V-KEMS Study Group Report

Modelling Solutions to the Impact of COVID-19 on Cardiovascular Waiting Lists

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WARNING: this report contains preliminary findings that have not been peer reviewed. The findings are intended to provoke further study and policy discussion and should not be treated as definitive scientific advice in response to the COVID-19 pandemic.

Whilst we expect these principles to help others formulate coherent and consistent guidelines, time has prevented any quantitative study of their effectiveness. This could be undertaken, but would require real data and time to build more detailed simulation tools. Thus, we are not able to make specific recommendations from the principles, e.g. we cannot infer that it is safe to do X if you follow principle Y.

Additionally, this report has been assembled in a short time frame, we have made every effort to ensure references and links are present. Where this is not the case, we apologise for the unintentional oversight.

Contents

1 Executive Summary

Seven million people have cardiovascular disease in the UK and it accounts for 27% of all deaths. During the first severe restrictions in the UK due to COVID-19 (March 2020), elective cardiac procedures and many outpatient consultations were postponed, and a substantial number of appointments have not yet been rescheduled. In addition, those with heart conditions did not present to their GP or hospital – either because they did not want to impact further on NHS re-sources, or through concern of being exposed to the virus. This has been exacerbated by the ongoing restrictions and has again been brought into focus by the third national UK "lock-down".

On behalf of the Virtual Forum for Knowledge Exchange in the Mathematical Sciences (V-KEMS), the Newton Gateway to Mathematics convened Modelling Solutions to the Impact of COVID-19 on Cardiovascular Waiting Lists, a Virtual Study Group, from 2nd – 4th February 2021. This brought together clinicians and mathematicians to explore if and how mathematical models could be used to provide insights and solutions to the problem of prolonged waiting lists for cardiovascular conditions.

Three issue were presented and then explored:

- The overarching state of the delivery of elective cardiovascular procedures and outpatient consultations at the national level as a result of the pandemic and how this plays out at regional or local (single NHS Trust) levels.
- An exemplar cardiovascular procedure - aortic stenosis – for which there is a particularly well-defined data-set and for which missed early intervention can lead to serious adverse outcomes (death) over the course of one or two years
- An exemplar cardiovascular condition – heart failure - treatment regimens for which are less well-defined, yet the missed appointments during the pandemic represent a major perturbation to care that may impact on the optimal management of resources within cardiology departments.

Over the study group, potential solutions were developed and these were presented on the final day. Following the study group additional modelling work has taken place and funding is being sought to take this forward.

2 Background

Cardiovascular disease is the leading cause of death for men in the UK and second-most for women. During the first lockdown from March 2020, elective cardiac procedures and many outpatient consultations were postponed and a substantial number of appointments have not yet been rescheduled. In addition, those who were suffering from heart conditions did not present to their GP or hospital – either because they did not want to impact further on NHS resources, or through concern of being exposed to the virus. Clinicians have been able to report what has been happening with respect to the reduction in emergency cardiac admissions and procedures, as well as quantify the excess deaths from emergency cardiac conditions. They have not quantified the impact on outpatient consultations.

It would be helpful to form a predictive model of the outcome of different strategies for recovery of the backlog in cardiac procedures and outpatient consultations, noting that a number of competing elements are at play including incident cases, prevalent cases, delayed cases, abandonment from changes in disease and deaths, as well as the capacity and capability of NHS services to respond. For example, given different strategies for recovery from this major perturbation to treatment, what would be the implications for treatment demand over timescales from say 6 months to several years? How should treatment be optimised given resource constraints? What would be the impact of additional waves of COVID-19 cases?

2.1 Aims and Objectives

This study group aimed to bring together researchers and clinicians to provide further insight into these complex challenges through a variety of mathematical approaches.

It was proposed that issues would be explored related to:

1. The overarching state of the delivery of elective cardiovascular procedures and outpatient consultations at the national level, as a result of the pandemic and how this plays out at regional or local (single NHS trust) levels.
2. An exemplar procedure - Aortic Stenosis – for which there is a particularly well-defined data set and for which missed early intervention can lead to particularly adverse outcomes over the course of one or two years.
3. An exemplar condition – chronic heart failure - treatment regimens for which are less well-defined, yet the missed appointments during the pandemic represent a major per-

turbation to care that may impact on the optimal management of resources within cardiology departments.

These were discussed in light of the following concerns:

- Where people are not presenting to clinics now, what will the impact of this be further down the line, as their health issue has not gone away? If people don't present for treatment but don't die, what impact does that have on resources?
- What could the knock-on effect of additional lockdowns be?
- If and when hospitals return to normal, what would be the optimal way to recover from the backlog and avoid a situation where more urgent cases in poorer condition are prioritised over routine earlier interventions, leading to perpetual worse outcomes for everyone.
- How can we configure a decision support system that could enable day-to-day answers to these questions on the ground?

3 Challenge 1 : The overarching state of the delivery of elective cardiovascular procedures and outpatient consultations at the national level, as a result of the pandemic and how this plays out at regional or local (single NHS trust) levels

3.1 Problem Overview

Cardiovascular disease (CVD) services have dropped during COVID-19 pandemic. From observation data, CVD related activity started to decline 1 to 2 weeks before the lockdown started. And after the lockdown, the activity fell by 31 % to 88 %.

CVDs are the major cause of morbidity and mortality in UK and patients are classified as vulnerable to COVID-19, so government guidance advised individuals with CVD to pay attention to isolation measures.

3.2 Previous and Related Work

There is a significant volume of previous work related to case prioritisation and admission and waitlist modelling. We briefly survey several of the existing pieces of work we have found, and in particular highlight an existing model developed within a unit of the NHS.

3.2.1 Admission Monitoring

Existing studies [1, 3] have highlighted changes in cardiovascular-disease related activity during the current pandemic. In particular, CVD services have dropped significantly during the COVID pandemic.

Using aggregate data for selected CVDs in nine hospitals, [1] report the percentage change in volume of CVD activity in three different time intervals compared to the corresponding dates in 2018-2019:

1. before the first case of COVID in UK - 28/10/2019-02/02/2020,
2. between the first case and start of lockdown - 03/02/2020-22/03/2020, and
3. after lockdown - 23/03/2020-10/05/2020.

Table 1 Hospital statistics as percentage change from corresponding dates in 2018–2019

		Percentage change from 2018 to 2019					
		Before first case		Between first case and lockdown		After lockdown	
	No. of hospitals	%	95% CI	%	95% CI	%	95% CI
Overall							
Total ED attendances	5	3.4	3.2 to 3.6	−8.8	−8.4 to −9.1	−52.8	−52.2 to −53.5
Total hospital admissions	8	1.1	1.0 to 1.2	−6.3	−6.0 to −6.7	−58.2	−57.5 to −58.9
Cardiac							
ED attendance with cardiac conditions	4	5.7	4.3 to 7.6	−9.6	−7.2 to −12.8	−40.2	−35.6 to −45.0
Admission with ACS	9	−1.7	−1.1 to −2.6	−15.7	−13.0 to −18.9	−39.4	−35.3 to −43.5
Admission with heart failure	7	6.1	5.1 to 7.3	−3.2	−2.2 to −4.5	−49.0	−45.7 to −52.2
PCI performed	7	−6.9	−5.0 to −9.4	−8.2	−5.4 to −12.2	−39.6	−33.7 to −45.8
Cardiac pacemaker and resynchronisation	8	2.3	1.0 to 4.9	0.0	0.0 to 2.8	−47.2	−38.8 to −55.9
CABG performed	6	−9.4	−5.0 to −16.9	−9.8	−4.3 to −21.0	−69.6	−55.2 to −80.9
Cerebrovascular							
ED attendance with cerebrovascular conditions	4	−1.9	−1.0 to −3.5	−6.5	−4.0 to −10.2	−31.8	−26.2 to −38.0
Admission with acute stroke/TIA	6	−7.5	−5.8 to −9.8	−11.9	−8.8 to −15.8	−49.2	−43.7 to −54.7
Stroke thrombolysis and thrombectomy	5	−5.6	−1.0 to −25.8	0.0	0.0 to 25.9	−45.5	−21.3 to −72.0
Carotid endarterectomy/stenting	4	30.8	12.7 to 57.6	25.0	7.1 to 59.1	−66.7	−30.0 to −90.3
Cerebral aneurysm coiling	5	−9.6	−5.7 to −15.7	−35.8	−26.9 to −45.8	−59.4	−47.1 to −70.5
Other vascular							
ED attendance with vascular conditions	3	0.6	0.1 to 3.2	−16.0	−9.9 to −24.7	−40.6	−31.5 to −50.3
Admission with aortic aneurysms	7	13.7	10.1 to 18.2	9.4	5.5 to 15.3	−53.0	−44.5 to −61.3
Admission with peripheral arterial disease	6	14.4	12.4 to 16.8	2.8	1.7 to 4.7	−49.2	−44.8 to −53.6
Admission with DVT or PE	6	11.5	8.6 to 15.0	−12.9	−8.9 to −18.2	−37.2	−30.6 to −44.2
Limb revascularisation, bypass or amputation	6	−1.2	−0.4 to −3.3	−3.7	−1.6 to −8.3	−68.2	−59.8 to −75.5
Aortic aneurysm repair	6	−18.8	−10.2 to −31.9	−20.8	−9.2 to −40.5	−88.2	−65.7 to −96.7
Peripheral angioplasty	6	15.0	10.1 to 21.6	9.1	4.5 to 17.6	−65.5	−54.8 to −74.8

After lockdown=23 March 2020–10 May 2020.
Before first case=28 October 2019–2 February 2020.
Between first case and lockdown=3 February 2020–22 March 2020.
ACS, acute coronary syndrome; CABG, coronary artery bypass graft; DVT, deep vein thrombosis; ED, emergency department; PCI, percutaneous coronary intervention; PE, pulmonary embolism; TIA, transient ischaemic attack.

Figure 1: Source: reproduced from [1]

The authors show a decrease of 58 % in total admissions and 53 % in emergency department attendances after lockdown compared with the previous year. They report that the CVD-related activity started to decline 1 to 2 weeks before the lockdown started. After the lockdown, the activity fell by 31 % to 88 %. We reproduce two of their tables below for ease of reference:

Mohamed *et al.* [3] show a deficit of over 45,000 in the cardiac procedural activity in England during the March–May 2020 compared to the same periods in 2018–2019. The authors argue that a "major restructuring of cardiac services is necessary to deal with this deficit," which is the motivation of this study group and the following analysis.

3.2.2 Case Prioritisation

Jain *et al.* [2] argue that current elective surgical prioritisations are based on "broad, rudimentary guidelines" and "in many cases is left to individual surgeons or a small group of health leaders who use their personal heuristics or preferences for decision making." The authors

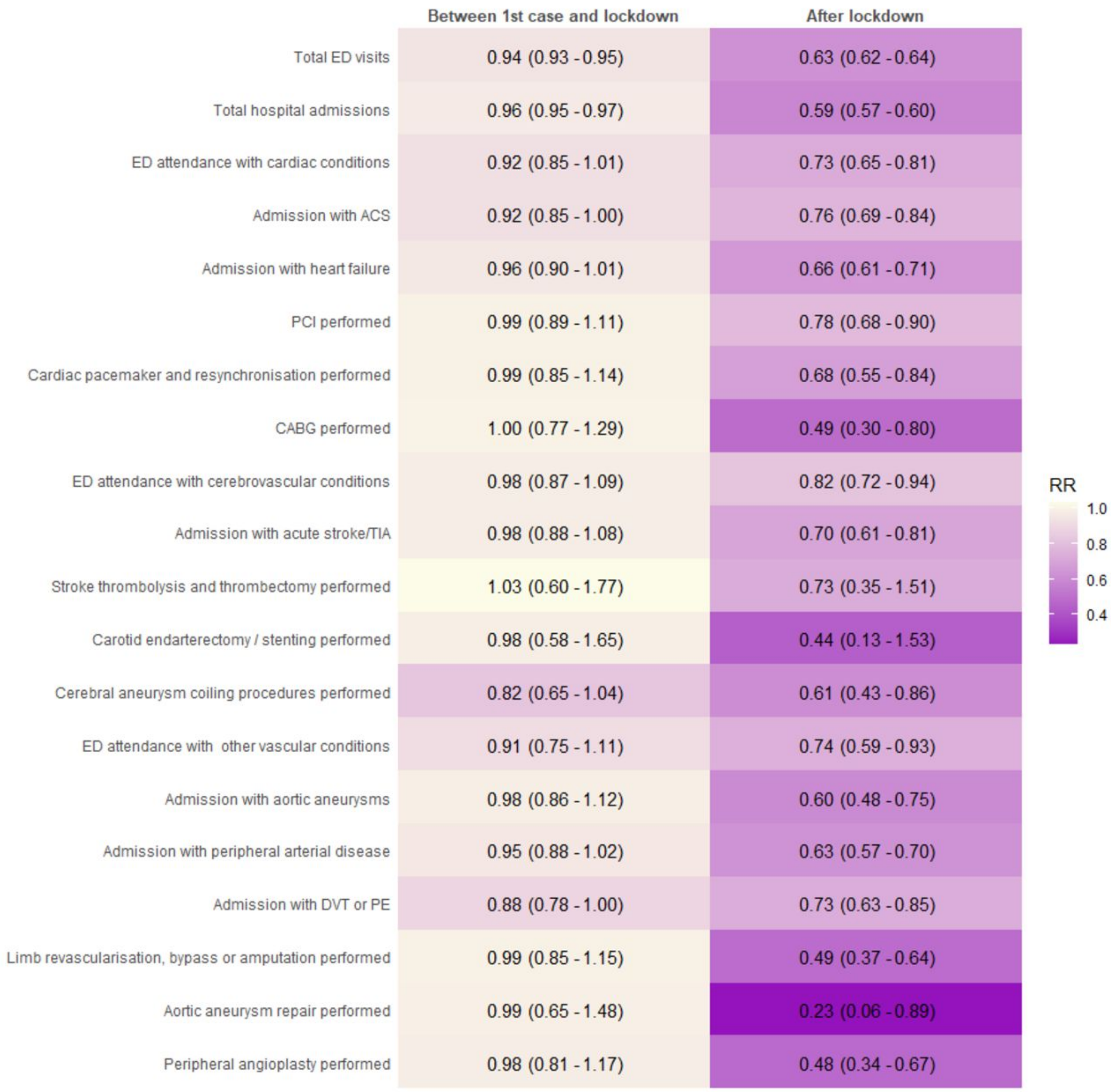

Figure 2: Source: reproduced from [1]. Relative reductions in hospital activities during the COVID-19 pandemic. Relative reduction (RR) comparing phase 2 (between first case and lockdown) and phase 3 (after lockdown) to phase 1 (before first case). ACS, acute coronary syndrome; CABG, coronary artery bypass graft; DVT, deep vein thrombosis; ED, emergency department; PCI, percutaneous coronary interventions; PE, pulmonary embolus; TIA, transient ischaemic attack

emphasize the need to develop "consistent, transparent, and bias-aware algorithms for surgical prioritization" that consider criteria such as COVID-19 risk factors, surgical risk factors, and capacity requirement factors.

There is a multitude of literature on COVID-19 risk factor. The findings of these papers can be included in a case prioritisation index.

To develop a deeper understanding of surgical risk factors, existing models can be modified to produce useful characteristics of CVDs or co-morbidity viewpoints. One can also develop a "digital twin" of patient physiology development in order to produce useful characteristics to identify how an operation will influence a patient.

Finally, based on severity, recovery benefit and other key characteristics, patients can be prioritised based on their need of hospital resources.

Veloso *et al.* [4] argue that clustering methods can be effectively used to predict re-admissions and produce base characteristics of readmitted patients. One possibility is to apply clustering methods and machine learning to develop case prioritisation rules for CVDs.

3.2.3 NHS Waitlist System Dynamics Model

Importantly, we found an existing model developed by the Strategy Unit within the NHS that specifically addresses the impact of COVID on waitlists for NHS England using system dynamics approach. The model uses an existing data pipeline and is implemented using Silico.

The overall schematic of the model is as follows (Source: Wyatt and Woodall 2020 [5]):

The model includes incoming referrals, constraints on hospital resources (including workforce), diagnostic constraints, and analyzes their impact on the overall waiting list. As such, the model is capable of studying the changes in these factors as well as in patient behaviour during the restoration and recovery period.

Currently, this model is designed to model a single specialty in a single trust at any one time, and has no cardiovascular-specific features.

3.2.4 Required Amendments for Cardiac-specific Use

For adaptation to CVD usage, we have identified a number of possible additions that might need to be made to this existing model, including:

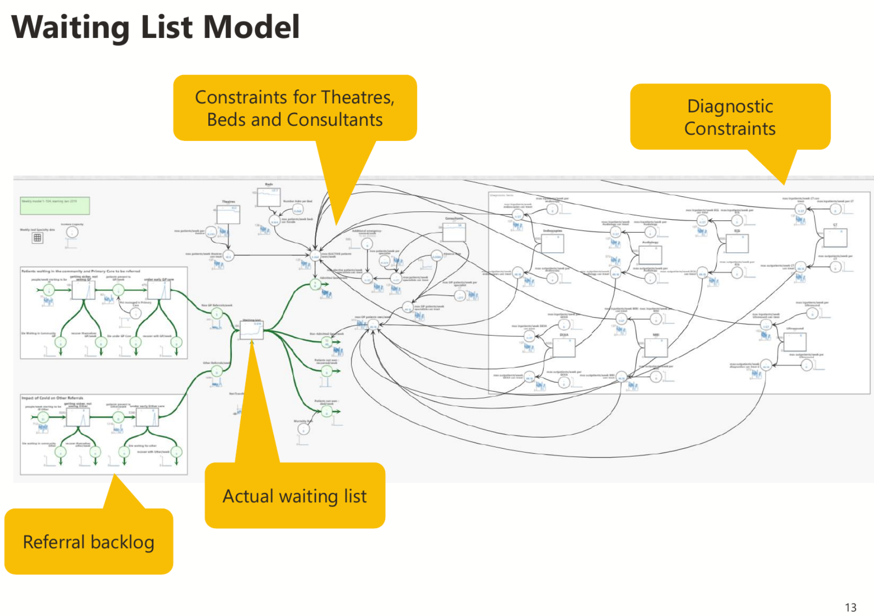

Figure 3: Source: reproduced from [5]. A schematic of a model for the overall NHS waiting list within the UK.

- Predicted demand (e.g. delayed referrals, COVID-19-induced disease)
- Referral details
- Disease progression / treatment pathways
- Comorbidities
- Interventions (e.g. switching between different treatments)
- Include cardio specific (or cardio-relevant) resources (staff, operating theatres, cath labs, etc.)
- Model an increase in available resources, either from private sector or from different trusts

Beyond the cardiac-specific setting, we have also identified more general additions that might broaden the scope of the existing Strategy Unit model:

- Larger-scale modelling of multiple trusts at once, or possibly all of England?
- Inter-trust movement of resources

- Ability to optimise parameters to find good solutions
- Model potential process improvements (e.g. task shifting, reducing inefficiencies, centralising procedures, etc.) to increase available capacity

3.3 Demand Modelling Directions

In addition to changes in the availability of resource to diagnose and treat cardiac disease, there has been a significant change in the demand from GPs and patients. It is not yet clear when demand will return, or in what temporal pattern it will return.

3.3.1 Influence Modelling - what will drive the return of demand?

We have generated three influence diagrams to help codify possible drivers of demand return during COVID-19. This set of influence diagrams are intended to explore the factors influencing the flow of cardiac patients and how they might change through and after COVID-19.

The first diagram gives an overview of the system prior to COVID-19. The blue sections show a simplified model of the flow of patients with cardiac conditions. The blue rectangles capture different stocks throughout the care process and the blue arrows indicate directions of flow. Regrettably, patients can die at any stage.

The green sections indicate influences on the flow of patients with the arrows indicating where they impact. The + signs on arrows indicate that an increase in the item at the start of the arrow will cause an increase in the item at the point of the arrow. The – signs on arrows indicate that an increase in the item at the start of the arrow will cause a decrease in the item at the point of the arrow. The green arrows without + or - are those for which it is harder to say how the impact will work.

There is a cluster of green influences related to GP referrals, which includes GP awareness of the waiting lists in hospital having an influence on whether they refer or not; some GP's might not refer if they think the list is too long, others might refer earlier if the list is long as patients may well get worse while waiting. There is another cluster of influences around capacity within the hospital impacting patients moving from waiting to seeing a specialist. The volume of emergency treatment impacts the availability of resources for elective (planned) treatment.

The second diagram adds on the changes that have been experienced through the pandemic,

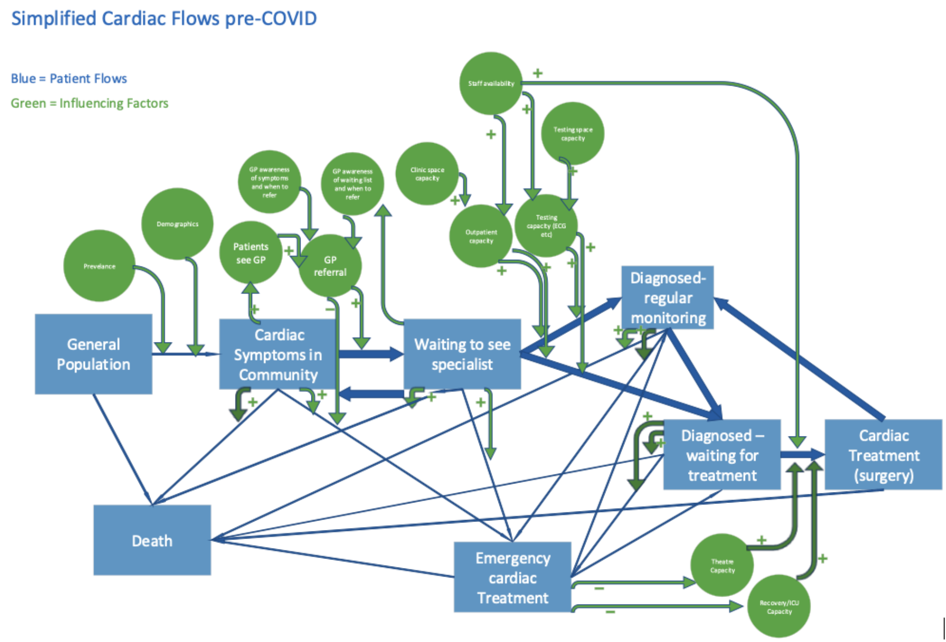

Figure 4: A schematic of possible drivers of demand for cardiac services pre-COVID-19.

these are all coloured in orange.

There may be changes to the demographics of the population, whether this is large enough to be significant remains to be seen. All of the other changes are indicated with + for an increase and – for a decrease:

- The rates of death from all areas are increased, this may be disproportional for those with cardiac conditions compared to the general population.
- Through the pandemic referral rates have been down, factors contributing to this may include patients putting off seeing their GP’s (to reduce contacts) and GP’s making fewer referrals as they are aware that hospitals have reduced capacity to see non-COVID-19 patients.
- Capacity for seeing outpatients and conducting tests has been reduced by the need to socially distance patients and reduced staff availability (sickness and treating COVID-19 patients).
- The reduced outpatient/treatment rates would be expected to increase the numbers waiting both to be seen initially and for treatment, although this may be being mitigated by the reduction in referrals.

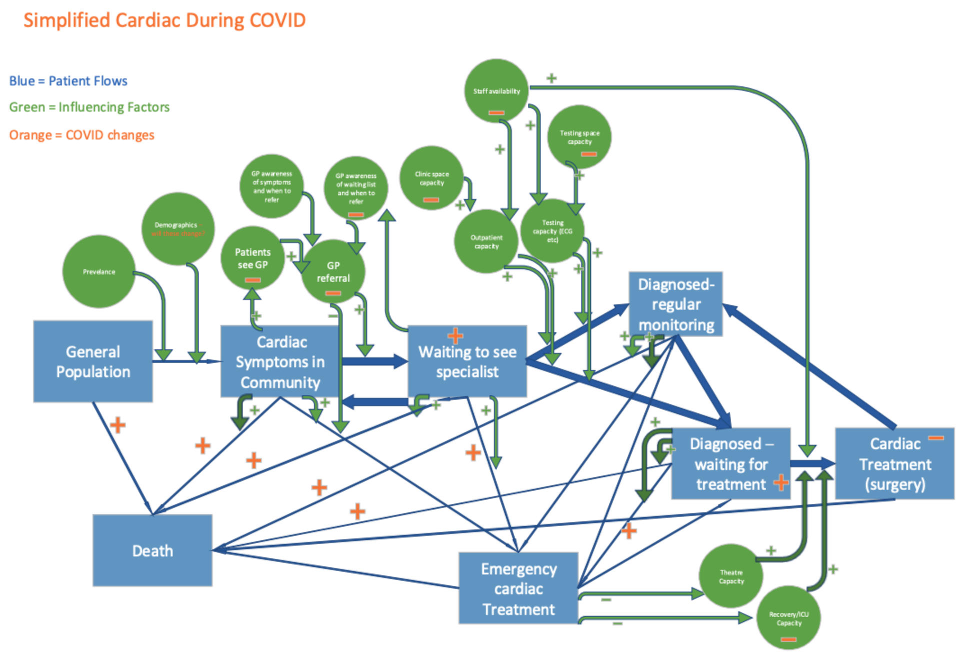

Figure 5: A schematic of possible drivers of demand for cardiac services during the COVID-19 pandemic.

- The reduction in referrals is not likely to represent a reduction in need and once people return to their GP's and GP's are aware that patients are being seen an increase in referrals is to be expected.

The third diagram explores where changes are to be expected as the pressures from COVID-19 reduce. Again, the changes from the first diagram are indicated in orange.

The flow of patients to see their GP's and then being referred is expected to increase due to the unmet demand discussed above. The rate at which this will happen is very uncertain.

The extent to which any impact of COVID-19 on the numbers / disease progression (both directly and as a result of delayed diagnosis/treatment) of patients is uncertain. This may impact both the numbers in the system and the rate at which patients require emergency treatment.

Staff availability may continue to be limited due to staff who have been treating COVID patients being exhausted and using annual leave that has built up. This along with constraints on building space and budgets will limit the ability to speed up seeing, testing and treating patients.

It is also uncertain if there will be any ongoing impact on the availability of ICU and other beds

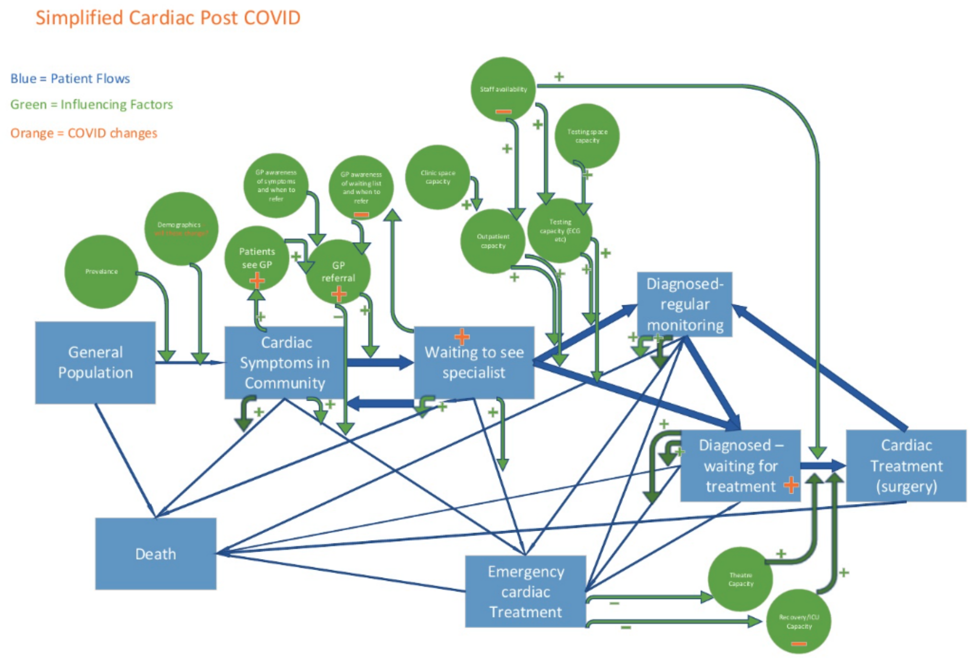

Figure 6: A schematic of possible drivers of demand for cardiac services during after the COVID pandemic, as demand returns to normal.

and if so, how long this will last.

3.3.2 What will be the Temporal Profile of Demand Return?

We first consider previous demand patterns during the early pandemic. Figure. 7 is a plot of monthly GP referrals for all reasons January to November. Figure. 8 shows a plot of cardiac referrals April - November.

While we see a decrease with the initial lockdown, we do not see any very obvious subsequent decreases with subsequent lockdowns in November. Further work is needed here for a number of reasons - in particular the cardiac-specific referrals are for all cardiovascular disease, and are thus too general.

We propose several possible temporal patterns of return:

- a simple linear return in which there is a roughly straight-line return from low to typical demand
- a stepwise return in which particular changes in policy prompt abrupt changes in de-

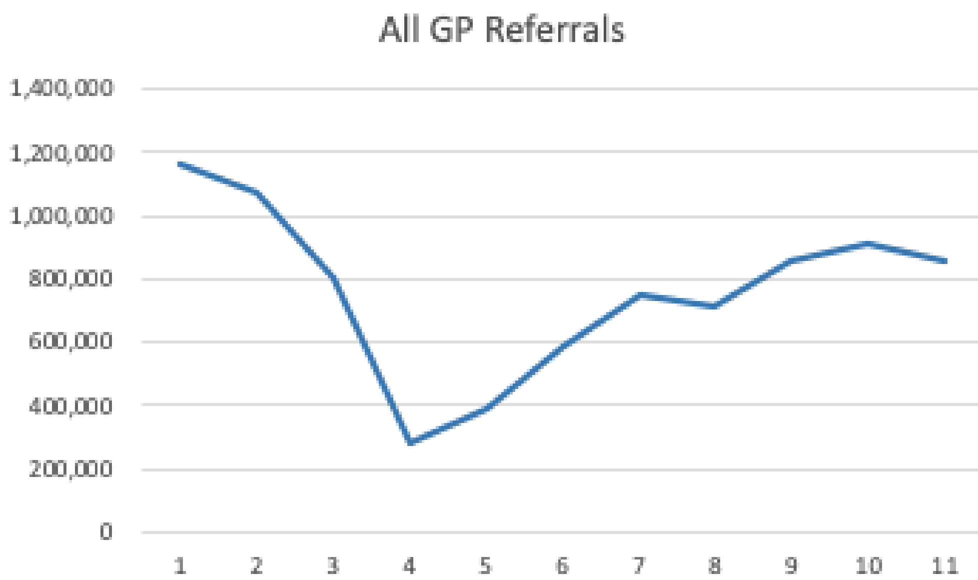

Figure 7: All GP referrals

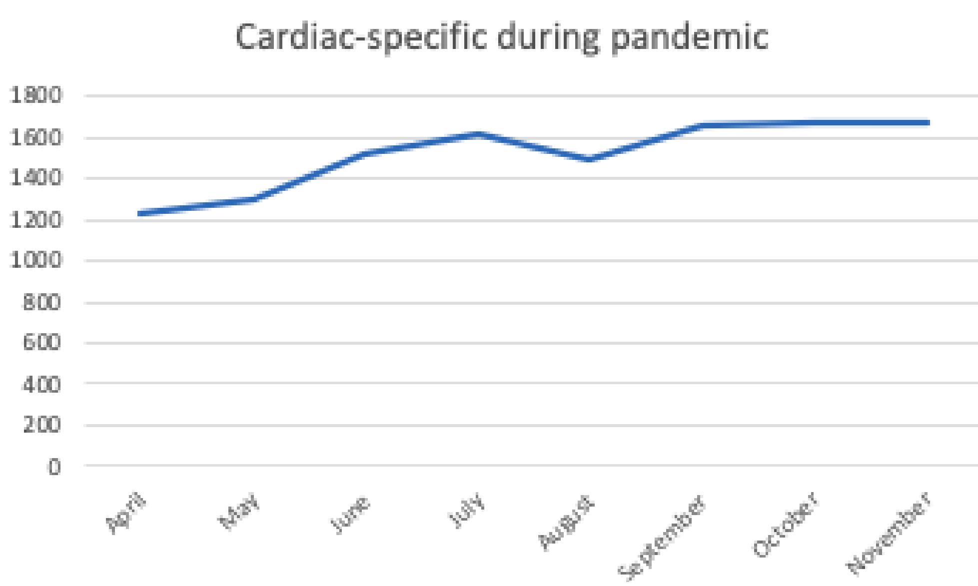

Figure 8: Cardiac and Cardiology GP referrals

mand

- a roughly exponential return in which return is flatter at the beginning, but then accelerates after some particular point in time
- an age-structured return in which referrals increase in age categories as those age categories are vaccinated - this may interact non-trivially with complicatedness of cases

We would propose further development of each of these and monitoring as demand returns to tell as quickly as possible which regime reflects reality.

3.4 Summary and Next Steps

We have found a variety of existing models that could be extended or combined to model the overarching state of the waiting lists, though all of them would require extension or expansion to serve this purpose. In particular, there are significant gaps in modelling the drivers and time profile of return of demand that should be addressed within a model of cardiac waiting list during and post-pandemic. We suggest work to adapt and extend an existing model (perhaps the model in [5]) as a next step.

References

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4 Challenge 2: An exemplar procedure - Aortic Stenosis – for which there is a particularly well-defined data set and for which missed early intervention can lead to particularly adverse outcomes over the course of one or two years

4.1 Pathway for AS Patients Flowchart (Ramesh Nadarajah)

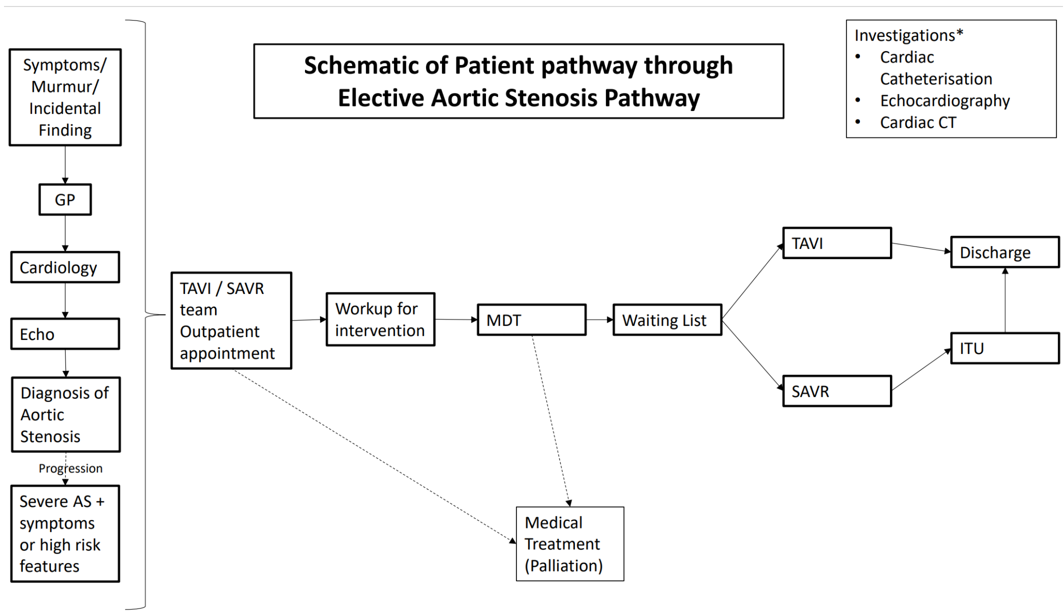

Figure 9: Schematic of patient pathway through elective AS pathway.

4.2 Dynamical System Model

In the DS model, we have modeled the entire NHS England as a single hospital with a single waiting list with a simplified process map. We have further assumed a “worse case senario”, in that all 5,000 missing patients show up at time zero, and the influx rate is equal to the influx rate pre-COVID-19, that is $f = \frac{r_T + r_S}{1-\rho} = \frac{5197+7830}{0.9}$ per year, assuming that 10% of people are only suitable for palliative care. We have also assumed that the probability of dying on any given day is a constant equal to a 40 % chance of death in a year. That is to say there is a 0.13 % chance of any person on the waiting list dying on any given day.

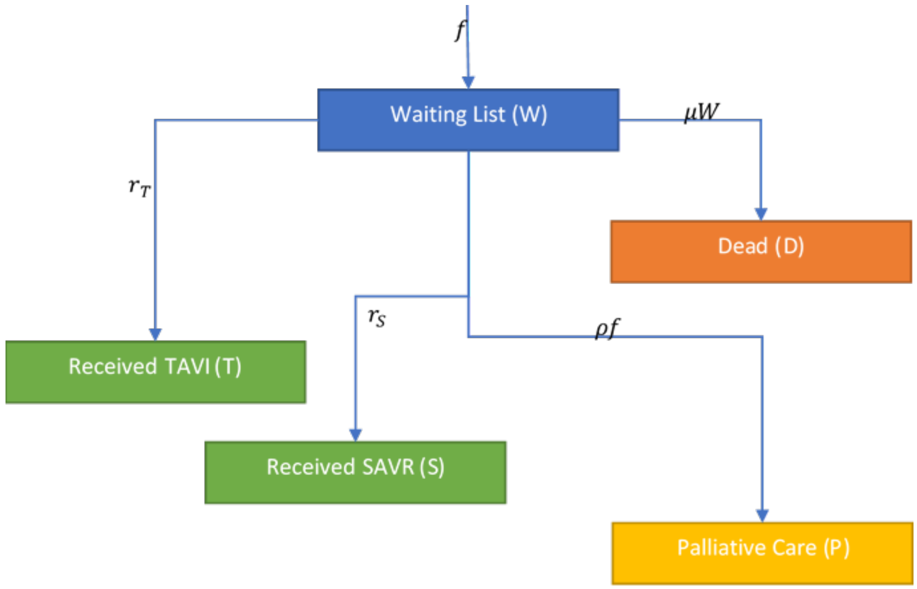

Figure 10

The dynamic equations are given by

$$\frac{dW}{dt} = f - r_T - r_S - \rho f - \mu W$$

$$\frac{dT}{dt} = r_T$$

$$\frac{dS}{dt} = r_S$$

$$\frac{dD}{dt} = \mu W$$

$$\frac{dP}{dt} = \rho f - \mu_P(P)$$

The number of dead does not include those who died on palliative care because they would have died on palliative care even if there were no backlog.

This means that in the do-nothing situation, Figure. 11 the waiting list only decreases due to death and we must wait for 5,000 people to die on the waiting list to end the backlog. As we can see below, that results in there still being a backlog to clear after 1,000 days.

So to clear the backlog it is clear that we need to perform more operations than we did pre-COVID-19 (under the assumptions of this model). First, we can model switching to a seven-day working week, Figure. 12. We have assumed that this allows an additional 20 % more operations per week compared to normal working. Here we find that the waiting list is cleared after ~ 500 days, and there are only 1,700 deaths on the waiting list compared to the 5,000 in the do nothing scenario.

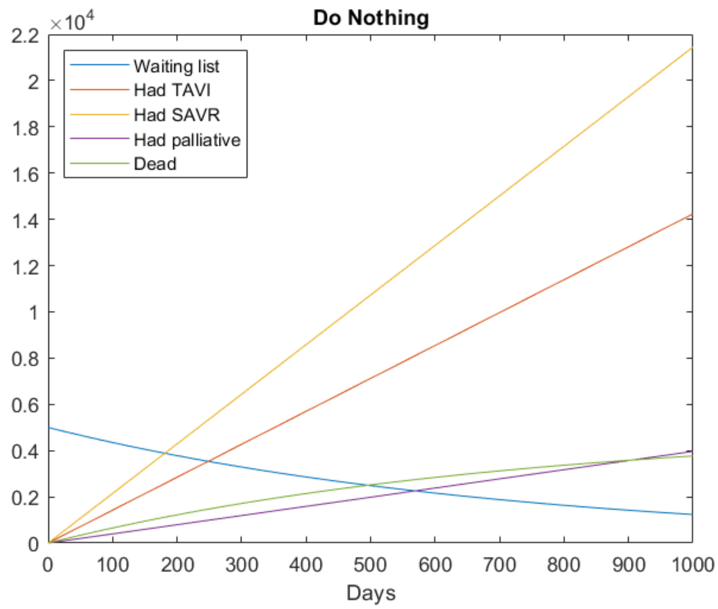

Figure 11: Do nothing scenario

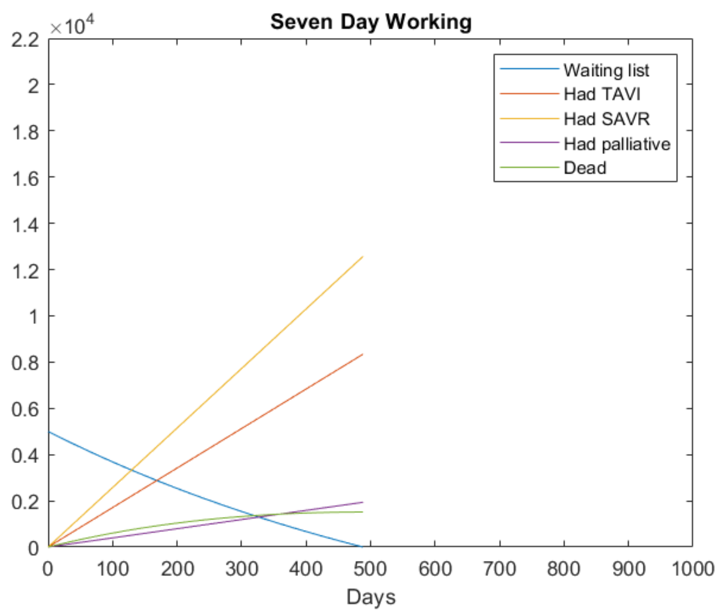

Figure 12: Seven day working scenario

We can also model a situation where we switch all patients to Transcatheter Aortic Valve Implantation (TAVI), except those who can only have Surgical Aortic Valve Replacement (SAVR), Figure. 13. For this simulation, we have assumed that for every three SAVR operations carried out, five TAVIs can be performed, and that 10 % of all incoming patients can only have SAVR.

This simulation is more promising, with only a year needed to clear the backlog and $\sim 1,100$ deaths as a result of waiting.

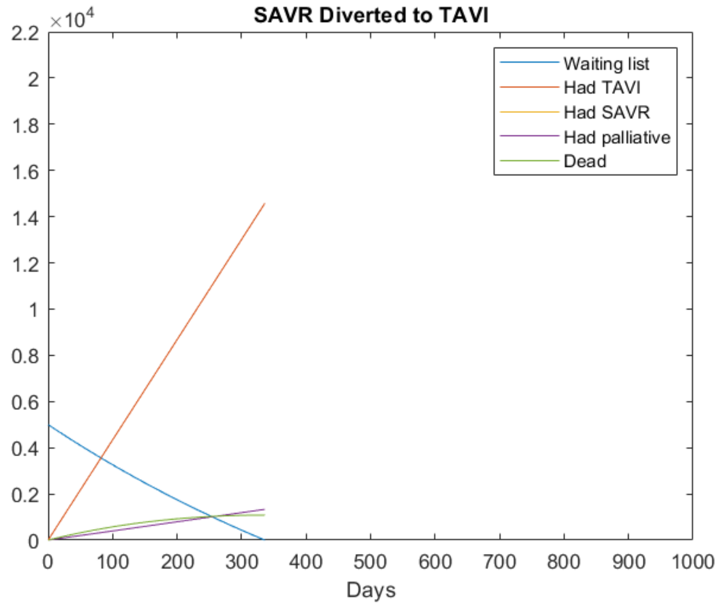

Figure 13: SAVR diverted scenario

Lastly, we can combine the two, naturally this has the biggest impact with all cases cleared within 220 days and a mortality of ~ 700, Figure. 14.

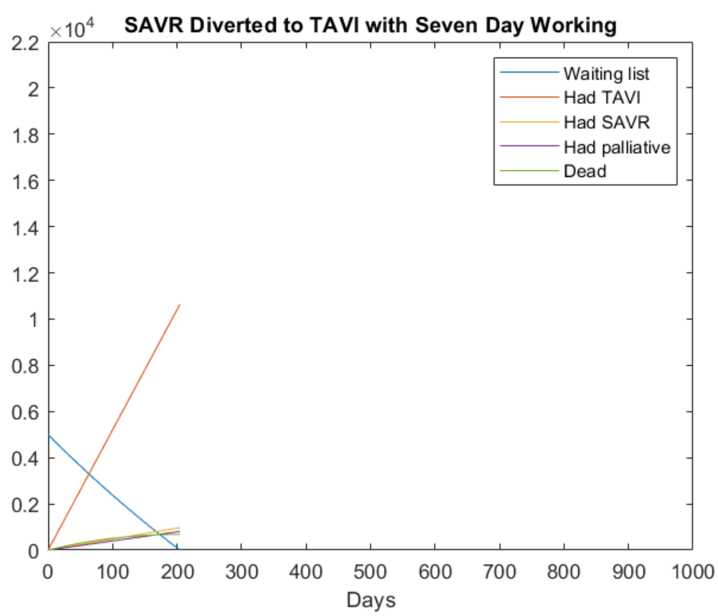

Figure 14: Seven day working with SAVR diverted

Mortality's in this simulation are likely to be over-estimates however. In real waiting lists patients would be prioritised based on risk of death which has not been accounted for in this model. To expand on this model one could create separate waiting lists based on how long one has already been waiting and progression of illness, this would allow us to think about optimising mortality by using different mortality rates for different stages on the list.

4.3 Model (draft diagram) from Houyuan Jiang

Practical challenge. In this section, we attempt to use a system dynamics approach to address the following practical question that was raised in the workshop: *How to clear the aortic stenosis waiting list*?

Methodology. System Dynamics is a modelling and simulation tool for studying and analysing structural behaviours of interdependent and dynamic systems in time that involve complex causal and nonlinear relationships, time delays and feedback loops between different compartments and components of the systems. It can be used to do what-if analysis or scenario analysis for the question such as: (1) *What would be the impact on the waiting list and the number of deaths if more operational resources (e.g., more TAVI operations) are introduced*? (2) *What would be the impact on the waiting list and the number of deaths if some more expensive and time consuming surgical procedures SAVR are converted into less expensive and time consuming operational procedures TAVI*?

Mathematical Model. Based on the discussion between the team and Ramesh, in the workshop, we focus on the three major components of the flowchart provided by Ramesh. We also follow the same principle to build our system dynamics model. One must note that the system dynamics model can be significantly modified to better reflect the real-life situation and/or extended to include many more components in Ramesh's flowchart and beyond. A prototype system dynamics model is built and the following is the stock-and-flow diagram of the prototype system dynamics model, Figure. 15.

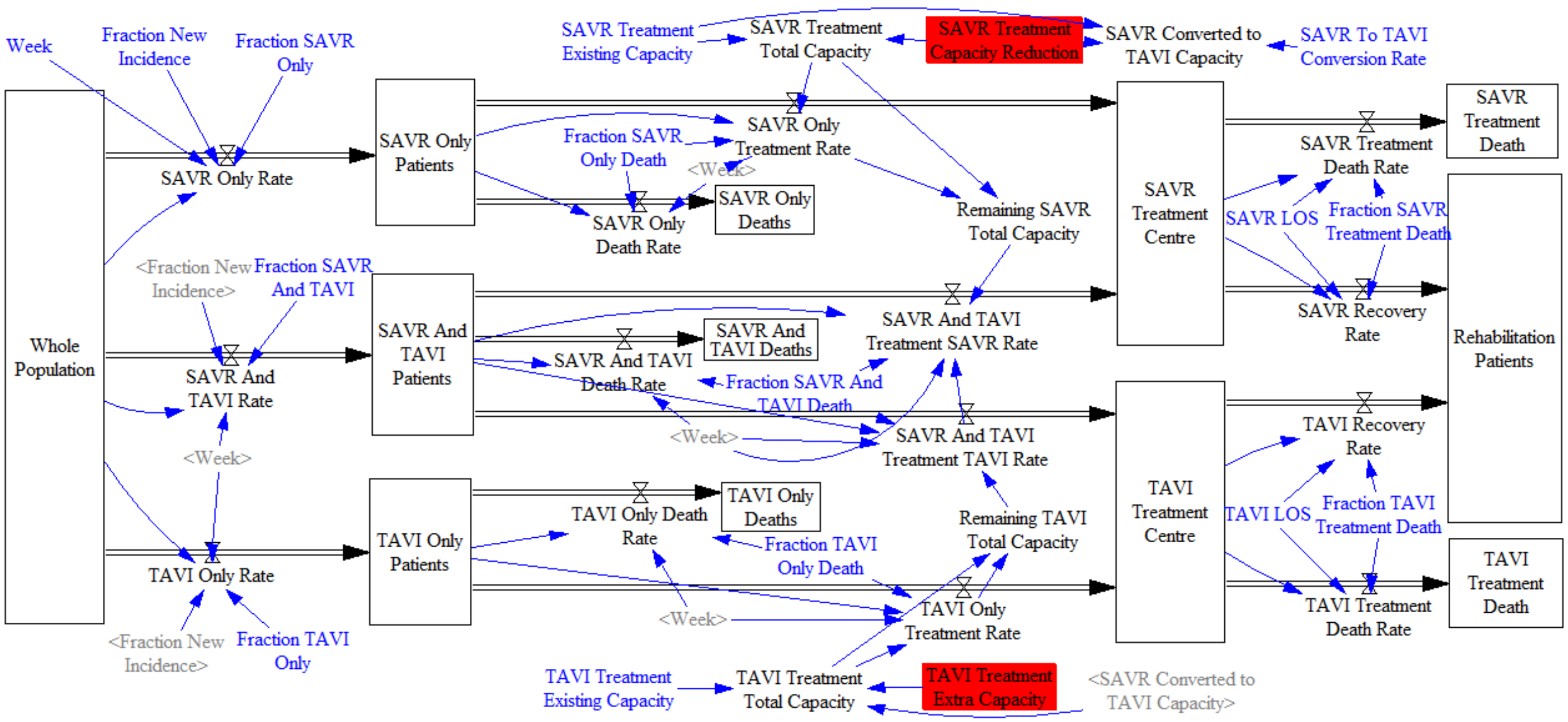
Week
Fraction New Incidence
Fraction SAVR Only
SAVR Treatment Existing Capacity
SAVR Treatment Total Capacity
SAVR Treatment Capacity Reduction
SAVR Converted to TAVI Capacity
SAVR To TAVI Conversion Rate
Whole Population
SAVR Only Rate
SAVR Only Patients
SAVR Only Treatment Rate
Fraction SAVR Only Death
<Week>
SAVR Only Deaths
SAVR Only Death Rate
Remaining SAVR Total Capacity
SAVR Treatment Centre
SAVR Treatment Death
SAVR Treatment Death Rate
SAVR LOS
Fraction SAVR Treatment Death
SAVR Recovery Rate
Rehabilitation Patients
<Fraction New Incidence>
Fraction SAVR And TAVI
SAVR And TAVI Rate
SAVR And TAVI Patients
SAVR And TAVI Deaths
SAVR And TAVI Death Rate
Fraction SAVR And TAVI Death
SAVR And TAVI Treatment SAVR Rate
SAVR And TAVI Treatment TAVI Rate
TAVI Treatment Centre
TAVI Recovery Rate
TAVI LOS
Fraction TAVI Treatment Death
TAVI Treatment Death
TAVI Treatment Death Rate
TAVI Only Rate
TAVI Only Patients
TAVI Only Death Rate
TAVI Only Deaths
Fraction TAVI Only Death
Remaining TAVI Total Capacity
TAVI Only Treatment Rate
Fraction TAVI Only
TAVI Treatment Existing Capacity
TAVI Treatment Total Capacity
TAVI Treatment Extra Capacity
<SAVR Converted to TAVI Capacity>

Figure 15

Data and assumptions. Thanks again to Ramesh's rapid response, we are able to use the following inputs that were provided by Ramesh on day three of the workshop.

- The English national population. It is assumed to be 56,000,000.
- The number of AS patients who can be treated per WEEK, with the existing 34 national SAVR centres. It is assumed to be 156 per WEEK (7830 per YEAR). Potentially it can be increased by 14 per WEEK.
- The number of AS patients who can be treated per WEEK, with the existing 41 national TAVI centres. It is assumed to be 104 per WEEK (5,197 per YEAR). Potentially it can be increased by 28 per WEEK.
- The corresponding number of TAVI patients for one SAVR patient, with the EQUIVALENT and most critical resources. It is assumed to be 4.
- The number of AS patients in the current (known plus unknown) waiting list. It is assumed to be 5000.
- The number of New AS Incidences of per YEAR. It is assumed to be 1 AS patient per 4,000 people per YEAR.

We have also used Ramesh's other inputs, which are omitted here for brevity. Note that many of the above assumptions may not be accurate or correct at this stage.

Analysis. In our initial experiments, we only consider the following three scenarios:

- **Base Scenario**: Based on the existing national SAVR and TAVI capacities, each week, 156 SAVR patients can be treated, and 103 TAVI patients can be treated. Thus, each week, approximately 250 AS patients can be treated.
- **Extra TAVI Capacity Scenario**: Each week, 156 SAVR patients can be treated, and 203 TAVI patients can be treated. Thus, each week, approximately 360 AS patients can be treated.
- **Convert 50% of SAVR Capacity to TAVI**: Each week, 78 SAVR patients can be treated, and 410 TAVI patients can be treated. Thus, each week, approximately 500 AS patients can be treated.

Preliminary results. We present our preliminary results in the following two charts. Figure. 16 shows the **waiting lists** for three types of patients in the next 100 weeks starting from 1 April, 2021: (i) The patients who can be treated by both SAVR and TAVI, (ii) the patients who can be treated by SAVR only, and (iii) the patients who can be treated by TAVI only. Figure. 17 shows the **cumulative numbers of deaths** for three types of patients in the next 100 weeks starting from 1 April, 2021: (a) The patients who can be treated by both SAVR and TAVI, (b) the patients who can be treated by SAVR only, and (c) the patients who can be treated by TAVI only.

Managerial insight. One could easily draw some initial conclusions. On both performance metrics: the waiting list and the number of cumulative deaths. The performance of the Base Scenario is the worst, which is not a surprise because it has less resources than the other two scenarios. The performance of the Convert 50 % of SAVR Capacity to TAVI scenario is the best. The waiting list can be cleared in a matter of twenty weeks. Furthermore, a significant number of deaths can be saved. Certainly, we should not read these numbers precisely rather we should focus on the qualitative insights that are generated because some modelling assumptions can be incorrect, some inputs can be incorrect, and the additional hypothetical/converted resources may not be available. It is anticipated that detailed results will be different when different assumptions on the model, inputs and interventions are made.

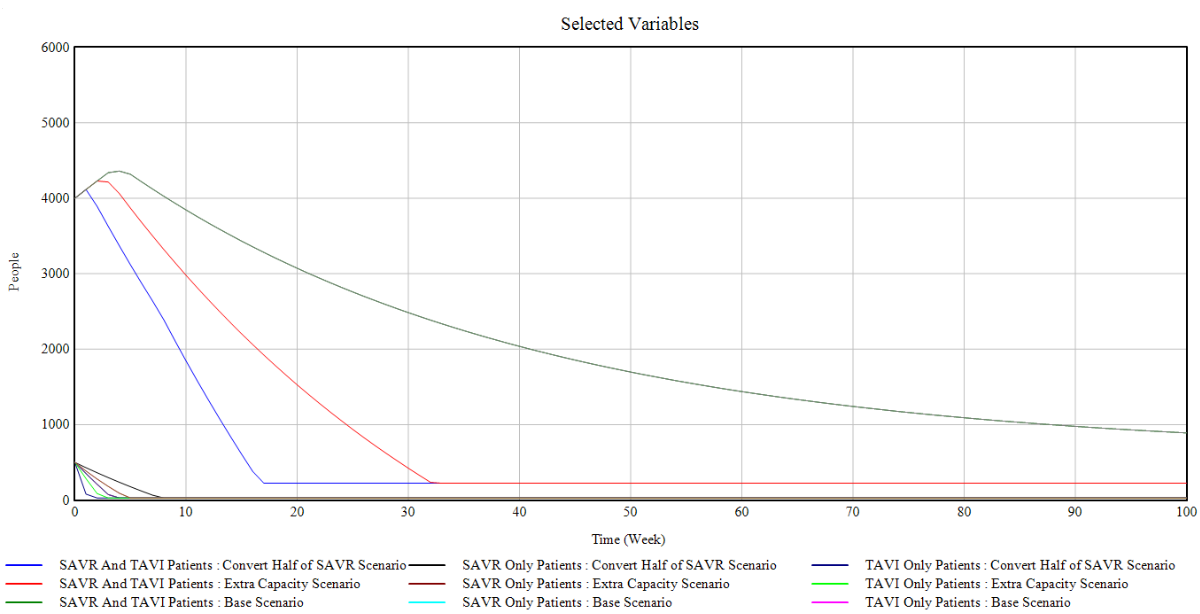

Figure 16: the **waiting lists** for three types of patients in the next 100 weeks starting from 1 April, 2021: (i) The patients who can be treated by both SAVR and TAVI, (ii) the patients who can be treated by SAVR only, and (iii) the patients who can be treated by TAVI only

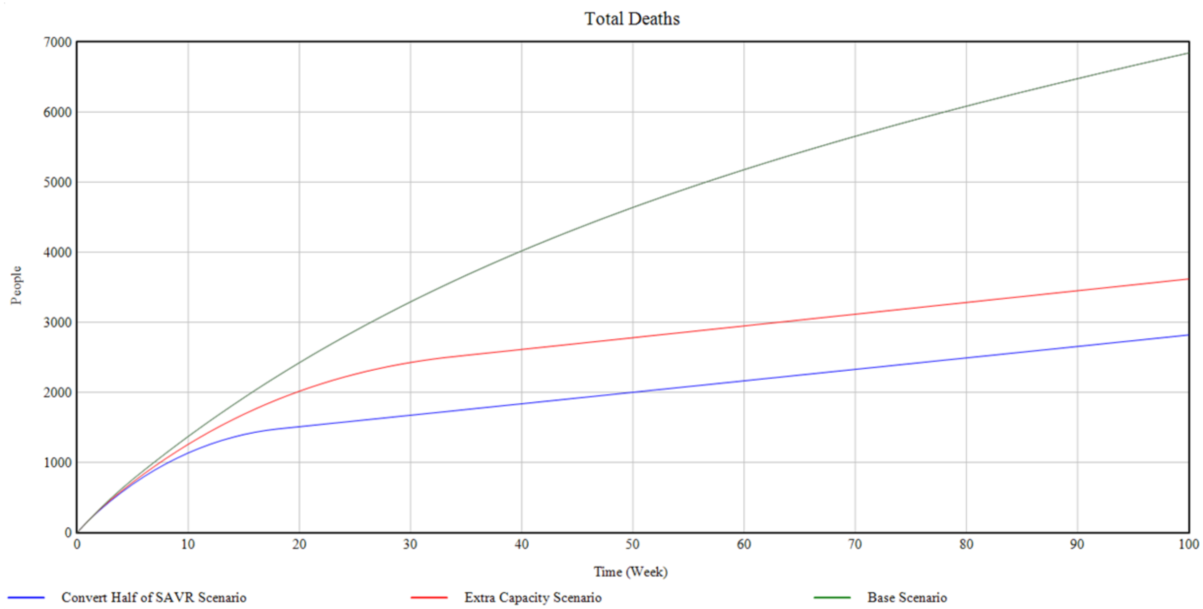

Figure 17: The **cumulative numbers of deaths** for three types of patients in the next 100 weeks starting from 1 April, 2021: (a) The patients who can be treated by both SAVR and TAVI, (b) the patients who can be treated by SAVR only, and (c) the patients who can be treated by TAVI only.

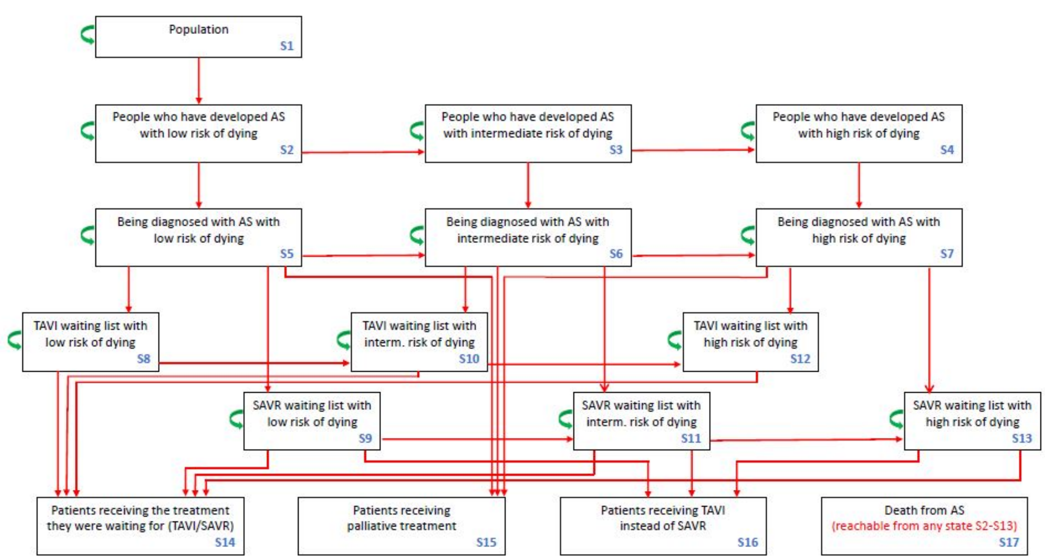

Figure 18: AS states

4.4 Markov Chain model

In this model, we use a 17-state Markov chain to represent the transitions between the various stages of the screening/treatment system for AS. The backlog (ca. 5,000) can be represented by populating conveniently the initial states for the waiting lists. It considers three risk-levels: low, intermediate and high. The 17 states are as follows:

(**State 1**): General population

(**State 2**): People who have developed AS associated to Low risk of dying of it

(**State 3**): People who have developed AS associated to Intermediate risk of dying of it

(**State 4**): People who have developed AS associated to High risk of dying of it

(**State 5**): People with AS (with Low risk of dying) in the process of being diagnosed their condition

(**State 6**): People with AS (with Intermediate risk of dying) in the process of being diagnosed their condition

(**State 7**): People with AS (with High risk of dying) in the process of being diagnosed their condition

(**State 8**): TAVI waiting list for people with AS (with Low risk of dying of AS)

(**State 9**): SAVR waiting list for people with AS (with Low risk of dying of AS)

(**State 10**): TAVI waiting list for people with AS (with Intermediate risk of dying of AS)

(**State 11**): SAVR waiting list for people with AS (with Intermediate risk of dying of AS)

(**State 12**): TAVI waiting list for people with AS (with High risk of dying of AS)

(**State 13**): SAVR waiting list for people with AS (with High risk of dying of AS)

(**State 14**): People with AS receiving TAVI / SAVR treatment

(**State 15**): People with AS receiving palliative treatment and not eligible for TAVI or SAVR

(**State 16**): People with AS receiving TAVI instead of SAVR

(**State 17**): People who have died of AS

All probabilities are averages probabilities per unit of time, which can be chosen to be days or weeks or months. Probabilities can be fixed in a first approximation or depend on time and/or the states in a more refined approximation. The capacity of the system can be represented by reducing the probability of accessing to SAVR / TAVI treatments.

This is a unidirectional Markov chain with four asymptotic outcomes after an infinite time. The **aim** is to minimise the number of deaths in a fixed time while resolving the backlog.

The model is currently implemented in Mathematica (but can be easily implemented also in MATLAB).

The **next step** is to estimate the probabilities from the background data.

4.5 Discrete Event Simulation model

We set up a discrete event simulation for the patient flow as outlined in the AS flowchart, Figure. 19. We focused on the pathway from referral to. treatment. We used a simplified representation as described below. We assumed, however, that there are patients who are suitable for either both TAVI and surgery or for only one of those procedures.

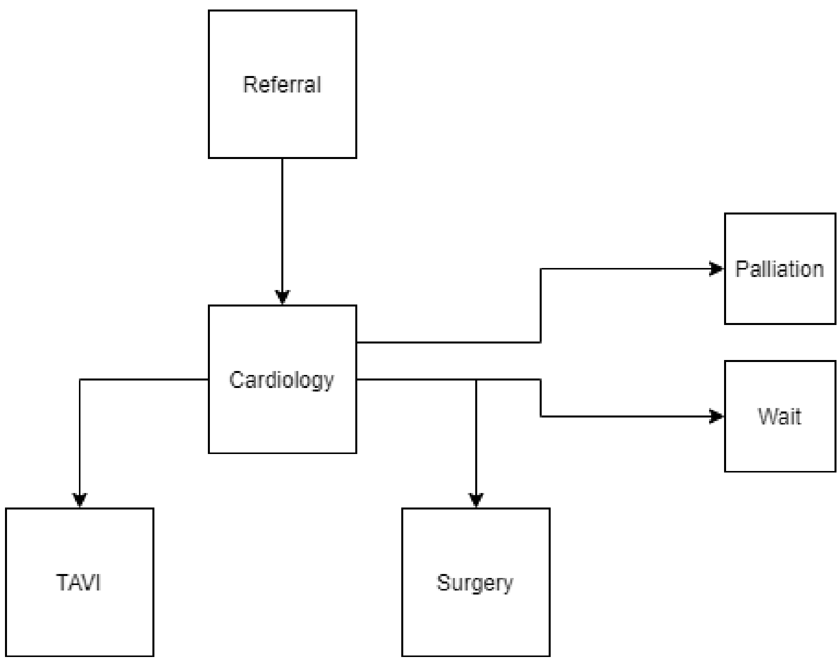

Figure 19: AS flowchart

We assumed that the bottlenecks are the availability of specialised cardiology diagnostics and the procedures. Figure. 20 is a sample output of the current state of the model with a large spike of backlogged patients coming into the system in addition to a steady background rate of new patients. Next steps are to set the parameters using the data outlined above and to add a more involved patient model to incorporate differences in mortality between different patient groups and their suitability for surgery.

In summary, this model is suitable for investigations on a localised level. As each patient is tracked individually, computations become more difficult when dealing with large popula-

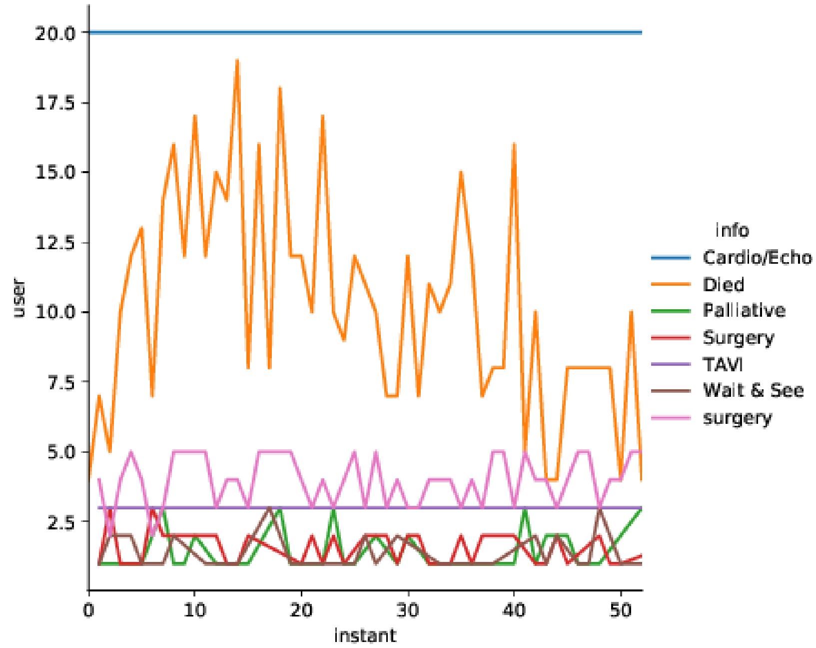

Figure 20

tions. When dealing with smaller numbers of patients, say on the level of a single trust, then the computational burden is manageable and the finer resolution of the model becomes more important to analyse fluctuations and outliers which might get lost in the system dynamics models.

5 Challenge 3 : An exemplar condition – chronic heart failure - treatment regimens for which are less well-defined, yet the missed appointments during the pandemic represent a major perturbation to care that may impact on the optimal management of resources within cardiology departments

5.1 Introduction - What is Chronic Heart Failure?

Chronic Heart Failure (CHF) is loosely defined as on-going poor heart function leading eventually to death by the heart ceasing to pump blood. It is not the same as heart attack known as Myocardial Infarction (MI), which is a clot in the blood vessels supplying heart leading to heart tissue death. There are many causes of CHF, for example age, high blood pressure, and the result of damage after MI.

5.1.1 The Normal Treatment Pathways

Primary diagnosis of CHF is via symptoms, such as breathlessness, chest pain and leg swelling. Patients attending a GP surgery or via an acute hospital visit with these symptoms are subject to a primary diagnosis. This will typically be via an Electrocardiogram (ECG) - via a number of electrodes connected to the chest - and a blood test for markers for chronic heart failure.

For cases where CHF is suspected, the patient will be put on a course of medication, and in all but the mildest cases, will be referred to a cardiology clinic for an outpatient hospital appointment. Here a secondary diagnosis is via an echocardiogram, which is an ultrasound image of the functioning heart. This procedure can also be carried out predominantly by cardiac physiologists. The results can be fed to the general practitioner or a cardiology consultant. There are also a cohort of trained heart failure nurses who can also aid GP's in management of less severe CHF patients.

As well as being able to detect specific damage, a key output of an ECG is a measurement of the Ejection Fraction (EF) from the Left Ventricle (LV) . Normal heart function should have ejection fraction of around 50%, and a marker for CHF is that Left Ventricle Ejection Fraction (LVEF) fraction is $< 40\,\%$. However in about half the cases of CHF the LVEF is normal, and the cause is due to other abnormalities of the cardiovascular system. Only in the case of low LVEF have drug treatments been shown to be clinically effective in increasing life expectancy.

stage/class	symptom
Class 1	No symptoms during normal physical activity
Class 2	Some symptoms when active
Class 3	Symptoms from light activity
Class 4	Symptoms when resting, unable to carry out physical activity

Table 1: The four stages of heart failure as defined by NHS England

CHF has four roughly-defined clinical classes and early diagnosis is key to a longer life expectancy. Median life expectancy post diagnosis is 5 years.

Old data from randomised control trials with the introduction ACE-inhibitor and beta-blocker drugs in 1987, and more recent expert elicitation, suggests that life expectancy is reduced by at least by a factor of 2, if heart failure is not treated with medication.

Class 4 is the most extreme and around 80% of patients in stage 4 have other underlying conditions.

Estimates suggest that around 650k people in the UK are currently diagnosed with CHF but other estimates suggest closer to 950k who are suffering from this condition [3]. In a normal (pre-COVID-19) case there are about 100K new diagnoses per year. The total number of outpatient cardiology appointments per year in 2018/19 was 3.8M, suggesting that each patient in a normal year will have multiple appointments in the normal management of the condition.

The aim of the treatment strategy of CHF is to manage the condition to avoid acute admissions due for example to MI or other complications. Nevertheless, CHF is thought to account for 5% of all acute hospital admissions.

Figure 21 shows the different treatment stages for CHF pre COVID-19, where decreasing numbers of patients are in each stage.

The number of patients per year with CHF is increasing slightly year on year, as is the median age (now ~ 65).

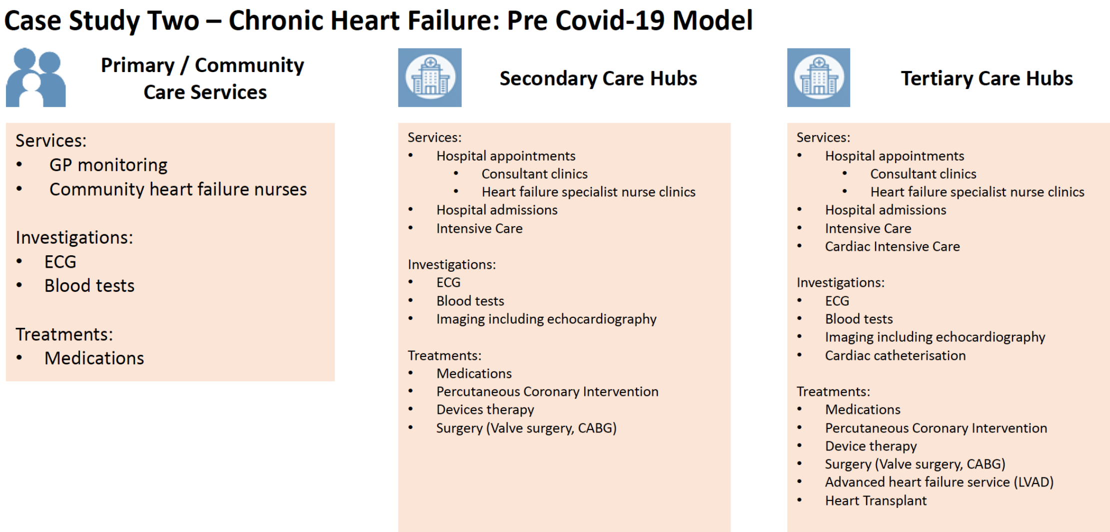

Figure 21: Treatment stages for CHF [3]

5.1.2 Effect of COVID-19

We were presented with a variety of data from a number of different sources [3]. In particular, various data sets were available pre-COVID-19 (prior to March 2020) and post the first lockdown (November 2019).

1. Data from July to November 2020 suggests that the first wave saw a much lower arrival of patients entering the system. Within primary care, the number of ECGs carried out was at 33 % of pre-pandemic levels and GP referrals were at around 20 % of pre-pandemic levels and the number of ECG s conducted in April and May 2020 was only 31 % of the number conducted in the same months of 2019 ($87K/274K$).

2. Interestingly, the cardiology waiting list was similar pre- and post-pandemic [3, 2]. The number of patients with in incomplete pathway in Nov 2020 was almost identical to that in April 2019 ($187K/185K$) and the median waiting time was actually lower 8.4 weeks/ 11.5 weeks).

   This is presumably due to a balance between the combined effect of decreased admissions (either acute or through referrals) and a reduced capacity of the service due to cancelled appointments and procedures.

3. Nevertheless, data suggests that the waiting lost for echocardiograms is up by 50 % post pandemic (115K versus 71K), although it is not clear if this is significant given that in normal times 135K would be carried out each month.

4. Other data suggests hospital admissions for CHF (both acute and referred) were down by 50% during the pandemic.
5. Deaths in the community due to CHF appear to have risen (up 31 %) and deaths in hospital to have fallen (down 29 %) during the first the pandemic, although it is not clear if these numbers balance. Other estimates suggest that around 2.2k excess death have occurred in patients **with** CHF, although only 10 % of those patients died **from** CHF.
6. These data suggest there may be more patients in the community who, when they present for diagnosis or treatment will

These data suggest that the effect of COVID-19 is not straightforward but that more acute patients are likely to present in a wave of patients post pandemic and that these are likely to be more acute that usual. It is necessary to study the treatment of CHF as a system to understand bottlenecks and potential interventions post pandemic.

5.1.3 The Question Addressed

The original questions posed by Ramesh Nadarajah [3] were

A With the total current level of demand, how long would it take to get through the backlog:

- Based on pre-March heart failure service effectiveness
- Current service effectiveness (assuming COVID-19 restrictions / ways of working continue throughout 2021)

B what new solutions could be implemented to improve the effectiveness of the CHF service, as as whole, and what impact would they have on the backlog?

However given the data summarised in the previous subsection, we realise that CHF services cannot really be modelled as a simple linear queue for which there is a backlog due to cancelled procedures. Rather it is an integrated system of disease progression and multiple treatment pathways. It seems that, at least in terms of cardiologist waiting lists, there is no current backlog. Rather there are significant patients within the system who have not presented themselves to the system, or are stuck in one of the treatment pathways (e.g. diagnosis using electrocardiograms). Thus a better set of questions to address might be:

Q1 How to capture the state of the service as a dynamic model in which patients both move through the healthcare system and their disease progresses?

Q2 Can we assess the effect of the perturbation caused by the first lockdown (March-July 2020) in order to predict future bottlenecks in the service?

Q3 What will be the cumulative effect of a second lockdown (from December to Summer 2021) before recovery from the effects of the first lockdown?

Q4 Can we suggest optimal interventions to the service to recover from these combined effects?

Q5 Does the perturbation to the service provided by the pandemic lockdowns and the recovery from them, offer an opportunity to better understand how the service currently functions (at a trust or national level) which could ultimately lead to service improvements when is stead state?

5.2 Mathematical Modelling

The model we designed during the study group includes two elements.

1. Progression of patients through the health system.
2. Disease progression following the natural history of CHF, which is affected by the treatment that patients receive.

5.2.1 Setting up the Problem

It is important to incorporate the second of these dynamics in order to accurately model the impact of patients either delaying seeking treatment or being on a waiting list for a long period of time. Figure 22 shows a typical course for heart failure. Note that death can occur at any point in this natural history, as the vertical downwards arrows show.

Within the model patients will progress through three different stages: mild, mid and severe CHF. All diagnosed patients will be on medication and patients with mid-level CHF may be offered an implant. Although some patients with CHF are offered a heart transplant, this is very rare and consequently may not be worth including in the final model.

Patients will also progress through the health system, and Figure 23 gives an initial overview of this movement. This shows four clear stages for the treatment and management of the condition that patients move between.

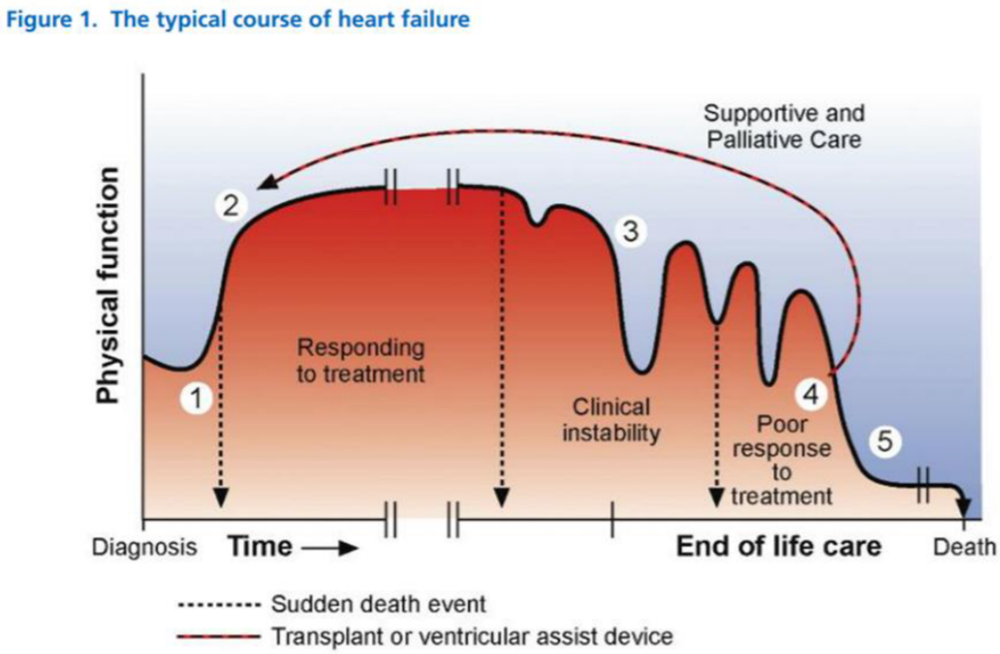

Figure 22: Typical course of heart failure from [1]. The five numbered phases here are separate from the four classes of the disease and are defined by response to treatment. Phase 1 is the initial presentation, diagnosis and treatment. Phase 2 is that of clinical stability, typically in GP care. Phase 3 is the onset of clinical instability that may be rectified via an intervention such as resetting of an arrhythmia. Phase 4 is an instability that does not respond to treatment. Phase 5 is palliative care during end of life.

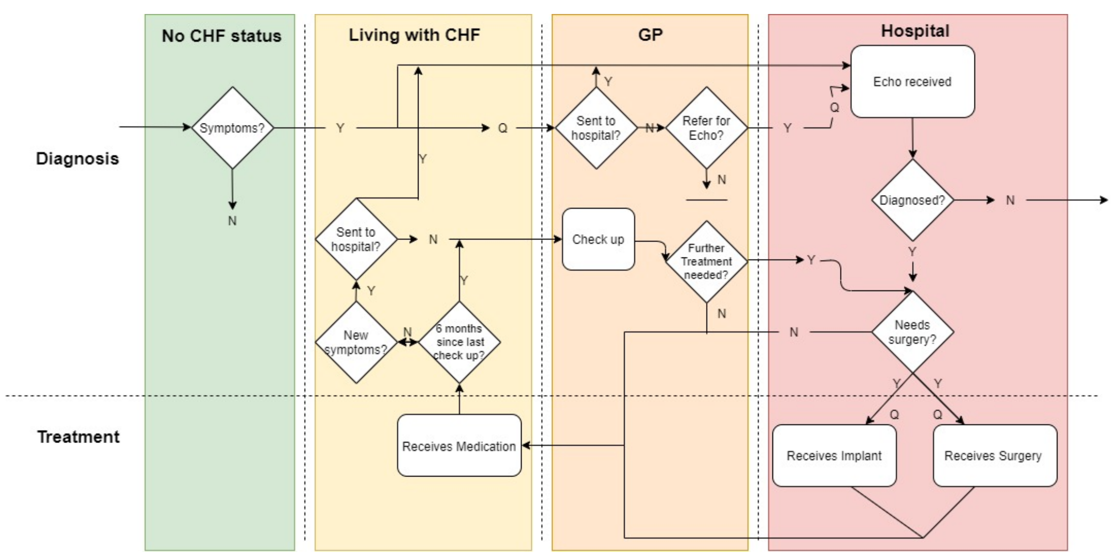

Figure 23: Conceptual model for the simulation

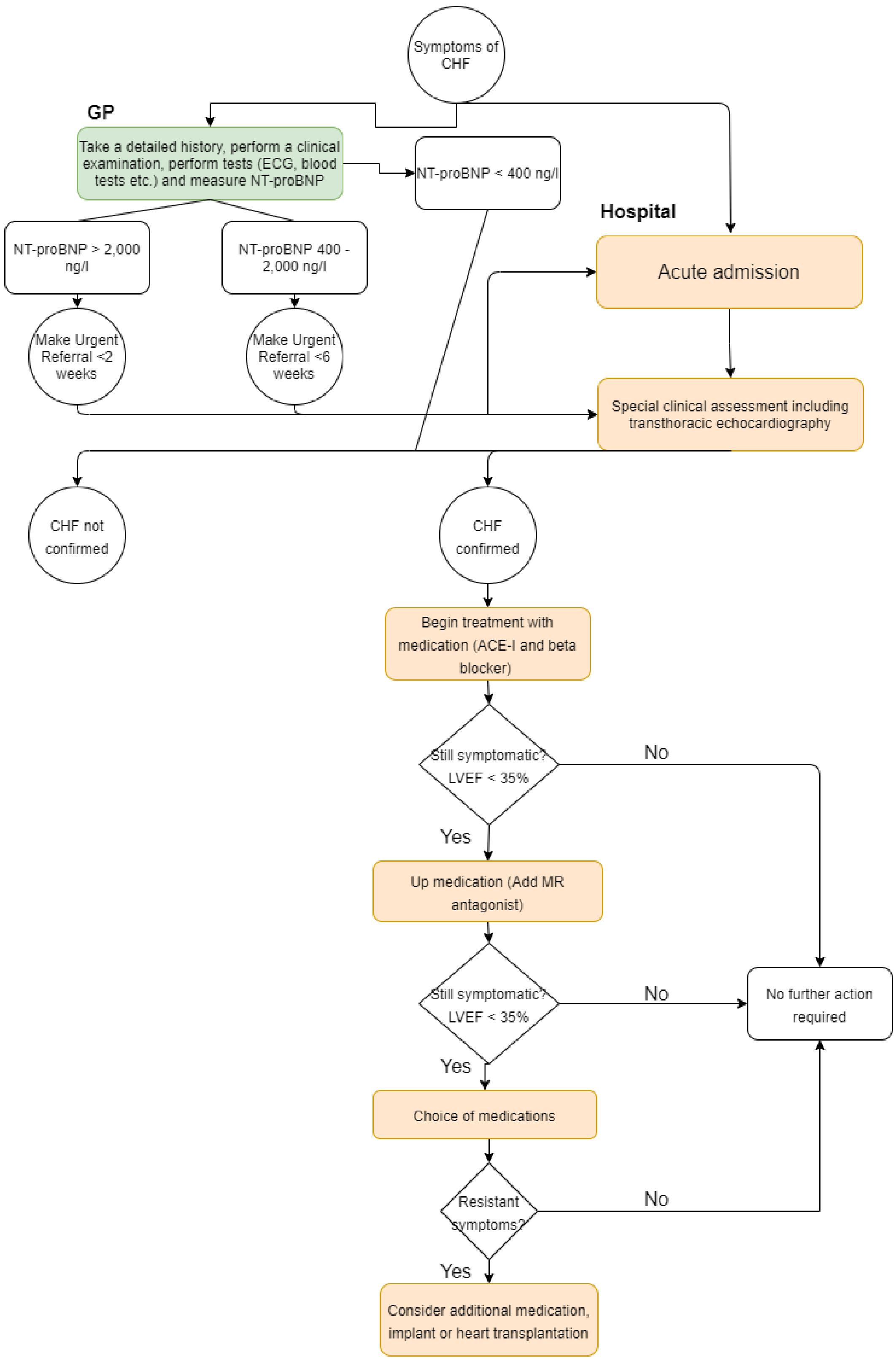

Figure 24: CHF Pathways: overview of simulation model

The most recent version of the model incorporates more of the medical details associated with separate CHF diagnosis via the GP or via a cardiologist outpatient appointment and is included as Figure 24. This is likely to form the basis of any simulation model that we develop.

5.2.2 Building a Model

We assume that a Discrete Event Simulation (DES) model will work best here, but are also considering Agent Based Modelling (ABM). In truth the distinction between DES and ABM is blurred in the case that we are considering dynamics of both patient flow and disease state.

A trial run on a much smaller subset of the problem using both Simul8 and SimPy suggests that SimPy is a good option for building the full model. See Fig. 25 for a prototype Simul8 model.

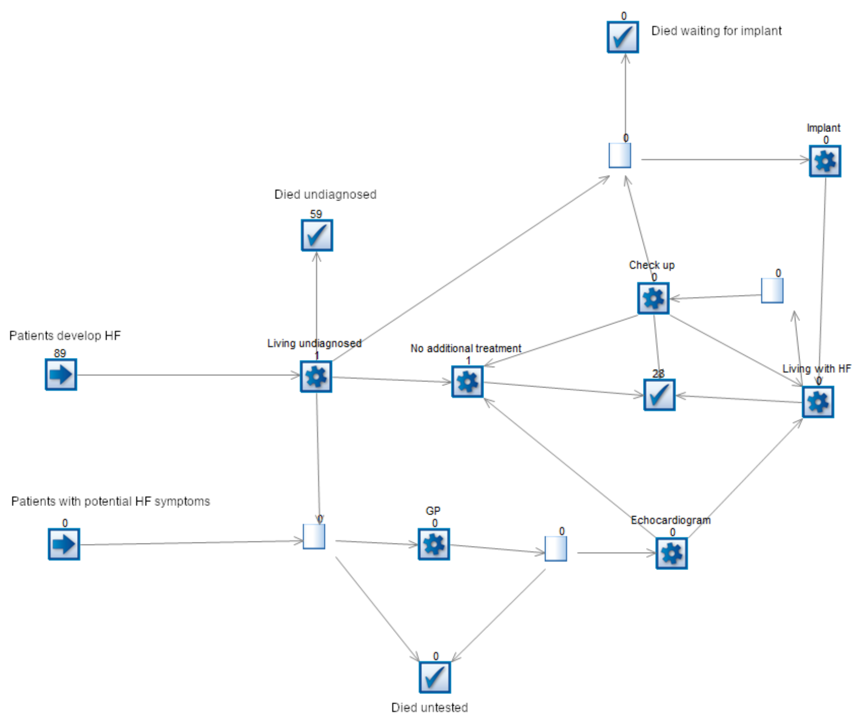

Figure 25: A preliminary simulation of patients flowing through a heart failure system

Once a full model is built we we intend to carry out the following steps

- Use data from the steady state (pre-pandemic) to parameterise a patient flow model, most likely using data from Leeds.

Parameter	Pre-Covid Value	Post-covid	Source
Total population with heart disease	920,000		BHF
Incidence rate of heart disease	0.3%		Ramesh, BHF
Acute admission	80%	50%	BHF
Diagnosis in GP	20% of cases		??
referrals having CHF	35%		Ramesh
referrals needing implant	$\sim 10\%$		Gale
referrals needing major surgery	3%		NICOR
Check-up gap on medication	6 months		
Hospital mortality rate	9.1%		NICOR
Duration of medication treatment	3 years		??
Duration need-implant (no treatment)	0.5 years		??
$+$ many many more			

Table 2: Initial parameter estimates with preliminary indications of the data sources (more work is required to chase these)

- Include the perturbation from the pandemic to allow for having different volumes of patients in the system in different disease states.
- Run the model to try to reproduce data for the immediate aftermath of the first pandemic wave (November 2021).
- Run the model forward to attempt to predict the effect of the second pandemic wave and what would happen subsequently.
- Experiment with the model using an optimisation wrapper to run what-if scenarios and suggest the best ways to proceed.

5.2.3 Data Requirements

We have some data available already to include in the model, as given in Table 2. Some of the unknown parameters can be obtained by simulating to steady-state in the pre-pandemic phase and fitting to known numbers.

5.3 Conclusion

The study group was remarkably short and only preliminary steps towards a solution could be found. Nevertheless all participants found this to be a stimulating and important problem, and there are plans to continue work.

5.3.1 Preliminary Findings

CHF is an interesting case study because it is really a complex (group of) degenerative condition(s) rather than a single acute condition that gets remedied by a procedure. Hence the traditional model of waiting lists to receive treatment may not be as appropriate. Below a few key facts about CHF.

- CHF affects 1-2% of population at any one time
- Current primary-secondary-tertiary care pathways are complex
- COVID-19 has not affected waiting lists in a simple way

What is clear from the data is that there is a wave of demand coming.

- Biggest build up is those not entering primary stage.
- There is evidence of bottleneck also at echocardiograms.
- There is an anecdotal observation that cardiology referred patients are in more severe disease state than before.

We have a reasonable idea of the flow of patients through the health system and have some of the parameter values that we need. Other parameters will need to be estimated based on data or by model-fitting. We believe that implementing as a DES is feasible and will give useful results.

5.4 Next Steps

We envisage several immediate next steps

1. Continue to build a SimPy model of patient flow

2. Use aggregated data and expert elicitation from the Leeds trust to parametrise and tune the model. This should be a collaborative step.
3. Investigate which treatment parameters can realistically be adjusted.
4. Investigate different optimisation wrappers that could be used to seek optimisation of parameters

Longer term possibilities might include

- Design of a stand-alone piece of software that can take data at a trust or national level to enable a real-time decision support tool to be built.
- Taking a continuum limit of flows and disease progression to build a more systems-dynamics approach that might enable some more mathematical analysis of the system sensitivities, robustness, instabilities and optimal control.

References

[1] Connolly, J. and Beattie, M. and Walker, D. and Dancy, M., End of life care in Heart Failure; a framework for implementation, (2014), NHS Improvement. `https://www.england.nhs.uk/improvement-hub/wp-content/uploads/sites/44/2017/11/heart-failure.pdf` date accessed 3/3/2021

[2] NHS England, Consultant-led Referral to Treatment Waiting Times, (2021) `https://www.england.nhs.uk/statistics/statistical-work-areas/rtt-waiting-times` date accessed 3/3/2021

[3] Nadarajah, R., Case Study Two, Chronic Heart Failure, (2021) Presentation to VKEMS Study Group on Cardiac Waiting Times 2nd Feb 2021

6 Conclusions

Over the study group, potential solutions were developed and these were presented on the final day. Following the study group, additional modelling work has taken place and funding is being sought to take this forward further.

- Group 1 found a variety of existing models that could be extended or combined to model the overarching state of the waiting lists, although all of them would require extension or expansion to serve this purpose. In particular, there are significant gaps in modelling the drivers and time profile of return of demand that should be addressed within a model of cardiac waiting list during and post-pandemic.
- The approach in Group 2 focused on discrete event simulation for patient flow and how using potentially different treatments (TAVI v SAVR) and optimising resources could optimise patients flow. This model is suitable for investigations on a localised level.
- Group 3 identified that CHF is an interesting case study because it is really a complex (group of) degenerative condition(s) rather than a single acute condition that gets remedied by a procedure. Hence the traditional model of waiting lists to receive treatment may not be as appropriate. The approach to this problem will be to implement a system model developed at the study group of patient flows and disease progression using aggregated data obtained in collaboration with clinicians at Leeds.

Next Steps: Each of the three problems now have potential solutions which need working through to provide a useful tool for use by those who plan care services. Funding is being sought for an academic (Ph.D Student, Postdoctoral Researcher or both) to further develop the models that were identified and formed at the Study Group.

7 List of Acronyms

ABM Agent Based Modelling

AS Aortic Stenosis

CHF Chronic Heart Failure

CVD Cardiovascular disease

DES Discrete Event Simulation

ECG Electrocardiogram

EF Ejection Fraction

LV Left Ventricle

LVEF Left Ventricle Ejection Fraction

MI Myocardial Infarction

SAVR Surgical Aortic Valve Replacement

TAVI Transcatheter Aortic Valve Implantation

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