5 Using prediction machines in policy

Predictive modelling supports policy at two levels. The first is the role of predictive modelling to help determine priorities for health policy, such as risk adjustment models for resource allocation, models of future demand for health, models of future health status, and labour market models. The second is how modelling is used to inform decision-making about health service delivery itself, either to groups of patients or to individuals. For instance, current health policy tends to prioritise the identification of the very high intensity users of unplanned secondary care.

Models therefore augment decisions through better use of information. Modelling the future, though, is always uncertain, so predictions are only useful when they provide guidance to decision-makers to some acceptable level of meaning.

In policy, the use of models depends on understanding what decisions the models are to provide help with. -- how can models help optimise the decisions we need to make?

Therefore, we are faced with technical questions leading to a better understanding of prediction machines:

Will a model help me make a better decision?

Does 'this particular problem' need a model to ensure a better decision?

What constraints affect the choices I can make using models in making better decisions (e.g. organisational, knowledge, legal)?

The link between prediction machines and time

Prediction implicates a future orientation and shifts us from considerations based on the immediate present to considerations in the future. The time frames chosen help define what sort of approach to prediction is most appropriate.

We also need to understand the role models can play by being clear about a distinction between 'real-time' applications and those that are predictive. Real-time applications provide decision-support functionality to help people make decisions now, in the present, while predictive applications involve modelling of future health states to create the possibility of anticipating the future, and perhaps based on modelling real time data. Prediction machines can be very useful in real-time applications in aiding present decision-making to avoid or preempt future problems, such as a potential exacerbation of a patient's health status.

To help put time into perspective, Table 2 maps out the temporal aspects of predictive modelling by providing thresholds across which different uses of prediction are applicable.

<table>
<tr><th colspan="5">Temporal Thresholds for Predictive Modelling</th></tr>
<tr><td rowspan="2">Who</td><td colspan="4">Model Focus on …</td></tr>
<tr><td>Individuals</td><td>Groups of identified people</td><td>Anonymous Populations</td><td>Society</td></tr>
<tr><td rowspan="2">Time</td><td>Short-term</td><td colspan="2">Medium-term</td><td>Long-term</td></tr>
<tr><td>A few days, weeks</td><td>1 to 2 years</td><td>3 to 15 years</td><td>Inter-generational to 50+ years</td></tr>
<tr><td rowspan="4">Focus

Exx.</td><td colspan="2">Identified people with disease conditions</td><td colspan="2">Whole populations health status</td></tr>
<tr><td colspan="2">Identified high-risk / high need individuals</td><td>Emergent high-risk and high need determinants</td><td>Impact of long baseline determinants of health</td></tr>
<tr><td rowspan="2"></td><td>Resource allocations based on financial cycles</td><td>Resource allocations based on economic models</td><td rowspan="2"></td></tr>
<tr><td colspan="2">Infrastructure and system resource needs for development</td></tr>
<tr><td>Exx</td><td>Disease progression

Prescription effectiveness and compliance

Waiting times

Seasonal consumer behaviour</td><td colspan="2">Epidemiology

Infrastructure planning

Resource allocation

Workforce planning

University enrolments

Immigration</td><td>Climate

Demography

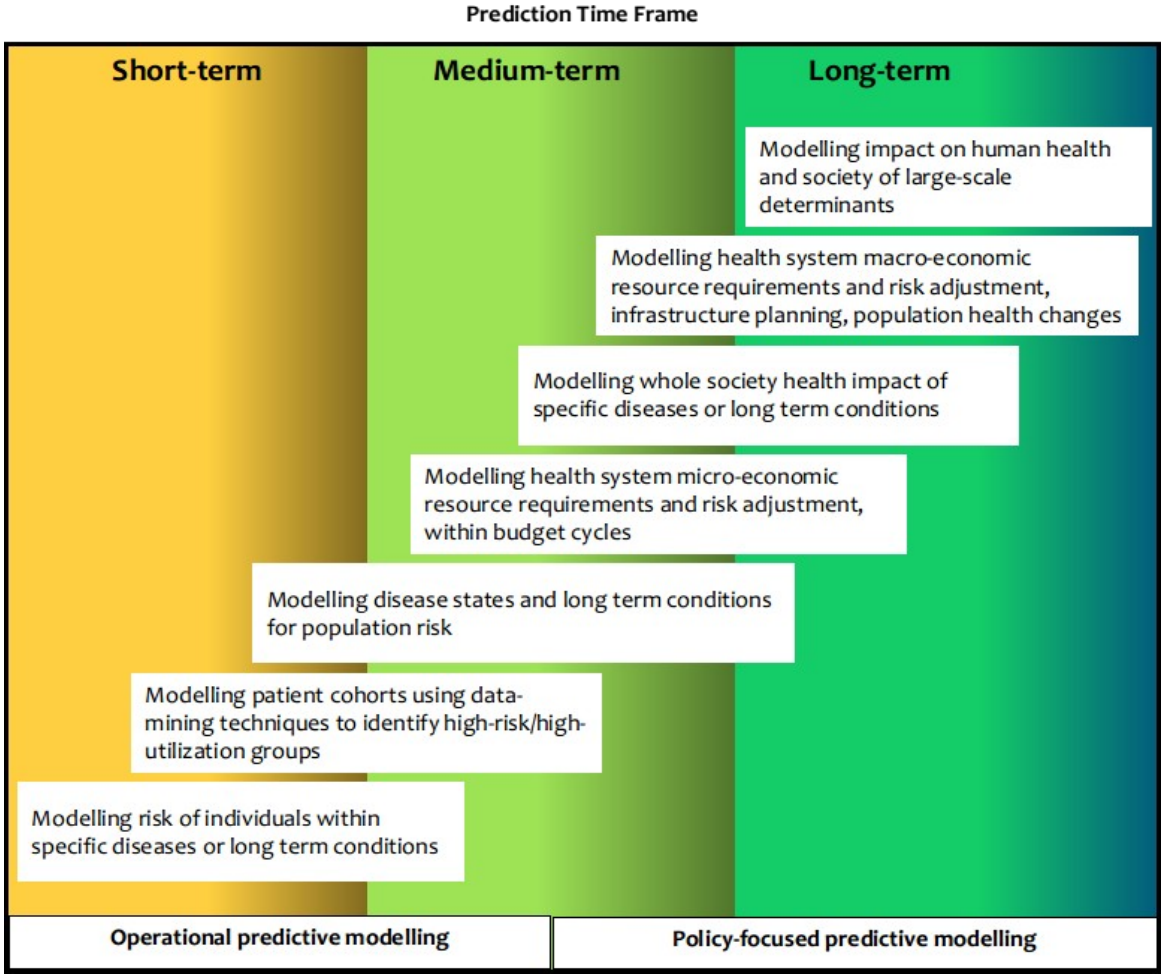
Pension reform

Culture change</td></tr>
</table>

Within this framework, the utility of a prediction is tempered with greater uncertainty, sources of small inaccuracies compounding into major errors, as well as ‘wild card’ events – i.e. the unplanned, 'black swans', as the time frame becomes more long-term.

As well, the time-frame of the modelling determines to what extent their utility is defined either in whole society terms and a general focus on policy or more decentralised and a focus of operational decision-making by health service organisations and health professionals.

Therefore, models are fit for particular purposes.



Short term predictive modelling

This represents prediction within normal clinical operational limits where decision-making and the availability of good quality information are closely linked.

Medium term predictive modelling

Epidemiological models can make the jump from the short-term to the medium term to model the movement of a pathogen through a population and across geographies, but can also be a guide to model future impacts of disease over years into the future. This explains the importance of modelling, for instance, for pandemics, as we have learned

Models in this time frame are affected by the accuracy of existing knowledge, the quality of the model's design itself, and the stability of human behaviour or institutions over the medium term. Most prediction machines in use in financial modelling and resource allocation also depend on stability in the health of populations over a one to two year time horizon.

Long-term predictive modelling

Long-term involves predictions over years and generations. Climate change modelling is an example of particular relevance to health status. Other long term prediction machines include socio-demographic predictions linked to migration of people, effects of ageing and taxation, or modelling the impact of changing the retirement age. These areas can be subject to high

degrees of speculation and suspicion by critics as they depend on specific often political or ideological assumptions.