Minority Report! Art, science and ethics of AI

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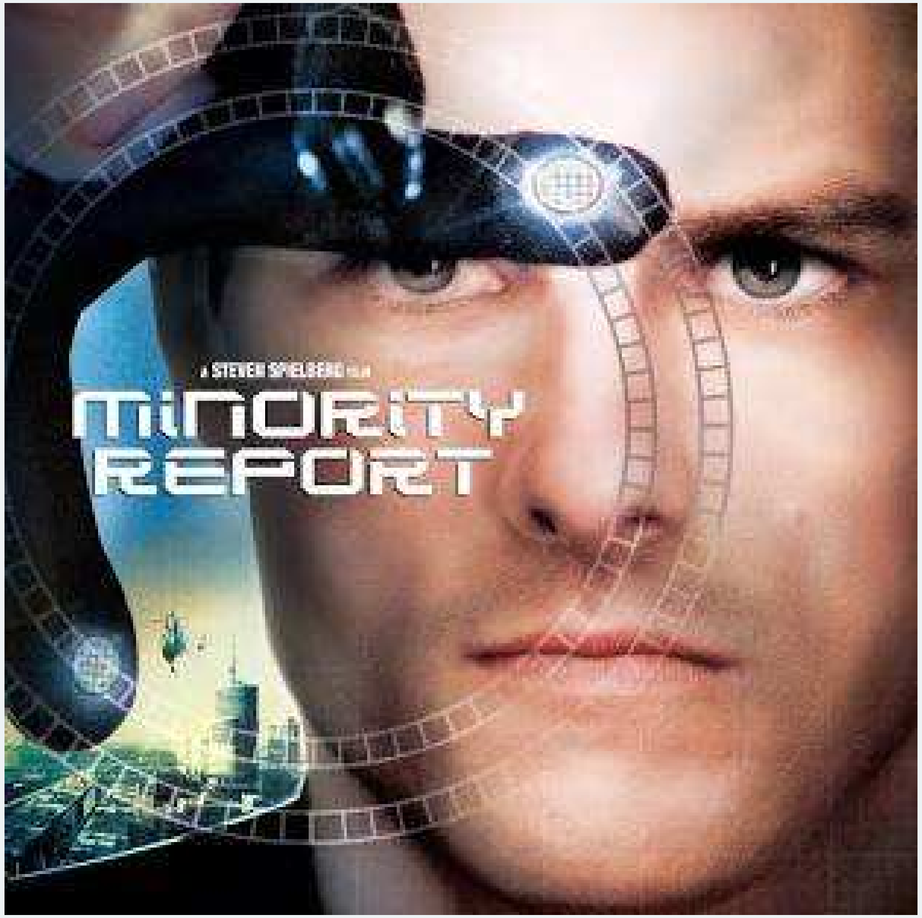
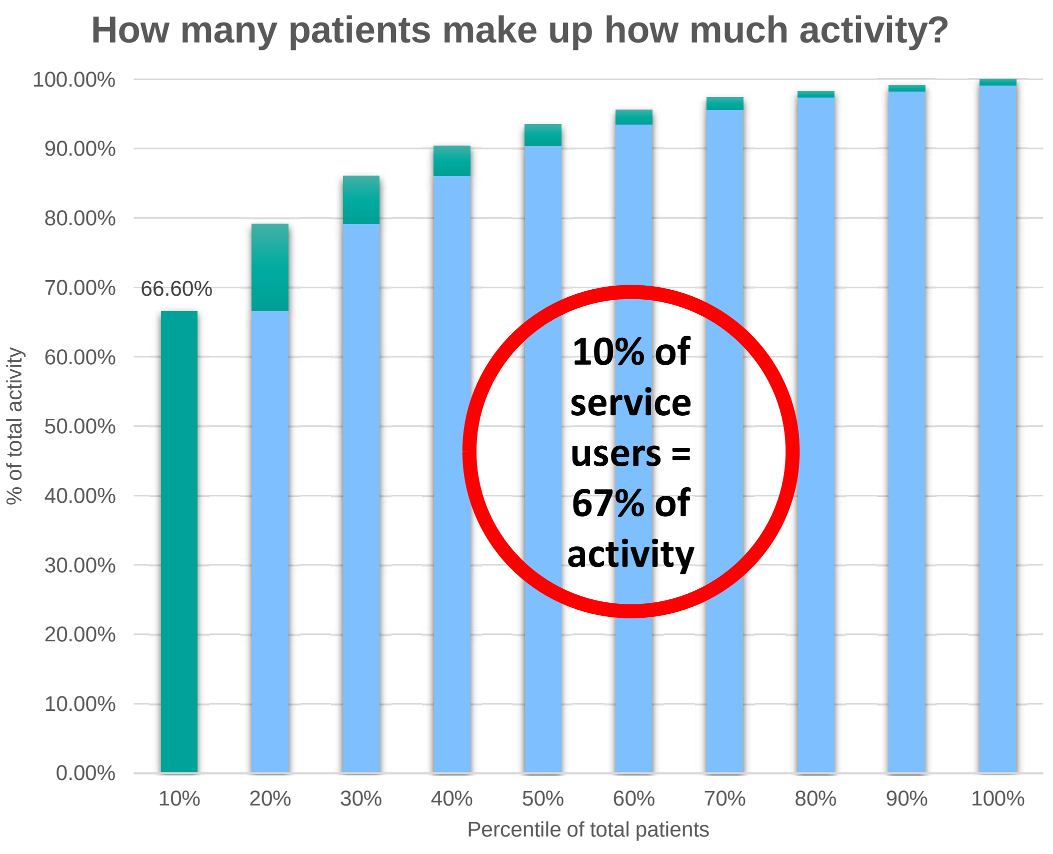


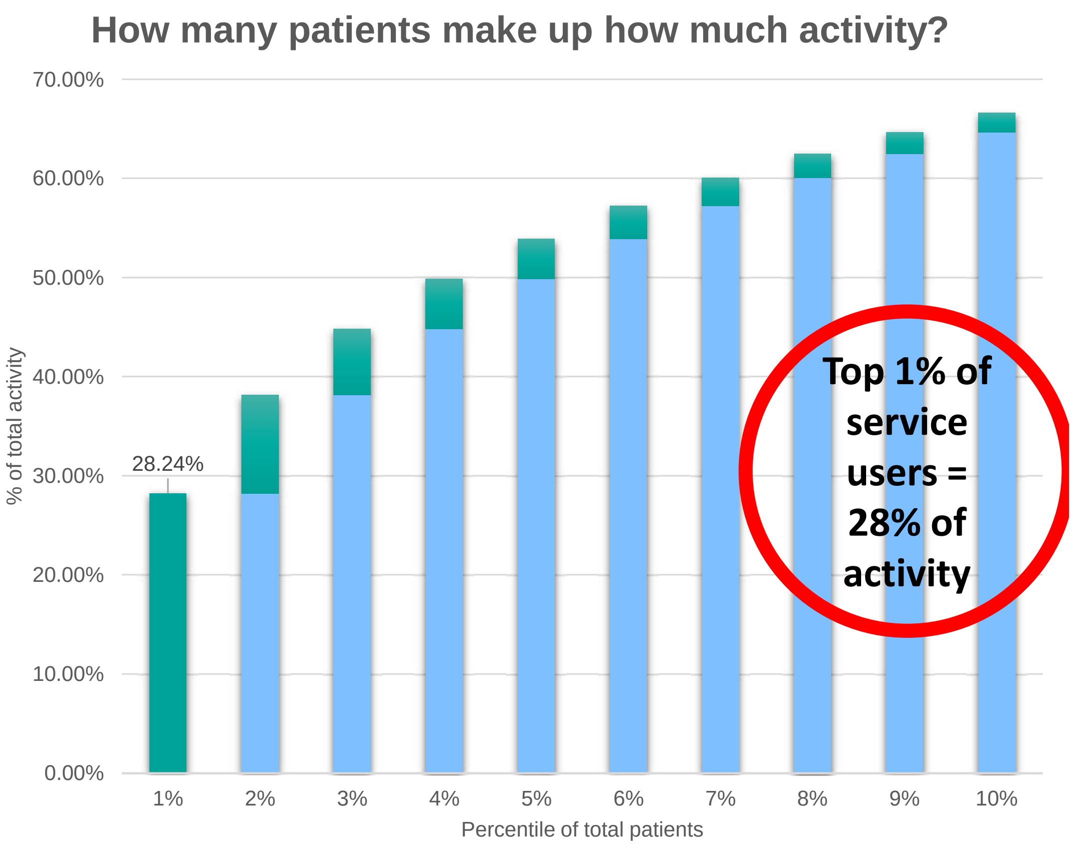
Forecasting in both history and fiction

- Alexander the Great relied on a variety of forecasts, including astrological omens and animal sacrifices, to predict outcomes before battles
- A notable example is the lunar eclipse before the Battle of Gaugamela, which his astrologers interpreted as a favourable omen for victory despite appearing blood-red
- Another instance was a favourable but painful omen associated with olive oil found at the start of his India campaign
- We never know all the predictions which did not happen! After all, in war it's a 50% chance!
- Hippocrates used careful observation of symptoms and the environment to predict the course of an illness, believing diseases had natural causes

Forecasting in both history and fiction

The Case for Change





Population Health Management

Taking a population health perspective on high users of health care

Rationale:

Social determinants of health both predispose patients to becoming high users and affect patient trajectory once in the high-user group.

Aspiration to identify key parameters that would associate people with being in the 1% and design services that proactively intervene earlier

Potential to Integrated Neighbourhood Teams

Potential to identify where to target our efforts

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Risk Stratification tools–UCL risk stratification tool

High risk		Medium risk		Low risk
Priority One **Hba1c >90 OR** **Hba1c >75 WITH any of the following:** • BAME • Social complexity** • Severe frailty • Insulin or other injectables • Heart failure ** Social complexity includes Learning disability, homeless, housebound, alcohol or drug misuse	**Priority Two** **Hba1c >75 OR** **Any HbA1c WITH any of the following:** • Foot ulcer in last 3 years • MI or stroke/TIA in last 12 months • Community diabetes team codes • eGFR < 45 • Metabolic syndrome (Except patients included in Priority 1 group)	**Priority Three** **Hba1c 58-75 WITH any of the following:** • BAME • Mild to moderate frailty • Previous coronary heart disease or stroke/TIA >12 months previously • BP≥140/90 • Proteinuria or Albuminuria (Except patients included in Priority 1 and 2 groups)	**Priority Four** **Hba1c 58-75 OR** **Any HbA1c WITH any of the following:** • eGFR 45-60 • BP≥140/90 • Higher risk foot disease or PAD or neuropathy • Erectile Dysfunction • Diabetic retinopathy • BMI >35 • Social complexity • Severe frailty • insulin or other injectables • Heart failure (Except patients included in Priority 1, 2 or 3 groups)	**Priority Five** **All others** (Except patients included in Priority 1-4 groups)

Population Health Management (John Hopkins)

How Do ACGs Work?

These groups consider factors like the number of chronic conditions, the severity of illness and the level of support a patient might need. The patients in a particular group have similar patterns of need.

Population Health Management (Optum)

PHM Correlation with event and outcomes

Performance of model – correlation between spend and risk score

Measure (annual spend £)	r (correlation)	r^2 (causation)
Finance total	0.97	0.94
Emergency admissions	0.92	0.84
A & E attendances	0.93	0.86
Elective admissions	0.94	0.88
Outpatient appointments	0.97	0.95
Primary Care appointments	1.00	0.99
Mental Health contacts	0.81	0.66
Community Care contacts	0.94	0.88
Social Care packages	0.96	0.91

Existing risk stratification validity

JUNE 26, 2025

Validation of [redacted] risk stratification in primary care

The [redacted] risk stratification algorithm demonstrated moderate discrimination (c-statistics 0.649-0.721) in predicting adverse outcomes, with enhanced performance when supplemented by provider input.

ABSTRACT

A prospective study of 47,940 primary care patients in 2019 showed that a proprietary commercial risk algorithm yielded moderate discrimination for predicting emergency department visits, hospital admissions, and mortality. * The commercial algorithm produced c-statistics of 0.684, 0.649, and 0.721, respectively. * When providers supplemented the algorithm with clinical and behavioral factors—what is termed provider adjudication—the corresponding c-statistics improved to 0.689 (emergency department visits, $p < 0.01$), 0.663 (hospital admissions, $p < 0.01$), and 0.753 (mortality, $p < 0.01$).

Key patient factors were associated with higher odds of being classified as high risk: male sex (odds ratio 1.24), age over 65 (2.55), Black race (1.26), polypharmacy (4.87), a positive depression screen (1.57), and hemoglobin A1c above 9 (1.89); all associations were statistically significant. * Subgroup analyses indicated that provider-adjudicated risk scores were more predictive among male and elderly patients, whereas no significant performance difference was found for Black patients. *

METHODS >

We analyzed 1 sources from an initial pool of 50, using 8 screening criteria. Each paper was reviewed for 6 key aspects that mattered most to the research question. More on methods

RESULTS

Characteristics of Included Studies

Study	Study Design	Population Size	Risk Stratification Method	Outcomes Mea

Types Risk Stratification

Clinical Judgement	Easy and accepted	Limited validation
Threshold Modelling	Less data	Poor accuracy
Predictive Modelling	Data hungry and complex	More accurate (but variable)

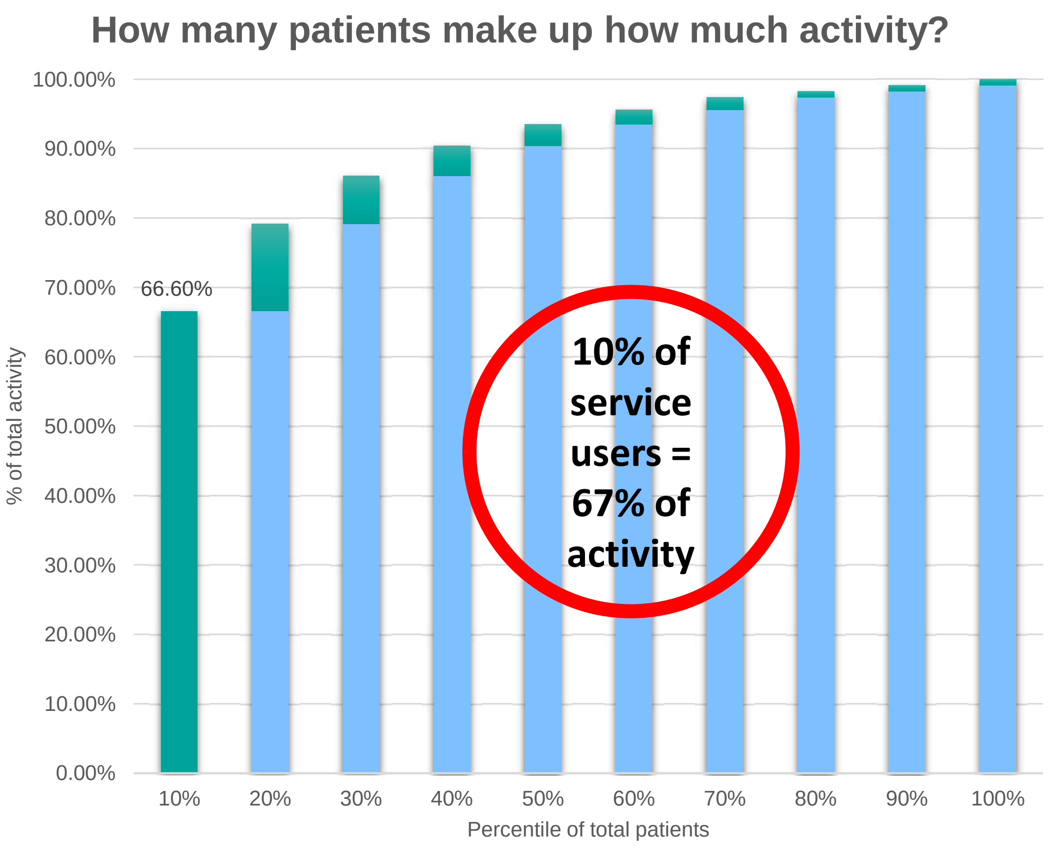
BMJ analysis of PHM models

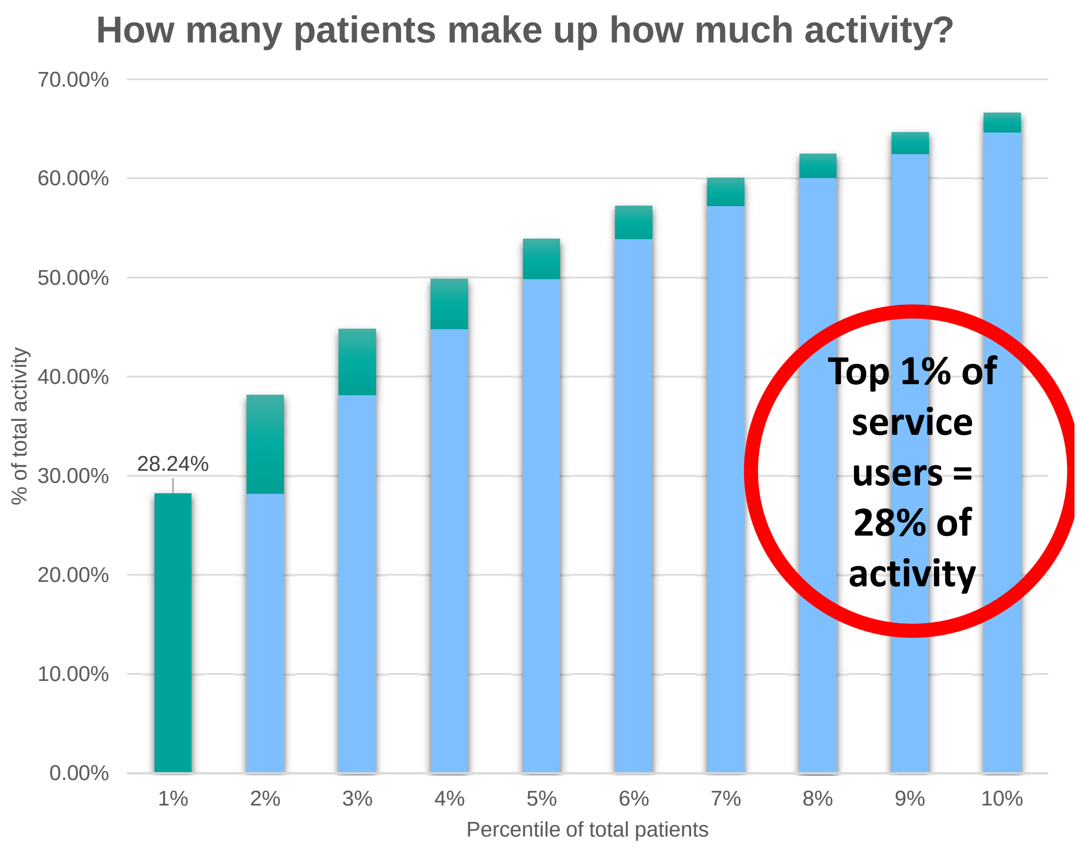
	Development Details	Number of Validations	Validation Countries	Study Designs	Validation Outcomes	Validation Results	Real World Evaluation
Charlson Comorbidity Index	Mortality RR = 2.0 (1.6-2.4)	10	1, 2, 1, 1, 1, 4	10 observational	Access of primary care A&E attendance Healthcare costs Hospital admissions Mortality	C = 0.58 - 0.78 R^2 = 0.11 - 0.42	
Chronic Illness and Disability Payment System	Healthcare costs R^2 = 0.18	2	2	2 observational	Access of primary care Healthcare costs	R^2 = 0.20 - 0.25	
Combined Predictive Model	Hospital admissions PPV = 0.29	1		Retrospective cohort	Hospital admissions		Significantly reduced hospital admissions p<0.001
Elder Risk Assessment Index	Hospital admissions C = 0.70	1		RCT	A&E attendance Hospital admissions Mortality		Increased: Mortality (p=0.008) Hospital admissions (p=0.24) A&E attendance (p=0.27)
Episode Risk Groups	Healthcare costs	1		Observational	Healthcare costs	R^2 = 0.23	
Hierarchical Condition Category	Healthcare costs R^2 = 0.12	8	8	7 observational 1 RCT	Access of primary care A&E attendance Healthcare costs Hospital admissions Mortality Readmission	C = 0.64 - 0.88 R^2 = 0.08 - 0.26	Non-significant increases in primary care access, A&E attendance & readmission with non-significant reduction in hospital admissions
Johns Hopkins ACG System	Hospital admissions	20	1, 7, 1, 2, 9	18 observational 2 cohort studies	Access of primary care A&E attendance Healthcare costs Hospital admissions Mortality	C = 0.53 - 0.86 R^2 = 0.10 - 0.64	Significantly reduced hospital admissions in prioritised group Significantly increased hospital admissions in non-prioritised group Non-significant reductions in A&E attendance, costs and admissions
Medicaid Rx	Healthcare costs	1		Observational	Healthcare costs	R^2 = 0.20	
Nairn Case Finder	Hospital admissions C = 0.79	1		Prospective cohort	Hospital admissions		Significantly reduced hospital admissions p=0.002
PacifiCare's Medicare Risk Program	Hospital admissions	1		RCT	A&E attendance Hospital admissions		Non-significant reductions in all outcome measures
Patients At Risk for Re-hospitalisation algorithm	Readmission C = 0.89	1		Retrospective cohort	Hospital admissions		Significantly reduced hospital admissions p<0.001
Predictive Risk Stratification Model	Hospital admissions	1		Retrospective cohort	Hospital admissions		p<0.001 Significantly increased hospital admissions
QAdmissions	Hospital admissions C = 0.78	1		Prospective cohort	A&E attendance Hospital admissions		p<0.01 Significantly increased hospital admissions
RxGroups	Healthcare costs	1		Observational	Healthcare costs	R^2 = 0.22	
RxRisk	Healthcare costs R^2 = 0.09	2	2	2 observational	Access of primary care Healthcare costs	R^2 = 0.18 - 0.21	
SCAN Health Plan Model	Hospital admissions	1		RCT	A&E attendance Hospital admissions		Significantly reduced hospital admissions p=0.02

VENNGAGE

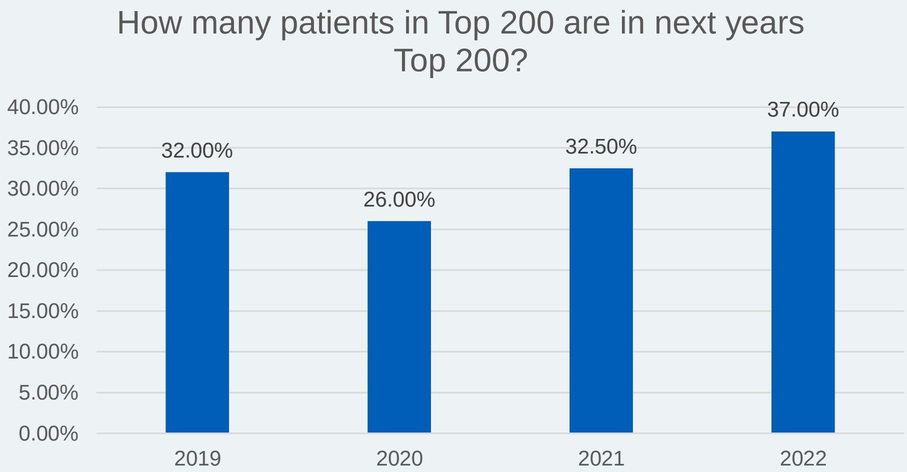
https://informatics.bmj.com/content/31/1/e101065

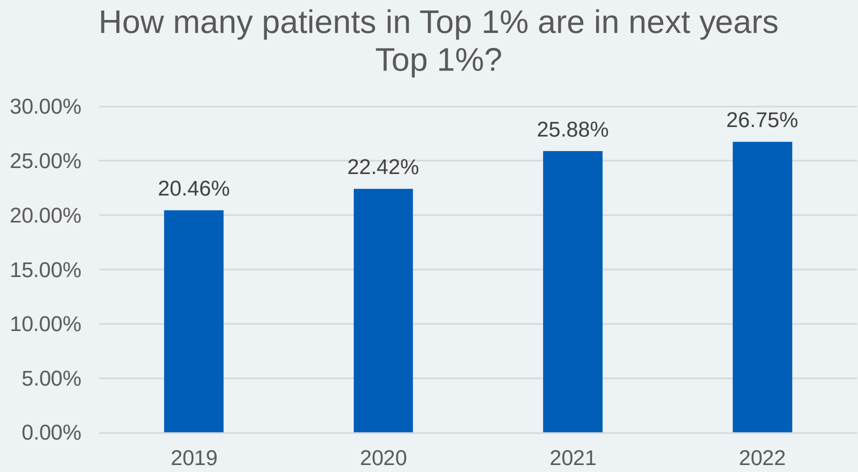
The Case for Change



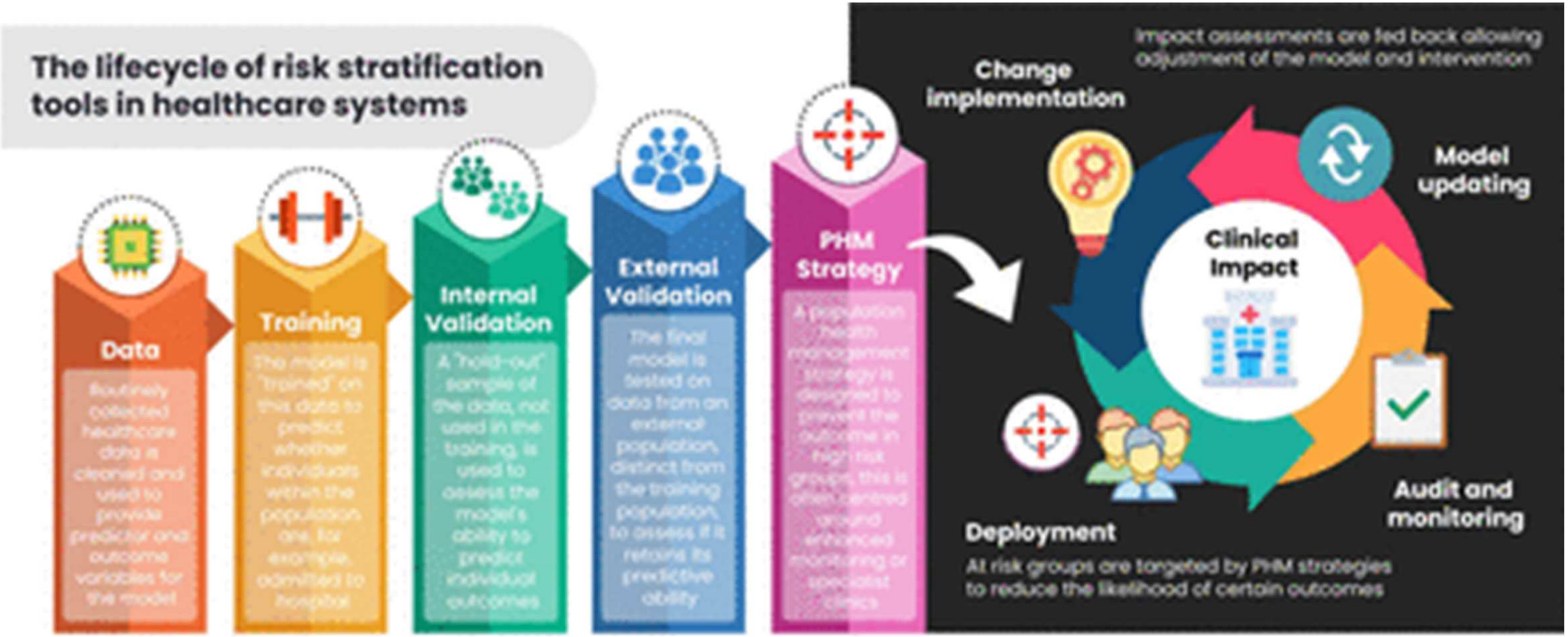


1% Year on Year





Risk stratification lifecycle



Predicting Type 2 diabetes patients at high risk

- Developed own AI explainable predictive model using Random Forest Tree and Light GBM
- Used 35 parameters from EMIS web to develop the model
- Outcome parameters were compared to existing tools
- AUC/ROC curve – 0.84
- **LightGBM train accuracy: 0.997**
- **LightGBM test accuracy: 0.767**
- **Classification metrics**

		precision	recall	f1-score	support
(Low risk)	0	0.77	0.48	0.59	100
(Higher risk)	1	0.79	**0.93**	**0.85**	206

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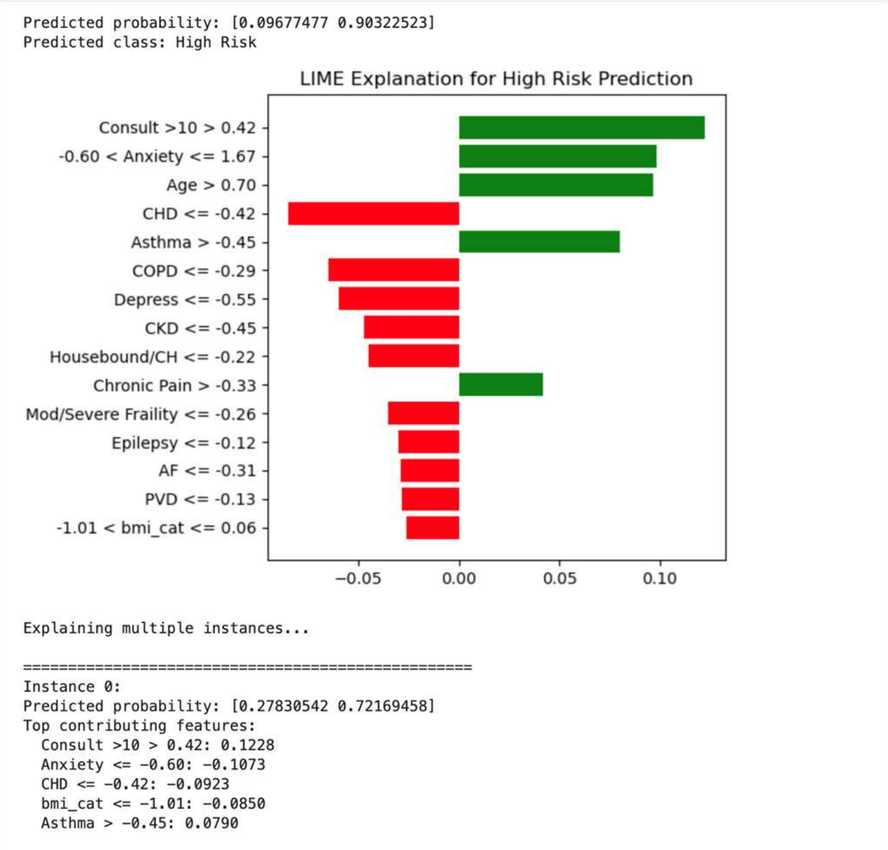

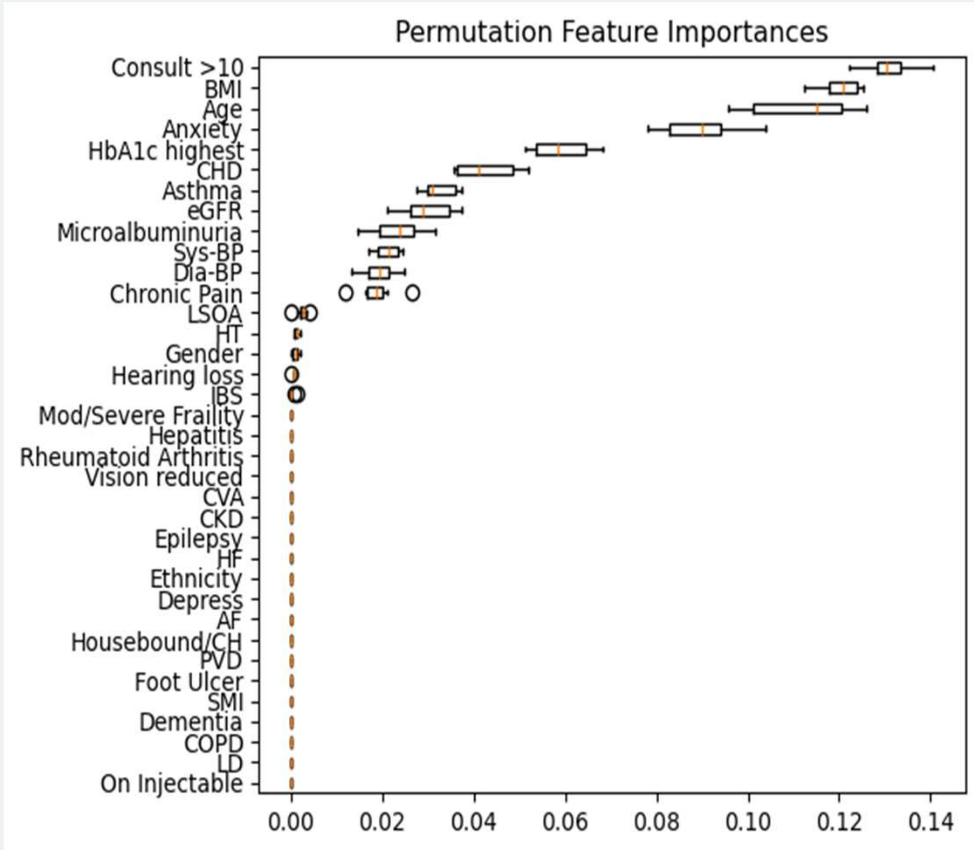

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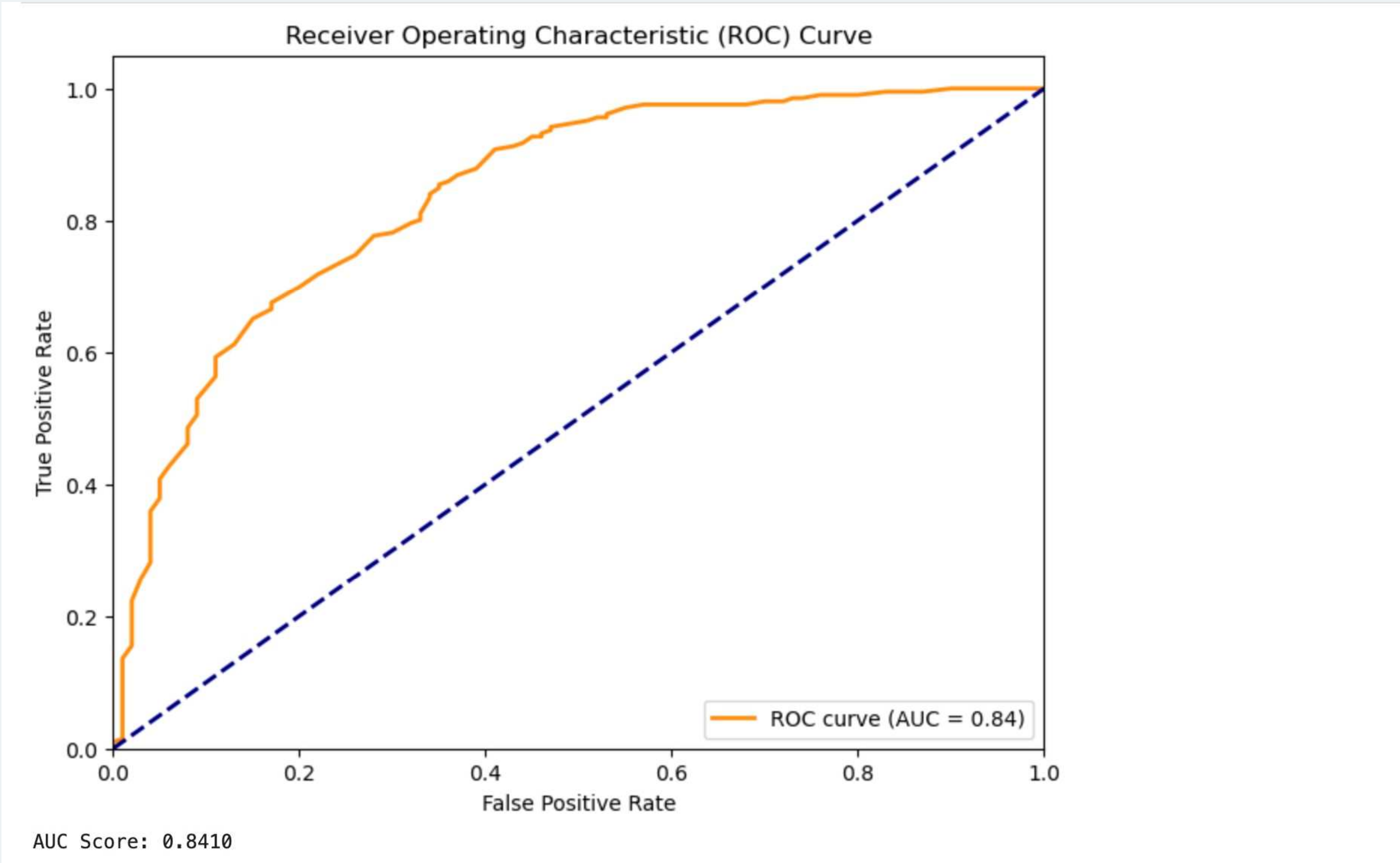

Other uses of prediction/forecasting in NHS

- Use of forecasting tools like ARIMA or Prophet to predict demand in primary and secondary care
- Forecast disease spread especially infectious diseases and pandemics
- Resource planning based on forecast of service requirements
- Human resources planning based on predicted demand/activity
- Quantile regression models (QRMs) and fractional polynomial models (FPMs) are potential probabilistic techniques for predicting extreme health situations/conditions.
- I have used Prophet library to forecast the predicted increase in demand for GP surgery appointments at PCN and National level
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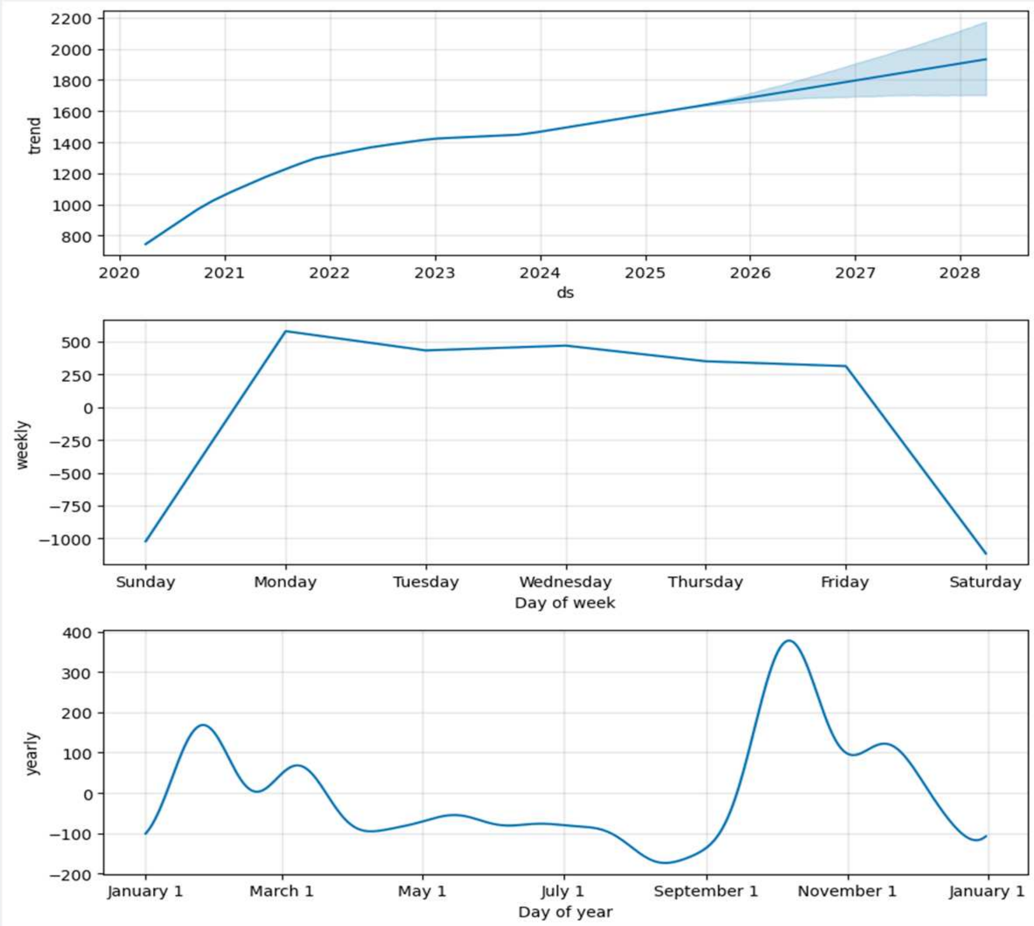
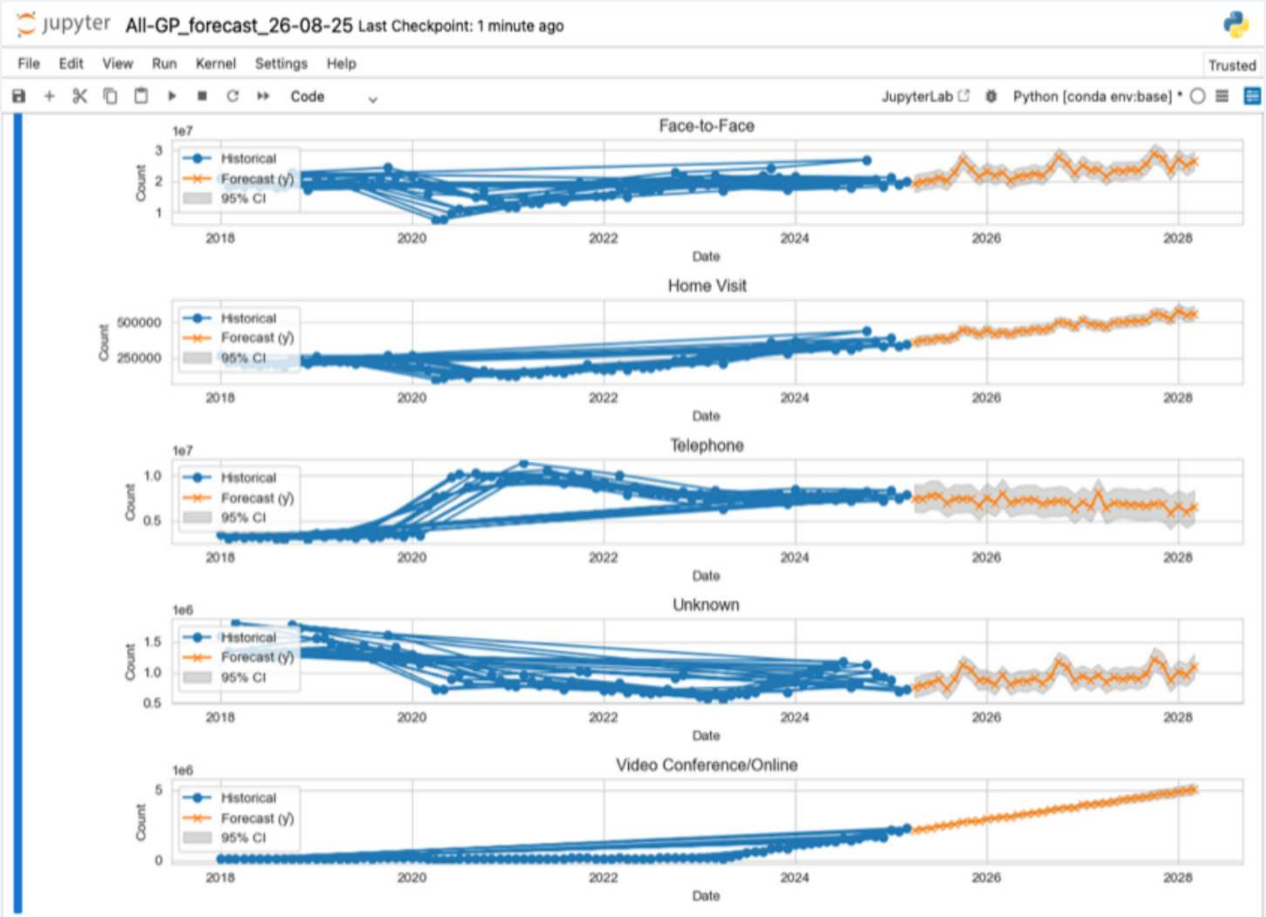
Forecasting appointments in our PCN



Predicted based on 220 thousand appointments over previous 5 years

Forecasting appointments in GP Practices England



Predicted based on 2.3 billion appointments over previous 6 years

Risks with data sharing

- Clinical Negligence scheme does not cover data loss/misuse at present
- Financial and non-financial losses (e.g. reputation, trust) for GP practices.
- BMA-GPC is pushing for Crown Indemnity for same
- Not all PHM models are explainable.
- Medico-legal implications.
- Top frequent users this year may not be the most frequent users next year.
- Studies may show benefit due to “regression to mean”

Ethical issues to consider

- Transparency - is the risk score explainable/interpretable
- Clarifying potential benefit (clinical and/or cost improvement)
- Benefit versus effectiveness (leads on from above)
- Potential diversion of cost and resources (leads to next issue)
- Fairness (Is it fair to spend more on lifestyle related issues?)
- Respect for autonomy (Does patient have a say in this?)
- Potential unintended harm
- Propagating existing biases- e.g. race based

PESTLE ANALYSIS

- Political- ? Support for digital transformation and AI
- Economic- Is present rate of growth of NHS funding and staffing sustainable?
- Social – Do taxpayers feel there is good value for money from NHS?
- Technological- Can Digital Transformation and AI help or hinder?
- Legal - Who carries the can for decisions? Politicians or bureaucrats or clinicians
- Environmental- Is digital less polluting or more! (AI is power hungry)

Any questions?

AI technologies used in our surgery:

- AI supported online consultation
- AI GP avatar for health campaigns
- AI Scribe
- Algorithm based bot for results filing
- Due to start AI automation for admin and referral tasks soon
- AI receptionist