

Lay Summary

Approaches to projecting future healthcare demand

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Introduction: To plan services and staff for the National Health Service (NHS), the government needs to know how much demand for services will rise and how much to spend on the NHS in future. These future estimates are known as *projections*: they indicate how much demand might rise or how much might be spent if certain assumptions hold true.

Published estimates of the amount of future NHS spend vary widely. This is partly because of uncertainty about how much demand for health care will rise in future, but also reflects differences in the statistical approaches used and the assumptions made.

Our aim was to describe and critically assess alternative statistical methods for projecting future healthcare demand and expenditure.

Methods: We assessed four ways of projecting future healthcare demand and expenditure.

1. macro-level modelling

There are two general approaches. ‘Extrapolation’ modelling bases projections on past trends in healthcare demand (or expenditure) that are assumed to continue. ‘Computed General Equilibrium’ modelling uses economic theory to define the relationship between past and future values of drivers of demand (or expenditure).

2. macrosimulation

Using information on baseline health care for groups of individuals, and making assumptions about how these groups will grow in size in the future, macrosimulation models project scenarios of future healthcare demand and expenditure.

3. microsimulation

Using data on individuals and modelling how individuals change their behaviour when there is a policy change, microsimulation models simulate and project the impact of policies on future healthcare demand and expenditure.

4. machine learning

Machine learning is a collection of different prediction ‘algorithms’ (set of rules) that ‘learn’ information directly from data without relying on a predetermined specification of a model.

First, we consider how appropriate these techniques are. This depends on the aim of the modelling exercise, for example, to assess the impact of policy changes, to understand causes of rising demand, or to project future healthcare expenditure. Second, we consider the costs of developing and running the statistical models. This depends on how much data they require, how expensive they are to develop and maintain and their running times. Third, we consider how accurate the techniques are in terms of the values they provide and how well they fit the data. We also consider how easy the techniques are to use and understand. Lastly, we assess how straightforward it would be to update them.

Discussion: Each of the four techniques has both strengths and limitations. The choice of technique depends on the policy maker's objectives – what they are trying to achieve and how they prioritise different aims, what data are available and the time horizon of interest, e.g. 5, 10 or 20 years. For example, machine learning and macro-level models would likely provide the most accurate models for longer-term projections, but macrosimulation or microsimulation models are more suitable for testing the potential impact of changes in policy.

Full paper available at

https://www.york.ac.uk/media/che/documents/papers/researchpapers/CHERP186_projecting_healthcare_demand.pdf

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