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An impactability modelling framework for population health management

Pre-requisites for developing an impactability modelling approach with an example for pre-diabetes

by the IFoA Population Health Management Working Party

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Title

An impactability modelling framework for population health management – Pre-requisites for developing an impactability modelling approach with an example for pre-diabetes

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Abstract

This paper proposes a framework for practitioners for developing an impactability modelling approach by describing the components of such a framework using the specific example of people with pre-diabetes and the intervention of the NHS Diabetes Prevention Programme. The proposed framework takes the pre-requisites of risk stratification as a foundation and then adds 4 additional components.

Keywords

Population Health Management; Impactability; Impactability Modelling; Risk Stratification; Pre-diabetes; Type-2 diabetes.

Preface

Population Health Management (PHM) aims to achieve the best mix of health outcomes across the diverse members of a population, given the mix of services available in the health and care system. In 2019, the UK's National Health Service (NHS) identified PHM as a key component of its Long Term Plan.

The actuarial profession is well-placed to support the demographic, risk modelling and analytical capability required to successfully embed PHM, whilst being highly focused on the public interest and ethical issues that can arise from such techniques.

The IFoA formed a Population Health Management Working Party (the 'WP') in 2018 in association with NHS England, to enhance the NHS's use of data and analytics in PHM and explore what value the actuarial skillset may bring to drive that change. Now in August 2021, in the midst of an ongoing global health pandemic, PHM approaches are more important than ever as health systems across the world manage the impacts of Covid-19, both the disease itself and also the many consequences of the societal changes that are taking place in response.

The initial paper of the WP investigated the current concepts and practices of impactability models in a broad sense. As the WP entered a second phase of work, a subgroup was formed to explore the possibilities of getting access to some real-world patient-level data in order to develop an impactability model. Due to the safeguards around accessing and using such data, it was concluded that, in line with IFoA policy, the WP itself would not be able to work directly on patient-level data. Instead, the WP embarked on a series of exploratory internal discussions, reflections on the first report, and a refresh of the literature review on the topic of impactability modelling. The aim has been to make a further contribution to the evolving field of impactability modelling that could support practitioners to develop their own models with actual data held by their own health system organisations. As discussions in the subgroup evolved, the concept of a framework of components for developing impactability models arose and led to the production of this short paper.

1. Introduction

The UK's National Health Service (NHS) has identified Population Health Management (PHM) as a key component of its long-term plan to develop integrated local healthcare systems that provide the right care at the right place and at the right time. PHM uses data analytics to tailor the development of interventions for local population segments. It aims to improve health outcomes across the whole population and reduce health inequalities between segments. Impactability modelling is an emerging field within PHM data analytics that continues to gain attention within the NHS and beyond.

This paper builds on the initial report by the Working Party by proposing a framework for impactability modelling and demonstrates this framework by developing an example relating to a population segment with pre-diabetes. This framework aims to set out the pre-requisites and components needed for a practitioner (e.g. a data analyst working within an NHS commissioning or commissioning support organisation) to develop an impactability model in a specific scenario. The target audience is practitioners, such as data analysts or business intelligence analysts within NHS organisations within integrated care systems, who have access to data and want guidance, or a framework, on how to develop impactability models themselves. The paper does not describe how to build a new model but instead sets out the components and pre-requisites needed to develop an impactability modelling approach. Working examples of 'impactability' and 'impactability modelling' are given in Section 3.

This paper uses the health condition of pre-diabetes as the example of a specific scenario because this is a prevalent condition amongst the populations of many countries, including the UK, and there are well-established, clinically validated preventative interventions available to address it. People with Type-2 diabetes have high utilisation of health services and so identifying individuals with pre-diabetes is one step towards reducing this future utilisation.

There are a number of ways that impactability models could be implemented in practice and the point of implementation depends on their purpose. This paper focuses on the scenario of having a defined intervention for a given condition and where that intervention has a finite number of places for the population.

- In this scenario, the aim of the impactability model is to support clinical decision-making regarding which individuals to offer the intervention.
- E.g. In a health system, there is a support group for people with pre-diabetes starting next month. The group meets for 2 hours once per fortnight over a 6-month period. It offers participants advice on diet, nutrition, exercise, smoking and lifestyle to reduce the risk of developing type-2 diabetes. It has places funded for up to 20 individuals. How should a General Practitioner ('GP') choose 20 individuals from its registered list of 8,000 to invite to the group?

There is not a single algorithm for generating an impactability score for any given condition or any given intervention. Instead, there is a range of approaches, metrics and scores that could be considered and these depend upon clinical judgement, the expectations of patients and society, and health policy in the country and region, and technical analytical considerations such as data quality.

Given that there is not a "one-size-fits-all" approach, this paper proposes a framework of components, rather than a single statistical or data 'model'. Rather than impactability modelling being applied consistently across all conditions and interventions, it is considered here as a framework of components, with each component being specific to the health condition and intervention(s) available. A vital component to consider is the specific "value" that is to be addressed by the impactability model. This 'value' could be a narrow clinical indicator, a process measure, a financial/economic indicator or a broad health measure. As well as the outputs from the impactability model being specific to the condition and the intervention(s) available to address this condition, they are specific to the organisation implementing the methodology.

Using the example of pre-diabetes, this paper describes and discusses:

- current practice of risk stratification for this condition in the NHS in England
- the components of a possible impactability modelling framework
- the data considerations for the specific example of diabetes
- the meaning of the “value” to be addressed by an impactability model in this setting
- the metrics that represent the “impactability score” in this setting and links these metrics to the "value" being addressed

Note on pre-diabetes versus Type-2 diabetes

Pre-diabetes is a clinically diagnosed condition.

- NICE defines prediabetes as an HbA1c of 42-47 mmol/mol (6.0-6.4%), a 2-hour post-challenge blood glucose of 7.8-11.0 mmol/L or a fasting plasma glucose of 6.1-6.9 mmol/L. 2.

Type-2 diabetes is also a clinically-diagnosed condition. The risk stratification tools discussed in this paper produce a score for individuals related to their chances of developing Type-2 diabetes over a future time period. People who get a high risk score may well have pre-diabetes already, but not always. The interventions such as the Diabetes Prevention Programmes are designed to reduce the chances of people acquiring Type-2 diabetes and are typically offered to people with a clinical diagnosis of pre-diabetes. However, it is possible that individuals without a formal clinical diagnosis of pre-diabetes but with a high risk score of developing Type-2 Diabetes are also eligible to join the Programme. Therefore the interventions and approaches described in this paper will be for people with pre-diabetes and/or people with high risk scores. The approaches described in this paper are not aimed at developing impactability models and identifying and treating people who have Type-2 diabetes already.

2. Current practice regarding risk stratification and pre-diabetes in the NHS

In practice, many GPs in the NHS throughout England have used risk stratification tools to identify the list of most "at-risk" individuals within their registered patients who are most at-risk of a specific outcome. The risk of developing diabetes can be one of these outcomes with either general or condition-specific risk stratification tools available. These patient lists are then used to inform proactive outreach by GPs and their teams to the individuals in order to offer them preventative interventions. These interventions can include health assessments for particular age groups and invitations to attend pre-diabetes advice groups such as the NHS Diabetes Prevention Programme[1].

It is rare that the risk stratification tools are run directly by the GP practices themselves, due to resource gaps. Typically, analysts working within NHS Clinical Commissioning Groups (CCGs) will run algorithms on the Electronic Medical Records (EMRs) to calculate risk scores for all registered patients across their health system (e.g. a Clinical Commissioning Group registered patient lists for all GP practices within their region) and then communicate the results to each individual practice, filtered on that practices own patient list. The GPs and health professionals in each practice will then review those risk scores and, alongside any additional information they have for their individual patients, and applying their professional experience and judgement, will identify individuals to whom to offer interventions, such as inviting to join an upcoming Diabetes Prevention Programme.

There are a number of open-source diabetes risk stratification tools. One of the most well-known is QDiabetes, which was developed to be run against data held on the Electronic Medical Records ('EMRs') of GP practices to support primary care:

- QDiabetes-2018

The code is available under an open source licence. It can be readily transferred into SQL or R and run on large datasets.

Another tool is one released by Diabetes UK, which encourages people to complete a short online survey themselves in order to then generate their personal risk score.

- https://riskscore.diabetes.org.uk/
- "The Know Your Risk tool is not a diagnostic tool. It is designed for people without a current diagnosis of diabetes and is intended to highlight a person's risk of developing Type 2 diabetes in the next 10 years. The results are not medical advice."

[1] https://www.england.nhs.uk/diabetes/diabetes-prevention/

3. **From risk stratification to an impactability modelling framework**

The risk stratification tools generate scores for all the registered patients. This supports clinical decision-making by suggesting an order in which to offer the intervention to the individuals with the highest risk.

Now consider approaches for how to support that clinical decision-making further by providing additional data or analyses alongside the risk score. I.e. Offering an impactability score, or a set of impactability metrics that can guide the health professional's choices beyond the risk score alone.

> Impactability modelling should always be viewed as a decision-support tool for health care professionals and not a purely mechanical approach to identifying or ranking individuals for interventions. The final choice rests upon the professional clinical judgement of the health professionals involved in the patients' care.

This approach, as a next step on from risk stratification, follows from the Lewis 2010 description of impactability models "which aim to identify the subset of at-risk patients for whom preventive care is expected to be successful" [2]. In addition, impactability and impactability modelling can be defined as[3]:

- ***impactability: defines the degree to which different sub-populations will benefit from a range of interventions;***
- ***impactability modelling: uses this information to tailor appropriate interventions within agreed boundaries for the 'value' gained from resources spent.***

In this definition, the **'value'** is one example of an outcome which could be measured in many ways. This includes narrow clinical indicators, process measures, financial/economic or broad health measures.

It should be made very clear which 'value' is being addressed by the impactability model. Therefore, a pre-requisite for developing an impactability score is to decide the 'value' being addressed and to communicate this as a fundamental building block of the impactability model. For example, any one of the five aims of the quintuple aim of population health management[4] could be the value of interest (see Appendix 1). There could be alternative values beyond these five, depending on the policies and strategies of the health system. In the literature, there is a lack of clarity on how the outcome variables of the models relate to a "value" or aims of the health system. For example, one literature review stated "in most cases the link to the PHM aims is weakly established or indirect"[5].

Following the identification of the value, a further pre-requisite is to define the metric that relates to this value and which will be used as the definition of the "impactability score" in the specific scenario being addressed. A model or algorithm is then needed to calculate the impactability score. These considerations lead to the concept of a framework of components for impactability modelling.

As a foundation for such a framework, it is helpful to revisit the pre-requisites for risk stratification. Lewis (2015)[6] framed risk stratification as analogous to screening programmes, listing 10 pre-requisites. These items, such as the existence of clinically validated interventions for preventing and/or slowing the progression to Type-2 diabetes double-up as pre-requisites for impactability modelling.

Table 1 below comments on each of these risk stratification pre-requisites for our example of pre-diabetes.

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[2] LEWIS, G. H. 2010. "Impactibility Models": Identifying the subgroup of high-risk patients most amenable to hospital-avoidance programs.
[3] IFoA PHM WP 2020. "Impactability Modelling for Population Health Management: A review of current concepts and practices"
[4] NHS ENGLAND, NHS DIGITAL & PUBLIC HEALTH ENGLAND. 2018. PHM Flatpack. A guide to starting PHM
[5] Robertson, J. 2019. MPH Dissertation: Impactibility modelling: A literature review and proof of concept using multi-state modelling
[6] LEWIS, G. 2015. Next steps for risk stratification in the NHS

Table 1: Pre-requisites for risk stratification (Lewis, 2015 based on Wilson & Jungner, 1986[7]) with examples for pre-diabetes

Key	Pre-requisites for risk stratification	Example for pre-diabetes in the NHS
1	The event being predicted should be an important health problem.	Pre-diabetes and Type-2 diabetes are important health problems in many populations across the world. Identifying people with pre-diabetes or a high risk of acquiring Type-2 diabetes in future in order to offer preventative interventions to prevent onset of Type-2 diabetes.
2	There should be an accepted intervention offered to high-risk patients.	NHS Diabetes Prevention Programme (DPP).
3	Resources and systems should be available for timely risk stratification.	NHS CCGs dedicate analysts to run risk stratification tools which can be readily accessed by GPs.
4	There should be sufficient time for intervention between risk stratification and the occurrence of the adverse event.	Yes, lifestyle changes by people with pre-diabetes can prevent the development of Type-2 diabetes. Both the risk scores described in this paper were developed in relation to a 10-year period of acquiring Type-2 diabetes.
5	A sufficiently accurate predictive risk model for the event should be available.	Two examples are: • https://riskscore.diabetes.org.uk/ • https://qdiabetes.org/ See section 0 for commentary on data requirements. These are both example risk models that generate a risk score for individuals that do not yet have Type-2 diabetes and indicates the likelihood that they will acquire Type-2 diabetes during the next 10 years.
6	The risk stratification tool should be acceptable to the population at large.	There is growing awareness of these tools in the England population
7	There should be an accepted policy about who should be offered the preventive intervention.	In the NHS in England, any health professional, or even the individual themselves, can refer to the Diabetes Prevention Programme. NHS practitioners may want to give explicit consideration to the likely effect of the intervention on health inequalities.
8	The natural history of the adverse event should be adequately understood by the organisation offering the preventive intervention.	Yes, highly qualified practitioners provide the Diabetes Prevention Programme and understand the journey to pre-diabetes and to Type-2 diabetes.
9	The cost of risk stratification should be "economically balanced," (i.e., it should not be excessive relative to the cost of the programme as a whole).	The cost of the CCG analysts running the risk stratification tools is considered to be tiny in comparison to the cost of running the DPP (£270 per participant on average)[8].
10	Risk stratification should be a continuous process, not just a "once and for all" occurrence.	Yes, the risk score calculations are repeated at regular intervals, e.g. weekly or monthly for the registered population of each GP practice.

[7] Wilson, J. M. G., Jungner, G., & World Health Organization. (1968). Principles and practice of screening for disease.
[8] NHS England Impact Analysis of implementing NHS Diabetes Prevention Programme, 2016 to 2021

For the broad working definitions of impactability and impactability modelling given above, there are a small number of additional pre-requisites needed to transform a risk stratification exercise into an impactability modelling exercise. This paper proposes 4 additional prerequisites for an impactability modelling framework, again using pre-diabetes as an example to illustrate the concept. These pre-requisites are as general as can be. The intention is that these pre-requisites do not exclude any approaches in the literature from being described as 'impactability models' but are a helpful way to frame and define their components.

Table 2: Suggested additional pre-requisites for an impactability modelling framework with an example application (in addition to the pre-requisites listed in Table 1 above)

Key	Additional impactability pre-requisites	Example for pre-diabetes in the NHS
11	The 'value' being addressed by the impactability model should be defined (acknowledging that there may be other values of interest which the model does not address).	One of the five aims of PHM such as: Reduce per capita costs in the health system. The “value” should be consistent with point 7 in Table 1 above.
12	There should be a metric (i.e. the 'impactability score') relating to the 'value', that can be defined and calculated based on available data at relevant timepoints, which can be calculated both for population segments which have followed the intervention/s identified in points 2 and 7 and calculated separately for segments which have not.	If the 'value' in point 11 is 'reduce per capita cost', the metric could be Return on Investment (ROI) or projected net cost savings in the health system over a defined future time period. The ROI or projected net cost savings would then be calculated for cohorts that have participated in the DPP and calculated separately for cohorts that have not joined the DPP.
13	There should be a robustly validated model for calculating the impactability score (that aligns to the 'value').	If the 'value' in point 11 is 'reduce per capita cost', two examples of robustly validated health economics models are: • UK Prospective Diabetes Study (PDS) Outcomes Model[9]; • University of Sheffield ScHARR Diabetes Prevention Model[10] Alternatively, there may exist purpose-built health economics models for local health systems.
14	The methodology for how every element of the impactability modelling framework should be monitored over time and be part of a continuous control cycle. This includes the metric relating to the 'value' and the choice of the value itself (e.g. to check continuous alignment with policy goals of the health system). This is similar to how risk stratification should be a continuous process.	If the 'value' in point 11 is 'reduce per capita cost', comparison of actual health service costs related to diabetes (direct and indirect) versus the expected costs in the ROI calculation. Regular checks that the Diabetes Prevention Programme and its aims are consistent with health system policy.

The next sections discuss the 4 additional components in turn.

[9] Hayes, A. J.UKPDS Outcomes Model 2: a new version of a model to simulate lifetime health outcomes of patients with type 2 diabetes mellitus using data from the 30 year United Kingdom Prospective Diabetes Study: UKPDS 82. Diabetologia 56, 1925–1933 (2013).

[10] Thomas, C. (ScHARR, University of Sheffield) SPHR Diabetes Prevention Model: Detailed Description of Model Background, Methods, Assumptions and Parameters (2015)

Definition of the 'value' being addressed by the impactability model

There are many values of interest and these will depend upon policy within the health and care system. The value chosen for the impactability modelling framework must be consistent with this policy. However, there will typically not be a single value which covers the entire policy and so the model should be completely clear about what it is aiming to address, and therefore what it is not addressing.

For the example of the Diabetes Prevention Programme, let's consider the value to be:

- reducing per capita costs in the health system.

This example is used to make the point that there is not a single value of interest. There are arguably more important values such as improving health outcomes, or reducing health inequalities (see later), but the point being emphasized in respect of impactability models is that there is not a single metric that addresses all values. The best approach is to state explicitly the value that the impactability model addresses so that users of the outputs can then interpret the results and apply them appropriately with regards to their understanding of the overall mix of values that the health system is aiming to deliver for its population. Of course, it is undesirable for the defined 'value' to be improved whilst other values of the health system are made worse by the consequences of the impactability modelling framework.

With this example value, the impactability model would generate scores for patients that gives some indication of the costs expected to be incurred and the costs expected to be saved as a result of that individual participating in the DPP.

For interventions there will be analyses done in advance of implementing them to assess whether, or not, they should be implemented. A pre-requisite for impactability modelling is that there exists already an accepted intervention (point 2 in Table 1). There were analyses and assessments of the DPP before its wide-scale rollout. The role of impactability modelling in this scenario is therefore to assist health professionals regarding who in their populations should be prioritised for offering this intervention. It is not questioning the validity of the intervention – this is already demonstrated. The impactability model aims to make the operational implementation of the intervention as effective as possible with regard to the value specified in the impactability framework.

Timeframes should be explicitly considered and specified as part of the 'value' being addressed.

Even with risk stratification there is already more than one ranking depending on the timeframe being considered. For example, both the Diabetes UK and the QDiabetes risk scores use a 10-year horizon. Using a different period would likely give a very different ranking. As an alternative to the period being specified as a fixed length for all, it could be specified in relation to the individual period to a specific age (e.g. risk of acquiring Type 2 diabetes before age 65) or across their lifetime. Therefore, the age of the individual is vital and is often an independent variable in the risk stratification and impactability metric calculations. Making explicit consideration of the timeframe in addition to inclusion of the age as a factor adds value to the impactability approach. The Q Research team has shown how lifetime risk rankings differ quite substantially for QRisk. A similar review for QDiabetes was not found https://www.bmj.com/content/341/bmj.c6624). Using QDiabetes to identify individuals may mean that it doesn't select young individuals with very high lifetime risks but who have low QRisk score because they are under 45. There are advantages in impactability metrics which consider this, and therefore suggest whether it's better to offer interventions to younger individuals or wait until later.

Aligning metrics (the impactability score) to the value(s) of interest

The metric must meet a number of criteria. It should be:

- clearly defined;
- measurable;
- capable of being calculated based on the data that is available;
- clearly communicated;

- consistent with the value under consideration;
- widely understood.

For the example of the DPP, with the example value of reducing per capita costs, there are numerous metrics that align to this value. One example is the Return On Investment calculated at the level of each individual to be offered the DPP. This is a measurement of the present value of the expected costs to be incurred for the individual to participate in the DPP and the cost savings for the individual across the entire health system as a result of benefiting from the DPP (e.g. lower expected future hospital admissions). Appendix 1 suggests additional possible examples of metrics aligned to each of the 5 aims in the quintuple aim of PHM for the example of pre-diabetes and the DPP. For example, the value of reducing health inequalities could be measured by a metric such as Patient Activation Measures (PAM) which uses survey data to score the level of knowledge, skills and confidence each individual has in managing their own health and care.

Where there are a number of possible interventions available to a health system, impactability modelling should help to optimise how the different interventions can be allocated to the population to achieve the optimal net benefit. For example, this means not simply giving all interventions to the high-risk segments. The existence of an intervention, or multiple interventions, is a key component for risk stratification but it is absolutely essential for impactability modelling. With risk stratification, the intervention needs to exist for the exercise to be useful but does not usually form part of the calculations or modelling. In impactability modelling, the intervention and the change in value it can achieve for different people or population segments is a fundamental part of the calculations for the impactability score.

When using the risk scores and impactability scores together, one issue to understand is the extent of dependence between the factors used in the risk score and the impactability score. There could be common variables in both scores which could lead to reinforcement issues.

Robustly validated model for calculating the impactability score

A robustly validated model for calculating the impactability score (that aligns to the “value”) is required. This could be a model that is built in-house by the local analytics team or it could use one developed externally, perhaps at a national level, or in academia. Externally developed tools may have the advantage of having undergone a rigorous development and testing process and calibrated with data covering a large population. A disadvantage could be that they are built with data that is not available at the local level or the calibrations of parameters within the calculation are not representative of the characteristics of the local population.

Let’s consider, again purely for the purpose of demonstrating the concept of components of a framework, that the impactability score is a metric aligned to the value of reducing per capita costs in the health system. For our example of diabetes, such a metric could be adapted from outputs of a robustly validated health economics model such as one of the following:

- UK Prospective Diabetes Study (PDS) Outcomes Model[11]
- University of Sheffield Diabetes Prevention Model.[12]

These models would need to be adapted to the local population and local data sources. They will likely require data in addition to that needed for the risk score calculation so consideration as to the source(s) of this data is needed.

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[11] Hayes, A. J.UKPDS Outcomes Model 2: a new version of a model to simulate lifetime health outcomes of patients with type 2 diabetes mellitus using data from the 30 year United Kingdom Prospective Diabetes Study: UKPDS 82. Diabetologia 56, 1925–1933 (2013).

[12] Thomas, C. (ScHARR, University of Sheffield) SPHR Diabetes Prevention Model: Detailed Description of Model Background, Methods, Assumptions and Parameters (2015)

As with any model, there are many technical considerations, and this paper will not go into the detail here. These would be specific to the metric of interest. These include: meeting technical requirements; validation of the calculator; frequency of recalibration; updating assumptions; outputs.

Continuous control cycle

Table 1 includes a component reflecting the continuous process of successful risk stratification and this is similarly critical for a wider impactability modelling framework. Every component of the framework should be reviewed at appropriate time intervals to ensure they remain valid. This approach aligns very much with the concept of the actuarial control cycle with the process of identifying the problem, developing the solution and monitoring the results as an ongoing iterative process, within the context of the health and care environment and wider society.

In particular for impactability modelling, feedback from clinicians and health professionals is crucial for continual refinement. The value, the metric and the resulting impactability scores should be reviewed with health professionals as part of a continuous improvement process. The format for sharing the results with health professionals is critical to ensure their engagement in the process. Ongoing communication is key and there should be feedback loops so the health professionals can contribute to refining the components of the framework, including the impactability score, according to their experience and expertise.

The output of the impactability modelling framework must be viewed as decision-support and not a definitive answer. It must always be the qualified health professionals who make the final decisions about patient care.

Other challenges to be addressed during the design of the framework and as part of the continuous control cycle include:

- Individuals who are offered an intervention and are considered to benefit from it may not choose to accept the intervention being offered;
- Individuals may attend an intervention but the extent to which they actively participate (and therefore see the benefits) can vary;
- Extent to which individuals have the ability to engage with an intervention. For example a structured education programme delivered entirely online may have limited benefit to an older cohort who could have relatively lower computer literacy, even if they are the cohort who would benefit the most;
- How can tools be made readily available to the health professionals who make intervention-related decisions and how timely is the data such that an impactability model will not highlight the same cohort every month.

Interaction between the value of 'reducing health inequalities' and other values

Given the importance of the value of reducing health inequalities, it is vital that health inequalities are not worsened even if other 'values' are improved as a consequence of the impactability modelling framework. This can be addressed by incorporating a value into the framework that expressly aims to reduce health inequalities and measuring this via a patient engagement metric such as PAM, as introduced above. If a given intervention is shown to be more impactful on a particular cohort of patients partly because they are simply more engaged in managing their health, it is important to consider how best to consciously counter this effect and avoid increasing health inequalities.

For example, low-PAM patients could be contacted more proactively by the providers of a diabetes prevention programme, to increase the likelihood that they actively participate. Or, an alternative version of the intervention could be tailored to low-PAM patients, which reduces barriers to their participation. Either approach would tend to require more resource input by the intervention provider; the impactability framework could then be used to inform decisions relating to this trade off, aiming to minimise both inequalities and resource use.

The main challenge with PAM is that it is based on survey data, meaning it is unlikely to be realistic to obtain PAM scores for every member of a population. A more practicable approach could be to target people with high predictive risk scores to complete a PAM survey. It is important to note that this approach would therefore mean undertaking the impactability modelling after completing the predictive risk modelling, since the predictive risk outputs would be used as an input to the impactability modelling process.

Another challenge with PAM data is to decide how to handle those people who choose not to complete the PAM survey when asked to do so. The resulting incomplete set of PAM scores presents a risk that the impactability process actually worsens inequalities across the high-risk population, if it is based on a partial picture of the inequalities that exist within the population. This risk could be mitigated by assuming that the missing PAM surveys are indicative of low levels of patient activation for all of those individuals – effectively deriving a low PAM score by the very fact that they did not respond to the invitation to complete the PAM survey.

Practical implementation of this impactability modelling framework

As an example, a health care system could explore using the findings of the PDS model to examine the cost impact (the 'value') of healthcare consumption for people with recently diagnosed type 2 diabetes, varying by blood glucose levels measured in primary care (a "stratified population"). This could then be overlayed with cohorts who did and did not attend the DPP (the 'intervention') to create an impactability score of how the value is impacted by the intervention across a stratified population. Finally, this impactability score would be applied to the pre-diabetic cohort who are being considered for the intervention. This could help identify the cohort that would have the biggest impact on the value of interest from the intervention.

4. **Considerations on data requirements**

When developing a statistical model for impactability, the data requirements have many common features with the data requirements for a risk stratification model. In this section we first explore the data requirements for risk stratification – and their possible sources – before returning to the subject of additional data requirements for impactability modelling.

In developing (and validating) a risk stratification tool a linked dataset is needed which contains information on the outcome of interest, in this case the likelihood of developing diabetes, together with information about risk factors, such as lifestyle factors, family history, other medical conditions and historic interactions with various healthcare organisations. A statistical model can then be used to estimate the likelihood of developing diabetes from the observed risk factors.

It should be noted that the data requirements for running the tool are different from those used to develop the tool. When running the tool only a dataset containing information on the risk factors is needed; however, unlike for the development stage, individuals need to be identifiable so that interventions can be offered to them.

Care is needed if risk stratification tools are deployed for populations, or in environments other than which they were developed. For example, the discriminating power of QDiabetes (and other risk stratification tools) varies across European countries[13] and we can speculate that it might be worse in more dissimilar countries where poor nutrition in utero and early life is common. Similarly, at an individual country level there will often be variations between geographies. A model that is developed at a national level may not be appropriate to apply to a specific sub geography that has its own demographic characteristics and approaches to the management of diabetes through specific patient pathways. As a result, users of a tool should always be informed of the basis of the model and any limitations that could apply to their specific geographies. This could be an issue even within the UK population from which the tool was developed as there are differences in health and lifestyle factors between different regions of the UK.

Choice of risk factors

Possible risk factors can be chosen by hypothesising which factors are likely to be important, for example, by including those risk factors shown to be important in academic literature and suggestions from health professionals involved in the model development. Data driven approaches to identify factors with statistical significance can be used - though for small datasets this can result in less robust models.

The number of factors ultimately used will however generally be a small number compared to the number of variables available in order to:

- Provide a model which is easy to use and understand; this will depend on the user it is aimed at; for example, the Diabetes UK tool designed to be completed by a layperson is simpler than the QDiabetes tool which is designed for clinicians.
- Avoid using factors which may not be readily available. This will depend not only on the datasets available but also on the target audience. For example blood glucose measurements are only available for a minority of patients and so have limited use for estimating diabetes risk in the general population. However, they may be of more use in targeting interventions amongst individuals already highlighted as high risk as these patients are more likely to have had a blood test.
- To avoid overfitting. The importance of this will depend on the size of the data set but a typical rule of thumb is for there to be at least 10-20 events (incidences of diabetes) per risk factor. To meet this criterion a model developer may create more aggregate groups (e.g. using the first 3 digits of a postcode/zip code as opposed to the full code).

[13] Non-invasive risk scores for prediction of type 2 diabetes (EPIC-InterAct): a validation of existing models

Risk factors in the two example risk stratification tools

The risk factors used in the 2 diabetes risk stratification tools that we are using as examples in this paper are listed below for comparison. The full definition of each factor is available within the links in the bibliography.

Table 3: Risk factors in the two example risk stratification tools

QDiabetes https://qdiabetes.org/	**Diabetes UK** https://riskscore.diabetes.org.uk/
• Age • ethnicity • deprivation • body mass index • smoking status • family history of diabetes • cardiovascular disease • treated hypertension • corticosteroids • schizophrenia or bipolar affective disorder • learning disabilities • gestational diabetes • polycystic ovary syndrome • prescribed 2nd generation "atypical" antipsychotics • prescribed statins • fasting blood glucose level • glycated haemoglobin (HBA1c) value	• gender • age • ethnic background • immediate family member with diabetes • waist size • body mass index • high blood pressure

These two examples demonstrate the variance in the number of input variables between different risk stratification tools. Compared to the Diabetes UK risk stratification tool, the QDiabetes model has a much longer list of input variables to its regression model. If all the data fields are available, and their data quality is high, then QDiabetes may give a better risk score than the Diabetes UK model. However, it is important to consider whether building additional complexity, via additional input variables, generates proportionally more accuracy to the model.

Choice of data source

The availability of datasets will be dependent on the organisation's role and the purpose for which the analysis is to be carried out. The governance around securely collecting and analysing personal medical data is critically important but is beyond the scope of this paper.

For diabetes, GP electronic records provide a rich source of data and contain information on both risk factors and the diagnosis of diabetes. For example they include:

- Demographic data (e.g. age, sex, postcode)
- Prescriptions (e.g. insulin as well as other prescriptions which may be risk factors)
- Diagnosis (e.g. for diabetes and other conditions which may be risk factors)
- Laboratory tests (e.g. including blood glucose or HBA1c)
- Clinical values (e.g. BMI, Blood pressure)
- Consultations/Appointments/Referrals (e.g. possible other risk factors)
- Whether an individual has already received a form of intervention e.g. referral to structured education programme

However, they only include data for those individuals who present to GPs and reflect only the information that can be collected in time limited appointments. This means that for many people, the records held by GPs may be relatively incomplete; for example, only one third of patients are likely to have had their weight recorded in the last year[14].

Other existing sources of data, when linked to GP records, may also be useful. These include:

- Local Authority data – this may provide better indicators of deprivation than the use of postcode from GP records and additional indicators at household level such as number of occupants in a household, council services received (e.g. assisted bin collections), receipt of adult social care funding and services, which could be risk factors.

- Hospital Episodes Statistics – this includes details of admissions, A and E attendances and outpatient appointments. The inclusion of maternity episodes may help cross-reference whether coding for diabetes within GP records is for gestational diabetes or not. Similarly this could identify individuals who are in regular contact with secondary care, e.g. through outpatient endocrinology clinics, but are not recognised on the primary care record as having diabetes.

- Community / Mental Health providers records – these may provide more information about possible risk factors or can provide information about an individual that may make them less suitable for a specific intervention. For example, an individual who is known to a mental health substance misuse team being offered an alternative to a drug based intervention if appropriate.

- Genetic databases – genetic variations can give a predictive measure of susceptibility to type 2 diabetes; however, studies suggest that they provide little improvement in estimating risk over the use of clinical risk factors[15] so their value is likely to be limited. Furthermore, there are practical challenges and data sharing issues that need to be addressed for these datasets to be linked.

This is not an exhaustive list and for other conditions other datasets may be relevant for example the National Cancer Registry or the National Death Register may be relevant where cancer or the cause of death is the outcome of interest.

Treatment of missing data

Risk stratification generally relies on the use of existing data, which has been collected primarily for clinical use rather than analysis, to identify the relevant risk factors. There is little scope to retrieve missing data and so any model development has to deal with this incomplete data. A simple approach would be to ignore incomplete data but this narrows the dataset and, depending on the reason for the missing data, can cause bias. Instead approaches should generally be used to impute values for missing data.

Missing data or erroneous data can also cause a problem when the tool is run. This is a particular problem when it is using information from multiple systems where there may be inconsistencies in coding. However, even within a single system there will be differences in how people enter data. For example, the risk stratification model used by COVID-19 Population Risk Assessment had difficulty in distinguishing between gestational diabetes and other types of diabetes[16].

Default values can be used where data is missing or obviously erroneous (e.g. extremely tall or short heights). The choice of the default values will depend on the action taken as a result of the process and how automated the process is. In some cases it may be appropriate to be prudent with these default values in order that those with incomplete records are flagged for further attention, but this needs to be balanced against the possible additional cost that this might have.

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[14] Determinants and extent of weight recording in UK primary care: an analysis of 5 million adults' electronic health records from 2000 to 2017

[15] Systematic Review of Polygenic Risk Scores for Type 1 and Type 2 Diabetes

[16] https://digital.nhs.uk/coronavirus/risk-assessment/population#gestational-diabetes

Alternatively, approaches can be taken to try to obtain missing data, for example via proactively weighing patients when attending appointments or via patient surveys. However, it may be difficult to get engagement from those not actively receiving treatment and patients' response to text messages varies considerably depending on patient groups and health conditions[17].

Equally it is important to recognise that a significant number of people may not consent to have their medical information shared. This will represent data that cannot be obtained and inform any modelling, but equally must ensure these individuals aren't discriminated against when it comes to selecting who will benefit from an intervention.

Impactability modelling data and assumptions

Impactability modelling may require further data but the type and source of this will depend on the choice of the "value" being addressed. Appendix 1 highlights the range of metrics which might be considered. For whichever metric is chosen, the development of an impactability model requires information on how this metric varies between individuals. For example, if quality adjusted life years (QALYs) saved is used as a metric then it might be known that an intervention has a greater QALY benefit when it is used at younger ages than older ages. It is likely that there will be a high level of cross-over between those characteristics which are used for risk stratification purposes and those that influence the impactability value. Hence once an impactability model is developed it is likely to need similar information to that of a risk stratification model in order to run.

Unlike the risk score, the intervention or interventions themselves must form part of the data and calculation processes for the impactability score. This means that it must be possible to calculate the impactability score separately for the cohorts that have and have not followed the interventions identified in points 2 and 7 in Table 1. Therefore the data must include a field that shows whether the individual person (or the segment, if using aggregated data) has received the specific intervention or interventions.

[17] COV.31: How do patients respond to text messaging in primary care

5. Summary and proposal

All impactability modelling frameworks are specific to:

- the risk being addressed;
- the intervention(s) available to address the risk.

This paper has described a framework for developing an impactability model for the specific example of people with pre-diabetes and the intervention of the NHS Diabetes Prevention Programme.
This framework uses the pre-requisites of risk stratification as a foundation and then proposes 4 additional components.

Table 4: Proposal for pre-requisites for an impactability modelling framework

Key	Pre-requisites for an impactability modelling framework
1	The event being predicted should be an important health problem.
2	There should be an accepted intervention offered to high-risk patients.
3	Resources and systems should be available for timely risk stratification.
4	There should be sufficient time for intervention between risk stratification and the occurrence of the adverse event.
5	A sufficiently accurate predictive risk model for the event should be available.
6	The risk stratification tool should be acceptable to the population at large.
7	There should be an accepted policy about who should be offered the preventive intervention.
8	The natural history of the adverse event should be adequately understood by the organisation offering the preventive intervention.
9	The cost of risk stratification should be "economically balanced," (i.e., it should not be excessive relative to the cost of the programme as a whole).
10	Risk stratification should be a continuous process, not just a "once and for all" occurrence.
11	The "value" being addressed by the impactability model should be defined (acknowledging that there may be other values of interest which the model does not address).
12	There should be a metric (i.e. the "impactability score") relating to the "value", that can be defined and calculated based on available data at relevant timepoints, with separate results for the population segments that have and have not followed the interventions specified in points 2 and 7.
13	There should be a robustly validated model for calculating the impactability score (that aligns to the 'value').
14	The methodology for how every element of the impactability modelling framework should be monitored over time and be part of a continuous control cycle.

Pre-requisites 5 and 13 are heavily reliant on the availability of appropriate and high quality data. There are many important considerations regarding the data and these are particular areas in which analytics professionals are critical to the successful design, development and implementation of impactability modelling frameworks.

This proposed list of components aims to provide a framework and checklist for analysts within NHS organisations as a starting point to develop their own impactability models.

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Appendix 1: Possible metrics aligned to the five aims ('values') in the quintuple aim of PHM

This table shows examples of metrics that could represent the impactability score related to each of the 5 aims of the quintuple aim of population health management.

Value (e.g. based on the "quintuple aim")	**Example metrics related to the example values**
Improve the health and wellbeing of the population	• Diabetes risk score at later timepoint • HbA1c measure • Transition rates from pre-diabetes to diabetes at later time periods • BMI readings • Smoking cessation rates • Alcohol consumption • Life years gained and quality-adjusted life years saved • Blood sugar control • Blood pressure; cholesterol • Prevalence of diabetes in the community
Reduce per capita cost of health care and improve productivity	• ROI as calculated by a suitably validated ROI Tool • Direct medical costs for those with diabetes: costs included hospital, emergency room, urgent care, and outpatient services, as well as costs of prescription medications and telephone calls to health care providers. • Indirect health care costs for those with diabetes, i.e. for services received but not related directly to their diabetes condition • Costs of identifying each participant, implementing and maintaining the interventions, and monitoring and treating side effects • Cost related to medical insurance • Total expected health cost savings resulting from the prevention program, over next 10 years, or patient lifetime
Enhance experience of care	• Results on patient satisfaction surveys • Expected number of future unplanned hospital admissions • Patient Activation Measure (PAM) scores • Volume of mental health issues across the population • Evaluation of a patient's initial stress to predict how they will be doing six months later • Measures of psychological distress
Address health and care inequalities	• Ratio of participants on the DPP from deprived areas, where “deprived” is defined as participants who reside in post codes that are in the bottom 20% of Index of Multiple Deprivation. • Ratio of years in life expectancy between least deprived area and most deprived area • Volume of interventions provided for individuals who previously haven’t engaged with the healthcare sector
Increase the well-being and engagement of the workforce	• Ratio of emergency care delivered to planned care delivered • Measures of stress for home care staff due to knowledge of impactability score

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