Health Economics Unit

NHS Midlands and Lancashire Commissioning Support Unit

Building on expert knowledge: Research and next steps on impactibility in health and care

Project reference: HEU/045

Date: 30 May 2022

Contents

Definitions and abbreviations

Definitions and abbreviations of terms used in this document.

Definitions

Health inequalities: Avoidable differences in health between specific population groups.

Impactibility: The likelihood that a patient will respond to an intervention and be willing to take part.

Impactibility analysis: A method of evaluating health interventions by measuring patients' responsiveness to said interventions.

Logistic regression: A method of statistical analysis that can be used to model the probability of a binary outcome.

Meta-analysis: A statistical analysis that combines the results of multiple scientific studies.

NHS Long Term Plan: The plan published by NHS England in 2019 which sets out its priorities for healthcare over the next 10 years and shows how the NHS funding settlement will be used.

Predictive model: A statistical model used to predict outcomes of events or interventions.

Preventive interventions/preventive care: Health interventions intended to prevent ill health developing and prolong healthy life (as opposed to treating an existing health condition).

Propensity to succeed: The approach to understanding an individual's likelihood to see positive outcomes from the intervention selected, based on personal behaviours.

Qualitative synthesis: A systematic search for, and interpretation of, research on a specific topic to combine the findings of a number of separate studies and draw conclusions.

Risk stratification: The process of assigning a health risk status to an individual and then using that status to influence care decisions.

Triple-fail event: A simultaneous failure to meet all three triple aim goals.

The triple aims:

- Improving the patient experience of care (including quality and satisfaction)
- Improving the health of populations
- Reducing the per capita cost of healthcare

(developed by the Institute for Healthcare Improvement)

Abbreviations

A&E	Accident and emergency
ACS(C)	Ambulatory care sensitive (condition) (conditions where effective community care and case management can help prevent the need for hospital admission)
HCP	Healthcare professional
NNT	Number needed to treat (the number of patients that need to be treated to prevent one additional bad outcome)
PCP	Primary care physician
PHM	Population health management
PM	Predictive modelling
PTS	Propensity to succeed

Abstract

Impactibility could offer an important opportunity for health system managers to achieve the triple aims of improving the individual experience of care, improving the health of populations, and reducing the per capita costs of care.

Though not a new concept, the definition of impactibility in healthcare has not been formalised across the system, and as such it is not being implemented as widely, consistently or effectively as the other pillars of population health management. This is the first part of a two-part report detailing the methodology and results of research into engaging the healthcare system to better understand and define impactibility for use within the NHS.

This report explains the theory of impactibility and its potential value and applications within healthcare. It also provides a definition of impactibility for the NHS, allowing better dissemination of information and further use.

Introduction

As a concept, impactibility has been around for a decade, and it is being used with varying success in its different forms around the world. By better understanding these existing uses and definitions, we can build definitions and models which will help the NHS bridge the gap after risk stratification and direct its resources to maximise population health.

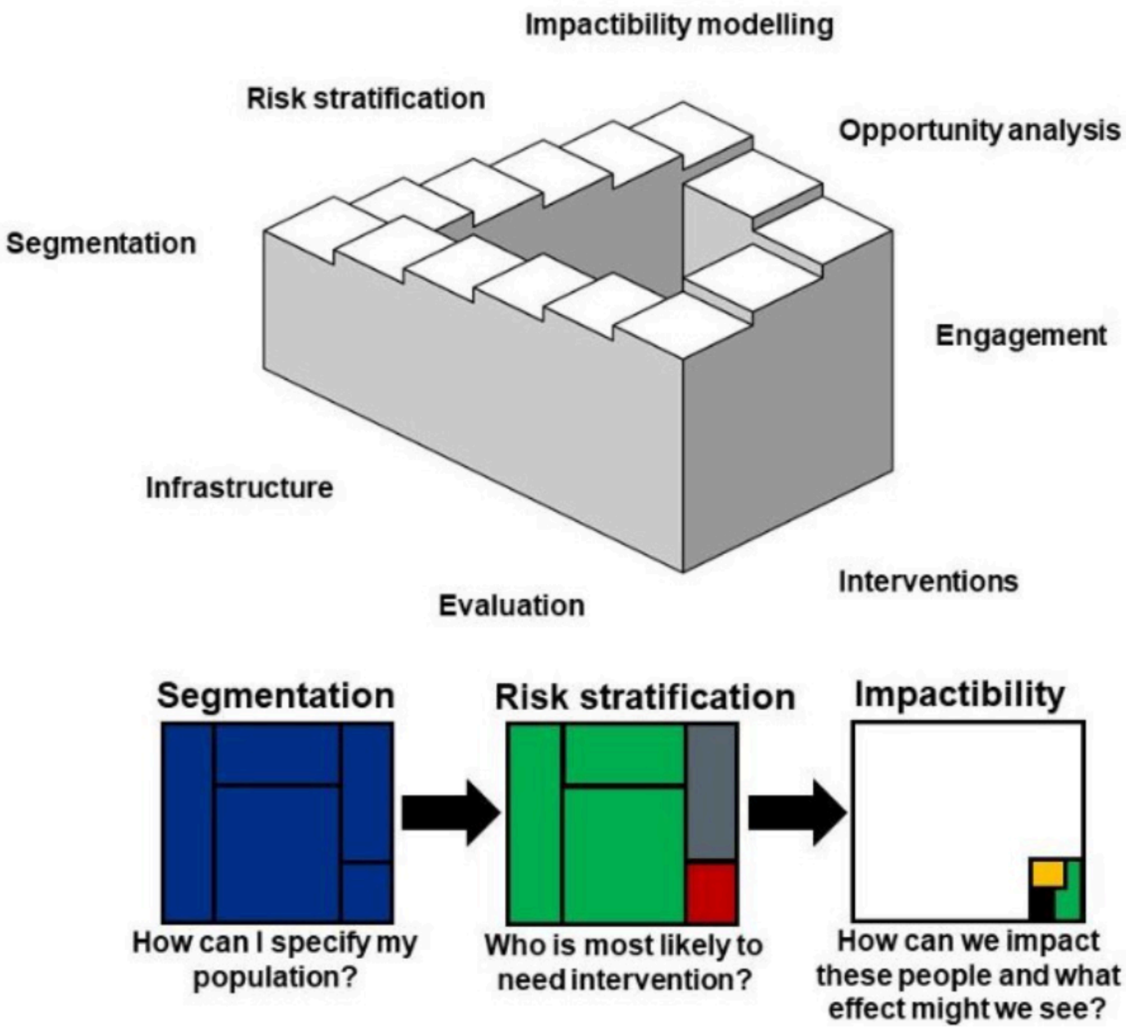
From this report, we can see that impactibility has the potential to be a crucial tool for the NHS and wider health and care systems, as it brings both greater efficiency and improved outcomes for patients. It supports the NHS Long Term Plan aim of delivering ‘the right care, at the right time, in the optimal care setting’.

Andi Orlowski, Director, Health Economics Unit

Impactibility:

- Is a key stage within population health management that builds on risk stratification
- Could support the NHS Long Term Plan aim of delivering the ‘right care, at the right time, in the optimal care setting’
- Does this by facilitating the targeting of preventive interventions to make the biggest difference
- Could be a crucial tool for the NHS and wider health and care systems, as it might bring both greater efficiency and improved outcomes for patients
- Could help achieve some or all of the triple aims

Figure 1: Segmentation, risk stratification and impactibility in relation



Impactibility models:

- Can augment access to and address inequalities of care when combined with clinical insights
- Can provide an opportunity to personalise preventive care delivery
- Help healthcare systems become more efficient, reducing wasted resources
- Have had varying success across the globe

1. Background

This report explains research into the current understanding and expectations of integrating impactibility analysis into population health management programmes across England.

The research project included a literature review, interviews and a series of workshops. These gathered ideas and inspiration from a range of experts and stakeholders with an interest in the topic.

The research is presented in two parts. Part one, this report, provides a summary of: learning from the literature review, the importance of impactibility to the NHS in England, and the next steps researchers will take in developing a model for impactibility analysis for NHS England that is freely available and easy to use for organisations and networks across health and care.

Part two of the report, published separately, will include the feedback captured during the workshop series and interviews with experts and representatives from across healthcare. (Some extracts from those workshops and interviews are also included as quotes within this report.)

This research and report is informed by two important publications:

1. *Bridging the impactibility gap in population health management: a systematic review*[1]
2. *Impactability Modelling for Population Health Management: A review of current concepts and practices*[2]

2. What is impactibility?

2.1 Definition

The definition of impactibility used in this document, in the strategic literature review and in subsequent workshops and interviews is:

'Impactibility is the identification of patients most likely to respond to care, based on quantitative and qualitative factors, and whose treatment will maximise the likelihood of achieving one or more of the triple aims (improving the individual experience of care, improving the health of populations, and reducing the per capita costs of care).

'Impactibility models aim to identify the subset of at-risk patients for whom preventive care is expected to be successful.'

In other words, some people are inherently more likely to benefit from an intervention than others, and this can be predicted and modelled by analysing data.

Impactibility modelling seeks to identify those people and, in so doing, reduce the number of patients who need to be treated in order to prevent one additional bad outcome (called the 'number needed to treat' or NNT).

Reducing the NNT means an intervention becomes less costly and more beneficial – the essential balance of cost vs benefit is improved. In purely financial terms, to save money, the unit cost of an intervention must be less than the average cost of the adverse event, multiplied by the ratio of the positive predictive value (those at risk who would have had adverse outcomes) divided by the NNT.[3]

See 3.2.4 for an exploration of inequalities and impactibility.

For more information, see *Bridging the impactibility gap in population health management: a systematic review*.[1]

2.2 The role and purpose of impactibility

Impactibility analysis could help healthcare planners and providers identify patients who would benefit from treatments or interventions and be most amenable to receiving them. This would allow us to direct resources towards measures which prevent people becoming severely ill or suffering an acute event.

Impactibility analysis is an important (although relatively new) part of the process of population health management (PHM). It aims to identify the subsets of at-risk patient groups for whom preventive care can be successful.

This additional analysis is needed because while risk stratification models can identify that an event is likely to occur, they cannot identify whether anything can be done to prevent it. Standard interventions may have little or no effect for some at-risk patients, who will continue to be at risk of triple-fail events (a simultaneous failure to meet all three triple aim goals), which may be harmful and/or costly and may result in poor patient satisfaction and adverse outcomes.

"It is key to the success of risk stratification to ensure that 'high-risk individuals' are not conflated with 'those most likely to benefit' as there is evidence indicating that these can be highly separated groups." [4-6]

Preventive care can be effective with patients at all levels of risk, not just those at high risk. This approach means health system leaders could make better use of the resources available to them, increasing the positive impact and outcomes of investment.

Impactibility builds on risk stratification, informing delivery of 'the right care at the right time in the optimal care setting', targeting those most likely to respond to particular types of preventive care.

"One of the potential benefits of impactibility is that you can actually focus on health inequalities, unpicking and/or focusing on some of the complexities within health inequalities."

"It's often multiple factors for individuals that drive their poor outcomes and the inequalities. They might have multiple conditions that are all sub optimally managed, and social factors (ethnicity, severe mental illness, etc.) are also a big component."

Abridged comments from workshop participants

2.3 The meaning of impactibility

The triple aims of healthcare (see page 3) are part of NHS England and NHS Improvement's PHM approach and use a new data-driven methodology, helping system leaders deliver NHS England and NHS Improvement's strategic plan.

While earlier approaches in the NHS and public health aimed to promote, protect and prolong healthy life through coordinated programmes offered to the whole population, PHM focuses on key outcomes for identified groups who often share more specific common characteristics, not just a disease diagnosis.

2.3.1 Building on risk stratification

Risk stratification models identify groups with high need or those at high risk of poor outcomes. The models are used by health system managers to make decisions on how best to allocate resources. However, targeting additional resources to the areas most used by these patients does not always lower risk or avoid unsatisfactory outcomes.

For example, how do we stop A&E readmissions? Some patients may be known to be at high risk of readmission but this does not necessarily mean readmission is avoidable. For these groups, standard interventions may have little or no effect.

Calculating and understanding the probability of a particular outcome for an individual may not be enough for healthcare professionals to intervene in the most effective way to delay or prevent poor outcomes, or halt the progress of a disease. They will often need additional information to decide on the most appropriate model to use. Impactibility analysis could support this.

> *"I want to explore the opportunities to make impactibility about personalised care and really root it in individuals."*
>
> Comment from workshop participant

2.3.2 Impactibility, the third pillar of population health management

Impactibility models conceptualised for PHM aim to:

"…*refine the output of predictive models by: giving priority to patients with diseases that are particularly amenable to preventive care; excluding patients who are least likely to respond to preventive care; or identifying the form of preventive care best matched to each patient's characteristics.*" [7]

Impactibility models therefore have considerable potential to reduce health inequalities and optimise health outcomes. However, if used indiscriminately, when only a small group of patients would benefit, the models could increase health inequalities and lead to worse health outcomes. **Table 1** shows the limitations of some approaches to impactibility as identified in the strategic literature review, which should be considered when building a model.

> *"I'm excited to see how we can do more productive cohort identification, not retrospectively look back at what we should have done, and move forward in a better way."*
>
> *"This is kind of the missing piece of the PHM jigsaw."*
>
> Comments from workshop participants

3. Impactibility in practice

Researchers from the Health Economics Unit carried out a systematic literature review looking at how impactibility modelling has been implemented or assessed in PHM since 2010.

Using the Ovid search platform, researchers searched four databases for relevant papers published between January 2010 and May 2020: Embase Classic & Embase, Global Health, Healthcare Management Information Consortium, and Ovid MEDLINE. Additional searches for grey literature (evidence not published in commercial publications) were carried out in OpenGrey.

Of the 1,244 records initially identified, 179 full-text items were assessed for eligibility after removal of duplicates and initial exclusion based on title and abstract. Of these, 81 were found to be ineligible and 78 were commentaries. Finally, 20 studies related to the development, application or validation of impactibility models for use in PHM were included in the review.

3.1 Literature review methodology

Search strategies were built iteratively, with relevant keywords and subject headings added based on initial reviews of relevant publications. The final set of search terms included alternative spellings of ‘impactibility’ and synonyms including ‘intervenability’, ‘amenability’ and ‘propensity to succeed’. Researchers also included words associated with the themes ‘care sensitivity’, ‘characteristic responders’, ‘needs gap’, ‘case finding’, ‘patient selection’ and ‘risk stratification’. Where relevant, these search terms were linked with the Boolean operator and to synonyms for ‘predictive model’, ‘population health’ or ‘preventive healthcare’. No additional restrictions were applied in terms of language, date or status of publication.

The database search results were exported to the systematic review software Covidence. Two reviewers independently screened titles and abstracts for relevance and reviewed the full texts that specifically referenced analyses of amenability, impactibility and propensity to succeed in relation to future events. The researchers excluded papers that concerned youth offending, aimed to increase screening detection rates or looked only at identifying individuals at high risk of a specific disease or health event. To achieve the widest possible overview of work in this emerging field, the researchers did not exclude studies based on assessment of methodological quality. Any conflicts were discussed with a third reviewer at each review stage.

A pragmatic forward citation search was conducted using PubMed for all articles included in the initial review round. These were added to Covidence and the screening process repeated. A targeted Google search was conducted to identify any additional publications containing the term ‘impactibility’.

For studies describing impactibility models, information about country of implementation, data sources, population studied, intervention and any reported outcome measures was extracted into a data table. Researchers performed qualitative synthesis to assess themes and to group papers by approach to impactibility modelling. Outcome measures, where reported, were not comparable across studies, and meta-analysis was not required.

3.2 Types of models reviewed

The models described in the literature fell into three key themes, defined by the review authors: ‘health conditions amenable to care’, ‘propensity to succeed (PTS) modelling’ and ‘comparison or combination with clinical judgement’.

3.2.1 Ambulatory care sensitive conditions models

Ambulatory care sensitive (ACS) conditions are conditions where effective community care and case management can help prevent the need for hospital admission.

In the first theme, six specific studies[8-13] with examples of ACS models were provided in the literature, five of which are described below.

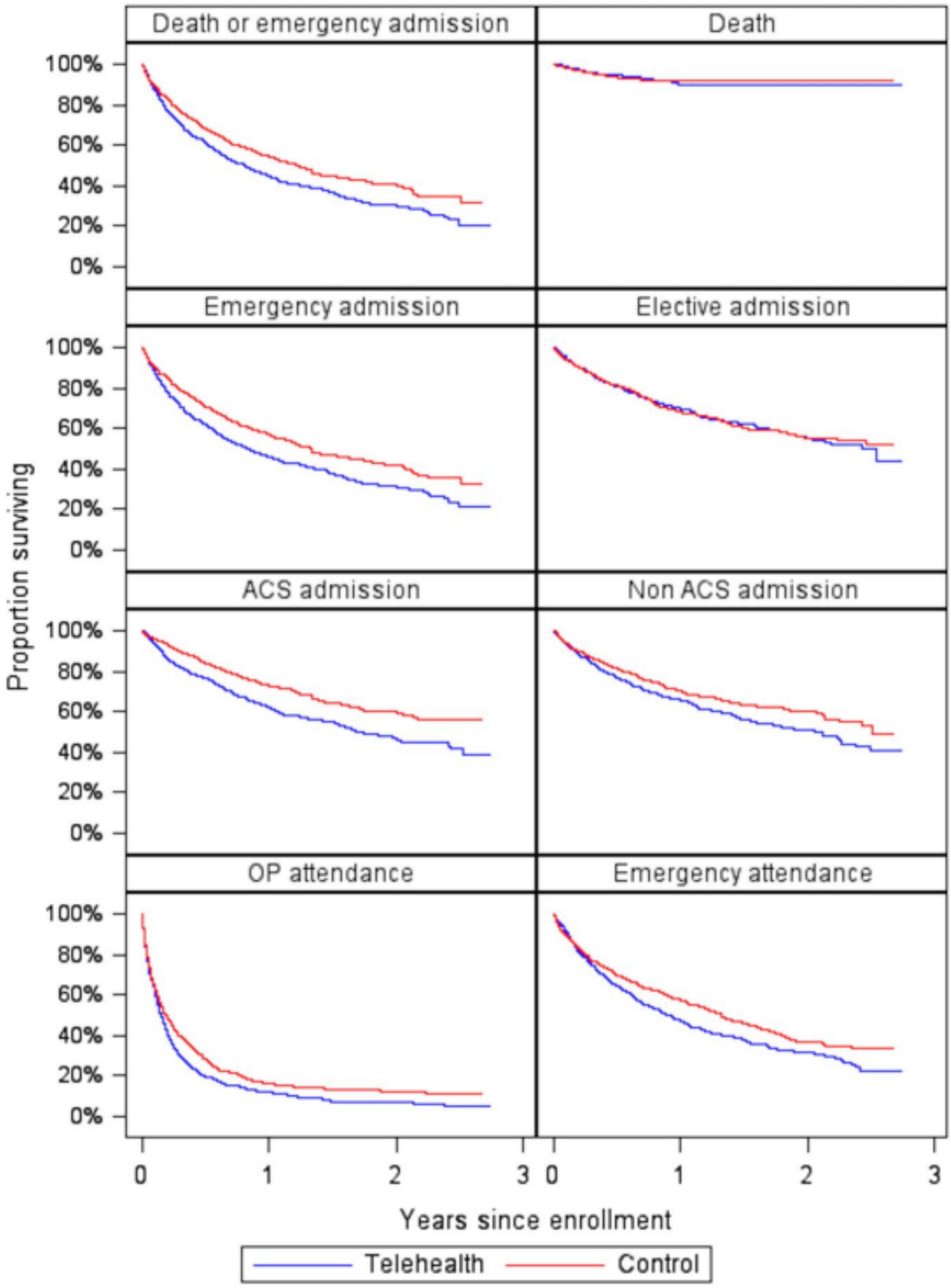
Researchers found that changes in practice did not reduce hospital admissions and sometimes increased them. For example, an observational study by Steventon *et al*.[10] reported that telephone health coaching by itself was not effective at reducing hospital use over 12 months and may actually lead to an increase in emergency admissions. Coaching interventions may need to be coupled with additional elements – such as telemonitoring, shared decision-making for preference-sensitive conditions, or predictive modelling – to be effective. More care coordination might also be needed.[10]

Two further 12-month observational studies by Steventon *et al*.[8,9] reported ambiguous effects of telehealth on mortality in the secondary care setting. In the first study, telehealth was associated with higher emergency admission and death rates than usual care (**Figure 2**).[8] By contrast, in the second, telehealth seemed to lower mortality and help patients avoid the need for emergency hospital care (**Figure 3**).[9] It is likely that the differences between these two studies might be due to the way in which telehealth is integrated into the wider healthcare system rather than attributable to the technology itself.[9,10] Therefore, redesigning care pathways for patients supported by the provision of telehealth may improve the effectiveness of such services over time.[8]

Guthrie *et al*.[11] also suggested that although input on organisational change from modelling was well accepted, it was not well integrated. As a result, depression as a factor for unscheduled care in patients with long-term conditions remained unaddressed. This finding might suggest that these models are too similar to risk stratification because they focus on diseases but leave underlying factors, such as psychosocial and socioeconomic factors, insufficiently addressed.[11]

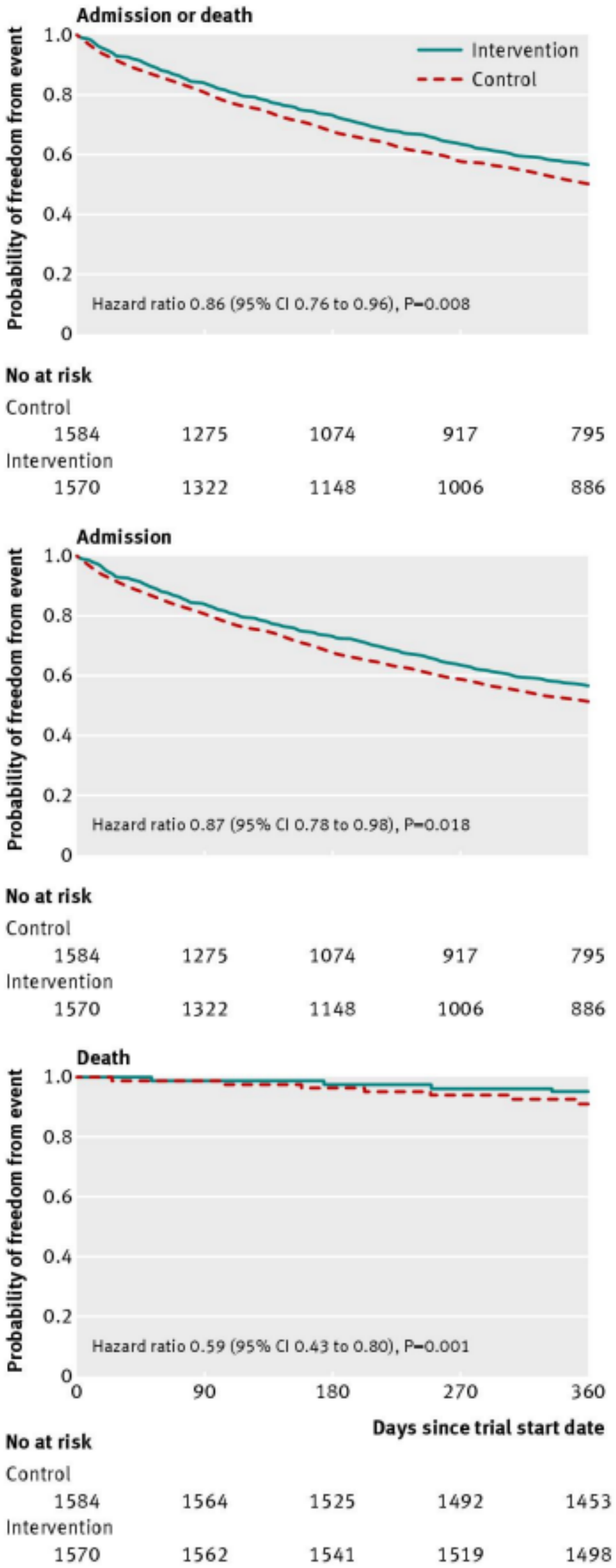
The fifth study, by Buja *et al*.,[12] showed no statistically significant difference between the ‘adjusted clinical groups’ system and a predictive algorithm applied as an impactibility model to identify patients with a high risk of at least one preventable admission.

Figure 2: Kaplan–Meier curves for time to the first emergency (unplanned) hospital admission or death (primary measure) and other secondary measures, including time to death and time to first admission, outpatient attendance and emergency department visit (n = 716 telehealth patients; 716 matched controls)[8]



(ACS, ambulatory care sensitive; OP, outpatient).

Figure 3: Kaplan–Meier survival curves for admission proportion[9]



In summary, the findings from these studies do not provide evidence that the ACS model can affect impactibility. However, some studies highlighted that the observed lack of impact might be due to the way in which the ACS model is integrated into the wider healthcare system, rather than being a failure of the model per se. Furthermore, Bardsley *et al.*[14] showed that different ACS conditions follow different trends, possibly even at the national or international level, highlighting the need to consider how the population for assessment should be selected.

3.2.2 Propensity to succeed

Propensity to succeed (PTS) describes prioritising those individuals most likely to benefit from a certain treatment or intervention.

The PTS model was assessed by eight studies[5,15-21] in the literature review and included a wide range of clinical, social and behavioural factors, mainly assessed by logistic regression to determine in whom treatment had been most successful. Six examples of studies evaluating the PTS model are described below.

Dubard and Jackson[5] concluded that variables related to medication adherence and historical use of care unexplained by disease burden were more important predictors of impactibility than diagnosis, specific events, disease profile and overall costs of care. PTS modelling generally led to improved accuracy in care planning, estimation of cost savings, engagement and/or care quality. These findings support moving away from delineated risk groups towards continuous risk predictions.[22]

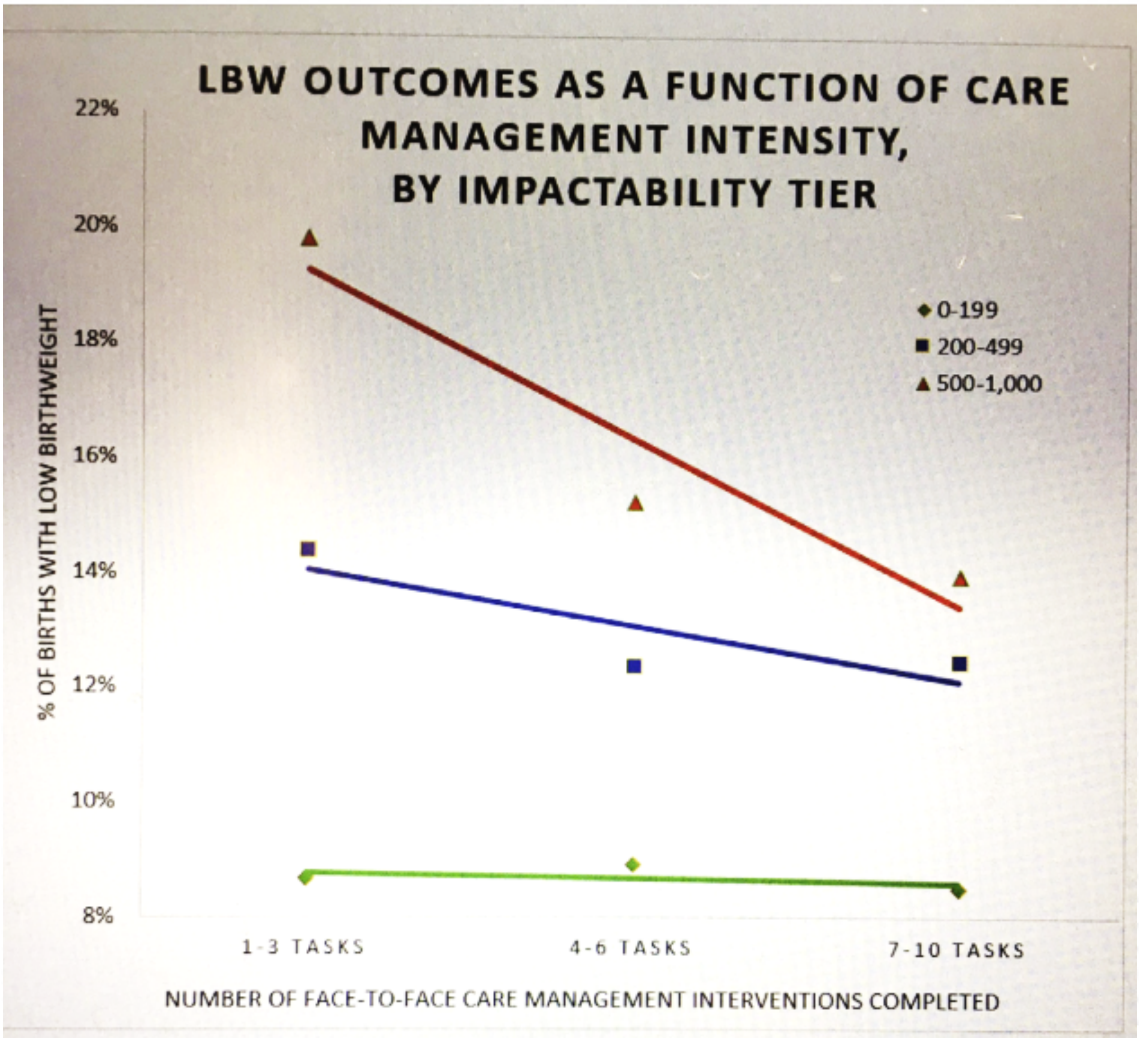
Hsueh *et al*.[19] used care management records to automatically quantify behavioural response in terms of goal attainment to identify patients in a high-risk care management programme who were most likely to benefit from being referred for additional interventions. Accuracy for goal attainment was greatest at the individual level (87.24%), outperforming population-level strategies (85.70%) and no planning (28.98%). This study suggests that increased patient behavioural understanding could benefit augmented intelligence for care management decision support.[20]

Mattie *et al*.[15] demonstrated the cost-saving potential of identifying patients most likely to benefit from a digital health intervention for care management. Based on results from this impactibility model, lower-risk members of the population could be targeted successfully with a digital health intervention.[15] Similarly, Hommer *et al.*[16] demonstrated the applicability of the PTS model to support a depression management programme, enabling more efficient use of health resources by targeting 'engaged' patients who were most likely to be successful.[16]

Menard *et al*.[20] identified that utilisation of the Maternal-Infant Impactibility Score™ to identify women who would benefit from pregnancy care management has the potential to prevent low birth weight outcomes in 8 out of 100 cases (**Figure 4**).[20]

In another example, Navratil-Strawn *et al*.[21] reported that the PTS model was appropriately stable and valid to identify patient characteristics associated with programme engagement (e.g., in a nurse telephone triage programme). The authors concluded that PTS modelling might help target and engage callers, thus increasing use of the nurse telephone triage programme, which should lead to more efficient use of healthcare services and reduce unnecessary healthcare expenditure.[21]

Figure 4: PTS model validation using 2015-16 data to confirm the relationship of high impactibility and higher number of care management tasks with reduced risk of low birth weight[20]



In summary, evidence from the literature shows that PTS can be useful to help identify patient characteristics associated with programme engagement. However, the results repeatedly underscored that considering the highest levels of risk and treatment costs did not equate to high impactibility.

3.2.3 Clinical judgement

In the third theme, six specific studies[6,23-27] assessing clinical judgement impactibility were identified in the literature. Four of these are provided as examples below.

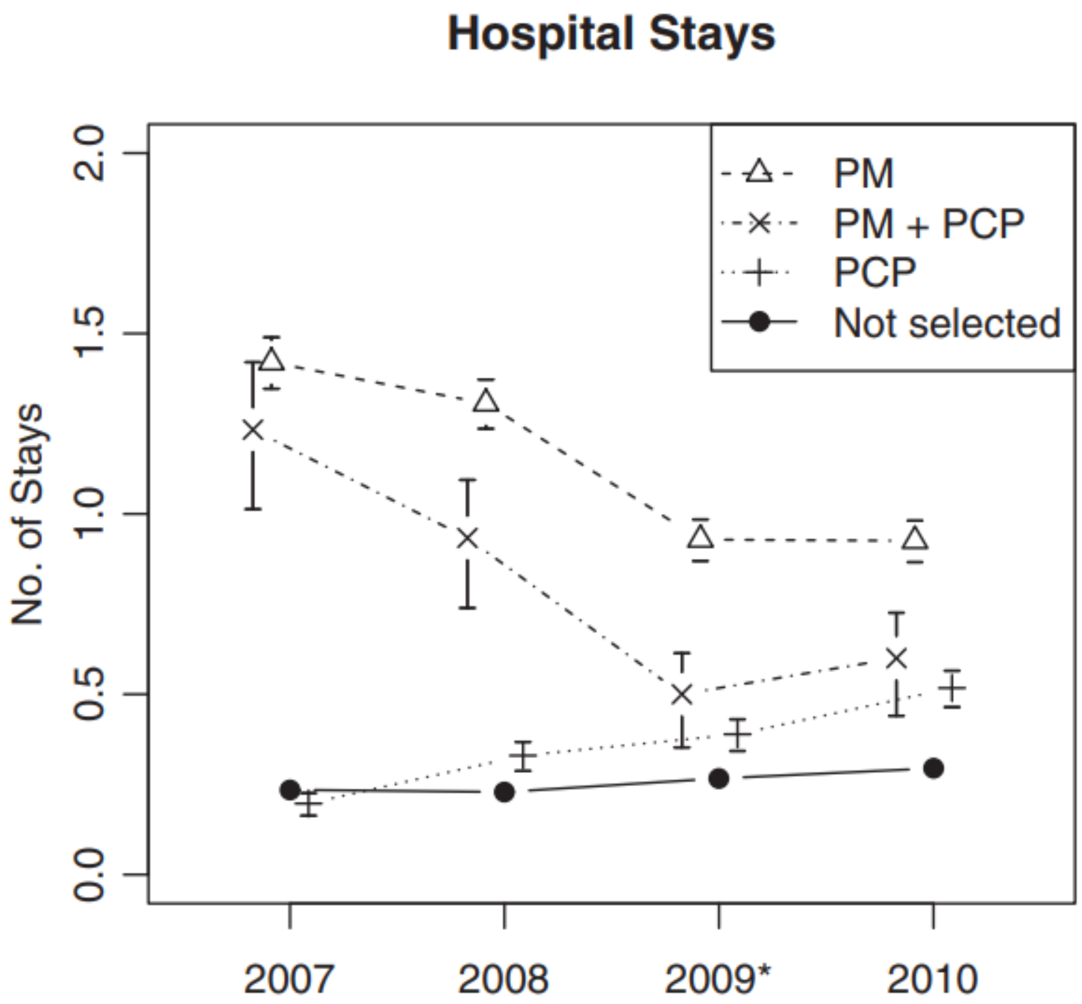
In the first example, Freund *et al*.[23] compared hospitalisation and mortality rates of patients identified for primary care-based care management using either software-based predictive modelling (PM) or the primary care physician (PCP) based on clinical experience. This observational study showed that PM identified patients with higher hospitalisation and mortality rates compared with PCP-identified patients referred for care management (**Figure 5**). PM was numerically more accurate than PCP at predicting risk of future hospitalisation. Still, rates for the latter increased over time, and patients had better receptivity to care management programmes; therefore, the authors recommended a combined approach between risk prediction and physician-determined impactibility.[23]

Similarly, Flaks-Manov *et al.*[6] showed that physician assessment of likelihood to benefit versus a PM assessment of risk have significant overlap (65%). Interestingly, the study showed that although 19% of patients had high predicted risk scores, they were not referred, whereas 16% of patients with a low predicted risk score were referred.[6]

Fleming *et al*.[24] noted that healthcare professionals (HCPs) often considered the ‘likelihood to benefit’ from care management to be challenging, mainly because they understood low patient engagement to be the result of difficult socioeconomic conditions.[24]

The fourth example, by Hudon *et al*.,[25] reported that care management intervention reduced psychological distress among patients and spouses. However, care management intervention did not have any significant impact on patient activation.[25]

Figure 5: Hospitalisations in patients selected by PCP or PM or both[23]



Mean number of hospitalisations per patient per year (Poisson rate estimates with standard errors) for patients independently identified as potential participants of a care management programme in 2009 (marked by asterisk) by primary care physician (PCP), predictive modelling (PM) or both (PM + PCP).[23]

In summary, the comparison or combination with the clinical judgement theme indicated that HCPs are routinely able to access real-time ‘soft intelligence’ about their patients that is not available to modellers.[28] For example, HCPs often look for more subtle signs of engagement and consider fluctuating trajectories of engagement due to living circumstances.[24] However, this approach is subjective, involving perceptions at system, HCP, clinical, patient and social levels.[29] Gathering such information can be highly resource-intensive, and how it informs decisions can depend on the quality and openness of the patient-provider relationship.

The application of identical information for two different patients might be affected by HCP sympathy or aversion, how well the patient is known, perceived patient characteristics or abilities (e.g., willingness to participate, language skills or cognitive status) and manageable care needs.[29] Furthermore, there is often a mismatch between risk classification by PM and perceived impactibility, and additional research is required to understand how combining PM data with physician insights might improve the selection of patients.[6] Impactibility models could have a complementary role in decision-making and might improve the individualisation of care management, even with a broad range of therapeutic options.[19]

3.2.4 Optimisation of these models and potential biases that could be inherent

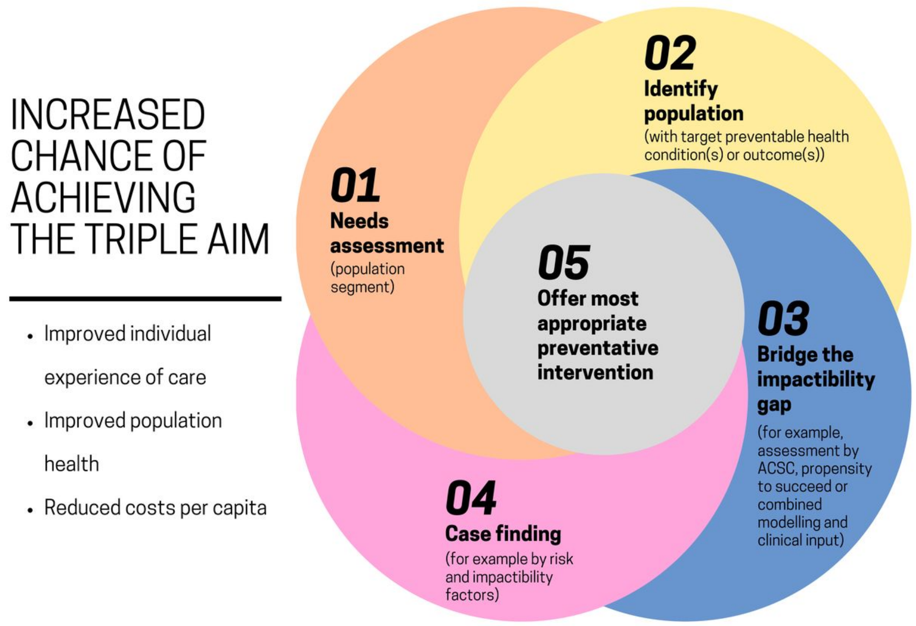
There are many possible reasons for differences in impact, including urban/rural setting, deprivation, literacy, language barriers, mental health challenges, behavioural or personality traits, and practicalities such as inflexible work or childcare constraints.[30-34]

Optimisation of impactibility modelling

"The challenge for PHM is to identify which interventions are most likely to succeed for an individual based on their wider circumstances and how those interventions may be delivered in a way that is most likely to achieve a positive outcome, thereby closing the impactibility gap." [1]

To optimise impactibility modelling, large amounts of data are needed on people's health behaviours and socioeconomic, clinical and environmental statuses, as well as broader data (e.g., genomic data) where possible. Many datasets are held by private companies but are not always accessible to or affordable for health system analysts. Completeness of data may affect modelling; for example, data are known to be less complete for people with higher levels of deprivation.[35] The different modelling approaches have various limitations and benefits (**Table 1**),[5-12,15-19,21,23,24,29,30,36-41] which might further influence the choice. If these issues can be overcome, impactibility models have potential to reduce the clinical burden in making decisions about resource allocation and improve the accuracy and objectivity of decision-making in PHM.

***Figure 6:** Use of impactibility modelling (step 03) to enhance identification of patients amenable to benefit and likelihood of achieving the triple aim*



(ACSC, ambulatory care sensitive condition).

Potential biases towards groups that are perceived to be likely to respond well to treatment, which could exclude some of the most vulnerable groups, have been identified as an important potential limitation of using impactibility as a PHM tool.[7,37,41-44] Thus it should be borne in mind that the purposes of considering impactibility in PHM are to improve access and equity of care and avoid wasting resources on providing additional costly interventions which will not benefit the recipients. Resources should be directed towards closing gaps in the evidence[43] and using the knowledge to develop better-tailored approaches for more people, possibly those in medium- and low-risk categories. This approach, based on the learning healthcare system model, in which best practice is implemented and updated by expanding knowledge of science, informatics, incentives and culture,[45] will provide practical case studies that can support efforts to develop and trial alternative ways of delivering care to meet the needs of people in different circumstances.

Achieving the triple aims using predictive models will require those models to have broad insights on which to base predictions.

> No single strategy used in the studies assessed can conclusively point to what information is required, but all go beyond previous healthcare resource utilisation. Some approaches are more easily adopted, as the data required are more readily available or less resource-intensive to implement.

Table 1: Practical benefits and limitations of different approaches to determining impactibility

Approach	Benefits	Limitations
Health conditions amenable to preventive care (gap analysis)	• Diagnosis data are readily available.[8-12] • Programmes are relatively simple to model and implement.[8-10,12] • Widely available data can be used to identify specific, evidence-based and scalable actions to address gaps in care.[38,39] • May reduce inequalities, as preventable health conditions are more common in deprived communities.[36]	• Does not factor in psychosocial and behavioural variables, such as willingness or ability to engage with care. • Suitable data to assess gaps are rarely available in real-world records.[7] • Integrating the model into the wider healthcare system is challenging.
Propensity to succeed models (behavioural response)	• Identify groups where an intervention is/is not likely to provide benefit, thereby are designed to avoid wasting resources where they are of no benefit.[5,15-18,21] • Care planning strategies are optimised at an individual and/or population level based on previous behavioural responses to a range of potential interventions.[19]	• Models would be enhanced by including educational, behavioural, psychological, social, economic and/or health information[6] but data would need to be consistently recorded and accessible. • Require interventional data rather than retrospective patient data.
Comparison or combination with clinical judgement	• Based on ad hoc, real-time information about capacity to access and engage with care.[40,41] • Healthcare professionals may be able to predict future deterioration in 'low-risk' patients with relatively good current health status (e.g., due to socioeconomic conditions).[25]	• Highly resource-intensive. • Relies on the quality and openness of the healthcare professional-patient relationship, and the ability of the data to capture this.[23,24,29,30,37] • May perpetuate biases (e.g., patients who come immediately to mind or those who have contact with other parts of the health service) or prejudices.[36]

		• Additional research is required to understand how combining predictability models data with HCP insights might improve the selection of patients.[6]

3.3 Literature review conclusions

Impactibility could build on other key PHM concepts, such as risk stratification (**Figure 1**),[46] by assessing more qualitatively which people might benefit most from certain health interventions and when proactive treatment might be appropriate (e.g., preventive care before an adverse health event, or a programme to prevent hospital readmission).

Not all people requiring medical care have the potential to benefit from preventive interventions. Based on current research, impactibility models can augment access to and address inequalities of care when combined with clinical insights. They also provide an opportunity to personalise preventive care delivery. Impactibility will achieve some or all of the triple aims.

PTS models improve the accuracy of selecting patients who are amenable to care, but very few prospective or comparative outcome data from real-world settings are available, so use of these models requires further research. Important factors – including model implementation, the effects of biases and prejudices, and the accuracy and availability of relevant data – should be included in these studies. Additionally, better understanding of why hospital admissions for ACS conditions (ACSCs) have not been reduced as much as anticipated would be beneficial. Disease-focused applications will be the subject of future research.

The analytical challenges in deriving meaningful insight about individual propensity are considerable, are ethically complex and require sensitive application of highly specialised knowledge. There are also inherent risks that strategies to improve population health through impactibility, however well intentioned, could worsen existing inequalities if they are not deployed with the greatest care.

4. Next steps

Following the systematic literature review, the next steps were to engage experts and stakeholders across the NHS to better understand their views on impactibility and its potential role in PHM. This engagement with the NHS community offered additional insight into the potential application of impactibility and their hopes and concerns for its use, as well as advice on which potential approaches should be adopted first.

To undertake this work, a series of interviews and workshops was conducted with participants from more than 20 organisations, with ethics approval sought and gained from Imperial College London. The detailed outputs of this engagement will be shared in the second report.

From this engagement, two potential approaches were proposed: one impactibility model which could predict an individual's first hospital admission for any ACS condition, and a second which takes into account a number of impactibility approaches, including gap analysis, PTS and HCP intervention for chronic obstructive pulmonary disease (an ACSC). Further details of these models will be shared in due course.

Our work continues in parallel with others. *Better, broader, safer: using health data for research and analysis*[47] – Professor Ben Goldacre's review into how the efficient and safe use of health data for research and analysis can benefit patients and the healthcare sector – was published in April 2022. It reinforces the important and lifesaving work of analysts working within the NHS and AphA, the Association of professional healthcare analysts.

He concludes: *"This data represents a spectacular opportunity to improve NHS care, and drive innovation in the life sciences sector. It is also a research resource of global importance, not least because the NHS population is larger – and more ethnically diverse – than other countries with similarly detailed health records. We should all regard it as a profound ethical duty to make the best use of this resource."*[47]

Key observations

More than 40 subject experts were consulted for this report, representing a variety of health and care organisations.

Impactibility is crucial to delivering on the NHS Long Term Plan aim of deploying ‘the right care at the right time in the optimal care setting’.

The research shows high levels of support across health and care in England plus an understanding of the challenges of implementing impactibility analysis and the exciting opportunities it offers.

Impactibility analysis uses data already available on wider determinants of health from Integrated Care System partners, supporting partnership working and shared goals.

Impactibility analysis might allow commissioners and providers to better target interventions for improved outcomes and greater efficiency.

Impactibility could support work to reduce health inequalities and ‘levelling up’ across England.

The new impactibility analysis model will include guidance and utilise open-source software for roll-out across England.

Further reading

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