
  + **Operating Times by Procedure Complexity**
  + **Standard phaco:** Most cases (95%) for experts are completed within 22 minutes; trainee times can extend into the 20–30+ minutes.

| * + Procedure Complexity | * + 50th percentile | * + 84th percentile | * + 97.5th / 95th percentile |
| --- | --- | --- | --- |
| * + Phaco CC 0–1 (attending) | * + 12.6 min | * + 17 min | * + ≈22 min |
| * + Phaco CC 0–1 (resident) | * + 20.5 min | * + 26 min | * + ≈32 min |
| * + Phaco CC 2–3–4+ (complex phaco) | * + 30 min | * + 40 min | * + 60 min |
| * + Very Major (CC 0–1, ECCE/conversions) | * + 35–40 min | * + 50 min | * + 70–90 min+ |
| * + Very Major (CC 2+, high- | * + ≈40 min | * + 55 min | * + 80 min+ |

* + **Distribution Shapes**
    - **Lower complexity:** Durations are tightly clustered (e.g., phaco CC 0–1 ≈8–12 min, low SD).
    - **Higher complexity:** Distributions are broader with longer tails (e.g., very major CC 2+ cases may exceed 60 minutes in 10–15% of cases).

|  |  |  |  |
| --- | --- | --- | --- |
| Rank | Procedure Category | CC Score | Estimated OR Time |
| 1 | Minor | — | 5–10 min |
| 2 | Intermediate | 0–1 | 10–15 min |
| 3 | Intermediate | 2+ | 15–20 min |
| 4 | Phaco +IOL | 0–1 | ≤10 min |
| 5 | Phaco + IOL | 2–3 | 10–15 min |
| 6 | Phaco + IOL | 4+ | 15–20+ min |
| 7 | Complex cataract surgery | 2+ | 20–30 min |
| 8 | Very major cataract surgery | 0–1 | 30–40 min |
| 9 | Very major cataract surgery | 2+ | 40–60+ min |

* + More details added in the “surgery time analysis.pdf”
* NHS suggest an ideal maximum waiting time shall be 18 weeks for a cataract surgery
* Independent providers usually get low complexity cases as compared to NHS
* The NHS needs cases of all varieties as they need to teach the students.
* NHS has most of the High complexity cases.
* Usually surgeons perform 2 planned activities of 4 hours each and 8 procedures per PA so 16 surgeries per day
* Independent providers usually go upto 30 procedures per Programmed activity as they get cases of low complexity.
* As we don’t have the data on the number of surgeons, operating theatres and utilization of the providers, we have estimated them based on the historical data from the 1st dataset and the information provided on the planned activities(provided by NHS)
* As this is not a new problem we have first referred how most of the other ICB’s have done this implementation
* Few of the references:
  + <https://www.sciencedirect.com/science/article/pii/S0895435696004295> heirarchical bayesian random effects model
  + Beliën, J., & Demeulemeester, E. (2007). Building cyclic master surgery schedules with leveled resulting bed occupancy. European Journal of Operational Research, 176(2), 1185–1204. <https://doi.org/10.1016/j.ejor.2005.09.016>
  + Cardoen, B., Demeulemeester, E., & Beliën, J. (2010). Operating room planning and scheduling: A literature review. European Journal of Operational Research, 201(3), 921–932. <https://doi.org/10.1016/j.ejor.2009.04.011>
  + Cochran, J. K., & Roche, K. T. (2009). A multi-class queuing network analysis methodology for improving hospital emergency department performance. Computers & Operations Research, 36(5), 1497 1512. <https://doi.org/10.1016/j.cor.2008.02.004>
  + Green, L. V., Soares, J., Giglio, J. F., & Green, R. A. (2006). Using queueing theory to increase the effectiveness of emergency department provider staffing. Academic Emergency Medicine, 13(1), 61–68. <https://doi.org/10.1197/j.aem.2005.07.034>
  + Günal, M. M., & Pidd, M. (2010). Discrete event simulation for performance modelling in health care: A review of the literature. Journal of Simulation, 4(1), 42–51. <https://doi.org/10.1057/jos.2009.25>
  + Helbing, D. (2001). Traffic and related self-driven many-particle systems. Reviews of Modern Physics, 73(4), 1067–1141. <https://doi.org/10.1103/RevModPhys.73.1067>
  + Landa, P., Sonnessa, M., Tànfani, E., & Testi, A. (2021). Discrete-event simulation modelling in healthcare: A comprehensive review. International Journal of Environmental Research and Public Health, 18(22), 12262. <https://doi.org/10.3390/ijerph182212262>
  + Moosavi, J., Fathollahi-Fard, A. M., & Dulebenets, M. A. (2023). Medical resource allocation planning by integrating machine learning and optimisation models. Artificial Intelligence in Medicine, 135, 102456. https://doi.org/10.1016/j.artmed.2022.102456 Santibañez,
  + P., Chow, V. S., French, J., Puterman, M. L., & Tyldesley, S. (2009). Reducing patient wait times and improving resource utilization at British Columbia Cancer Agency's ambulatory care unit through simulation. Health Care Management Science, 12(4), 392–407. https://doi.org/10.1007/s10729 009-9103-1
  + Wu, P. P. Y., & Mengersen, K. (2013). A review of models and model usage scenarios for an airport complex system. Transportation Research Part A: Policy and Practice, 47, 124–140. <https://doi.org/10.1016/j.tra.2012.10.015>
  + Yu, C., & Liu, J. (2020). Reinforcement learning in healthcare: A survey. ACM Computing Surveys, 53(4), 1–36. <https://doi.org/10.1145/3394457>
  + Zhang, Y., Zhang, Y., Haghani, A., & Zeng, X. (2018). Time series forecasting of emergency department patient flow. IEEE Access, 6, 42946–42956. https://doi.org/10.1109/ACCESS.2018.2861076
* I have also referred papers related to waiting times in public transport and saw how they deal with a similar situation.
* I also studied how the traffic flow is at the airports with new flight coming in and landing and few of them taking off and the time each aircraft stays at the airports. This gives us a very important parallel as this is a very close problem as there are multiple factors involved like late arrival of the plane, technical issue that needs to be resolved before the next take off, delayed on ground, too much traffic and how all the decisions are taken by the ATC and how they have modelled.
* My approach is to first do a basic mathematical modelling of the whole current scenario and get a baseline about how the waiting list is just purely based on number of surgeons, patients, operating theatres, providers, etc. Then merge all the patients into 1 single patient list and then see if there is any difference into the waiting times and utilization.
* I plan to model the list by using the M/C/c or M/G/c queueing system and then evaluate the results of both and see which fits better.
* After that I want to run a Discrete event simulation
  + This phase’s primary focus will be on capturing real-world complexity beyond static models through flexible representation of resource availability and complex patient pathways. We will use Python’s SimPy library to implement the DES, which will model individual patient flow from referral to treatment, incorporating stochastic arrival rates, patient priorities, and scheduling constraints. The DES will also test various scenarios, such as shared weekend sessions, patient reprioritisation, and dynamic routing. It will also facilitate experimentation with merged versus fragmented PTLs. Günal and Pidd (2010) demonstrated the utility of DES in capturing such hospital dynamics.
* And then do some time series to see and predict the patient load expected in the future.
* Finally apply various Reinforcement learning algorithms like CEM (cross entropy method) to get how a basic algorithm performs and then use DQN
  + **Why DQN is Best for This Problem**
  + **Comparison with Other RL Algorithms:**

| **Algorithm** | **Pros** | **Cons** | **Why Not Chosen** |
| --- | --- | --- | --- |
| **Q-Learning** | Simple, guaranteed convergence | Can't handle 27D state space | State space too large (10^27 states) |
| **SARSA** | On-policy, safer | Slower learning | Need faster convergence |
| **Policy Gradient** | Direct policy optimization | High variance, unstable | Healthcare needs stability |
| **A3C/A2C** | Parallel training | Complex implementation | Overkill for this problem |
| **PPO** | State-of-the-art, stable | Computationally expensive | DQN sufficient here |
| **DDPG** | Continuous actions | Problem has discrete actions | We choose from 6 providers |

**Why DQN is Perfect Here:**

* **Discrete Action Space**: We choose 1 of 6 providers (perfect for DQN)
* **Complex State Space**: 27D continuous state (neural network handles this)
* **Experience Replay**: Learn from past allocations efficiently
* **Stable Learning**: Two networks prevent oscillation
* **Proven in Healthcare**: Successfully used in similar medical scheduling

Implementation:

To implement we first got the dataset 1 with no dated so we did the following:

* EDA
  + Did an EDA and saw summarised the data and checked for nulls etc and filled up the values
  + We then found out the no o surgeries done per year, per HRG, inpatient vs outpatient, locationwise, providerwise, day of monthwise, season wise, monthly per HRG, day of week wise, quarterly growth, complexity wise, independent vs private providers, HRG code complexity and approx. demand historical
  + After that as we did not have any waiting time we generated the fabricated data based on the dataset 1 and tried to calculate the provider capacity, no of surgery rooms, surgeons, so that we can start to implement a pseudo model and evaluate if our model is working fine or not
* M/G/c queue implementation.
  + In this we will first understood how the M/M/c queues work and derive why M/G/c is a better fit for our usecase.
  + WE have only considered top 6 providers as they do a major chunk of surgeries and modelling them will make more sense and avoid the model to route patients to far away and not reliable providers.
  + Then we coded the implementation as shared in the file MGC\_queue.py
  + This has given us a baseline mathematical result that we can use to compare and estimate how combining lists can make a difference to utilization and waiting time.
  + We also don’t know the current waiting times in the providers so we have assumed that in independent providers it is 18 weeks (based on capacity) and 26weeks in NHS based providers
* DES simulation
  + We first understood what DES is and how important it is for real life simulation.
  + After getting a baseline result from the M/G/c queues we then do a DES in which we try to model as many things as possible.
  + Providers, patients, surgeons, capacity, current waiting time, cancellations, patient priority, backlog, day of the week/month, etc.
  + Then compared the standalone vs consolidated patient list
  + In the meanwhile we also got more data for just FY 24-25 so we cleaned it and implemented the queue and then for DES to give us exactly how much time the patients have waited for their surgery. We have also considered that the max no of transfers is 25% of the patients.
  + WE then get the results and compare it with the baseline
* Reinforcement learning
  + After getting the results from the basic mathematical queueing system and real world simulation, we then try to use and learn from the data and then use reinforcement learning as a tool to teach a learner what is good and what is bad and what is the reward function we need to improve and what behaviour we need to punish
  + We first try with the basic CEM(cross entropy method) to get an overview of how the RL system is performing and then understand the other models and see which one will best fit our usecase
  + After getting the CEM results I compared it with the DQN model.   
    Note we compared why DQn will be the best
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  + So we implemented it and compared the results
  + Note in the RL evaluation we just use the DES as a simulation method but change the routing method algorithm based on RL.