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MODELING OF WAITING LISTS FOR CHRONIC HEART FAILURE IN THE WAKE OF THE COVID-19 PANDEMIC

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ABSTRACT

The Covid-19 pandemic has disrupted access to health services globally for patients with non-Covid-19 conditions. We consider the condition of heart failure and describe a discrete event simulation model built to describe the impact of the pandemic and associated societal lockdowns on access to diagnosis procedures. The number of patients diagnosed with heart failure fell during the pandemic and in the UK, the number of GP referrals for diagnostic tests in November 2020 were at 20% of their pre-pandemic levels. While the numbers in the system have fallen clinicians believe that this is not reflective of a change in need, suggesting that many patients are delaying accessing care during pandemic peaks. While the effect of this is uncertain, it is thought that this could have a significant impact on patient survival. Initial results reproduce the observed increase in the number of patients waiting.

1 INTRODUCTION

One of the secondary impacts of the Covid-19 pandemic has been the rise in the numbers on wait lists for elective procedures. Statistics from the UK showed that 4.7 million people were waiting to begin treatment in February 2021, the highest number since 2007 when records began (O'Dowd 2021). Returning wait lists to pre-pandemic levels will take years and considerable additional funding (Wood 2020) but there is also a need for changes to practice to improve efficiency and deal with the different nature of demand that health

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services will be seeing as we recover from the pandemic. In this article we consider the particular case of chronic heart failure (CHF) but we anticipate that the solution may have relevance to other conditions. Our aim is to show how changes in patient behavior during lockdown and reductions in the availability of appointments due to additional cleaning and other hygiene measures affect the length of waiting times for CHF patients.

CHF is loosely defined as ongoing poor heart function leading eventually to death by the heart ceasing to pump blood. There are many causes of CHF; for example, age, high blood pressure, and the result of damage after a heart attack, otherwise known as a Myocardial Infarction (MI). Expert clinicians cite median life expectancy post CHF diagnosis to be 5 years. CHF diagnosis is confirmed using an echocardiogram (echo), an ultra-sound scan for the heart which can be performed by consultant cardiologists or specially trained medical staff at heart clinics.

The number of patients per year with CHF is increasing slightly year on year, as is the median age (now approx. 65). Estimates suggest that around 650k people in the UK are currently diagnosed with CHF (The British Heart Foundation 2021) but expert clinicians believe closer to 950k are suffering from this condition. Pre-Covid-19 there were 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 typical year will have multiple appointments in the normal management of the condition (A. Campbell and A. Champneys and C. Currie and A. Heib and C. Lamas Fernandez and L. E. Morgan and P. Ross 2021).

During the Covid-19 pandemic the number of people diagnosed with CHF has fallen. From July to November 2020 the number of GP referrals were at 20% of pre-pandemic levels and the number of diagnostic echo tests from April and May 2020 were 31% of the number conducted in the same months of 2019. At any given time there is a population of undiagnosed people living with CHF in the UK. Some of these individuals will have been referred for diagnostic tests, but data suggests that many who may have developed CHF are yet to be identified. The impact of this on the health service is that more acute CHF patients are likely to present in a wave of patients post pandemic and these are likely to be more acute than usual. It is necessary to study the treatment of CHF as a system to understand bottlenecks and potential interventions post pandemic.

Questions of interest, identified by cardiology clinicians at Leeds General Infirmary are:

- Given an estimate of the current (mid-pandemic) level of demand for echos, how long will it take for service to return to pre-pandemic levels?
- What new interventions could be implemented to improve the effectiveness/efficiency of the CHF service as a whole and what impact will this have on the backlog?

CHF services cannot be modeled as a simple linear queue for which there is a backlog; rather it is an integrated system of disease progression and multiple treatment pathways. It seems that there is no current backlog on cardiologist waiting lists. Instead, there are significant numbers of patients who have not presented themselves to the system, or are stuck in one of the treatment pathways (e.g. waiting for echo diagnosis).

In this paper we present a discrete event simulation model of CHF patient pathways-to-diagnosis aiming to capture the sate of the service as a dynamic model in which patients both move through the healthcare system and their disease progresses. The model will be used to address the above questions, with this paper presenting our preliminary findings.

This project was initiated in the Virtual Forum for Knowledge Exchange in Mathematical Sciences (V-KEMS) Study Group on Modeling Solutions to the Impact of Covid-19 on Cardiovascular Waiting Lists (A. Campbell and A. Champneys and C. Currie and A. Heib and C. Lamas Fernandez and L. E. Morgan and P. Ross 2021), which covered a wider range of questions on this topic.

In Section 2 we introduce relevant background on the use of simulation for modeling patient pathways. In Section 3 we describe a generic model of CHF patient pathways-to-diagnosis, and describe how we modeled the input models and parameters used to drive this model in our experimentation using aggregate data from Leeds Health Trust. In Section 4 we present initial findings using this model and in Section 5 we conclude the paper with a discussion of what we have found so far and some thoughts on using this model to wider effect across the UK.

2 LITERATURE REVIEW

We now breifly look into the literature of modeling of cardiac conditions and waiting lists in relation to the Covid-19 pandemic.

In a quick response to the pandemic Currie et al. (2020) discussed prospective challenges that lay ahead and how simulation modeling (agent based, system dynamics and/or discrete event) might be used to respond to these. The potential impact of the pandemic on non-Covid-19 patients was identified in this paper with overloaded health services being unable to offer their usual level of care, and discrete event simulation suggested as a modeling tool to help with redesigning systems to cope with the changes in demand.

Salenger et al. (2020) discuss the reduction in adult cardiac surgery and the need to complete such procedures in a timely manner once restrictions ease. Their investigation considered increased hospital operating capacity post pandemic. Although a simple way to reduce the backlog, we must consider the impact this would have on medical practitioners. This is backed up by work carried out in the UK modeling the impact of Covid-19 on elective waiting times (Wood 2020) who use a discrete-time simulation model to execute a batch of events on each day of the modeling period. Their results suggest that returning to normal levels on wait lists will take considerable time and investment. Negopdiev et al. (2020) and Fowler et al. (2021) also consider the impact of Covid-19 on elective waiting times and use expert opinion combined with statistical models to estimate how long the health system would take to recover from cancellation/postponement due to Covid-19.

Due to the high numbers of patients waiting to begin treatment across a range of treatment areas there have been a number of recent publications in the modeling of waiting lists. Clarke et al. (2020) suggest a geographical approach to managing the after shock in elective surgery in England. They use an unsupervised graph-based clustering framework considering pooled waiting-lists delivered across a network of surgical providers to identify new surgical care models. Outside of the main academic literature, Wyatt and Woodall (2021) use a system dynamics model of waiting lists for planned care, which suggests that the return to normal levels on wait lists is likely to be a long process, made more complex by the lack of knowledge on patient and physician behavior.

3 MODEL DESCRIPTION

We use the STRESS checklist (Monks et al. 2019) to ensure that we have included all details of the modeling study in the paper and split our description into four sections covering the conceptual model and how it relates to the real system; a description of how the model is built; a list of parameter assumptions; and a description of the model outputs.

3.1 Conceptual Model

The conceptual model, given in Figure 1, explains the patient pathway from developing symptoms of heart failure to diagnosis. Patients enter the healthcare system through two routes, either via the GP or as an acute admission via the hospital. It is also possible for the patient to leave the model at any point when the disease becomes fatal. The path to diagnosis finishes with an echo test.

Patients are assumed to enter the model when they develop symptoms of CHF. This does not mean that all patients entering the model have CHF, but all patients follow the pathway until being diagnosed positively or negatively. We assume that patients enter the model according to a Poisson arrival process. One of the suspected impacts of the societal lockdown periods imposed to reduce Covid-19 transmission, has been a reduction in the number of patients seeking care for non-Covid-19 conditions, such as heart

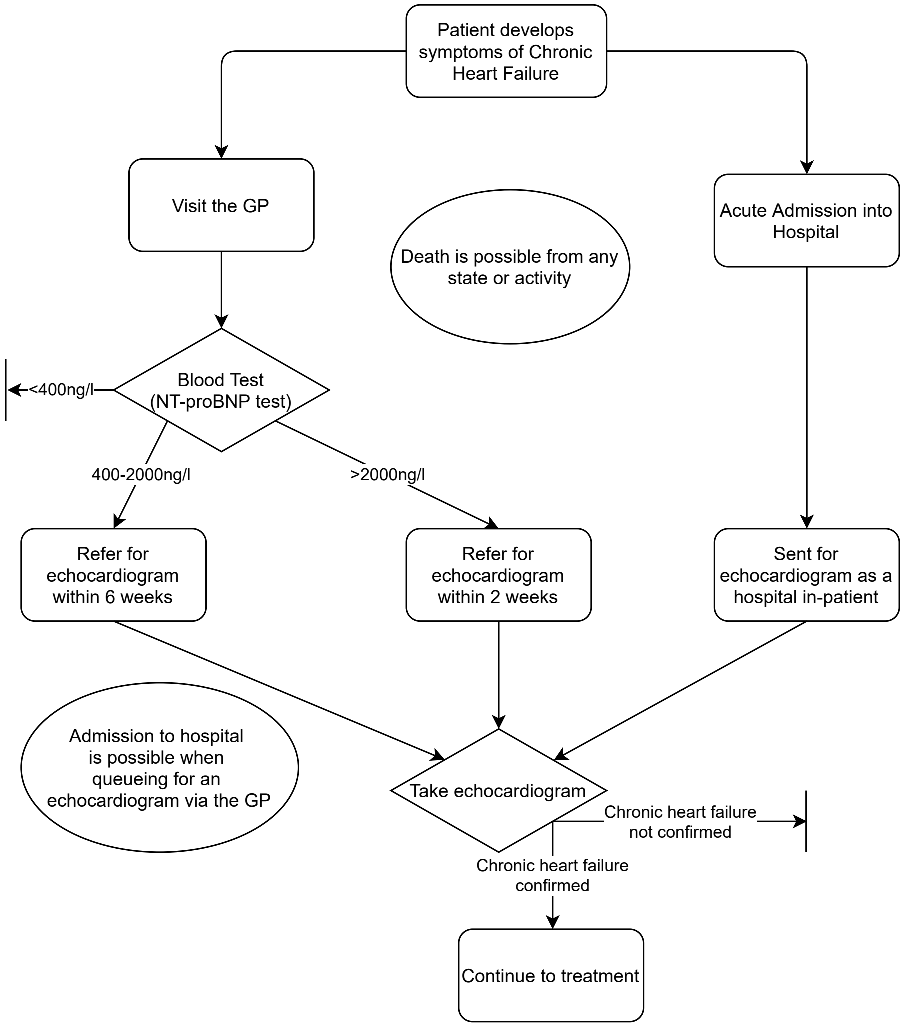

Figure 1: The conceptual model.

failure. We describe this effect through a delay. When the model simulates pre-pandemic times, after developing symptoms, patients wait a randomly generated time before deciding to visit either the GP or the hospital. If this decision occurs during a lockdown, then patients will be delayed an additional amount of time before visiting the GP or hospital. This delay has been modeled to have a rough maximum of about 2 months with a mode at about 2 weeks. This has been carefully modeled to match the 30% reduction in patients seeing the GP over coronavirus, specifically over a lock down. In future, it is expected the delay will be dependent on both the length of the lockdown, as patients might wait until the lockdown is over, and the severity of symptoms, as patients are less likely to wait if they have severe symptoms. Parameters are given in Table 1.

When a patient visits the GP with suspected heart failure a test is taken to measure the concentration of the NT-proBNP hormone in the blood. NT-proBNP is a hormone that helps regulate blood volume and a relatively high concentration of of this hormone is indicative of potential heart failure. If more than 2000 ng per litre is found in the blood the patient is referred to an echo appointment within 2 weeks. If this concentration is between 400 and 2000 ng/l the patient is referred to an echo within 6 weeks. Else, if there is less than 400 ng/l the patient does not get referred and leaves the system.

The alternative route occurs via an admission into the hospital. If a patient is admitted to hospital with suspected heart failure, it is likely they will be sent for an echo. This echo occurs with minimal delay whilst the patient is still in the hospital.

The echo is a complex resource to manage as it has two queues: a queue for inpatients and a queue for outpatients. In the model, we define in advance time periods where the echo will draw from the inpatient queue and time periods where it will draw from the outpatient queue. Estimates from a system expert suggest that 70% of the time the echo is used for outpatients, and outpatient echo tests are performed during weekdays. Then 30% of the time the echo test is used for inpatients and can be performed any day of the week. While the inpatient queue is first in first out, the outpatient queue is prioritised dependent on the result of the NT-proBNP test. The echo is observed to be the bottleneck in the system; particularly as a result of the Covid-19 pandemic when capacity has been reduced due to social distancing rules and additional cleaning requirements.

If the echo result suggests that the patient does not have heart failure, they will leave the system. Alternatively, if heart failure is confirmed then the patient will continue to treatment. The treatment is heavily dependent on the hospital. As treatment does not appear to be a bottleneck, it is not part of this initial model but a future extension will include modeling of different treatment types including medication based, implant and surgical treatments.

3.2 Model Design

The model is written in Python 3.8.3, using the simulation package SimPy 4.0.1 (https://simpy.readthedocs.io/en/latest/), a process-based discrete-event simulation framework based on standard Python. With SimPy, simulation environments can be created where events are handled. Calling process functions within the environment generates events through user-defined generator functions. For this research, the principle generator function defines the paths through which patients with suspected heart failure move from un-diagnosed to diagnosed. Other generator functions were also defined, one to impose delays on patients seeking medical advice during the pandemic, and another to manage the number of echos performed each day as this value has changed during the pandemic.

The key entities in the model are the patients who have the following attributes: blood test result and age. The echo is modeled as a resource with a fixed capacity per day, as given in Table 1. Other activities in the model, for example, visiting the GP and acute admission, are assumed to have an infinite resource. The justification for this is that heart failure patients make up only a small proportion of the total demand for these services. The impact of the pandemic on GP attendance/capacity is hard to approximate as GP surgeries have employed alternative strategies such as telephone appointments to meet demand. This leads us to believe that any back-log of appointments is less of a problem than the back-log for diagnostic procedures like echocardiograms where anything but in-person appointments are simply not possible.

3.3 Parameter Assumptions

At this stage of the modeling project, the majority of the parameters used are derived from expert opinion or from publicly available data. Expert opinion was provided by cardiology clinicians from Leeds Health Trust. Although model parameters currently align with the Leeds cardiology department, pathways-to-diagnosis for CHF patients are similar across the UK. Table 1 lists the parameters, their values and, where relevant, the source used to derive their values. It is assumed that 6 patients per day develop symptoms for heart failure. This has been inferred from national data, where 200,000 people per year are diagnosed with heart failure, divided down to the regional level in Leeds. The age of patients arriving to the system is determined directly by NHS data via an empirical distribution.

Considering the different pathways to diagnosis via the GP, hospital or death we take advantage of statistical modeling. For the blood test result we assume a simple linear model in which age is a covariate. For the time between symptoms and visiting the GP, the hospital or death we use survival analysis models.

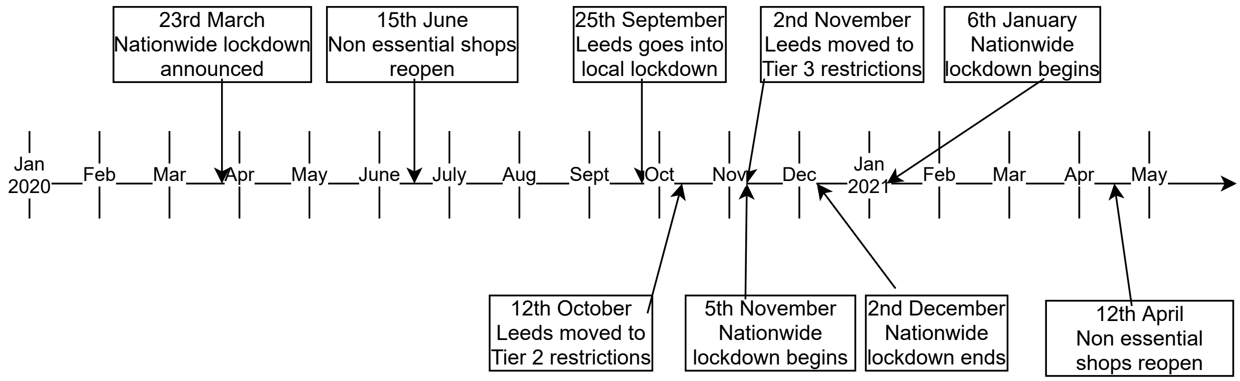

Figure 2: A timeline of Covid-19 restrictions in Leeds.

In particular, the Cox proportional-hazard model (Kleinbaum and Klein 2012). This models the risk of one of these events happening based on a patient's covariates. The covariates we have chosen are age and NT-proBNP hormone blood test result. The latter is used as a proxy of overall health of the patient since a higher NT-proBNP concentration in the blood is related to a higher chance of heart failure.

For the echocardiogram parameters we stick to a deterministic 40 minutes for each echocardiogram appointment as suggested by cardiology clinicians. In reality, echo tests can last between 15 minutes to an hour but this time scale is short in terms of the time scale of the simulation so the simplifiying assumption is acceptable. The echocardiograms are split between the inpatients and outpatients at a ratio of 3:7

We take the day of coronavirus affecting the UK as the date of the first lockdown beginning. This is 23 March 2020. After this point, the total available echo tests a day reduced from 10 to 8. This reduction occurred due to increased cleaning requirements between each echo appointment. Cardiology clinicians suggest that the impact of this reduction in appointments has affected mostly the outpatient service. For this reason, we have reduced the daily capacity of outpatient echos from 7 to 5.

Capturing the behavior of people during the Covid-19 pandemic is difficult. In future we hope to model this behavior based on the severity of symptoms of the patient. For now, we chose a random delay to match a 30% reduction in seeking help for symptoms. This effect only occurs during a lockdown to capture the reluctance of patients to seek help; as lockdowns are lifted and then reimposed, the delays react to reflect attitudes becoming better or worse over the year.

We want to capture patient confidence over the last 15 months of Covid-19 restrictions. Using Leeds as our base city we define two periods of stricter restrictions. A detailed timeline can be seen in Figure 2. The first lockdown restrictions begin at the start of the first lockdown in England on 23 March 2020. We have chosen to define this period of lockdown as ending on the 15 June when non-essential shops reopened. After the summer, Leeds entered a local lockdown on the 25 of September and moved through regional and national restrictions until a full England-wide lockdown on 6 January 2021. We define the date this lockdown ended as 12 April 2021, the date non-essential shops reopened.

3.4 Model Outputs and Validation

The key model output in this article is a time series of the number of people waiting for an echo. In order to compare the impact of delayed treatment, the model will also output the number of deaths that occur before receiving an echo and the total number of deaths observed over a given time period.

Throughout the construction of the conceptual model we had regular contact with cardiology clinicians at Leeds Health Trust, this enabled us, to an extent, to perform white box validation of the behavior of the patient pathways. When we gain access to aggregate level patient data we will be able to quantitatively validate the behavior of the base-line model.

Table 1: Model parameters including the distribution used, their values in the base case, covariates and the source (where relevant) for their values.

Parameter	**Distribution/ Model**	**Base Value/ Covariates**	**Source**
Patient Arrival	exponential	Exp(1/6)	BHF
Age	empirical		NHS
GP Path			
NT-proBNP Result	Linear	Age	NHS
Time to see GP	Cox P-H	Age, NT-proBNP Result	NHS
Hospital Path			
Time to hospital admission	Cox P-H	Age, NT-proBNP Result	NHS
Death			
Time to Death	Cox P-H	Age, NT-proBNP Result	NHS
Echocardiogram			
Echo appointment time	deterministic	40 minutes	NHS Direct
Inpatient echos per day	deterministic	3	NHS
Outpatient echos per day	deterministic	7	NHS
Covid			
Lockdown delay to see GP	Gamma	Gamma(2, 14)	
Inpatient echos per day	deterministic	3	NHS
Outpatient echos per day	deterministic	5	NHS
Lockdown 1 start		23-03-2020	
Lockdown 1 end		15-06-2020	
Leeds restrictions start		25-09-2020	
Restrictions ease		12-04-2021	

4 PRELIMINARY RESULTS

Figure 3 shows the average number of people in the queue each day between January 2020 up until December 2021. Similarly, Figure 4 shows the average number of days that a patient had to wait for their echocardiogram as an inpatient and an outpatient. This simulation was run after a warm up period of 6 months from an initial state in which the queue lengths are zero. Results are output daily showing the number of patients on the wait list for an echo as both an inpatient and an outpatient. In the results presented below we ran 100 replications of the simulation model and take the average at each day. We also include 90% confidence intervals (CIs) estimated by finding the 5th and 95th values in a non-decreasing list of outputs.

The top plot of both Figure 3 and 4 represents the queue/ wait times for people getting echocardiograms as an outpatient and the bottom as an inpatient. The outpatient queue begins with a large number of people waiting for the test. This is normal behavior since they queue for the test for 2-6 weeks before they receive it. The inpatient queue begins at zero. This is perfect behavior since we wish for patients admitted to hospital to be seen whilst still in hospital without any delay

Lockdown 1 begins on the 23rd March 2020. At this time people delay seeing the GP about their symptoms. After the first lockdown the queues for the GP increase dramatically whilst people gain confidence in contacting their GP. As a result of both patients stalling seeing the GP and the longer queue times for outpatients the hospital queue times jump dramatically after some delay. This occurs since people are getting ill waiting for their outpatient echocardiogram. This is a big problem since, on average, these inpatients would have to wait 20 days for an echocardiogram.

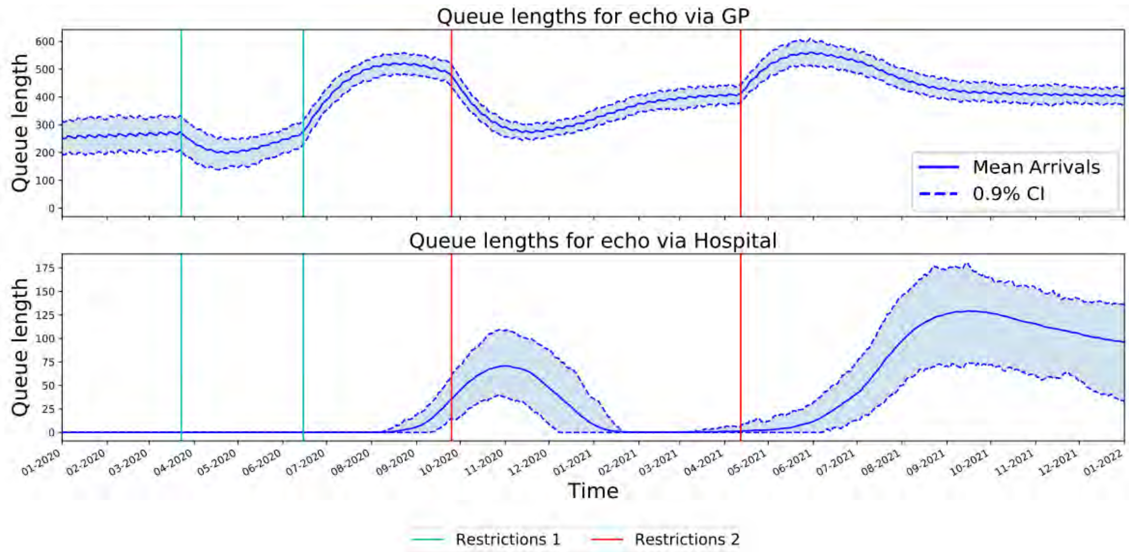

Figure 3: Average number in GP and Hospital queues from Jan 2020 - December 2021 with 90% CIs.

Figure 4: Average wait times for both GP and hospital queues from Jan 2020 - December 2021 with 90% CIs.

On the 25th September 2020 Leeds started a local lockdown which then led to the city being placed in different regional and national lockdowns. Over this lockdown the outpatient queue reduces again and this reduction results in the inpatient queue going back to zero. Towards the end of the second set of restrictions the queue numbers for the outpatient queue return to their pre-Covid numbers and we begin to see a similar effect of the first lockdown during the second.

The concerning part of these results come after the second lockdown. Both queues peak as restrictions ease and people gain confidence in seeing the doctor again but during the second peak the inpatient queue does not settle back to zero as quickly as the first. This is a problem as there is a need to carry out inpatient echocardiograms quickly so an appropriate treatment plan can be administered. Under the assumptions of our modelling estimates suggest that ill patients could wait 30 days to be seen. It is clear from this simulation that the Covid-19 restrictions have caused an increase in inpatients with chronic heart failure, and that this impact could cause long-term backlogs at the point of diagnostic testing. Looking into the results more closely we suspect the cause of this is the delay in accessing the GP due to the national/local lockdowns, which has the knock on impact of more outpatients becoming ill enough to need acute care.

5 CONCLUSION AND FUTURE WORK

In this paper we presented a model for CHF patient pathways-to-diagnosis using discrete event simulation. Initial results show that, without taking any intervening action, the number of outpatients waiting for a diagnostic test may increase, and the number of inpatients waiting for a diagnostic test is likely to be much higher than pre-Covid levels with a slow recovery trajectory. The behavior of the number-in-queue measure aligns with our initial belief that post-lockdown more acute CHF patients are likely to present, and that those patients are likely to be in a more advanced stage of disease than usual. Future work will consider how the average time spent waiting for diagnosis impacts on outcomes such as average survival time.

The preliminary results above sought to replicate the number in system from the start of the pandemic and infer the impact this would have in the near future (December 2021). Note that the estimates of the average number in the GP and hospital queues in Figure 3 do not account for any future lockdowns that might occur past April 2021. Instead they illustrate what we might expect to happen if no action was made to reduce waiting lists for diagnostic echo tests. This provides us with a baseline ‘no action’ scenario which could be compared to the output of alternative scenarios where a single or a number of interventions are taken to reduce waiting lists. For example if the number of echocardiograms was increased back to pre-Covid levels this could be used to clear the backlog of inpatients waiting for tests, or used for outpatients with the aim of reducing the number of those waiting for diagnosis that are rushed to hospital. One future step in this project will be to design a set of experiments to estimate the impact of possible interventions. To ensure feasibility the suggestion of interventions will be led by cardiology clinicians.

One of the interesting dynamic elements in this problem is the fact that patients can deteriorate whilst waiting for diagnosis, and ideally we would like to be able to model this deterioration. One way of doing this would be to use a hybrid simulation approach where the pathways/healthcare system are modeled using discrete event simulation and the health of individual patients is modeled using system dynamics. One of the barriers to this modeling is that there is little understanding of how CHF progresses without treatment, and our model parameters are driven by expert knowledge and/or empirical data. Using the proxy of the NT-proBNP hormone from the blood test we might estimate the rate of deterioration of a patient with CHF but without treatment by looking at the hormone level through time after referral. This would require multiple readings of the NT-proBNP instead of just the single hormone reading on the first visit to the GP.

At the end point of this project we aim to have a model of patient pathways-to-treatment for CHF, and a tool that can be used by cardiologists to enable them to test different interventions to improve patient outcomes and speed up the return to pre-Covid functionality. This means extending the model beyond the stage of diagnosis, the key issue in this paper, to incorporate different treatment regimens. It is our current understanding that the pathway-to-diagnosis for a CHF patient is similar in most medical settings in the UK. The treatments post diagnosis can however be quite different and depend on the available health care provision in an area. To deal with this we plan to construct our model in a modular fashion to allow different treatment options to be plugged in depending on which treatments are available. The extension of the model to treatment post-diagnosis will allow us to estimate treatment outcomes based on survival times to more accurately see the impact of possible interventions on CHF patients. The modular design will also allow the model to be extended to other illnesses. For example, cancer screening rates have also seen reductions during lockdown periods causing worsening outcomes for patients (Maringe et al. 2021).

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