WEB PUBLICATION

Predictive Health:

Policy for predictive modelling and long-term health conditions

Strategy & Policy

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This work was prepared under contract with the Department of Health, England.

The inclusion of references to specific predictive models, including commercially available models or naming of specific suppliers of those models is purely illustrative, and should not be construed as an endorsement of these models.

The views and conclusions in this report are those of the author and do not necessarily reflect the views of the Department of Health.

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A short history of prediction….

The probable is what usually happens. Aristotle

It is a truth very certain that when it is not in our power to determine what is true we ought to follow what is most probable. Descartes, *Discourse on Method*

It is remarkable that a science which began with the consideration of games of chance should have become the most important object of human knowledge. … The most important questions of life are, for the most part, really only problems of probability. Laplace, *Théorie Analytique des Probabilités*, 1812

The Americans have need of the telephone, but we do not. We have plenty of messenger boys. Sir William Preece, chief engineer of Britain's General Post Office, *The Economist,* 1876

We have a computer here in Cambridge; there is one in Manchester and one at the National Physical Laboratory. I suppose there ought to be one in Scotland, but that's about all. Douglas Hartree, Physicist, 1951

Satellite TV in Britain "will be a flop." Michael Tracey, head of the Broadcast Research Unit, *Sunday Times* (London) 1 December 1988

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1 Report's conclusions

Predictive modelling is emerging as an important knowledge-based technology in healthcare.

The interest in the use of predictive modelling reflects advances on three fronts:

- The availability of health information from increasingly complex databases and electronic health records;
- Better understanding of causal or statistical predictors of health, disease processes and multifactorial models of ill-health;
- Developments in nonlinear computer models using artificial intelligence or neural networks, exploiting developments from other industry areas such as climate modelling, environmental impact assessment, modelling consumer behaviour, and modelling the economic impact of interest rates.

These new computer-based forms of modelling are increasingly able to establish technical credibility in clinical contexts. Our current state of knowledge is still quite young in understanding the likely future direction of how this so-called 'machine intelligence' will evolve and therefore how current relatively sophisticated predictive models will evolve in response to improvements in technology which is advancing along a wide front.

The timing of this report coincides with increased attention to their applicability in healthcare, with a pilot project on the use of weather forecasting and the management of chronic obstructive pulmonary disease, and other developments in England.

From a policy research perspective, therefore, this report peels back this area of scientific and technical activity to identify a research agenda for further policy consideration, and draws conclusions in the following areas:

- the design and use of predictive models is not value-free and raises important questions of individual rights and liberties of citizens and patients which may conflict with both the use of predictive models and the implementation of current policy on long-term conditions;
- the superior ability of predictive models to predict clinical outcomes, compared to human judgement, has implications for the use and adoption of such models in clinical decision-making, and for the knowledge-management policies which support that;
- public safety and other regulatory considerations are implicated since predictive models are often 'life-critical' systems which need to be subject to independent scrutiny before they are adopted into routine use.

The policy environment is as of May 2005, in England.

2 Introduction

The heightened interest in using new methods of data analysis and mathematical models is based on the availability of more and better quality patient- and health-specific information. Decisions to use predictive models reflect the need to better align available health system resources, using predicted resource requirements and future health status of individual patients.

2.1 Why is there policy interest in predictive modelling?

Rising concern about the effectiveness of health systems has encouraged new thinking on the management of chronic diseases and long-term health conditions. Integral to very new thinking has been the use of predictive models. This interest is based on advances in three areas which taken together provide a fresh constellation of analytical tools and potential capabilities:

- The availability of health information from increasingly complex databases and electronic health records;
- Better understanding of causal and statistical predictors of health, disease processes and multifactorial models of ill-health;
- Developments in nonlinear computer models using artificial intelligence or neural networks, exploiting developments from other industry areas such as climate modelling, environmental impact assessment, modelling consumer behaviour, and modelling the economic impact of interest rates.

This has heightened attention on the role of prediction to improve health system performance and service delivery. However, understanding of the different needs of different health-seeking groups of people becomes important along with the possibility of greater customization in how health resources and services are organised and provided to these different groups. In this respect, the use of predictive modelling also reflects our emerging realisation that generic health systems need to be replaced by a 'just-in-time' and personalised approach.

The health needs of people have been analysed and found to fall into one of three categories: [1]

- the *well*, who need information on well-being, staying well and avoiding disease;
- the *newly diagnosed*, who have an immediate need for disease specific information and speedy treatment options;
- the *chronically ill and those with long term health conditions* who need information and stable, well-integrated care services.

A consequence of thinking about prediction is the possibility of stratifying healthcare resources based on their consumption by these different groups.

Traditional healthcare systems can be thought of as a 'generalised health problem-solving system', reflecting population-level risk and resource allocation. Moving toward aligning resources more around use will shift the health system away from this toward a more differentiated approach to meeting health needs. Predictive modelling adds an analytical capability to inform both what groups people are likely to be in the future, and what resources they will consume or need. This, of course, presents a reassessment of how population health risks are apportioned to different groups.

Those individuals with long-term health conditions require different clinical and other healthcare resources. As well, current policy points to the need to adopt a different delivery model than for individuals who are well or have acute health concerns.

Predictive modelling, though, is attractive in the management of long-term conditions for three reasons:

1. Long-term conditions can be stable over the long term, and are often candidates for routine management using care plans and guidelines, and offer more opportunities to engage the patient in the their own self-care;
2. Long-term conditions can be very complex and variable, and efforts to understand this complexity better can improve anticipated requirements for these people;
3. Long-term conditions benefit from dedicated and highly coherent care.

Predictive modelling of health populations has traditionally focused on understanding the determinants of ill-health across and within anonymous populations, in order to arrive at large-scale models of how to organise and distribute health system resources across a variable population. The current interest in predictive modelling is now supported by our increased ability to construct rule-based models which can access large databases of information on the health of individuals within a population.

It is felt by proponents that predictive modelling offers the possibility of customising design of health service delivery to specific groups of patients, and thus improve the delivery of well-integrated and planned healthcare, which operates not just on the basis of "the present", but increasingly on future information.[2] This is where predictive models take the health agenda beyond current interest in case management of high risk/high utilisation individuals toward a proactive care management approach where future health is modelled to inform present decision-making around resource allocation and care management.

During the winter of 2004-2005, the Met Office and a number of Strategic Health Authorities, NHS Trusts and Primary Care Trusts in the English NHS participated in a 'Health Forecasting' project. The project was designed to ascertain if the provision of a 'health forecast', linking weather reports with a predictive model of Chronic Obstructive Pulmonary Disease [COPD], could serve to improve the responsiveness of the health system. The focus was to test whether improvements were possible from the ability of care providers to act in advance of relevant potentially exacerbating weather conditions or improve organisational decision-making in the management of COPD. The Department of Health commissioned an evaluation study by the London School of Hygiene and Tropical Medicine to assess this project with results to be reported separately.

The Health Forecasting project sits within a wider context on the use of forecasting methods and predictive models. Recent policy on managing long term health conditions has broadened thinking on the design, financing, and structure of care programmes, particularly for those people with long term health conditions and who may require complex and even customised care. NHS interest in the use of predictive modelling is paralleled in the UK insurance industry's interests in predicting future health and risk modelling,[3] which also includes modelling the impact of climate change on health.[4]

A new approach to care is clearly evolving, bringing together the use of predictive models with new ideas on the design and delivery of healthcare services. This is a complex area, and coupled with the often complex nature of long term health conditions, points to the need to understand better both how we think about and solve complex problems, and how we use predictive models.

Predictive models can be complex, and this report is neither a detailed nor systematic review of the technology, techniques or science of modelling. Rather, this report maps out the policy issues and identifies an agenda for policy research to better understand the implications for the use of predictive models in the context of long term health conditions, and elsewhere.

Predictive models are not new as people have tried to anticipate the future in one form or another for hundreds of years, and prediction is a central feature of clinical diagnosis and treatment. An individual's 'future health' is of considerable personal interest, too. As the determinants of future health become better understood, patients, clinicians and policy makers will want to know how to take advantage of this new capability. Since patients are increasingly engaged in their own self-care management, their use of predictive models is implicated and it will be particularly interested in predictive health behaviours if the implications of present life-style choices can be more confidently communicated.

Pearl, in **Causality,** raises important questions about the relationships between knowledge, causes, outcomes, and inferences. This report will endeavour to balance the technical and more model-theoretic issues with those critical issues of 'future health' that reside in the human condition.

Pearl asked two questions that provide a useful focus for this paper:[5]

"1. what empirical evidence is required for legitimate inference of cause-effect relationships?

2. given that we are willing to accept causal information about a phenomenon, what inferences can we draw from such information and how?"

In other words, do predictive models help us better understand and act on the causality of health conditions, and given that, what are the implications?

Choosing a predictive model on the basis of technical criteria will not be wise if we are unclear what our need for such a model is in the first place. And since predictive models have a large role to play in clinical decision-support systems, will decision-makers be able to distinguish whether the model is helping with decision-making or determining the decisions themselves.

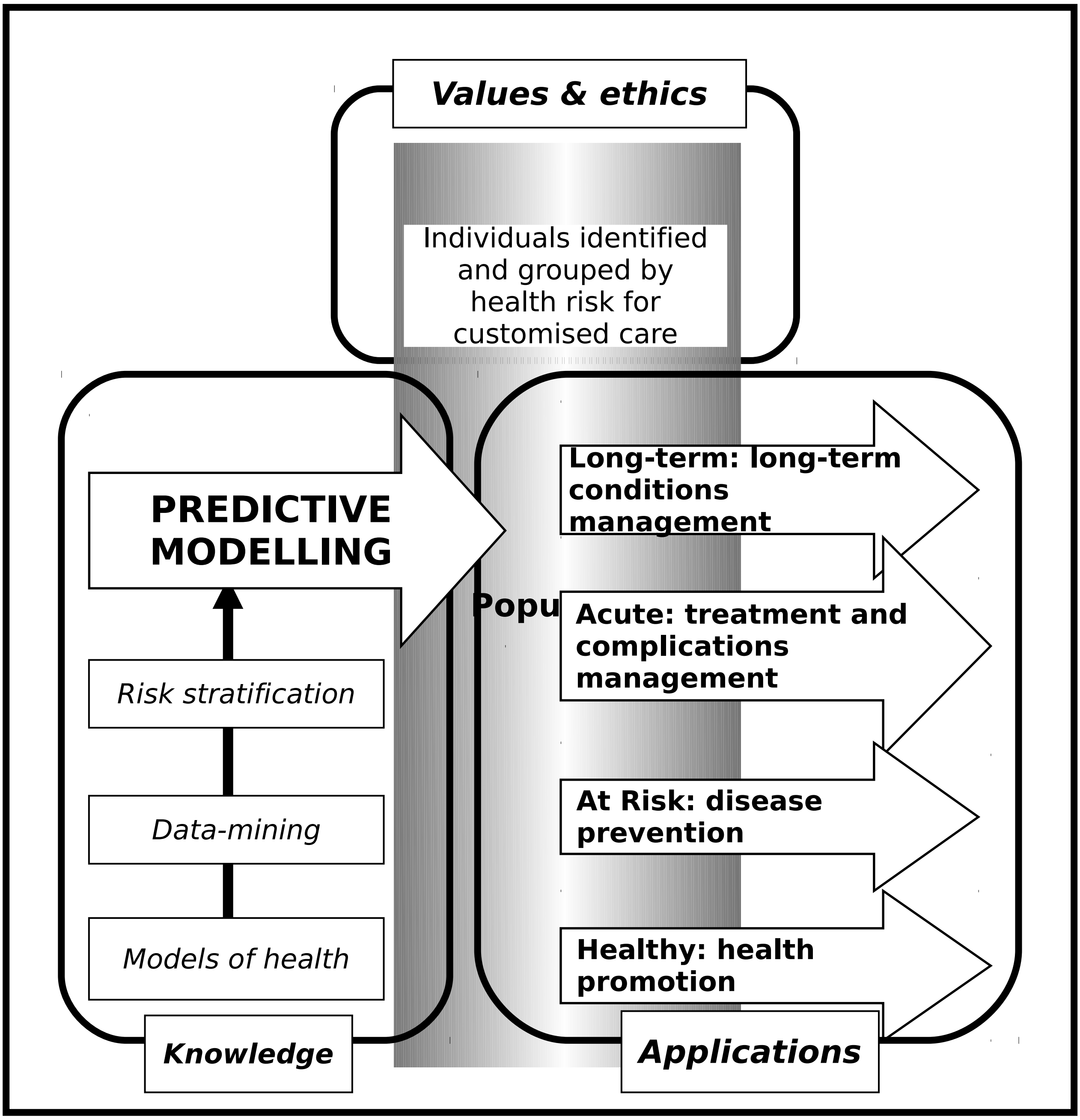
The outcomes of models depend on the quality of the evidence and a level of confidence in the model itself. However, there is potential for confusion between conclusions derived from inferential methods and conclusions from deductive methods. This may not be fully appreciated at both the policy and practice levels as it has not been determined whether any particular modelling method produces better results than any other. Modelling practitioners, for instance, report using a pragmatic approach, a 'best fit' approach, to match problems with modelling methodology.

For policy-makers this means that it is not known what modelling approaches produce the most appropriate approach to assessing policy. For practitioners, it means that there is at present no guidance as to what sorts of modelling approaches are most suited to operational use – basically, although predictive models produce predictive results, we have no way of being sure that any particular modelling approach is better than any other.

2.2 Conceptualising predictive modelling

The Diagram summarises the conceptual model for predictive modelling, identifying the three areas of policy interest. The objective here therefore is to define the sphere of policy interest around the use of predictive models, as aids to and analogues of reasoning. These areas in turn identify the policy research themes.

Diagram 1: Conceptual model of predictive modelling



Source: Tremblay

2.3 Who may find this report of interest

This report addresses a spectrum of policy issues arising from the use of predictive modelling. It is felt that these issues will be of interest to a variety of different communities. For the purposes of this report, these communities are identified in the following sections.

2.3.1 Policy-making community

This community comprises people concerned with framing and identifying policy research issues on the use of predictive modelling and investigating policy priorities for research in the near term (up to 2 years). The report notes that there are relevant issues for current policy which is either silent or does not fully take account of these issues. Included here are people concerned with knowledge brokering, and transfer of knowledge from the research literature into usable policy-oriented knowledge.

This report raises concerns around social justice and patient consent within the current long-term conditions policy.

2.3.2 Regulatory community

This community comprises people concerned with safety of new methods and technologies used in health systems, and which are likely to have an impact on how health services are delivered to individual patients, how services are designed around defined groups of identified patients (not abstract populations), and how models are used in clinical and managerial decision-making. This community also includes health system regulators with an interest in how health providers or purchasers model their service delivery using predictive models as a way of managing future demand, making resource allocation decisions in the short term, or financial models which use risk-based population models to interpret likely future requirements.

The report raises concerns on the regulation of predictive modelling and its use by licensed professionals.

2.3.3 Knowledge management community

This community comprises people who:

- research and develop predictive models (mathematical models, machine or artificial intelligence, neural nets, cognitive models of human reasoning, etc.),
- research and develop the probabilistic or deterministic rules, and
- provide epidemiological or physical data
- on the health of populations (or defined cohorts of people), or
- on the causal (deterministic) nature of specific illnesses or disease processes within humans.

Knowledge brokers who explore the relevancy of undifferentiated research knowledge (e.g. research knowledge in limited circulation academic publications for example and which has not been assessed for its practical application or relevancy) are included to the extent that they are concerned with the potential application of new knowledge to compelling problems facing policy-makers.

The report concludes prioritisation is needed to guide the development and future use of models.

2.3.4 User-community

This community comprises people (patients, health professionals in direct patient care and health managers) who use predictive models for a variety of operational reasons, including:

- to data-mine health records to identify specific individuals or cohorts of identifiable individuals at some clinical or health risk,
- to model *future* health risk profiles of individuals (e.g. with long-term health conditions),
- to model *future* health system resource utilisation around specific individuals or groups of patients,
- to develop specific case management practices for use with individuals identified through predictive modelling.

The report concludes that the role of predictive models as a component of clinical decision support, and use by patients is little understood.

2.4 The "Predictive Modelling Value Chain"

The research shows that there is no "map" for future model building that identifies health priorities. There is no consensus on what priority to assign to what health concerns. And there is no consensus on those areas where predictive modelling offers the most advantages.

In order to cut through this problem, a "Predictive Modelling Value Chain" is proposed to identify what actions are appropriate by what groups, which collectively produce the best likelihood of deriving maximal benefit from predictive modelling. This Value Chain below identifies the knowledge and questions that are appropriate to the production of predictive models. It is suggested that the relevant community of interest view the report's research agenda in terms of the core questions that need answering.

Diagram 2: Predictive Modelling Value Chain

	Determining Health Priorities ➔	**Assessing Knowledge Requirements ➔**	**Building and Using Models ➔**
Core Questions	What are the health priorities?	What do we know about these health priorities? What is our capability to develop predictive models?	How do we design and build these models? How are models to be used? What do we learn from using these models? What is the impact on health outcomes?
Responsible Community	Policy-making community	Knowledge management community	Knowledge management community
	User community		Regulatory community
			User community

Source: Tremblay

2.5 Summary of policy research agenda

The following summarises the possible match between the report's sections and these communities of interest. The research agenda, composed of 'research focus' topics, is summarised for ease of reference. [Please use this Table when reviewing the policy research agenda in Section 6.]

Table 1: User's Guide to the Report's Contents				
Report Section	**Community of Interest**			
	Policy	**Regulatory**	**Knowledge Mgmt**	**User**
3. The art and science of models	**Yes**	**Yes**	**Yes**	
4. Predictive modelling and implications for long term health conditions	**Yes**		**Yes**	**Yes**
5. Human reasoning and machine intelligence	**Yes**	**Yes**	**Yes**	
6. Policy Research Agenda				
6.3.1. What is the disruptive impact of wider use of predictive models on the public's expectations of health system service delivery? Research Focus 1: Study should focus on the possible impact of predictive modelling on public expectations of service delivery and care. Research Focus 2: Public perception of increased use of predictive modelling needs to be studied, as wider use may be perceived as a shift toward a more 'insurance-type' health system based around individually-assessed risk, away from risk distribution across society.	**Yes**			
6.3.2. What is the impact of the use of predictive models on fundamental values and organising principles of the NHS? Research Focus 3: Are there implications for social just from predictive models and patient profiling?	**Yes**			

Table 1: User's Guide to the Report's Contents

Report Section	Community of Interest			
	Policy	**Regulatory**	**Knowledge Mgmt**	**User**
6.3.3. How can predictive models be used to explore future health? Research Focus 4: A research programme to link predictive modelling with longer term health research, including climate change, is needed. Research Focus 5: How should the implications of wider use of predictive models be calibrated with policy-oriented priorities and vice versa?	**Yes**			
6.3.4. Should predictive models be certified or licensed? Research Focus 6: A review of the potential regulatory impact of the use of predictive modelling, should deal with two issues: 1. should predictive models be subject to scrutiny, quality assurance, or quality standards; 2. does the use of machine reasoning by licensed health professionals have implications on their professional regulation and conduct?		**Yes**		

Table 1: User's Guide to the Report's Contents				
Report Section	**Community of Interest**			
	Policy	**Regulatory**	**Knowledge Mgmt**	**User**
6.3.5. What is the readiness of the NHS to use predictive models? Research Focus 7: The potential use of predictive models needs to be assessed within a commercial context, with a view to determining the readiness by NHS organisations.	**Yes**	**Yes**	**Yes**	**Yes**
6.4.1. How can predictive models improve decision-making? Research Focus 8: We need to know how decisions are made that involve the use of predictive models.	**Yes**			
6.4.2. How should providers use predictive models? Research Focus 9: Organisationally-oriented policy research should focus on how predictive models can aid managerial and clinical decision-making, including resource use modelling.	**Yes**	**Yes**		**Yes**

Table 1: User's Guide to the Report's Contents				
Report Section	Community of Interest			
	Policy	Regulatory	Knowledge Mgmt	User
6.4.3. What is the role of predictive modelling in PCT commissioning? Research Focus 10: Organisationally-oriented policy research should focus on how predictive models can aid priority-setting, health modelling, resource modelling and decision-making by PCTs.	**Yes**	**Yes**	**Yes**	**Yes**
6.5. Recommendations				
6.5.1. Rights-based challenges to policy Recommendation 1: The Department of Health should ensure that policy takes account of the potential disruptive implications of rights-based challenges to existing policies from concerns raised by risk profiling and predictive models.	**Yes**			
6.5.2. Creating a research community Recommendation 2: The Department of Health should encourage the formation of a multi-disciplinary research community to study the nexus of machine intelligence and predictive modelling in healthcare.	**Yes**		**Yes**	
Source: Tremblay				

2.6 Using predictive models to support the evolving policy environment

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.

Current health policy identifies a priority on improving the management of long term conditions, in particular, "identification of the very high intensity users of unplanned secondary care"[6] as well as improved patient control of the management of their healthcare.[7]

Models therefore are an aid to making better 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, taking account of the decisions that need to be made.

For policy itself, the use of models depends on understanding what decisions the models are to provide help with. Indeed, this is the essential policy research question, itself – how can models help optimise the decisions we need to make?[8] Therefore, we are faced with technical questions leading to a better understanding of predictive models:

- 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)?

2.7 The policy link between predictive models and time

Prediction implicates a future orientation and shifts us from considerations based on the immediate present to considerations in some future time, whether later today, tomorrow, next year or some years hence. These time frames are necessary in order to know what sort of predictive approach is most appropriate.

This is a useful distinction to keep in mind in framing a policy research agenda. Policy makers 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, rather than reacting to it in real-time. Predictive models 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. Diagram 3 further illustrates this.

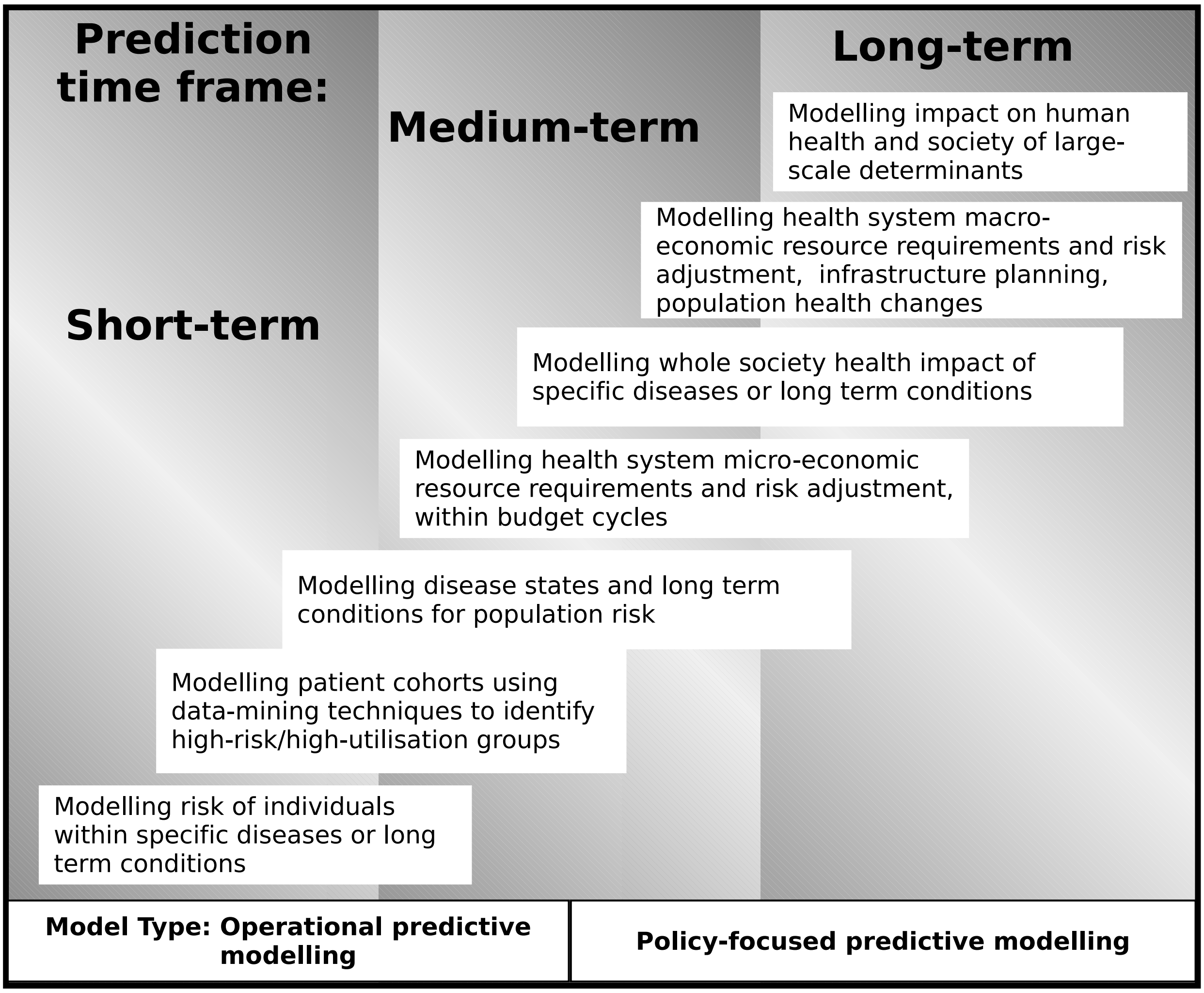
<table>
<tr><th colspan="5">Table 2: Temporal Thresholds for Predictive Modelling</th></tr>
<tr><th>Focus is on →</th><th>Individuals</th><th>Groups of identified people</th><th>Anonymous Populations</th><th>Society</th></tr>
<tr><td>Time</td><td>Short-term</td><td colspan="2">Medium-term</td><td>Long-term</td></tr>
<tr><td>Temporal threshold</td><td>A few days, weeks</td><td>1 to 2 years</td><td>5 to 15 years</td><td>Inter-generational to 50+ years</td></tr>
<tr><td rowspan="4">Predictive modelling interests</td><td colspan="2">Identified people within disease conditions, using causal or statistical models</td><td colspan="2">Modelling health status and disease with population risks</td></tr>
<tr><td colspan="2">Modelling individuals and cohorts using data-mining techniques to identify high-risk individuals</td><td></td><td>Modelling impact of long baseline determinants on human health</td></tr>
<tr><td rowspan="2"></td><td colspan="2">Modelling resource allocations/needs based on budget cycles or financial models</td><td rowspan="2">Integration of long-timeline forecasts from other policy areas to determine health impacts</td></tr>
<tr><td colspan="2">Modelling infrastructure and system resource needs for development</td></tr>
<tr><td>Examples of health models</td><td>Disease progression
Prescription effectiveness and compliance
Waiting times</td><td colspan="2">Epidemiology
Infrastructure planning (e.g. PFI)
Resource allocation</td><td>Climate
Demography</td></tr>
</table>

Table 2: Temporal Thresholds for Predictive Modelling				
Focus is on →	**Individuals**	**Groups of identified people**	**Anonymous Populations**	**Society**
Other examples for comparison	Seasonal consumer behaviour	Workforce planning University enrolments Immigration		Pension reform Culture change
Source: Tremblay				

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, 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 is an appropriate focus for policy-makers, or more decentralised and a focus of operational decision-making by health service organisations and health professionals.

Diagram 3: Models are fit for different predictive purposes



Source: Tremblay

2.7.1 Short term predictive modelling

The ‘health forecasting’ project, which triggered the key policy interest in this work deals with health predictions over 7 to 10 days. This represents prediction within normal clinical operational limits where decision-making and the availability of good quality information are closely linked. Weather is accurately predicted a few days in advance, and hence health decision-makers have a limited frame within which to act.

There are many clinically relevant predictive models which operate in the short term.

2.7.2 Medium term predictive modelling

Epidemiological models can make the jump from the short-term to the medium time frames 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, influenza; as the medium term predictions become more short term, certainty rises, as does the need to act.

There are many predictive models in use are of this sort, including:

- Economic models for resource allocation and budgeting,
- Data-mining for cohort identification,
- Epidemiological population health models.

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 predictive models 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.

2.7.3 Long-term predictive modelling

Long-term involves predictions over years and generations. Climate change modelling is an example of relevance to this paper. Other long term predictive models include socio-demographic predictions linked to migration of people, effects of ageing and taxation, or modelling the impact of changing the retirement age for state-pension reform. These areas can be subject to high degrees of speculation and suspicion by critics of long-term policy modelling as they depend on specific assumptions which need to be constantly updated with new physical data, or other information.

3 The art and science of models

Information tools which use information about individual's health status to forecast future needs for healthcare resources are called 'predictive models' [9]

A predictive model is composed of statistical, probabilistic or physical prediction rules, using historical or descriptive data which characterises specific predictors used by these rules. These models can be quite simple or complex. Most commonly, they will be software programmes running on computers using either simple spreadsheets or more complex neural networks and artificial intelligence. Data-mining methods are frequently associated with the use of predictive models, to sort through databases for patterns or to establish relationships within that data.

People are commonly aware of weather forecasts which are predictions of tomorrow's weather. We are also aware of predictions from our doctors that taking a particular medicine for a particular condition will help us get well again, or that if we lose weight we will reduce the risk of a stroke. These are all predictions.

3.1 What are predictive models?

Predictive models in healthcare use data such as patient claims data or health records to find people who fall into specific categories of risk in order to 'predict' their likely future health risk. These models also produce profiles of risk for different types of people as well as model future consumption of health care resources. Models can also identify the future implications of early interventions to achieve optimal future health outcomes. Depending on the predictive model, the results can be used by clinicians to guide patient care, by administrators to guide resource planning, by purchasers/payers to guide funding and incentive structures, and by people to stay healthy or manage their wellness.

The use of models is also determined by the time-frame over which we want to apply a prediction, specifically:

- predicting next week's health needs and likely demand from this week's (such as linking weather forecasts to health information to produce a short-term weather-linked prediction, e.g. temperature and chronic obstructive pulmonary disease);
- predicting next year's health needs and likely demand from this year's (this involves both clinical risk profiling of serviced populations as well predicting resource consumption; there are many of these types of models around, mostly in the US and used by insurers to do risk modelling; providers use these models to determine optimal future allocations);
- predicting future health needs and requirements, with an horizon of 20

years or more (these are long-baseline predictions on the order of climate change, or life stages of people).

3.2 Examples of predictive models

Predictive models come in all guises, but broadly speaking fall into models which are either statistical (probabilities) or deterministic (physical laws). All models endeavour to control for varying degrees of uncertainty, with deterministic models being less uncertain since they are based on actual physical behaviours, than statistical ones, which infer behaviour.

Where there are high levels of scientific knowledge, and confirmation of physical causal links, simulation models can be developed. But where scientific knowledge is low, statistical inferences or probabilities prevail, and models use statistical prediction rules.

Some statistical models are simple regression models, for instance, working with limited data to produce simple linear projections. More complex models, which work with highly dynamic or variable data, involve the use of neural networks and artificial intelligence as a way to model relationships. The latter also provide the opportunity to learn new things from data.

Considerable interest lies in the use of non-linear models, which are sensitive to randomness, complexity, or instability in the information that is available. Non-linear predictive models take account of predictions where these features prevail. Newer techniques are based on the use of artificial intelligence/neural networks which have the ability to recognise patterns, adapt to changing data, and 'learn'; what interests developers of neural networks is the ability of input data to a neural network and get descriptive behaviour as an output. Good non-linear models will work from physical models (that is, use quantitative and heuristic information), or use knowledge of non-linear relations within the real world.

Understanding what models are and what they can and cannot do is central to knowing how to apply prediction in healthcare. Indeed, the likelihood that these models are more likely to be statistical in nature means that it is very important to ensure that those who use them understand the nature of uncertainty and the meaning of probabilities in healthcare. Since patients are central to new directions in the management of long-term conditions, modelled health outcomes will similarly need to ensure that patients fully understand how to use these models.

The table provides examples of predictive models in use in healthcare.

Table 3: Examples of predictive models in use		
Focus	**Name of model**	**What model does**
Risk stratification	APACHE IV™	predicts the risk of dying in hospital
Diabetes modelling	ARCHIMEDES	Predict effectiveness of different therapies in managing diabetes
Reduction in clinical variance	COLLABORATIVE CARE™	Identifies patients who will benefit most from proactive intervention to improve compliance
Diagnostic cost grouping	DCG™	Separates patients into risk groups
Climate modelling	HadCM3	Coupled atmosphere-ocean general circulation climate prediction model
Identification of patients; resource allocation	RISK NAVIGATOR™	Identifies high cost patients and forecasts resource allocation for payers and insurers
Health profiling and risk	RISKSMART™	predicts health status of populations using historical cost data, and patient census-based provider profiling
Future cost of care	RxGROUPS™	Predicts future cost of care from pharmacy data

In addition to these, predictive modelling has taken place across a wide spectrum of clinical areas:

- Acute stroke outcomes [10]
- Childhood meningitis [11]
- Colorectal cancer outcomes [12]
- Complications after angioplasty and chronic renal failure [13]
- Coronary heart disease and Type II diabetes [14]
- Diagnosing SARS [15]
- Diagnosis of pigmented skin lesions [16]
- Identifying febrile young girls at risk of urinary tract infection [17]

- Injury surveillance [18]
- Obstructive sleep apnea [19]
- Patient's utilisation of primary care [20]
- Pneumonia, sepsis and meningitis in young infants [21]
- Psychosocial factors and rheumatoid arthritis. [22]

While many models can operate with relatively simple statistical approaches, more complex methods, which align data-mining methods with modelling use neural networks, which attempt to model the behaviour of the human brain; the use of neural networks in healthcare is increasing. [23] Neural networks are defined as a 'computational system consisting of a set of highly interconnected processing elements, called neurons, which process information as a response to external stimuli". [24]

Neural networks are developing in a number of areas, including clinical diagnosis, image interpretation and analysis, and drug development, but where they are an emergent paradigm is linking data-mining to health outcomes within populations, in particular, to find individual high-risk patients. Lisboa's literature review [25] shows that neural networks are finding favour with practitioners; however, given they require huge amounts of data to be particularly effective, they are replacing other statistical methods for more limited applications. Limitations in available data are cited as the main factor inhibiting wider use.

3.3 Designing predictive models

The key question faced by those who design models is whether the database is good enough. Epidemiological data is highly aggregated and tends to reflect a linear exposure model. Research in other areas using different types of data has shown that non-linear exposure models, for example, may more accurately predict health outcomes. [26]

This pits the two conceptions of scientific truth – inductive versus deductive – relevant to the design and structuring of predictive models against each other. More practically, designing predictive models will pit inductive reasoning against deductive reasoning, and that means that different communities of knowledge may not necessarily have common ground.

Epidemiological conclusions are inductive, and draw inferential conclusions from data, while mathematical modellers develop mainly deductive models built on physical realities, and are rarely inferential. However, even in physical predictive models, there is a use for statistical prediction rules to replace causal relationships where good physical data are missing.

Predictive model development, therefore, must be achieved through a collaborative, multi-professional approach. Modellers say that they adopt an intuitive approach (what one person characterised as 'pattern recognition') to selecting what mathematical approach to use, which suggests that the role of judgement is potentially great in directing a model in a particular theoretical and design direction. This may not necessarily be a bad thing, but it does need to be understood in context, as the mathematical methods to be used are quite general, while their application is quite specific. What counts as evidence for good policy-making comes under scrutiny when models are used.

Models must also be able to predict extremes across a normal population of people. Physical models are the standard as they reflect the most empirical understanding of relationships in the world, but not everything easily produces empirical relationships. When there are no physical causal relationships to work with, statistical models are the only choice.

Should we be building more simulation (deductive) models and encouraging more associated research on physical causality, or encouraging wider use of statistical models by encouraging more inductive model making but with greater attention to ensuring that they are interpreted correctly by users? The policy research agenda will need to take into reflect, but it cannot be determined without reference to what we already know in any area of enquiry.

Models must be relevant to health issues; that is to say, they must work in the real world and be useful to real people with real problems. However, it is reported by those interviewed that models are being developed in areas where it is relatively easy to achieve modelling outcomes, rather than in areas where there is a social consensus. The reason for this reportedly lies in the research funding criteria which are seen as not appropriately prioritising predictive modelling and failing to identify health priorities for modelling research.

3.4 How do models work?

Predictive models rely on the availability of data and an understanding of the determinants of ill-health. Predictive tools are used to risk-stratify people in order "to optimise the utilisation of available clinical resources" [27] for specific reasons.

- Health service systems are increasingly adopting information and communications technologies to improve a variety of aspects of patient care, service administration and system management. This is producing large databases of clinical and life-style information about individuals creating the opportunity for predictive models to interact with this information.
- Our greater understanding of the determinants of ill-health and disease creates opportunities to systematise approaches to diagnosis, and treatment, through guidelines; predictive models offer the opportunity to combine the databases of clinical and life style information with guidelines, diagnostic and measurement scales, and evidence-based practices, to augment clinical judgement by health professionals.
- Focusing on specific groups or individuals leads to the use of a model to predict events and thereby offer the possibility of reducing uncertainty

or risk or to anticipate and plan for future health-related events.

Predictive models are not new and have wide use in such diverse industries as engineering (e.g. dynamic modelling of structures), marketing (e.g. modelling and predicting consumer demand behaviour), finance (e.g. modelling and predicting economic impact of interest rate policy) and now in healthcare.

Predictive models are in regular use in most countries, primarily in clinical decision-support, and in protocols. It is in the United States where they are most closely associated with management of chronic disease, in risk profiling by insurers, and resource management by hospitals.[28] [29] The interest in their use in these applications is rising in the English NHS as it moves away from "financing to supply-side questions: how best to expand output, improve quality, and increase responsiveness, while avoiding cost inflation."[30]

Predictive models are designed to achieve a wide range of results in additional to improving clinical outcomes, such as:

- Improving staff efficiency through better use of matching rota with demand,
- Reducing administrative costs and improving financial performance through better anticipation of the impact of future events,
- Focusing patient counselling and patient education, particularly around the patient's future health.

Predictive models are widely used in disease management programmes, which organise patient care resources and patient involvement using a variety of techniques. In these programmes, predictive models produce a rank-ordered list of patients designed "to make decisions about the level and type of intervention a person should receive and the distribution of resources involved in that intervention". [31]

In order to do this, a variety of steps are followed to measure future risk in individuals and identifiable cohorts such as: [32]

- data preparation – collecting, evaluating, and integrating patient's health status and claims data or clinical history;
- identification of patient-specific risk markers – applying grouping and risk marker identification algorithms, episodes of care and categories of pharmaceutical treatments;
- creation of a risk profile – summarising the presence or absence of clinical risk markers;
- calculation of future health risk – assessing overall risk by adding assigned risk weights of all markers.

The result of applying these steps is a model comprising a set of (statistical or deterministic) rules which operate over relevant patient information to create a prediction for subsequent use in decision-making about identified individual patients.

The quality of the clinical information available on the patient is critical if the prediction rules, which comprise the model, are to produce useful results. Importantly, such models require effective distinction between categories of medical risk, specifically, to distinguish between future medical risk that can and cannot be actioned, and between patients who are stable and those whose health is unstable.

Predictive models offer information that is generally easily integrated into existing care programs and case management because they produce results which are clinical in nature, consistent and, given model robustness, statistically significant. [33] It is more difficult to understand how to apply predictive modelling in clinical contexts for patients having complex and unstable health conditions.

3.5 What do we know about the efficacy of predictive models? [34]

There are many ways to measure whether models produce good outcomes, and contribute to improved health. Berwick has observed that productivity in healthcare is less well-measured in terms of traditional input/process measures based on consumption of resources, rather than outcomes in terms of production of health: "The people of the UK should be not asking, 'How many events for the pound?' but rather, 'How much health for the pound?' At least, that is what they should ask if they desire an NHS that can keep them healthy and safe at an affordable price for as long as is feasible." [35] The use of predictive models would be compatible with this thinking.

Measures can include the following:

- Improvements in care;
- Clinical or economic indicators of outcome, such as quality of life, patient satisfaction with their self-concept of well-being;
- Comparison with other available clinical methods;
- Educational activities and impact on patient knowledge and behaviour;
- Secondary prevention activities (e.g. exercise, weight reduction);
- Return on investment in the care programme (e.g. improved outcomes, clinical savings);
- Component cost reductions or savings (e.g. reduction in hospitalization) and

Much of these measurements, though, depend on the results being used. Importantly, understanding whether models are more accurate than clinicians or managers becomes relevant.

Use of models has been researched for many years. A study by Meehl in 1954 reported 20 examples of predictive modelling, [36] with Meehl reporting (in 1986) over 140 models at work, many of them in clinical contexts. [37]

There is mounting evidence that predictive models appear to be more accurate than unassisted (i.e. the clinician does not have the use of the model) clinical judgement.[38] The literature on clinical judgement describes how individuals have an overconfidence bias when drawing conclusions from evidence [39] which leads to greater reliability on subjective views and less on objective evidence, with research showing that this overconfidence has an impact on professionals regardless of their sphere of expertise. [40] Predictive models are seen as producing more accurate results than unassisted judgement. For example:

- Models have been used to diagnose patients as either neurotic or psychotic using the MMPI [41]. The model proved more reliable than clinical psychologists; when given the predictive model results before they made their diagnosis, psychologists were still less accurate; [42]
- Models have been used to predict newborns at risk and proved more accurate than doctors; [43]
- A model correctly diagnosed 83% of progressive brain dysfunction, with clinicians doing no better than 63%. [44]

As well, research continues on developing various predictive models, which appear to perform very well, but which lack empirical validation in real-world clinical applications. [45]

Finally, predictive models are also designed with a purpose in mind, namely to inform and improve decision-making. The question is deciding how they get used:

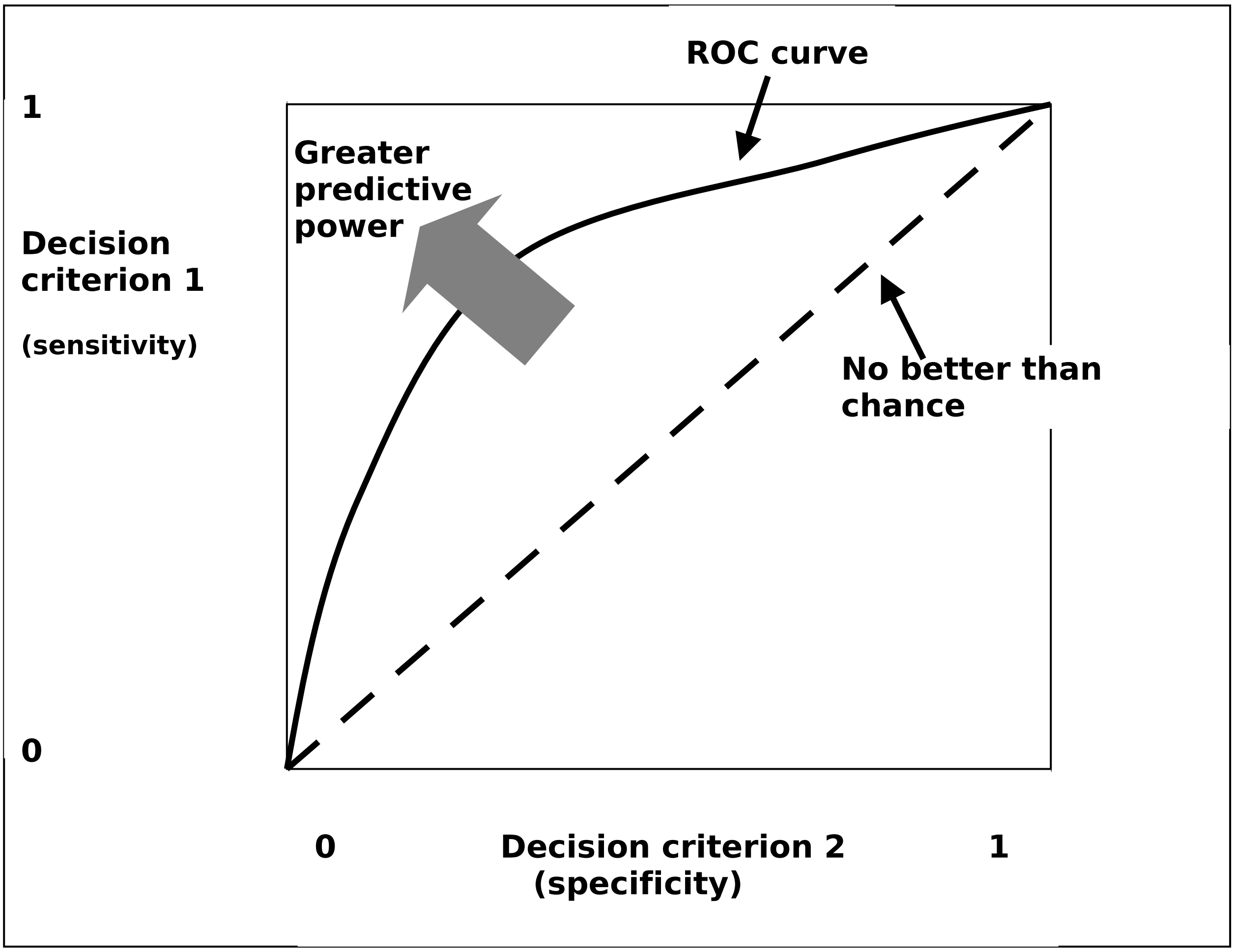
> "In recognizing the decision-making role of the clinician, computerized decision support systems serve not to instruct on a decision on a predicted outcome, but to modulate the clinician's own decision by adding new evidence through associative recall from historical data." [46]

3.6 Predictive power of models

All predictive models are 'biased' in some way to the extent that they favour certain scores (e.g. higher) over others (e.g. lower) on some relevant scoring system, and are unable to take account of problems of individuals within low-scoring groups, who should otherwise be identified.

The predictive 'power' of models is frequently assessed through ROC ("receiver-operating characteristic") curves[47] which are used to determine the probability that a randomly chosen patient is correctly identified by the model. [48] The more the ROC curve diverges from the diagonal, the more likely it is to produce results better than chance, with the area under the curve representing the measured score for the model. This measure is widely used and understood but offers just one way to assess models. [49]

Diagram 4: Illustrating Predictive Power using the ROC curve



source: Tremblay

3.7 Predictive models and social justice

The pure technical scoring of predictive power as a measure of the accuracy of the model may conceal design problems particularly with models that are based on neural networks, but can affect all models. This relates to the extent to which these models take account of the wider social context in which ill-health sits. This relates to the extent models interpret social reality in a particular way and not just the extent to which they deal with identification of individuals within defined clinical parameters. The concern here is that the use of models is not just an issue of assessing models for their technical accuracy, but of understanding the extent to which the use of models is compatible with our notions of 'social justice', or can have an impact on basic principles of equity and equal treatment of individuals. [50]

The research supports the view that individuals override the conclusions of predictive models on intuitive grounds, and particularly where they appear to violate notions of social justice; following the advice of a 'socially unjust' model would not be appropriate and therefore there does seem to be a need for a 'human override'. [51]

Additionally, neural networks are 'trained' to predict by learning on a pool of population data. Selection of this data by the model designers is a source of error and may lead to unacceptable social bias or unfair allocation of clinical resources if this training is not well done. [52]

It is apparent that understanding the difference between fairness to individuals versus groups does need further consideration in the policy context. [53] The problem is the need to ensure that the use of predictive models and associated risk stratification takes account of any bias in the models. At a policy level, it is important to determine what specific position is consistent with social values where models may reallocate resources in ways that do not seem fair, even if they are powerful.

What if the models are just, and right? Our own views of our own infallible judgement, when compared with automated results of models, suggests that this is the most important source of clinician non-compliance. It suggests that further study will be needed not just on the acceptability or not of predictive models in use, or their design and development, but human attitudes to the use of the results of machine-based intelligent predictive systems. The wider use of decision-support tools is a policy priority for most health systems around the world; if the evidence-based enabled through predictive models is more accurate than unaided/aided clinician judgement, on what basis can clinicians override these systems?

Where social institutions supported by public policy are concerned, issues of social justice are paramount. Given the possibility that individuals may have had experience of predictive models from other contexts as mentioned, such as private medical insurance, the use of profiling, and models, and decisions arising from that, may have implications for patient consent to treatment and the disclosure requirements necessary for ensuring informed consent.

Profiling, which is a core competency of predictive models, can result in a variety of undesirable consequences when put into the wider social context, and which may be deemed unacceptable. These include:

- Is explicit patient consent required for profiling and the use of predictive modelling?
- Does profiling improperly put individuals into specific social groups?
- Does profiling create disproportionate redistribution of health resources in a way which may question whether it is equitable?

Models, therefore, need to be understood in terms of the extent to which they respect 'social justice' considerations including resource allocation, substitution of human judgement, and social acceptability.

Implications for policy: setting standards for predictive models

There is no accepted set of standards for the use of predictive models in day-to-day use. While there are databases of predictive models [54] there is little discussion on whether these models require some form of quality assurance.

There is a view that it would be appropriate to subject predictive models to a type of 'clinical trial' to determine at least the following: [55]

- Assessment and scoring of predictive performance;
- Classification of the type of model and its most appropriate clinical or other area of use;
- Whether special training or knowledge is needed to use, or select for use;
- Assessment of underlying logic and the model's 'knowledge base', including quality of statistical prediction rules, structure of any neural nets.

In addition, important work is proceeding under the European Commission's Framework VI on e-health around the BIOPATTERN work on developing computational intelligent techniques for analysis of patterns of clinical evidence for diagnosis and treatment. [56]

The BIOPATTERN work is already producing useful insights, with Lisboa's literature review [57] offering specific areas of concern for policy researchers with respect to problems with the use of predictive models, including:

- Over optimistic assessment of predictive performance, which has implications for what scope models will have in determining the extent to which health priorities can be delivered better through the use of models;
- Poor model selection procedures when many variables are involved, which means that the user community in particular will need to be well-informed on the scope and limitations of models;
- Models that lack clinical credibility raises the obvious issues of acceptability by the user community, particular if model credibility is high, supported by policy, but models themselves are not accepted as legitimate aids to clinical and patient decision-making;
- Poorly distinguishing between exploratory research on models, and "pragmatic studies aiming to establish the utility of a predictive model", which is a key concern of this paper, to ensure that predictive models meet both the needs of policy makers and of users.

4 Predictive modelling and implications for long term health conditions

The current policy objective is to deliver improved and increasingly customised healthcare to patients with long-term conditions. This can be enabled through the use of predictive modelling by building anticipatory capacity for decision-making, improved responsiveness by providers, as well as optimisation of resource allocation by purchases.

It is a design feature of the NHS to pool health risks at the level of the whole population. That way, individuals do not bear the full costs of ill-health; this is particularly important when considering long-term conditions where ill-health may extend throughout a person's life. By pooling risk, the NHS ensures that available resources can be provided to those who need it most.

The proactive and anticipatory management of long term conditions is a departure from the traditional approach of providing healthcare in a reactive manner. The emerging consensus is to create an integrated system of healthcare interventions, linking patients, providers, and purchasers/payers of care, using guidelines and models designed to optimise clinical resource use, the patient's quality of life, and total cost.

This means that the management of populations of patients will be different from the way acute or primary care has traditionally been provided, which in turn requires new approaches to procuring/paying for care programmes, since the priority is to treat and manage the whole patient, rather than manage service components offered by different providers.

Predictive models support better management of long-term conditions specifically, in a variety of ways. This includes:

- Identifying patients with long term conditions, from amongst the general population,
- Making the provision of health information to the patient easier to enable greater self-management and informed decision-making,
- Creating the rules that are used to prompt patients to obtain services based on a regular schedule,
- Prompting specific health system behaviours by health professionals or providers to implement appropriate practices consistent with both best practice, and specific to individual patients,
- Providing better information for decision-making to enable more effective integration of care,
- Modelling care options and likely future options to provide direction to improve value-for-money for the health expenditure.

4.1 Understanding the patient perspective

One consequence of keeping patients outside of decision-making in healthcare is that individuals become insulated from the consequences of the decisions or life choices that they make and which have an impact on their health. For instance, would patient behaviour be different if individuals knew about the costs of their care; or would patient use of predictive models improve their understanding of their health condition and improve longer-term compliance?

Integral to the long-term conditions policy is understanding how to ensure patient engagement given the many barriers patients experience. Research on consumer decision-making in health has identified many factors that influence patient engagement, and many practices that can contribute to wider and more satisfying patient involvement: [58]

- For good decision-making, patients need to have good information about the different options of care available;
- Patients do not always identify information on health that is relevant to their own situation, and therefore fail to draw links between research they read on a particular condition, and their own circumstances;
- Patients have difficulty integrating information provided about care options, partly because they cannot link it to their own condition, and party because it is poorly presented to them in an appropriate decision-making context;
- Patients do not always understand the implications on their personal health risk of the choices they make, so they are unable to assess whether a particular choice is a good one for them;
- The way information is presented helps consumers make better decisions, particularly in areas where there is low salience; that is, where public knowledge and understanding are low, presented in overly high literacy levels or with overly complex presentational material, or where research finding are poorly understood or lack clinical consensus amongst health professionals.

Given the complexity of healthcare, predictive models could become a new ‘black box’ within which to further conceal clinical decision-making and inadvertently remove patients from decisions that affect their lives if their use is limited to purely clinical decision-support settings. But giving patients access to these models would be compatible with methods to widen patient engagement in their care by increasing salience.

There is a caveat, though. Many people may have had a negative experience from the use of predictive models if they have ever been refused health insurance, since modelling risk is a central aspect of underwriting these policies, and setting the risk-based premia.

For these people, the use of predictive models by the NHS to identify high-risk individuals may appear more as evidence that the models are designed to reduce their entitlement of NHS benefits. Their use may not be seen or understood as a resource allocation and efficiency-enhancing activity by health service providers or a way to better align purchasing intentions with available provider resources.

The risk is that while these models may be used to enable more precise allocation of resources to individuals that markedly differs from expectations, this may be perceived as socially unjust if the practice cannot be adequately explained.

4.1.1 Implications for policy: building public understanding

Building public understanding is necessary if the use of predictive models is to be successful. In particular, potential conflict with the founding principles of the NHS may need to be explicitly addressed to ensure that the universal access principle is not reinterpreted into an 'entitlement principle'. The actions of decision-makers to adopt predictive models for the better management of long term conditions in advance of ensuring widespread public salience could further contribute to resistance. The role of patient consent to be profiled by predictive models is a critically important component, given the evidence that the design of predictive models can have implications for notions of social justice and equitable distribution of resources.

4.2 Health system requirements

Within the wider health system context, predictive modelling raises a number of issues which impact on whether models are workable. Clearly, for models to produce results that people will have confidence in to use, they must use those results, so clinical practice compliance becomes an important area of interest.

Since patient involvement is essential if self-management of care programmes are to work in the first place, patient engagement with a care programme is important, and must reflect the relationship between actual health behaviours and what the models are predicting. Patient satisfaction becomes a critical determining factor, putting potentially considerable pressure on health systems to design care programmes that patients want and value (and not just those that are easy to manage, meet the needs of health professionals, or cheap to run).

Finally, cost measurement must move up the list in terms of priority, not necessarily in the context of using cost to determine thresholds for patient engagement, but to better determine the best use of resource to achieve the desired outcomes.

This means that it is important to understand what organisational or system-wide factors in the design and delivery of care may exacerbate care, or hamper patient self-management of their care. This offers potential challenges to the autonomy of how health system decisions are made *for* patients, without their active engagement. Policy has already identified the need to structure care options in such a way as to maximise patient autonomy. [59]

In addition, the use of models by the public is a real possibility. Since predictive models are computational 'equivalents' of clinical reasoning processes, they serve to give patients direct access to this reasoning, without necessarily having to engage with a clinician directly. Patient-accessed predictive models may create the conditions for greater patient understanding of the determinants of diseases and ill-health, and for patients living with long-term conditions, a knowledge-based support to self-management of their own care through a surrogate.

4.2.1 Implications for policy: determining the appropriate style of policy intervention

The consequences of predictive models raise issues for policy makers and how to deal with the wider use of predictive models.

For instance, how should government decide between policy options designed to mitigate undesirable predicted consequences of a particular health condition and options designed to promote desirable predicted outcomes. The choice is non-trivial as it determines the style of policy – to be interventionist for instance, or promote healthy choices – how to choose the nature of interventions – clinical, administrative – and mechanisms for implementation – e.g. user charges.

4.3 The purchase of care

NHS purchasers should be aware that the use of models as a way to inform decision-making about what care is needed.

New providers of care, for example, can base their healthcare offering to PCT purchasers on a variety of options, such as superior risk modelling of relevant patient populations. Organisations seeking market entry to the NHS, offering services based around predictive models, are also likely to be able to make clinical care offerings based on the following:

- Their ability to determine the total cost of untreated healthcare needs, particularly with fragmented management of long-term conditions;
- Superior modelling of the natural history of health conditions coupled with better understanding of the cost of treatment;
- Superior ability to model likely population health outcomes within target groups;
- Well-designed patient education and compliance programmes specific to a long-term condition;
- Well-designed professional development programmes to promote improved practice compliance and continuing professional development;
- Able to provide appropriate educational resource materials, and communication plans to support patient self-care.

- Superior ability to select patients for non-compliance and respond with appropriately designed compliance strategies.

Existing NHS providers may lack these capabilities, or not be in a position to develop commercially viable offers when compared to new market entrants from countries where the use of predictive models is better established.

On the other hand, effective inducement by PCTs to use models appropriately can open up a wide range of service delivery options by existing NHS organisations. The test will be the extent to which these providers have the organisational flexibility to provide services that meet the needs of patients with long term conditions.

4.3.1 Implications for policy: role in purchasing

Predictive models may give PCTs greater leverage in their purchasing power, but it is not clear yet what impact greater use of these models would have on how providers deal with risk. However, establishing purchasing criteria around these types of considerations may incentivise NHS providers to adopt more comprehensive and patient-centric service models that respond better to individual patients.

4.4 Dealing with long-range predictions: the special case of climate change

It was felt appropriate to review the use of models in climate modelling and health, as this represents a particularly challenging 'wicked problem' within current policy. If the climate modelling and associated predictions are to be believed, climate change will have a major impact on health of people and may have a significant disorganising impact on health care delivery systems. It may also create factors conducive to the emergence of new long term conditions, or influence the nature of existing long term conditions or their prevalence in society. [60]

Climate models are usually simulation models of the atmosphere and attempt as much as possible to assess the chaotic nature of weather processes using physical data collected from measurements of the atmosphere. Climate modellers have developed a variety of mathematical approaches to take account of these. Climate change models involve taking account of the following

- Impact on habitats of animals, birds and plants,
- Changes in disease vectors,
- Changes in the relationship between disease conditions and weather variables.

According to the Hadley Centre briefings conducted as part of this paper's research, it is difficult to form correlations of health variables with weather variables as health variables are not very well understood in this context. Health variables would involve changes in the host, the pathogen, or the mode of transmission, for instance, and knowing what thresholds were applicable in triggering a change within a climate model. This means that it is difficult to model future health under climate change scenarios without knowing what the health priorities are.

The key question, therefore, is how to build these climate and related environmental factors into predictive models of health. If these factors have yet to be fully understood within climate models, it is premature to draw conclusions from these predictive models, meaning that at present the climate modelling in use in the UK cannot inform NHS future planning.

Furthermore, there is apparently little on-going research on the relationship between changes in weather and changes in health. Most of the modelling research focuses on models of disease states *within the human body*, and not the human body *within the wider human ecology*. Our knowledge of health and climate is not as robust as one would have expected given the current national priority on climate change itself.

While the Department of Health has developed a policy paper on climate and health[61], this document does not appear to have led to a correlated policy research programme, reflecting the advantage of UK leadership in climate change. The absence of a 'climate and health' policy portfolio within the Department of Health, and no formalised links between climate centres such as the Hadley Centre and the Department of Health or the NHS to inform policy and practice contribute to the lack of direction and activity. It can be harder to invoke the Precautionary Principle in policy when the health issues are 30 to 50 years or more in the future and the health service infrastructure is focused on meeting immediate demands for service. It is also felt by some in the research community that the Department of Health should raise its profile within the Green Ministers Group, to reflect the increasing importance of climate change.

A long term perspective, though, is relatively easy to conceptualise: will the NHS air-condition its hospitals as a response to climate, for instance? A decision here has an immediate impact on energy consumption in the UK, and on the design of healthcare facilities – most of today's healthcare facilities will need to be renewed within 30 years, anyway, and decisions on that will need to be started within the next decade. Similarly, future planning about the use of e-health technologies will also need to take much longer time frame if only to anticipate the sorts of professional skill sets, working conditions and clinical service environments to design for.

Clearly, building predictive capacity for health will require much greater understanding of the determinants of health, not just in the medium and short-term but the longer-term time frames of the sort associated with climate change.

It is suggested that potential impacts of climate change on health policy will have implications in at least these areas:

- The impact of climate change on present resource allocation formulae will necessitate a review at least of the distribution assumptions and risk models involved, as the future distribution of resources will increasingly be influenced by factors that are not part of current models.

- While there are relatively high levels of uncertainty in climate change models, the implications will need to be taken into account; therefore, people will need to know how to translate that uncertainty into real actions, with some guidance in the present and near future being needed for healthcare providers, purchasers, and planners. This in turn will require new thinking if the NHS is to build appropriate anticipatory capacity. Finally, it is also by no means clear what information is needed by whom in order to inform effective and appropriate decision-making and planning to achieve these results.
- The current health system infrastructure comprises buildings, systems, processes and service arrangements designed and built for one climate and environment that will increasingly become unsuitable if the climate change scenarios are right; the closest we currently come to understanding these are large-scale environmental disasters.

4.4.1 Implications for policy: policy for long-term health issues

Climate change illustrates how health policy will need deal with very long-range health issues.

As the facts of the changing climate become known, we will need to develop ways to learn from the climate change predictive models in order to inform health policy and health system design. This is a challenge because good policy inevitably depends on good evidence and knowledge, while our ability to respond to longer term determinants of change undoubtedly reflects less certainty, which may necessitate greater use of the Precautionary Principle in advance of confirming evidence.

To achieve a level of pro-active engagement in this area, it will be necessary to prioritise health impacts and changes based on how they exist in the present and constantly renew those assessments into the future, in a rolling programme of policy development which is sensitive to emerging evidence of the role of the atmosphere as a global distribution system for disease and a potential source of ill-health. This necessitates a flexible but focused policy response.

To make this effective, we will also need to determine our human health priorities in order to develop suitable predictive models and thereby improve the causal science underlying the climate models and their ability to predict the burden of ill-health. Only then can health system decision-makers begin to establish priorities for action.

It is possible to begin to understand aspects of this by engaging in international comparisons on health with countries that have climate conditions much like ones that will come to characterise the UK climate in years to come. This provides an empirical basis for looking at possible futures through the lens of the present day. [62]

5 Human reasoning and machine intelligence

Predictive models encode in their operation personal and professional knowledge and represent one form of computational, or machine, intelligence. For the purposes of understanding this issue, it is useful to work with a distinction between decisions made by humans, and the results of modelled analysis as it would appear in a predictive model. It may be appropriate to think of predictive models as evidence of advances in computer-based mathematical models to augment or indeed enhance the judgement of humans.

It appears that: [63]

1. Humans are generally poor at predicting complex outcomes, because people are inconsistent and would generally fail in test/retest situations.
2. Humans are poor at distinguishing valid from invalid predictions, as people tend to hold many false beliefs about the predictive value of variables, generally because people do not often have to deal with feedback of decisions.
3. Machines are generally good at predicting complex outcomes because they are ruthlessly consistent, and pass in test/retest situations.
4. Actuarial models do not themselves code false beliefs, but can reflect the false beliefs of their designers, and therefore the intensions of model designers are critical.

That is to say, humans are very good at producing the observational information necessary to construct predictive models, while predictive models are very good at working with information and producing predictions based on the integration of disparate information. [64] Research has also been recently summarised to show the sources of error in clinical decision-making, suggesting that, in this case, doctors can learn to make better decisions by being aware of the bias and distortion they bring to a decision-making situation. [65] The wider research on comparing clinician decision-making with model-based decisions suggests that where complex issues are involved, models perform better.

Understanding causality has been a priority for thousands of years. It drove thinking about the real world for Plato and Aristotle who thought about first causes. It certainly kept the early physicians busy with attempting to understand the causes of ill-health, with humours, the soul, spirits, and so on. [66]

From the perspective, though, of thinking about predictive modelling, this history is particularly relevant as it raises important questions about the notion of science that underpins these models.

Models which are based on basic scientific principles, and hence a model of causality based in physical reality, are not the same as models which are based on correlated assumptions and probabilistic relationships, which are inferred from reality, but which may not have (known or knowable) physical analogues. This much we have already explored.

From the perspective of causality, we can argue from considerable certainty in a deductive context as the real-world is properly understood. Climate models are, besides being incredibly complex, functions of physical laws and causality as much as possible, and simulate the real world of climate. However, when we move toward models that depend on statistical distributions from which to induce, or infer, "associations among variables, estimate the likelihood of past and future events…" [67] we are now looking for new evidence from the available data. We are in effect seeking to predict an outcome from available data under dynamic and changing conditions. As Pearl notes: "Associations characterise static conditions, while causal analysis deals with changing conditions." [68] The consequences of this are mainly in understanding the evidence base from which predictive models derive their data – a physical world, an associative world, or a dynamic world.

5.1 Models, reasoning and 'distributed cognitive systems'

Models are abstract representations of a system, or some aspect of the real world. Some models are descriptive and informal, and some are mathematical. Often, well-constructed mathematical models are necessarily constrained to available and useable data, and therefore may not fully accommodate other relevant considerations such as:

- Regulations or commitments, promises of performance, or other factors designed to determine quality;
- The initial conditions that are assumed in the first place for modelling physical relations within the models themselves;
- Forecasts of changes in various aspects of the model components, by assuming, for example, stable future resources or ignore factors influencing demand for a service;
- Cultural and social values, norms, ethics.

Knowledge management and utilisation are key aspects of concerns in healthcare, with increasingly vast amounts of new knowledge being produced, perhaps faster than individuals can assess the potential implications for human capabilities. Health professionals often work in group contexts in which the main form of information exchange is through verbal face-to-face exchanges and not exchanges supported by information systems; [69] the likelihood that human frailty will intervene thus increases.

Predictive models are akin to attempts to integrate a variety of clinical, management and patient perspectives into an informed approach to solving a specific clinical problem. It therefore raises issues of whether these models are designed with that breadth of understanding and knowledge in mind.

If we think of complex issues that involve diverse knowledge and user communities, we have what has been termed a 'distributed cognitive system'. [70] If this is the case, then predictive model development may tap into knowledge in a more complex and multi-professional way and that the process of developing models may, in itself, be a productive knowledge production process.

Simply replicating in a predictive model a simplistic medical model of ill-health (on the analogue of replicating very primitive notions of clinical reasoning) misses the potential to adopt multi-factorial models of the determinants of health and well-being. The knowledge problem for health, therefore, is how to maximise the capabilities of predictive models to exploit this distributed cognitive system, as much as using the development of predictive models as a way to create and benefit from distributed cognitive systems.

This model is particularly relevant if we believe that health problems are complex, or 'wicked', and thus requiring a new way of problem-solving. Predictive modelling opens up the possibility of better understanding of these complex problems, partly due to the technology, and partly due to the social structures that lead to the development of these models.

It is increasingly apparent that the 'problems' that patients, clinicians, researchers and policymakers face in health are more complex than simple, and that assumptions that they are 'linear' may produce less optimal results. In addition, there is increasing dissatisfaction with 'intellectualised' solutions to problems, separated from the practical realm, where real problems demand real solutions. Policy makers are constantly searching for new knowledge to inform the development of policy options, but the body of practical knowledge are not the same as (and smaller than) the body of intellectual knowledge.

5.1.1 Implications for policy: decision-making and utility

The core challenge is distinguishing between abstract and theoretical conceptions of health problems (and the models that describe them) and real-world conceptions where users (patients, for instance) define the health needs. [71] The problem for clinical practice as well as policy is that predictive models are very good at what they do and should be expected to get better as advances in both theoretical and practical research continues. [72] They may become more reliable in the end that human judgement under certain circumstances.

With this in mind, priority should be given to:

- identifying the characteristics of useful predictive models and their applicability and utility in clinical and administrative decision-making, and
- determining how decisions are made when the options are model-assisted human judgement, un-assisted human judgement and predictive models alone.

5.2 Getting knowledge into models: the role of knowledge brokering

The distinction between useful knowledge (practical, applicable) and useless knowledge (theoretical) refers to the ability of people to understand useless knowledge in the context of potential applications. Academic knowledge, in papers and journals for instance, is characterised as useless knowledge to the extent that applications are unknown or unspecified. Potential applicability requires additional reflection in the context of problems to be solved.

The reliance on knowledge production from universities, i.e. to see universities as the source of knowledge on solving problems, raises the question of whether universities are indeed the right institutions to undertake the work of developing models for real-world application. In addition, the traditional approach to knowledge transfer in universities is embedded in a process characterised by study, courses, and publication, from teacher to student. This takes time, and may not meet the more immediate needs of practitioners for access to knowledge for practical application.

Since much current research and development of predictive models involves academic institutions, the extent to which their development reflects the tensions inherent in the knowledge model of higher education needs to be reconciled. Writing in the *Chronicle of Higher Education*, Stanley Katz observed: “I think the public (and public officials) have come to see research universities as self-aggrandizing money machines populated by professors who have lost interest both in teaching and in creating immediately useful knowledge.” [73]

While this is not to apply generally to higher education, it does show that the application of new knowledge requires specific expertise and skills and in many cases different sorts of institutions which may need to be created. [74] [75] More generally, criticism is mounting of academic institutions for their failure to put their research into practice, or increasing the usefulness of research findings to practitioners. It is also the case that academic institutions are not the only sources of new knowledge. [76]

Do other types of knowledge transfer organisations need to exist, and would they be more fit for the specific knowledge demands facing decision-makers today?

Knowledge brokering is an emerging skill-set that is seen by many as critically important to the better application of increasingly complex information. Brokering is designed specifically to bridge the useful/useless divide. The Canadian Health Services Research Foundation is seen by many as a world leader in the development of brokering in healthcare.

5.2.1 Implications for policy: knowledge brokering

Knowledge brokering,

> “brings researchers and decision makers together, facilitating their interaction so that they are able to better understand each other's goals

> and professional culture, influence each other's work, forge new partnerships, and use research-based evidence. Brokering is ultimately about supporting evidence-based decision making in the organisation, management and delivery of health services." [77]

This definition reflects current thinking about the use of evidence and in particular the link between researchers and practitioners; however, it fails to address the possibility that the production of knowledge itself is part of the brokering process, and that the 'researchers' involved may be limited by their own models of thinking about and solving complex health problems. Thus, those who produce 'useless knowledge' may not be the right people to focus on 'useful knowledge' nor indeed to solve these complex problems. It is a conceptual problem, as much as a practical one, and made all the worse by the potential limitations of the university as monopoly producer of new knowledge. [78]

This means that additional care is needed in framing the research agenda for predictive modelling since, in the main, predictive problems will be ones which transcend traditional bodies of knowledge and are grounded in real world concerns. In general, then, 'useful' results of policy research will draw on theoretical and practical concerns, with a wide community of individuals and contribute to both academic knowledge and practice, but the end result is to inform the development of policy options for policy makers.

5.3 "Wicked problems": implications for predictive models

The concept of *wicked problems* was originally proposed by HJ Rittel and MM Webber in the context of social planning and define more generally what a wicked problem is. [79] Needless to say, wicked problems have clear implications for how we organise health systems and in particular those elements of health systems which are embedded in the solutions to wicked problems. There are also significant contributions to our understanding of wicked problems from complexity theory and its application in health. [80]

Many problems do not have an easily analysed linear structure, and it is perhaps more a function of academic models of analyticity than pragmatic approaches to the real world that encourages people to adopt linear problem-solving methods.

Experts, for example, may move away from linear differential diagnosis processes when confronted with presenting situations for which the normal clinical rules of engagement appear to fail. [81] It may be argued that true professional competency lies in knowing when the ordered approach is the wrong one, requiring a different framing of the situation. Expert judgement challenges the overtly conscious models of reasoning (of replication of judgement by non-experts, for example) by using other ways to weight evidence in search of a solution.

The problems that are likely to be most amenable to the most advanced use of predictive models will also tend to be those problems that are wicked – non-linear, and complex.

Traditional thinking, cognitive studies, and existing design methods often advise following a linear process from problem to solution, beginning by gathering and analysing data to understand the problem better and then formulation of potential solutions. It is also suggested that as problems become more complex, the need to simplify it into this linear process increases.

Unfortunately, complex problems are not like this, and from the perspective of predictive model use, probably inappropriate. Rubery has concluded:

> "Since science cannot provide clear answers to our 'wicked problems', we need to recognise the incomplete information we do have will quite legitimately be valued differently by different sectors of society. We need to be more open about the limited nature of the 'evidence' upon which we are likely to be able to base our interim judgements and any actions." [82]

While linear problems readily fall to sustained analytical methods (and indeed some linear methods are used to bombard complex problems with potential solutions), they are still problems with difficult solutions.

And because predictive models are software-based, it is appropriate to ensure that the technical aspects of software design are fully understood. Software researchers and developers are familiar with 'wickedness' and software. For instance, Conklin and Weil [83] have looked at wicked problems and software design, concluding that

- A wicked problem is an evolving set of interlocking issues and constraints.
- A linear approach to solving a wicked problem simply will not work.
- Solving a wicked problem is a fundamentally social process.
- There is no way to prevent the introduction of new constraints to a wicked problem.

Research by the Knowledge Media Institute at the Open University has concluded that:

> "Wicked problems possess a number of distinctive properties that elude design methods which assume that the problem is already understood sufficiently for it to be analysed using automatic tools, or top-down methods." [84]

Table 4: Characteristics of Wicked Problems
There is no definitive formulation of a wicked problem: formulating the problem is the solution.
Wicked problems have no stopping rule: problem solvers stop not because they have the answer, but because they are out of time, money, patience or the answer is 'good enough'.
Solutions to wicked problems are not true-or-false, but good-or-bad – values are inherently a large part of the problem and the values employed vary among stakeholders.
There is no immediate and no ultimate test of a solution to a wicked problem – solutions to wicked problems vary because they are so inextricably bound to their environment and generate 'waves of consequences over an extended – virtually unbounded – period of time.
Every solution to a wicked problem is a "one-shot operation", because there is no opportunity to learn by trial-and-error, every attempt counts significantly and solutions cannot be undone.
Wicked problems do not have an enumerable (or an exhaustively describable) set of potential solutions, nor is there a well-described set of permissible operations that may be incorporated into the plan.
Every wicked problem is essentially unique – despite many similarities, each wicked problem also has distinguishing characteristics that make it unique.
Every wicked problem can be considered to be a symptom of another problem because of their connectedness to the environment and to other problems, 'solving' a wicked problem may exacerbate other problems.
The existence of a discrepancy (between actual and desired states of affairs) in representing a wicked problem can be explained in numerous ways. The choice of explanation determines the nature of the problem's resolution – the choice is the one most plausible to the decision-maker.
The planner (designer) has no right to be wrong – scientists may formulate hypotheses that are later refuted, but planners seek to improve some aspect of the world.

There are implications for predictive models arising from the characteristics of wicked problems. [85]

There is no definitive way to frame the problem

The framing the problem is the problem and successful formulation is the solution. Some features of a system are evident only when it works properly and are not a distinct or separate feature of it.

This means that it matters how a problem is framed and approached; the power of organisations to frame a problem, and hence determine what a solution looks like becomes a central issue. Choosing the focus of predictive models itself reflects assumptions about what are the 'real' problems. And this is the essential contribution of good policy to set the priorities for model development.

No stopping rule

It is hard to know when you have solved a particular problem, such as when is a system 'safe' or when have you accurately predicted risk of obesity within a group of people.

The Heinrich Triangle [86] is a conceptual/analytical model which suggests that in safety, for every major accident there a many smaller near-misses. By focussing on the many near-misses, the likelihood of major accidents is reduced. Predictive models are sensitive to the consequences of Heinrich-like consequences if designers are unable to determine from the available data when something is safe; all we can achieve is a consensus on when something is 'safe enough'. What does 'healthy enough' mean in the context of long-term conditions, and the use of predictive models – what healthy state is being predicted in the first place?

Problem is about good/bad, not true/false

There are no unambiguous criteria that tell us when we have solved the problem. Predictive models are statistical inferences and thereby reflect the 'goodness' of statistical fit, rather than conformance with a deterministic reality.

As such, predictive models produce results that are good, or indeed acceptable to people, or not, rather than true. Continuous improvement in the modelling produces higher degrees of confidence in its accuracy, but as long as the models are statistical, the results are never, strictly-speaking, true. The model itself depends, critically, therefore, on how designers frame the health problem, and understand the extent to which any model is merely an approximation of reality which is embedded in the wider performance of a health system and society itself.

Much confusion is created if people believe a model *is* the reality, rather than a model *of* reality.

No immediate or ultimate test of a solution

The consequences of a particular solution feeds back to the problem, altering starting conditions, so it is impossible to know when all the possible consequences of the solution have played out.

Is there a causal link between solutions and outcomes or can it only be inferred? Statistical prediction models acknowledge the non-deterministic nature of causal links and designers should understand this, but decision-makers, and users of the results of models must also know this.

Every implemented solution to a wicked problem is 'one shot'

You cannot unravel the solution easily, and thus separate it from consequences that arise from it. Wicked problems are not closed or bounded by what we know; instead, solutions create their own unintended consequences, and it is impossible unwind or undo solutions that fail.

Since health problems are also likely to be problems of *systems*, the predictive model will have implications and impact outside of the policy or research domain. The relevancy to the care of people with long-term health conditions is compelling, as it is necessary to take account of the wider world in which these patients live and which has determining influences on the course of their health and the efficacy of clinical interventions.

There is no well-defined set of potential solutions

Healthcare stakeholders differ in their views of not only what the key problems are but they also have their own ideas of what constitutes an acceptable solution – recall that solutions are good, not true. It is a matter of judgement when enough potential solutions have emerged from which to select one around which there might be general agreement. It is then another matter to choose a particular solution. This will test the ability of decision-makers to decide on a solution.

Predictive models are context specific and reflect a consensus on a solution. While a particular model may be very good, it is only a model with particular assumptions; another model with other assumptions might also be worth considering but with different results.

The problem is essentially unique

Health problems are unique and there are no classes of solutions that can be readily applied.

Solutions in one domain are not evidence they will work in another; risk in one situation is not a predictor of risk in another. Models are only models of what they model, and as far as our current state of knowledge goes, are not generalisable to other domains.

The problem can be considered a symptom of another problem

The problem is part of an interlocking network of issues which change over time, embedded in a dynamic social context.

'Systems of systems within systems' is a better way of understanding these sorts of problems, rather than linear process flows which has tended to be the determining model of the ‘process redesign’ paradigm. Predictive models respond to more multifactorial and non-linear conceptions of ill-health and therefore are not just a model of a simple process into which a patient is fitted but try to model the patient’s behaviour and responses in particular circumstances.

Problems can be explained in many different ways

Various stakeholders have different and changing views of what the problem might be, what might be the cause, and what might solutions be.

The absence of causal, deterministic relationships means that highly determined statistical models will prevail in decision-making and this means that how individuals or groups make decisions will need to be taken into account. This will complicate the process of deciding and challenge thinking about clinical causality; not all relevant decisions will be completely determined by empirical evidence but also involve statistical correlations. No doubt, this will not affect the relevancy of very narrowly defined predictive models but will have relevancy where the health issues deal with the more complex and long term health of people. Indeed, it is good evidence that a problem is wicked when there is failure to agree on its causality.

The solution designer has no right to be wrong

Science has hypotheses which may or may not be right or supported by the evidence; the designer of a solution to a wicked problem is expected to get it right. Rittel observed that people who try to solve wicked problems are caught up in the social context of the solution, and therefore cannot separate themselves from the outcomes. [87]

A failed solution is a failure, not a hypothetical outcome. This means that the failure of predictive models is a failure with human consequences, for how healthcare is delivered or organised. Designers of predictive models, therefore, are constructing a particular approach to solving a complex health problem, and cannot separate themselves from the decision-making and web of clinical relationships that determines how information is processed in decision-making.

5.3.1 Implications for policy: wicked problems in policy development

Health issues have specific features:

- They are of interest to many different groups of people each with their own perspective, which may involve areas of disagreement, in framing the problem, as well as specifying the solution. A simple example might be different views on how to respond to a crisis of obesity: patients and clinicians may view the problem differently, and have their own ideas of a solution, while policy-makers may see things from a different perspective, which may in turn differ from how health system managers may view a solution. A predictive model may be good at identifying the problem at a population level, helping policy makers frame their thinking, but may not help inform clinicians' ability to identify particular high-risk individuals – context matters.

- Problems, errors and mistakes arise in healthcare as consequences of the operation of the various systems in use, and though errors from design, too. So, errors from design decisions need to be distinguished from factors arising from the actual operation of the system itself. Predictive models produce errors since they can 'accurately produce wrong results', as a consequence of design, data selection and simplification.
- Solutions to health problems are not readily translatable from one context to another since the efficacy of solutions can be seen as attributes of the ways those systems work, and not as a physical certainty about how people, or organisations behave.

5.4 The 'symmetry of ignorance'

Rittel also developed the notion of the 'symmetry of ignorance' [88] to characterise the differences between the tacit knowledge of different stakeholders and where disagreement arises. The research using this notion has evolved into a major element of knowledge management, where it is used to characterise a type of wicked problem in which there is:

- Variable positions by stakeholders;
- Apparent diffusion of organisational power amongst interested groups;
- Poor problem framing;
- Multiple potential solutions;
- No clear evidence of what would make a solution right or wrong, only good or bad.

Poor framing means there is weakness in the cognitive models used to frame the debate, and hence guide the solution-finding process.

To develop predictive models in this context is to see them as goal-seeking, toward a particular patient-centred objective. Predictive models thus represent a deliberate cognitive framing of knowledge that crosses a variety of conceptual and knowledge boundaries and domains of practice.

Some people have suggested ways to overcome the problem of the symmetry of ignorance. The notion of a 'distributed cognitive system' or 'collective mind' to characterise the knowledge base appropriate for dealing with complex problems is emerging as a framework integral to this report's conclusions. Predictive models in this context embody the knowledge, practices and assumptions of a disparate community of interests. The predictive model becomes that which everyone can agree on as representing the knowledge and practices applicable to a particular problem.

Because of the number of stakeholders, the dynamic nature of the problem formulation, and changing constraints, it is not possible to reach an ideal solution for a wicked problem. Since there is no definitive *problem*, there is also no definitive *solution*.

Herbert Simon, the Nobel-prize winner, described this process as 'satisficing'. [89] According to Simon, the nature of the design process is such that it is virtually impossible to find the best solution, because the space of possible solutions is so large. Instead, you stop when you have a solution that is 'good enough'.

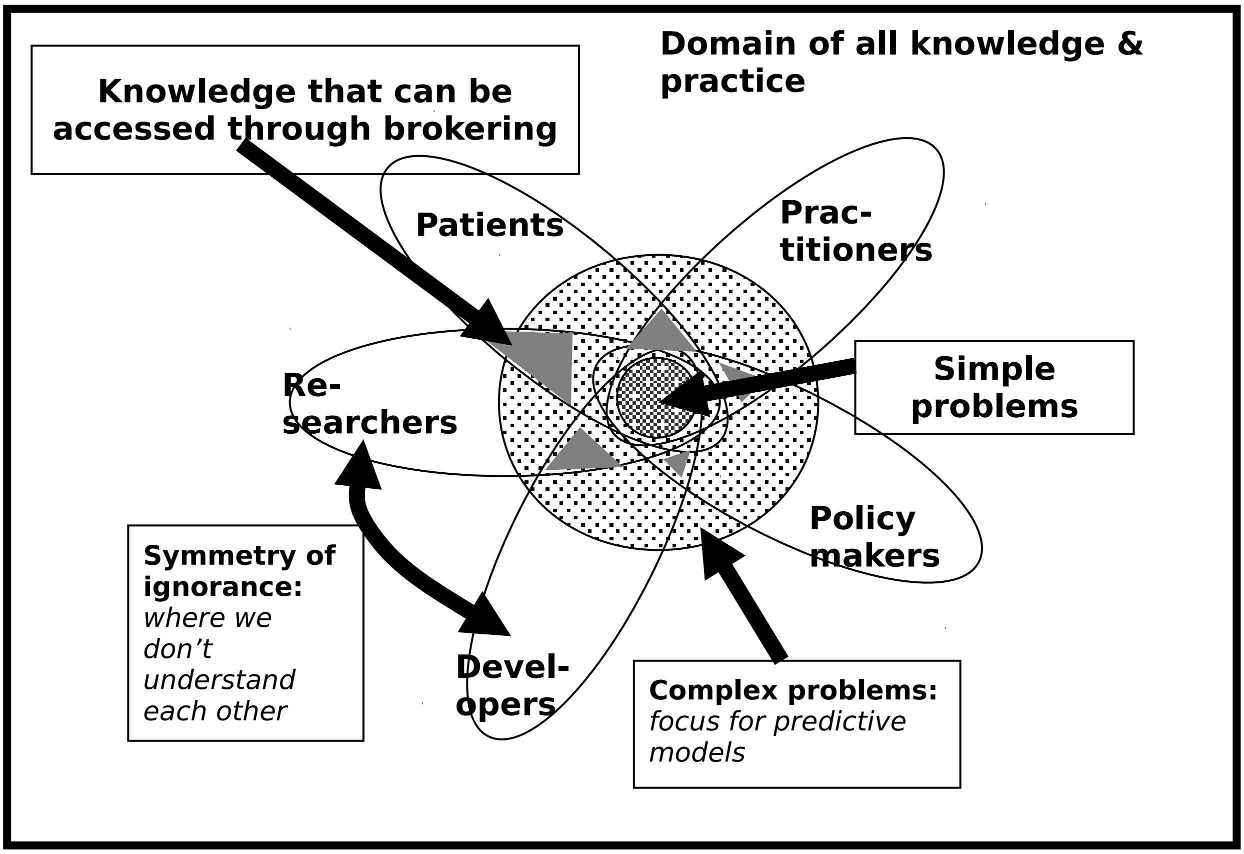
Overcoming ignorance is less about the search for perfection, and more about 'satisficing' to facilitate communication and guide action; models may not be good enough to replace individual professional reasoning unless there is evidence that humans are more easily satisficed than predictive models. The choice is determined by whether humans can understand a higher or more complex standard of satisficing of a neural network. For policy, though, "Real-world policymaking is about satisficing, not maximizing." [90]

There are important implications given the research evidence that shows that predictive models are more accurate than unaided clinical judgement. If, instead, one thinks about predictive models as an aid to better human reasoning, rather than an automated replacement, the importance of models lies in their ability to produce coherent approaches to health problems that transcends disciplinary practice and knowledge boundaries. Merely replicating the patterns of mundane problem-solving is less useful than exploiting a wider knowledge base, and would only serve to 'underpower' the predictive model.

5.4.1 Implications for policy: symmetry of ignorance and mutual comprehension

The Diagram endeavours to put this pictorially, to highlight where brokering overcomes the symmetry of ignorance, and where complex problems lie. Predictive models make better sense when seen as part of the brokering process than 'just' a model of a simple process. Models work best when they transcend individual areas of knowledge and competency. Developing a programme to develop predictive models can itself push our understanding 'outward'. The purpose of a policy research agenda in predictive modelling can be seen as trying to achieve this.

Diagram 5: Map of where models and knowledge brokering overcome symmetry of ignorance



Source: Tremblay

Satisficing raises issues about the evidence-base for policy making, when looking more generally at the role of modelling of policy options in other areas of concern. [91] From the perspective of predictive modelling and long-term conditions, it suggests a need to understand the limits of knowledge that underpin models, and ensure that clinical judgement and patient engagement reflect these more complex assumptions.

6 Policy Research Agenda

6.1 Policy research, policy-making and causality

Policy and causality are linked with policy development trying to unite three strands of thinking:

- about what we know or do not know about a problem or issue of importance,
- what the evidence is for or against particular approaches – ‘evidence-based policy-making’, and
- whether chosen methods of implementation are likely to deliver the desired outcomes.

Policy research informs that process. This paper identifies research issues for how policy relates to the real world, as all policy is really about a desired future, and which put health policy development into a relationship with what is known about predictive modelling.

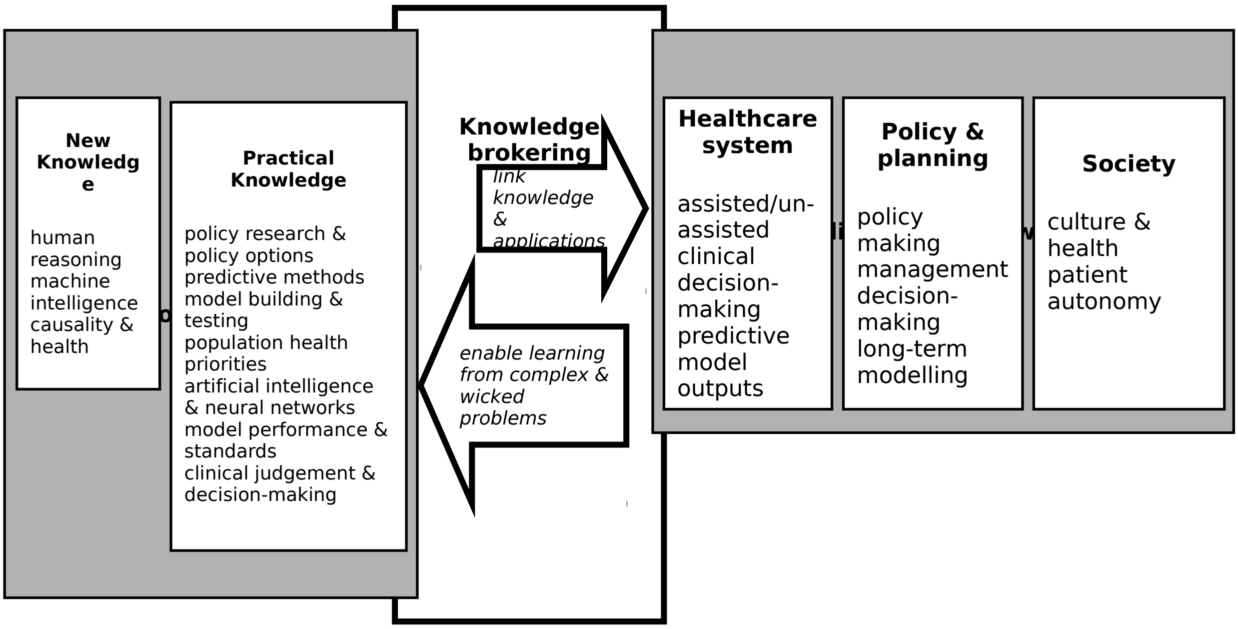
When policies cause more than expected, we want to understand these ‘unintended consequences’, to decide if they are a problem, a feature of wicked problems, with additional research issues.

So, policies ought to produce desired changes through chosen and acceptable methods of implementation. Of course, we cannot be certain that institutions chosen for policy implementation (e.g. primary care trusts) or instruments (e.g. payment by results) will produce the desired results (e.g. improved healthcare, more responsive healthcare, better value for money). More often than not we *infer* that these methods will produce the desired results as the evidence that policy is deterministic can only be evaluated after the policy has been implemented through various forms of evaluative studies; in that respect, policy research can only inform plausible policy responses, not a science of policy-making as policy lacks the needed certainty.

Policy research on predictive modelling sits in the arena linking together what people do, what policy intensions are, and whether what people do will implement those policy intensions.

The following diagram maps out the policy themes and identifies the key areas for subsequent research focus. The policy research agenda, below, endeavours to provide coverage of this map.

Diagram 6: Mapping policy research in the use of knowledge for predictive modelling



Source: Tremblay

6.2 Developing a research community around predictive modelling

Interviews with both practitioners and researchers emphasised the importance of ensuring an appropriate research community exists to take forward the necessary research, not just to inform policy, but to develop and evaluate models. The knowledge management literature, too, points to the general difficulty for society's collective ability to solve real problems using fragmented research communities.

The way the proposed policy research agenda is developed should exploit the widest possible multidisciplinary community as possible in two areas.

- The first area is how to link health policy priorities to predictive modelling itself. It is apparent that there is little direct guidance to the research and development community either directly or through targeted research grants on the development of predictive models to address health system priorities. As this report has also observed, there are potentially significant social ramifications of the use of predictive models that also needs to be integrated into the scientific priorities.
- The second area involves developing specific ways to ensure that the widest possible research community and expertise is involved in developing the research to inform policy. Owing to the nature of the complexity of health problems, it is appropriate to ensure that the largest possible communities of interest work together on these

priorities. The silo-nature of much research was cited by many during interviews, and is a common finding in the knowledge management literature.

6.2.1 Aligning health system priorities and predictive modelling

Interviewees suggested a number of approaches. An important way to begin, given the complexity of predictive models themselves, would involve bringing together a group of computer literate scientists to undertake a structured research programme on machine-based learning (e.g. neural networks) to produce their best stochastic work. They would begin with good clinical and related data on human health, and use data-mining methods to identify the complex combinations of health and related factors that are necessary in order to support risk stratification, a key output of a predictive model. Importantly, risk stratification is a central feature of programmes to better manage long-term conditions.

By ensuring a decision-centric approach coupled with a focus on high-quality and operationally relevant predictions, the group would identify the key decisions needed that arise from the modelled results. Some researchers suggest these decisions may turn out to be more relevant managerial than clinically they will relate to resource use under specific clinical conditions, rather than just improved diagnosis and treatment identification.

Given the importance of patient engagement in the health system, there are additional considerations to engage with public acceptability of this approach.

The result, it was suggested, would be a consensus on what predictive models areas would be most productive for development to support present and future health priorities.

6.2.2 Building a knowledge brokering community

It is a common feature of the research for this paper that predictive modelling challenges traditional models of knowledge demarcation, and that complex or wicked problems will be most amenable to modelling. Interviewees reported weakly connected communities of like-minded researchers and poorly developed research links and communication. Theoretical differences between inductive and deductive methodologies also affect the extent to which disparate knowledge communities can understand each other and establish a basis for collaboration.

Connectedness between researchers appears to be weak across borders, but with identified pockets of excellence. Career paths, study programmes, research funds, and policy-relevant projects are not well-developed.

Much important work on modelling is not done for healthcare, suggesting that health modelling problems might be more attractive to people working outside health in order to bring new perspectives and a wider knowledge base to bear.

The predictive modelling community as such is, therefore, small, weakly coupled, and without clear research priorities or ear-marked funding.

The proposed research agenda is premised on involving communities of expertise that do not normally interact. This approach should encourage innovative responses to complex health problems that transcend traditional problem-solving approaches, and thereby require more collaborative and multi-professional engagement.

One suggested approach would focus around establishing a practical bias within the research community using a 'big-tent' approach. This gathering would start literally 'anywhere' in respect of show-casing working predictive models to a multi-professional and user group community, and be designed to build understanding of what models can and cannot do. In addition, the research community in virtue of its fragmentation needs leadership to focus on priorities for the development of an understanding of models to inform policy-makers. Such a predictive modelling 'champion' would take responsibility for developing a deliberately disruptive research agenda designed to achieve a variety of outcomes, such as the following:

- Trigger interest within the research community to study the capabilities of predictive models;
- Create links between researchers working in disparate and unconnected areas of knowledge, specifically to overcome the 'symmetry of ignorance';
- Focus on problems with impact and scale for the health of people;
- Enable knowledge brokering to facilitate knowledge sharing, and ensure that research findings are accessible to the widest possible communities of interest, including patients, health systems leadership, service delivery professionals through open-access publishing, and not limited to small-circulation academic journals;
- Enable dissemination strategies and events focused on benefits realisation of predictive modelling and use specific predictive models as 'magnets' for further innovation in order to attract the attention of practitioners and hold multi-stakeholder interest;
- Build confidence amongst user-communities in models through trials and use in real-world situations.

Knowledge brokering approaches with far-reaching dissemination strategies and a clear focus on benefits and outcomes mean that traditional demarcations of knowledge and professional capabilities may fail to naturally organise themselves around priorities for modelling. This is a significant risk if policy research is organised around how formal knowledge communities (e.g. universities) organise themselves, or how funding agencies pre-quality certain types of researchers or research communities over others. Therefore, some care is needed in identifying who, with what knowledge and capabilities, needs to come together.

To actually build a model in a particular area necessitates bringing together clinical experts, people who understand population health, people who understand data-mining, social scientists who understand human behaviour and economists who understand costs, benefits, inputs and outputs, and mathematicians and specialists in cognitive science who can develop and build models. One approach suggested in the interviews would be to do this for flu, but with wider potential use: [92]

Put all these people together in one place and review everything known about a priority health problem;

1. Identify trends, collect data, build relationships;
2. Overlay a conceptual model which captures both causal and statistical links between the various areas of interest;
3. Develop hypotheses for testing;

Examples: develop predictive thresholds around:

- Determining the likelihood of pandemic,
- Manner of population and geographic spread,
- Identifying who (specific individuals as well as populations) is at risk
- Determining what outcome actions are most appropriate in terms of the model's results for individuals most at risk, those who get flu, and health system performance around:
  - Stopping negative consequences,
  - Starting preventative or pre-emptive measures.

The following sections detail the proposed policy research agenda which could useful draw upon these methodological suggestions.

6.3 Policy Research Questions

Policy Research Questions represent an area of general enquiry the answers to which, it is suggested, are likely to have an impact on policy direction or assumptions.

6.3.1 What is the disruptive impact of wider use of predictive models on the public's expectations of health system service delivery?

Would the successful use of predictive models with individuals with long term conditions lead to a new way of thinking about how disease and ill-health in general should be treated? Is it likely that the public will raise expectations of what they perceive to be an anticipated standard of care to a higher standard? The current implementation of the long-term strategy could be driven by determining the areas that are most amenable to systematic management through predictive models and associated care programs. But increasing public engagement in service design and development may create public expectation that customised care models have wider applicability than that currently of interest to health professionals or envisioned within policy.

Policy priority has been to ramp up expenditure as a measure of GDP, and this has focused mainly on increased expenditure in traditional areas, such as service delivery infrastructure, salaries and equipment. Expenditure on 'non-traditional' forms of service delivery is still in its infancy, and at present is characterised by infrastructural innovations such areas as Walk-in Clinics, and Independent Treatment Centres. Service delivery experiments with novel funding or patient identification and management approaches are beginning and appear to depend more on administrative details, such as PCT purchasing strategies, than the novelty and potential impact of the innovation itself.

PCTs are in the early stages of understanding the potential for alternative providers, under the new primary care contracting arrangements.[93] But, is it reasonable to assume that the health system would have no limit to the extent to which it will fund healthcare programmes based on a predicted pattern of resource use and healthcare compliance? Predictive models underpin commercial offerings by some contractors who might offer novel associated services to manage defined cohorts of patients who may seek to expand the size of this market.

Since the policy focus is on long-term conditions, could a shift to greater use of predictive models act to increase pressure from stakeholders (e.g. patients and organised patient interest groups) to increase the size of the perceived pool of long-term conditions, with associated greater expectations of customised care as a result. A cost-neutral approach – i.e. that paying for customised care is the purpose of the long-term conditions policy – may in the end exceed current planned allocations particularly since predictive models work by reallocating resources and risk. These factors individually or together can be disruptive when coupled with a commitment to patient freedom of choice. It is possible that confusion could emerge between a long-term conditions policy based on "high need for care" and one based on "ability to benefit".

Research Focus 1: Study should focus on the possible impact of predictive modelling on public expectations of service delivery and care.

We need to know:

- To what extent the public's expectations of service delivery might change in response to wider use of customised service delivery based on long-term conditions approaches, in particular; that is, what if policy designed for the few becomes of wider, or more general, interest to the many; [94]
- To what extent public engagement in service design and delivery will alter current expectations in the medium term and have a potentially disruptive impact on the health-professional-led service design and use of modelling;
- How do we assess the calibration of health policy and public expectations under a policy of user choice?

Research Focus 2: Public perception of increased use of predictive modelling needs to be studied, as wider use may be perceived as a shift

toward a more 'insurance-type' health system based around individually-assessed risk, away from risk distribution across society.

We need to know:

- What is the public acceptance of alternative approaches to risk profiling particularly if these approaches appear to reallocate risk into smaller groups of patients for special treatment;
- Might this reallocation 'appear' to the public as an insurance-like approach to determining entitlement for benefits?

6.3.2 What is the impact of the use of predictive models on fundamental values and organising principles of the NHS?

NHS values are core to the selection of appropriate policy, as well as acting as a guide to NHS organisations and contracted-in 3rd parties (e.g. independent treatment centres). While predictive models are merely software systems using health information, their role is potentially disruptive of policy intensions, unless their wider potential is fully understood. The Evercare™ programme, for instance, offered a particular approach to patient management, reflecting a particular commercial use of risk profiling and resource allocation (through the Evercare™ nurses). The challenge and decision facing PCT commissioners and the policy environment was whether a contracted-out approach was better than an internal reallocation of resources to develop a similar programme. The real problem, though, was whether the PCTs were prepared to consider the organisational consequences of independent delivery of such a programme. [95]

It may be useful to visualise the value challenges to the NHS in the following table, and determine the policy responses in each case. The problem is about how we value people under different service/risk models, and whether every person is entitled to equal consideration even though a predictive model may identify some people as more risky and therefore in greater need of explicit resource consumption. But what if the consumption of the resource is not matched by an improvement in risk? Indeed, the very ethical question being asked here is 'are those people identified for specific treatment though predictive models more worthy of special consideration than those not identified'? The Table illustrates, not exhaustively, the types of questions that are embedded in the values underpinning the use of predictive models when put into a context of risk/benefit.

<table>
<tr><th colspan="4">Table 5: The model user's dilemma: ability to benefit, or high-risk?</th></tr>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Benefit: based on patient support of their care programme, as determined by predictive modelling of patient behaviour</td></tr>
<tr><td>High likelihood of patient support</td><td>Low likelihood of patient support</td></tr>
<tr><td rowspan="2">Risk: based on health determinants, costs and benefits, as determined by predictive modelling of health risk</td><td>High risk patient</td><td>Patient is at high risk based on health determinants and modeled as likely to benefit.
Are these the patients to target most?</td><td>Patient is at high risk based on health determinants but modeled as likely not to be supportive and hence lower likelihood of benefit.
If customised resources are to produce benefits should patients least likely to comply be avoided?</td></tr>
<tr><td>Low risk patient</td><td>Patient is at low risk based on health determinants and modeled as likely to benefit.
Are these articulate consumers of health resources who may seek wider use of predictive models to expand the scope of customised care for themselves?</td><td>Patient is at low risk based on health determinants but modeled as likely not be supportive.
Are these the people to be excluded from customised care based on predictive models as not sufficiently risk to warrant special treatment?</td></tr>
<tr><td colspan="4">Source: Tremblay</td></tr>
</table>

There are serious social justice considerations embedded in the questions in this table. It is possible that rights-based challenges to the clinical/administrative use of predictive models may be considered by disaffected groups if they perceive their use as exclusionary (when contrasted with otherwise available treatment options). Since the ways that these models learn to data-mine and apply decision rules may reflect (unintentional human or design) bias, it must be concluded that the use of predictive models cannot be seen as value-neutral.

The introduction of decision-support into the predictive realm can be driven as much by considerations of cost and service efficiency as concerns for social inclusion and social justice. To the extent that models suffer from these deficiencies, they offer considerable benefits to health systems as they seek to better allocate scarce resources. However, the substitution of human bias with machine bias does not make the results any less unjust.

These considerations also need to be embedded in the context of the policies around health informatics and Connecting for Health, in particular centrally-held (that is, not patient-held) health records. This is an issue of concern at present as it raises questions of how to balance individual rights and patient choice with the NHS's administrative requirements for the management of its internal health record system. Where other countries have introduced patient-held health records, the patient's consent is critical to subsequent use of data for predictive modelling purposes; the perceived efficiencies and technological ease of central records may not outweigh public concerns and individual consent.

In the current climate of implementation, the public may not fully appreciate the extent to which centrally-held health records can be used for profiling through data-mining by predictive models in the absence of patient consent. Additionally, the public may wish to take a view on how this is done as part of their own confidentiality and control of health information. [96]

Information security, privacy and individual consent become key elements of the balancing act between individual liberty and the ability of the health system to better manage long term conditions. While the focus of information security has been on the disclosure of health information, the ability of predictive models to sift through electronic health records to identify individuals at some health risk is central to their utility and the core to their potential misuse.

Emerging legal opinions in other jurisdictions are creating new thinking of the balance between individual liberty and the state's ability to determine the shape of public services. For the UK, these are the rulings of the European Court of Justice on portability of health benefits within the EU.[97] There is also a recent Canadian Supreme Court ruling that it is a violation of individual liberty for the state to limit individual access to extra healthcare through private health insurance.[98] Constitution-type rights may bestow on an individual a right to protection from profiling by predictive models which may discriminate in prohibited ways.

Research Focus 3: Are there implications for social justice from predictive models and patient profiling?

We need to know:

- Is patient profiling by predictive modelling prohibited by law or could it violate social justice conventions?
- Are predictive models sufficiently technically robust to avoid statistical sources of discrimination that are prohibited (such as ethnicity, race, gender or age) the effect of which is to unfairly include/exclude specific individuals or groups?
- Can patients withhold consent to be 'data-mined' by predictive models and thereby to be identified and profiled for health risk?
- What are the consequences for policy of a conflict between individual rights (protection of privacy, prohibition of discrimination, etc.) and wider policy considerations on the management of long-term conditions?

6.3.3 How can predictive models be used to explore future health?

The focus of the paper has been emergent issues for predictive modelling and long term conditions. A special case, though, is climate change and its impact on health. There is global interest in this area, and the UK is seen as a leader in the development of climate models. This leadership appears not to extend to climate and health, and despite the production of a Departmental paper some years ago[99], the level of activity appears to be focused on shorter-term considerations. As a particular application of predictive modelling, this area raises important considerations about how future health determinants will change: e.g. evolving ecologies, shifting patterns of disease, new health challenges, new vectors of disease, new socio-cultural determinants of ill-health, and thermal stress from poorly insulated houses. Many of these areas are of present interest, but longer term modelling is absent.

Creating an independently funded Institute for Future Health would be an appropriate focus for policy-making and service delivery action to ensure that the shorter-term political priorities are informed with a sustained research and implementation agenda that extends well into the future, uncertainties notwithstanding. The various public health observatories seem mainly focused on meeting current and short term public health needs and are perhaps not suited to undertake longer timeline forecasting across a whole spectrum of future health issues, of which climate change is just one major factor. [100] It may be appropriate to explore creating a formal mandate for an existing research community to undertake a more complex and nuanced research and policy focus on this area, but importantly, to take that agenda forward in a cross-disciplinary manner. Additionally, a multi-disciplinary policy and research environment will permit greater understanding of issues which are genuinely long-term, with potential for present action.

Research Focus 4: A research programme to link predictive modelling with longer term health research, including climate change, is needed.

This could be achieved through establishing a coordinating research centre such as an 'Institute for Future Health' to encourage research and inform longer term policy-making.

This programme should ensure operational, strategic, and policy level links between the Department of Health, the NHS, and the research community, to inform decision-making with useful, policy-ready knowledge. This might be achieved by creating suitable links with the Hadley Centre (on climate change and health) and other research institutes focused on longer term health issues.

- There is a need for a funded mission on health and climate change.
- Related to this is the possibility of developing a more nuanced understanding of determinants of future health through measures different from current measures of health. [101]

Research Focus 5: How should the implications of wider use of predictive models be calibrated with policy-oriented priorities and vice versa?

This research would examine the extent to which:

- 'future determinants' could be developed for long-baseline prediction.
- long-baseline models could calibrate operational use of predictive models with policy priorities.

6.3.4 Should predictive models be certified or licensed?

The potential for wider use of predictive models raises questions about their accuracy, design, underlying logic plus clinical and other assumptions that went into their design. Model assumptions may skew prediction in ways which may undermine social justice, but they may also be in error, or come to be wrong over time as their evidence base changes.

Therefore, should the predictive models use in healthcare be subject to external scrutiny, 'licensure' or approval in the same manner as new medicines or devices?

Regulatory authorities should be informed of the scope of the possible policy research programme on predictive modelling and encouraged to identify areas of possible interest in these issues and invited to comment or participate.

Research Focus 6: A review of the potential regulatory impact of the use of predictive modelling should deal with two issues:

1. **should predictive models be subject to scrutiny, quality assurance, or quality standards;**
2. **does the use of machine reasoning by licensed health professionals have implications on their professional regulation and conduct?**

The scope for research should encompass the following:

- What are the policy and regulatory implications of increasing machine learning, reasoning and 'intelligence' for healthcare?
- What standards should apply to the development and use of predictive models?
- Is there a measure of predictive power that can meaningfully communicate model performance to users and the public?
- How does the model handle uncertainty in the data and how is that expressed to help users' understand the limitations of models?
- What is the capability of the models to 'learn' or produce new knowledge and how does that alter the models predictive power and impact?
- Are there implications for the regulation of health professionals where machine intelligence/predictive models are used to enhance or replace clinical judgement governed by professional license?

6.3.5 What is the readiness of the NHS to use predictive models?

The commercial exploitation and development of predictive models is well-developed in some markets, particularly the US, where models are used by both providers and insurers who have developed sophistication in understanding their use and functional capabilities. Considerable interest in their use has driven investment and development in models and produced a variety of commercially acceptable applications. In particular, predictive models are widely used in disease management, patient experience, and outcome-oriented care management programmes.

The general utility of these models is considerable and generally only limited by the data that they require. In most cases, clinical models are built on medical knowledge and might be seen as largely transplantable from one clinical context to another and indeed from one country to another. Not only is their suitability for this unknown, but their applicability and portability untested.

Commercial interests may perceive the current interest by the Strategic Health Authorities in predictive modelling, as well as the trial of Evercare™, and other current activities associated with current long-term conditions policy as evidence that the NHS is 'open to business' to suppliers of these models. But this interest may be ahead of the readiness of NHS organisations to exploit their use.

Research Focus 7: The potential use of predictive models needs to be assessed to determine the readiness by NHS organisations.

Studies are needed in two areas.

- The first area would focus on understanding the readiness of NHS organisations (by providers and purchasing organisations) to use these models, including what the organisational, clinical and managerial factors relevant to exploiting the capabilities of predictive models. In addition, a skills audit would determine what the state of knowledge of modelling is and what expertise resides in what organisations.
- The second area is to understand better the commercial market and services of those using predictive models, as distinct from the research-only models, in such areas as disease management, case management, data-mining tools, patient-experience programmes, compliance programmes, as a start.
- We need to know at least:
- A taxonomy of types of models (spreadsheet, neural network, statistical, causal, etc.), their areas of application and functional characteristics;
- A catalogue of sources, designers, developers and providers of these models (companies, suppliers, researchers and developers, etc.) by country (UK, European Union, US, Australia etc).

6.4 Policy Experiments

Policy Experiments outline broad hypotheses to be explored to develop suitable policy options.

6.4.1 How can predictive models improve decision-making?

The research evidence confidently concludes that predictive models outperform unassisted clinical judgement, including when predictive results are provided to support clinician reasoning. This has implications for decision-support, knowledge management/utilisation strategies and evidence-based healthcare.

The use of predictive model outputs to inform decision-making to improve patient outcomes depends on whether predictive models are defined as an aid to clinical judgement or define the structure of clinical reasoning within a set of rules (guidelines, protocols, etc.).

Given the proliferation of models of all sorts, and the increased interest in powerful models based on machine intelligence, it is appropriate to better understand at least these factors:

- How do we ‘rate’ or ‘score’ decision-making which uses predictive models in terms of outcomes, when the model outperforms clinical judgement?
- Does the out-performance by models of clinicians’ judgement have

relevance or impact on health system performance from a patient perspective? from a clinician perspective?

- Does the use of predictive models which take account a wide range of data inputs (which they do very well) likely to impact communication patterns by clinicians and thus alter team-based working, or forms of information exchange with patients?

In general, models are seen as informing, or augmenting human judgement, by interpreting complex data better and providing a prediction within some degree of confidence. That view, however, reflects the preferences of clinicians, and may not fully exploit the capabilities of these models.

Research Focus 8: We need to know how decisions are made that involve the use of predictive models.

Do the models that are developed reflect the decisions that people need to make; do the decisions that people need to make guide what models are developed?

We need to know what types of models are appropriate for what types of decisions:

- How does a particular predictive model optimise, or not, decisions that people need to make (e.g. about a patient's diagnosis, resources available or to be used, etc.)?
- How do organisational factors (such as organisational design, communication patterns, use of information, skills, processes and technologies in use) affect how predictive models are used by decision-makers?
- Does the use of predictive models have an impact on clinical decision-makers, or on patterns of communication between professionals?
- Are there circumstances when superior results by a predictive model should pre-empt (assisted or unassisted) clinician judgement?
- What areas of decision-making should be prioritised for the development and use of predictive models?
- What is the role of predictive modelling in informing the methods we use to establish long term health priorities?

6.4.2 How should providers use predictive models?

Health system providers are more likely to see the immediate benefit of predictive modelling as improving their ability to manage future resource consumption and this is clearly in their interests as indicated by use in other countries. Increased and more nuanced use of predictive models should be expected by providers for a number of reasons:

- Modelling will help better align available resources with contracted demand for services;

- Modelling will better enable providers to reduce uncertainty of future resource consumption by patients with long-term conditions since they account for the bulk of provider activity and cost;
- Modelling is consistent with good provider business practice and improved managerial control of resources, infrastructure and service development through operational research capabilities;
- Clinical use of modelling is indicated in the literature as producing superior decisions and therefore acts to improve risk management in the context of patient care.

It is also likely that provider ability to differentiate themselves from each other will be enhanced through better use of patient information. Long-term conditions lend themselves more easily to predictive modelling through better resource management, and providers may emerge (either from existing NHS organisations, or new market entrants) with dominant capabilities in this area. These capabilities are clearly in the interest of PCTs as it reduces commissioning risk, and may positively impact contract outcomes.

Research Focus 9: Organisationally-oriented policy research should focus on how predictive models can aid managerial and clinical decision-making, including resource use modelling.

This focus should also prioritise our understanding of what might incentivise better use of information to drive performance improvement and user satisfaction.

We need to know:

- What are the long-term benefits of providers possessing operational research capabilities around predictive models that impact specific patient cohorts, including long-term conditions?
- What sorts of models are available/need to be developed to facilitate better predictive modelling by providers?
- Does the use of predictive models by service providers (NHS, independent, voluntary) bestow any competitive or commercial advantage for patient outcomes through clinical contracting-out that is relevant to the current policy on service provision?
- How can providers use predictive modelling to improve managerial and clinical control of resources, service outcomes, and patient outcomes?

6.4.3 What is the role of predictive modelling in PCT commissioning?

The focus on population health models tends to favour descriptive approaches and priority setting separate from identified individuals and cohorts at risk. The challenging use of a predictive model is whether it can profile a population and target resources to specific individuals and groups in such a way that the PCT can incentivise providers.

The problem in this respect is that PCTs need better, non-linear models of health need, which also incorporate a pricing structure. Modelling opens up possibilities not envisioned in current policy, such as the use of tariff unbundling, for instance, to permit subtler forms of incentives to address predicted health outcome expectations.

Central to effective PCT use of models would be if it unlocked provider control of patients, by:

- Helping PCTs to link their commissioning intensions to improved health modelling of their catchment populations.
- Ensuring that PCTs get the risk stratification right by identifying provider propensity to have adverse outcomes and disproportionate levels of resources *in the future*.

An experimental approach to commissioning offers the opportunity to test the role of predictive modelling and commissioning in three areas: knowledge, organisational arrangements and social values:

Knowledge

Experiments around knowledge and the use of information derived from predictive models on risk, pricing, resource allocation, and utilisation would identify how predictive models can exploit better our understanding of the future performance of health systems and the potential influence on that performance by PCT decision-making. We also need to understand the implications of the risk-based reallocation of resources by PCTs that depart from current national formulae for resource allocation.

Organisational arrangements

These experiments would seek to test the points of compatibility between predictive modelling and provider configuration, taking account of commissioning incentives and organisational typologies (clinical, independent centre, acute facility, out-of-hospital environment, etc.).

Another experiment would explore the extent to which the GP Contract and predictive models are compatible, for instance, in whether predictive models can be used to test market contestability by new health market entrants.

Social values

Experiments are needed to determine how potentially disruptive predictive modelling impacts the organising principles and policy beliefs as embodied in the structure and organisation of the NHS.

It is suggested that this experiment test current assumptions around a flat-tariff system and methods used to attract new market entrants, 3rd party contractors and other organisations as part of the development of the NHS health market.

Predictive models have implications for all these areas, by appearing to encourage grouping patients together for treatment[102], and which may require more subtle payment models to encourage both innovation and better health outcomes. There are potentially significant implications for the structure and process of regulatory systems which enforce the policy environment, when there is this sort of contracting out of whole cohorts of patients to providers which use predictive models to organise and manage care.

Research Focus 10: Organisationally-oriented policy research should focus on how predictive models can aid priority-setting, health modelling, resource modelling and decision-making by PCTs.

'Experimental commissioning' should be considered as a way of testing the impact of a mixed health economy and the PCT commissioning role since predictive models have a role in modelling future health, and in health risk and pricing/performance.

We need to know:

- The potential for predictive modelling to reallocate funds using a different risk adjustment process to align resources toward high-use/high-risk individuals, as this differs from currently used risk/resource allocation models.
- What structure and use of predictive models produce the best returns in terms of more individualised risk modelling and of resource allocations?
- What are the points of compatibility between predictive models and their use by PCTs that can encourage providers to optimise their service configurations?
- Does the use of predictive modelling require a more nuanced NHS pricing model?
- Can PCT commissioners use predictive models to 'buy their patients to the front of the queue' and would this behaviour be a distortion of clinical priorities, evidence of proper clinical priorities, or violate individual rights to equal treatment?

6.5 Recommendations

Although this report is intended to focus on identifying a research agenda, the following are recommended basic preparatory requirements for taking forward this agenda.

6.5.1 Rights-based challenges to policy

The potential impact of wider use of predictive modelling is great, rather than small and benign, and given the state of knowledge in this area, the implications for current policy need further study.

Recommendation 1: The Department of Health should ensure that policy takes account of the potential disruptive implications of rights-based challenges to existing policies from concerns raised by risk profiling and predictive models.

6.5.2 Creating a research community

The current research environment is reported to be fragmented, with no defined research focus for the use of predictive models for operational healthcare use. This suggests that policy knowledge on predictive models is not well-organised around key healthcare priorities and future policy risks being constrained by a lack of appropriate useful policy-oriented learning.

Recommendation 2: The Department of Health should encourage the formation of a multi-disciplinary research community to study the nexus of machine intelligence and predictive modelling in healthcare.

7 Appendix: Methodology and identifying the relevant knowledge base

Knowledge of predictive modelling was taken to include identifying the following:

- Material published in academic contexts, and in general circulation, or produced by governments, organisations or individuals regardless of repository (print, electronic media);
- Individuals authoritative in the field.

This was determined in the following ways.

- Knowledge on the subject of predictive modelling was identified using high-level search terms all in the context of 'health', 'clinical' or 'medicine' and variations therein:
- Predictive modelling (two 'l's); Predictive modeling (one 'l')
- Clinical judgement ('e'); clinical judgment (no 'e')
- Decision-making; decision-support
- Artificial intelligence, neural network

Subsequent searches were context-specific to the relevant knowledge terms identified for knowledge-mining. This included web-site-specific searches to identify organisations which maintain lists or inventories of documents focused on the area of priority.

PubMed/Medline was used to identify print-based and electronic documents within academic publications, including material in less common circulation or limited to specialist audiences.

Google, Google Scholar, Copernic Agent, and Kartoo were used at different times to identify the relevant literature in the wider knowledge community and outside academic contexts, including official publications of governments, reports by organisations and individuals and journals.

Individual author names were searched to identify additional produced material such as conference presentations, or personal web-sites for additional content.

A variety of individuals were contacted by email for specific publications, additional information and comments, thoughts and reflections.

Individuals were asked to identify other individuals, key knowledge or sources of relevant knowledge for further search and study. A small number of people contacted did not respond.

8 Appendix: People consulted

People who provided information and insights in the preparation of this report		
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9.1 Web resources on predictive modelling

There are many resources on predictive modelling, and too many to list meaningfully. The following are a few that provide an overview.

Kmi.open.ac.uk is the Knowledge Management Institute within the Open University.

www.biopattern.org/index.html is a Framework VI European Commission funded Network of Excellence called BIOPATTERN to develop computational models in e-health.

www.chcs.org/publications3960/publications_show.htm?doc_id=274475 site provides a summary of the use of predictive models within the US Medicare/Medicaid managed care system.

www.coiera.com/ailist/list-idx.htm Enrico Coiera maintains a list of AI systems in clinical use.

www.medal.org is the Medal (medical algorithms) project based in the US, and which houses over 6000 medical algorithms, using computational formula, table look-ups, surveys or formulas.

www.medg.lcs.mit.edu/ site is the MIT resource on modelling in healthcare and decision-support. Primary focus is around the Clinical Decision Making Group on application of technology and artificial intelligence to clinical situations.

www.openclinical.org. site includes resources to support clinical decision support, including access to specific models for use by clinicians. Some resources focus on patient-specific areas, while others focus on wider issues to do with patient management and resource use in clinical contexts. Site intends to be a definitive resource of models, with commentary and descriptions. Models are not critiqued.

www.pkc.com is a company developing the work of Dr Lawrence Weed on the role of knowledge couplers in healthcare.

9.2 Endnotes

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[52] See for example, Fair Allocation of Intensive Care Unit Resources, American Thoracic Society, March 1997, which makes specific reference to the use of predictive models and the role of human overrides: "These considerations do not mean that predictive models have no value, only that they have limitations and should not be relied upon for individual allocation decisions. [Predictive models] are an important way of systematically combining clinical outcome data in order to inform clinical decisions and will be essential in the future to establishing a stronger scientific basis for defining outcomes in critical care medicine."

[53] This is reported by Dawes.

[54] These directories include: Open Clinical, CHCS in the US, and MEDAL; please see References for web details.

[55] Lisboa raises similar points; I have endeavoured to put these and others into a broader policy context.

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[72] The question of human versus machine intelligence is a dynamic field of speculation as much as research, and care must be taken in understanding the various claims. A measure used by some is the Turing Test, which is seen by many as a measure of when machines will have surpassed humans in intelligence; the Turing Test was formulated as a measure of machine versus human capabilities by Alan Turing, On computable numbers, with an application to the Entsscheidungsproblem, *Proceedings of the London Mathematical Society*, Series 2, Vol 42 (1936-7)230-265. Many take the view that this is likely, such as Ray Kurzweil [**The age of spiritual machines: when computers exceed human intelligence,** Texere Publishing, 2001], while others such as John Searle argue this is unlikely [Is the mind's brain a computer program? *Scientific American* 1-1990(262):26-31] Useful insights can be gathered from reviewing: John McCarthy, Making robots conscious of their mental states, Computer Science Department, Stanford University, www-formal.stanford.edu/jmc/consciousness/consciousness.html accessed 15 July 2005]; Hans Moravec, When will computer hardware match the human brain? *Journal of Evolution and Technology*, 1-1998]

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[75] See also, M. Gibbons, et al, The new production of knowledge: the dynamics of science and research in contemporary societies, Sage, 1994.

[76] The literature on this is extensive and embrases a variety of intellectural domains. But a useful and thoughtful commentary can be found in: A Van de Ven & PE Johnson, Knowledge for theory and practice, forthcoming 2006, *Academy of Management Review*, available at http://webpages.csom.umn.edu/smo/avandeven/Vandeven&Johnson%20Know%201-25-05.pdf , accessed 15 June 2005. The points raised go to the heart of predictive modelling knowledge, that knowledge is needed for practical reasons and that practical knowledge is of equivalent status to theoretical knowledge.

[77] www.chsrf.org.

[78] These concerns have found real shape in the history of innovative organisations, which has produced a variety of quasi-academic organisations with a focus on producing useful knowledge, such as Bell Labs (now Lucent) and the Santa Fe Institute. This is based on Tremblay's consultancy research on the nature of innovation, available at www.policyinsider.com.

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[96] It is an emergent issue in other national jurisdictions, with one view that the health information is the patient's, and the documentary record the provider's. The latter needs the permission of the former to construct a record.

[97] The rulings can be searched on the Court's website: curia.eu.int/en/transitpage.htm Helpfully, many organisations compile records of them for easy reference: e.g. European Public Health Alliance: www.epha.org/r/20 .

[98] www.lexum.umontreal.ca/csc-scc/cgi-bin/disp.pl/en/rec/html/2005scc035.wpd.html?query=%22zeliotis%22&langue=en&selection=&database=en/jug&method=all&retour=/csc-scc/cgi-bin/srch.pl?database=en%2Fjug~~query=zeliotis~~language=en~~x=0~~y=0~~method=all

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[102] These are called 'carve-outs' when care is out-sourced, and 'carve-ins' when the organisation develops an in-house programme. The patients are grouped around common risk profiles, where similarity of care requirements also involved improved resource efficiencies.