COVID-19: Generate and apply local modelled transmission and morbidity effects to provide an estimate of the variation in overall relative healthcare resource impact at general practice granularity

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Abstract

Introduction: Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) is the name given to the 2019 novel coronavirus. COVID-19 is the name given to the disease associated with the virus. SARS-CoV-2 is a new strain of coronavirus not been previously identified in humans.

Methods: Two key factors, case incidence and case morbidity, were analysed for England. When taken together they give an estimate of relative demand on healthcare utilisation. To analyse case incidence, the latest values for indicators that could be associated with infection transmission rates were collected from the Office of National Statistics (ONS) and Quality Outcome Framework (QOF) sources. These included population density, %age >16, at fulltime work/education, %age over 60, %BME ethnicity, social deprivation as IMD2019, location as latitude/longitude, and patient engagement as %self-confident in their own long-term condition management. Average case morbidity was calculated. To provide a comparative measure of overall healthcare resource impact, individual GP practice impact scores were compared against the median practice.

Results: The case incidence regression is a dynamic situation but it currently shows that Urban, %Working, and age >60 were the strongest determinants of case incidence. The local population comorbidity remains unchanged. The range of relative healthcare impact was wide with 80% of practices falling at 20%-250% of the national median. Once practice population numbers were included we found that the top 33% of GP practices supporting 45% of the patient population would require 68% of COVID-19 healthcare resources. The model provides useful information about the relative impact of Covid-19 on healthcare workload at GP practice granularity in all parts of England.

Conclusion: Covid-19 is impacting on the utilisation of health/social care resources across the world. This model provides a way of predicting relative local levels of disease burden based on defined criteria, thereby providing a method for targeting limited care resources to optimise national/regional/local responses to the COVID-19 outbreak.
Take home message for the clinician

We have developed a model that provides a way of predicting relative local levels of disease burden based on defined criteria, thereby providing a method for targeting limited care resources to optimise national/regional/local responses to the COVID-19 outbreak.

1 | INTRODUCTION

The coronavirus, first detected in China in 2019, is genetically closely related to the SARS-CoV-1 virus. SARS emerged at the end of 2002 in China and it caused more than 8000 cases in 33 countries over eight months. Around one in ten people who developed SARS died.1

By the 12th March 2020, the COVID-19 outbreak has caused a total of around 142 539 confirmed (9769 new) cases reported globally with around 1200 in the United Kingdom alone. Of these proven cases, around 5393 deaths have been reported because of the virus (around 3.8% mortality rate).2 Unlike influenza, there is no vaccine and no specific treatment for the disease.

The implications for countries after a period of unprecedented demands on all aspects of health and social care resources, a degree of reconfiguration of services will be required in the longer term. In the United Kingdom, emergency planning is well underway although a key challenge is the capacity of secondary care to manage admissions of unwell patients and primary care (GP practices) to manage those who not requiring hospital admission.3 During an outbreak, decision-makers face surges in resource demand which require resource prioritisation and re-allocation.4 Predicting areas of greater need is, therefore, critical to optimise the value of limited resources and funding in the response to the COVID-19 pandemic.

Response to infectious diseases is carried out in different phases, the Government has recently under the advice of Public Health England moved the disease from containment strategy to delay strategy where slowing the onward transmission rate is the priority. Later stages might require other strategy changes.

This paper describes the development of a resource allocation prediction model for COVID-19 based on a regression analysis of published case rates in England across upper-tier local authority areas (UTLA) against key local population metrics aggregated up from local GP practices.

It is worth noting that these published case numbers are only those that have tested positive either from existing patient contacts or sufficiently symptomatic to be triaged to healthcare services. At this time around 3% of those tested show positive results, while it is estimated that unreported cases could be more than 20 times higher than reported; however, the latter remains the only marker for local levels of the condition. The situation is also changing on a real-time basis as the case numbers grow and move from initial infection to community transmission, and the mitigation measures start to work through.

What’s known?

- The coronavirus, first detected in China in 2019, is genetically closely related to the SARS-CoV-1 virus.
- For countries around the world, there have been unprecedented demands on all aspects of health and social care resources.
- In the United Kingdom, a key challenge is for primary care (GP practices) to manage those who not requiring hospital admission.

What new?

- We have shown that for England, the top 33% of GP practices supporting 45% of the patient population will require 68% of COVID-19 healthcare resources.
- This model provides a method for predicting relative local levels of disease burden based on defined criteria and thereby providing a method for targeting limited care resources to optimise national, regional, and local responses to the COVID-19 outbreak.

2 | METHODS

Two key factors were analysed which when combined would give an estimate of relative demand on healthcare utilisation in England. These factors were case incidence and case morbidity. GP Practice level data were used as this provided the most geographically granular source of published public population data. To analyse case incidence, the latest values for indicators that could be associated with infection transmission rates were collected from the Office of National Statistics (ONS) and Quality Outcome Framework (QOF) sources. These local factors included.

- Urban/Rural (Population density as people/sq km),
- Practice Location as latitude and longitude
- % Practice Population age >16 in fulltime work/education,
- % Practice Population age over 60
- % Practice with BME ethnicity
- Practice average social deprivation as IMD 2019
- % of Practice population with longer-term health conditions
- Patient engagement as % reported self-confidence in their own long-term condition management.

A dataset was then created by aggregating data from all the GP practices within each UTLA. A stepwise regression analysis was then performed linking these metrics against the latest number of identified cases of COVID-19 in each UTLA area as published by Public Health England5 divided by the total population. The factors are inter-related and the total number of factors was kept small, while maximising the model variation capture.
Applying the regression coefficients for the final chosen indicators to actual practice values gave an estimate for the relative COVID-19 incidence values for expected local cases/population, this was divided by the result of the same calculation applying the national median practice values to give the practice relative incidence rate as % of the national median.

Relative case morbidity was calculated by applying the published odds ratio (OR) analysis taken from international COVID-19 data on mortality to the local GP practice population percentage prevalence for the number of patients by age groups and with comorbidities including diabetes, coronary heart disease, chronic obstructive pulmonary disease (COPD) and cancer, and then divide by the same.
value calculated the using national average values to give a relative practice relative case morbidity for COVID-19 infection.

Multiplying the practice relative incidence rate by practice relative case morbidity gave the overall practice health care resource impact/patient relative to the national median. Then multiplying this by practice population size divided by the national median practice size gave a total health care resource prediction relative to the median practice.

It was not appropriate or possible to involve patients or the public in the design, or conduct, or reporting, or dissemination plans of our research.

Ethics permission was not required as the analysis utilised data available in the public domain. No patient identifiable data were used. The modelling reported in this paper used aggregated anonymised data.

3 | RESULTS

The situation is very dynamic and fluid with the number of cases being published daily, the first publication on 8th March, 2020, gave 224 cases in 74 UTLAs. The chosen factors and their significance within the statistical model are also changing with time.

The current regression model data were updated on the date of submission of this paper (16.03.2020) from 149 UTLAs of which 136 had recorded one or more out of a total of 1,421 cases in England. The analysis of COVID-19 incidence of infection showed significant positive relation to three key factors: population density, % of the >16 population in full-time at work/education, and % of the population over 60 (r² = 0.45 and all P-values <.05).

The relative accuracy of the model can be seen in Figure 1 where the model and actual outcomes of cases/population for each UTLA in England are divided into three terciles. Each UTLA is plotted geographically and divided into terciles with the model colour on the outer and the actual colour on the inner. About 50% of the model's values fall in the same tercile as the actual, 41% in an adjacent tercile and 9% have a two tercile difference (if a model contained no link these values would be 33%, 45%, 22%, respectively).

The application of the extrapolation using regression coefficients and OR combined with each practice’s actual population characteristics shows a wide variation in expected cases and overall local morbidity. Combining these two gives a measure of overall expected COVID-19 healthcare resource impact and this divided by the median GP practice value gives a relative impact. In Figure 2 below, the median practice is shown as 100% of relative healthcare impact, with the highest 10% of GP practices > 210% and lowest

![Figure 2](https://via.placeholder.com/150)

**FIGURE 2** Outcome of GP Practice Health Resource Impact Model showing expected COVID-19 impact/patient on each practice as % to the median value. The results are then multiplied by practice size, sorted, and added cumulatively to show how much of the overall impact might fall on certain practices

| Parameter                           | Mean value | Median value | Estimate coeff | P-Value | Standardised beta |
|-------------------------------------|------------|--------------|----------------|---------|------------------|
| UTLA population                     | 400 053    | 309 923      |                |         |                  |
| Actual cases/000 population         | 0.024      |              | 0.014          |         |                  |
| Constant                            | -0.10351   |              |                 | <.0001  | 0                |
| Urban/rural (population/sq km)      | 3131       | 1925         | 7.47E-06       | <.0001  | 0.75             |
| >16 in FT Work/Edu as % Pop         | 51.9%      | 51.0%        | 0.137          | .036    | 0.18             |
| Age %>60                            | 17.8%      | 18.2%        | 0.155          | .013    | 0.26             |

**TABLE 1** Regression results Linking Reported 1421 COVID-19 Cases on 16-3-2020/000 population to three selected factors in 149 UTLAs with 60 million population
10% having < 15% of the median. It was multiplied by the relative practice population number and summed cumulatively to show that 33% of GP practices carry the highest COVID-19 impact by the number of cases and severity, they support 45% of the patient population and would carry 68% of COVID-19 healthcare resource impact. Specific practices at risk can be identified by their position on these curves.

The authors note that two additional datasets, if and when available, could enhance the predictive capability of the model: local total number of tests and split of tests by numbers and result, by known associate or community to give estimates for the level of non-detected, self-managed, and populations.

The model both in factor inclusion and resulting values will have to be adjusted on an ongoing basis as the epidemic goes through the recognised infection phases.

4 | CONCLUSION

The COVID-19 outbreak has impacted on the utilisation of health and social care resources across the United Kingdom and the rest of the world. Linking local case data to local population characteristics provides a method to estimate the difference in expected levels of disease between different populations at the required levels.

The factors identified as relevant in the current regression model align with the current strategy of increasing work from home and closing education and reducing social contact especially among older people which should reduce transmission rates. As the situation progresses, the transmission drivers will modulate and as further data are available the model can be reviewed, evolved, updated and reissued.

This analysis could not evaluate directly the impact of COVID-19 on 111 services, ambulance services, accident and emergency (A/E) departments, and admissions into hospital. However, the impact of expected local incidence and severity of COVID-19 infection cases will also vary across these services and so place different levels of pressure on these resources. While all services will be impacted considerably, this analysis of variation at general practice levels can if useful be added together for localities to show which hospitals and other services would be more or less impacted to assist in prioritisation of limited resources (for example personal protection equipment and ventilators, etc).

This model provides a method for predicting relative local levels of disease burden based on defined criteria and thereby providing a method for targeting limited (and perhaps soon to be scarce) care resources to optimise national, regional, and local responses to the COVID-19 outbreak. We hope that our model will aid precious resource allocation at this very challenging time (Table 1).

CONFLICT OF INTEREST

No author had support from any organisation for the submitted work; no financial relationships with any organisations that might have an interest in the submitted work in the previous three years, no other relationships or activities that could appear to have influenced the submitted work.

AUTHOR CONTRIBUTION

Mike Stedman conceived this piece of work and led on the data analysis while creating the first draft. Mark Lunt reviewed the statistical methodology and checked all the estimates, while also reviewing the paper at all stages of drafting. Mark Davies assisted in the writing of the paper at all stages and provided the necessary resources for the work. Martin Gibson provided objective scrutiny of the work. Adrian Heald developed the methodology with Mike Stedman, assisted in the writing of the paper at all stages.

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REFERENCES

1. European Centre for Disease Prevention and Control; 2020. https://www.ecdc.europa.eu/en/novel-coronavirus-china/questions-answers. Accessed 16 March 2020.
2. WHO COVID-19 Situation Report 54. https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200314-sitrep-54-covid-19.pdf?sfvrsn=dcd46351_6. Accessed 16 March 2020.
3. Kings Fund; 2020. https://www.kingsfund.org.uk/blog/2020/03/spring-budget-mean-health-and-care. Accessed 16 March 2020.
4. Stein, M.L., Rudge, J.W., Coker, R., et al. 2012. Development of a resource modelling tool to support decision makers in pandemic influenza preparedness: The AsiaFluCap Simulator. BMC public health, 12(1), 870. https://bmcpublichealth.biomedcentral.com/articles/10.1186/1471-2458-12-870. Accessed 16 March 2020.
5. https://www.gov.uk/guidance/coronavirus-covid-19-information-for-the-public. Accessed 16 March 2020.
6. Estimation of risk factors for COVID-19 mortality - preliminary results Francisco Caramelo, Nuno Ferreira, Barbara Oliveira. https://doi.org/10.1101/2020.02.24.20027268

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