Drivers of crowding in type 1 EDs: econometric model and its implementation in R

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Key question

What drives crowding in type 1 A&E departments?
Our analysis aims to take a whole system approach looking at the drivers of crowding covering pre-hospital, within A&E, rest of hospital and wider healthcare capacity.

To the best of our knowledge our analysis quantifies robustly, for the first time, the effects of key factors on ED crowding.

1. We **isolate** and **quantify** the effect of each factor of crowding we consider.
2. We develop 3 **new ED crowding metrics**.

Why is crowding important?

Previous research shows that crowding is associated with **increased patient mortality**, **reduces the quality of care**, **compromises patient privacy and dignity**, and **compromises the ability to deliver basic nursing care**. COVID-19 has made ED crowding worse, by requiring longer, deeper cleans, and social distancing.

Crowding can occur for three types of ED patients – **majors**, **minors** and **resus**.

Majors are patients with more complicated injuries or illnesses, such as shortness of breath or hip injuries

Minors are the least seriously injured or ill patients, with injuries such as ankle or wrist injuries

It is expected to be less of a problem in **resus,** as these are the most seriously injured or ill patients

Our crowding metrics

Overall crowding: Number of patients staying at ED. This metric counts the number of patients who are present at each time slot irrespective of whether they were discharged in a later slot or arrived in an earlier one.

6 hours + stays: Number of patients staying longer than 6 hours at ED. This is a subset of the overall crowding metric. It counts the number of patients who would have been staying for 6+ hours by the end of the slot or their discharge time – whichever is earlier.

Cubicle crowding: Number of majors and resus patients staying in the ED per cubicles (majors and resus). We sum the overall crowding metric for majors and resus patients (for a given site/day/time slot) and divide by the number of majors + resus cubicles for that site.

Econometric model

Econometric analysis enables us to isolate the impact of the different factors on crowding in ED's. We created separate models to look at three measures of crowding for **majors, minors and resus**. We divided the day into six 4-hour slots. We estimate the effect of the various factors on "overall crowding" and "6+ hour stays" for each slot and type of patient. We also look at the effect of the various factors on "cubicle crowding" for major+resus patients (and for each of the 6 time slots).

$$y_{it} = \boldsymbol{\gamma_{it}}'\boldsymbol{PreHosp} + \boldsymbol{\mu_{it}}'\boldsymbol{InED} + \boldsymbol{\omega_{it}}'\boldsymbol{RestHosp} + \boldsymbol{\sigma_{it}}'\boldsymbol{WiderCap} + \alpha_i + \varepsilon_{it}$$

Crowding metric by acuity type | Vector of pre-hospital factors | Vector of within ED factors | Vector of wider hospital factors | Vector of wider capacity factors | Fixed effect (time-invariant)

We use a fixed effects OLS regression model.

Our data is aggregated to a daily-site-level panel structure.

Sites may differ along a number of dimensions that are difficult to measure and may affect the relationships we observe between our variables and crowding metrics. Such difficult to observe factors may include geographical differences (i.e. how easy access to a site is) or how each site deals with patients on the cusp of breaching the four hour standard.
While we cannot directly measure the effect of those factors on crowding, our modelling approach, through the fixed effects, minimises the danger that our results are affected by their non-inclusion.

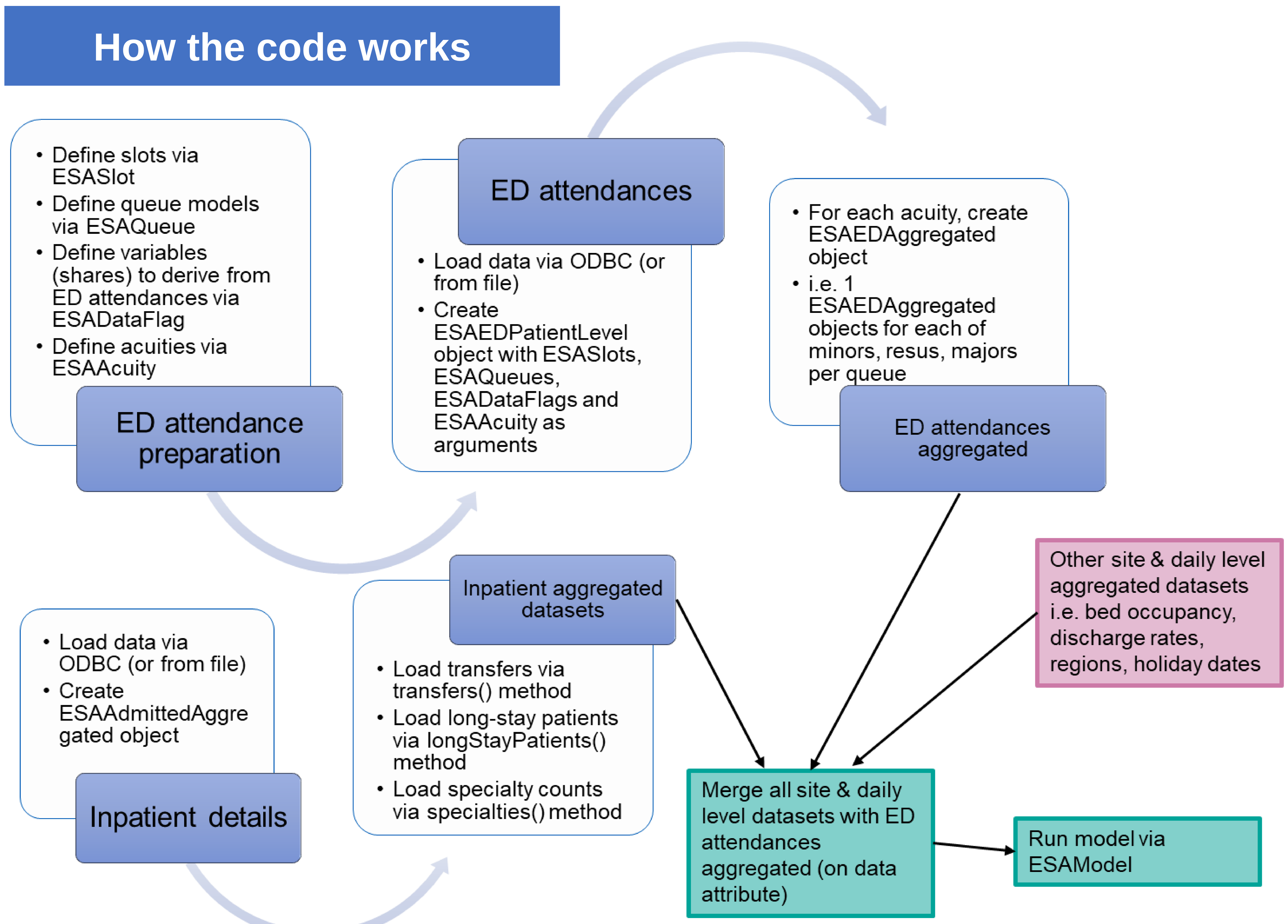
Developing our code

We developed a package in R, available on NHS England's GitHub that is database-agnostic, user-friendly and customisable

The code is open source meaning other teams at NHSE&I and the wider system can run and build on the model using their own data

We use packages such as data.table, fixest, R6 and ggplot2

How the code works



Resources

Access our code (with example) at GitHub: http://github.com/NHSEngland/ESA_ED_Crowding

Watch an in-depth tutorial on using our code recorded at the NHS AnalystX Mini-huddle: https://future.nhs.uk/DataAnalytics/view?objectID=33635440

Read our previously published work in the Emergency Medical Journal: Steven Paling, Jennifer Lambert, Jasper Clouting, Júlia González Esquerré, Toby Auterson (2020) **Waiting times in emergency departments: exploring the factors associated with longer patient waits for emergency care in England using routinely collected daily data**.

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