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Bridging the impactibility gap in population health management: a systematic review

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Abstract

Objectives Assess whether impactibility modelling is being used to refine risk stratification for preventive health interventions.

Design Systematic review.

Setting Primary and secondary healthcare populations.

Papers Articles published from 2010 to 2020 on the use or implementation of impactibility modelling in population health management, reported with the terms "intervenability", "amenability", and "propensity to succeed" and associated with the themes "care sensitivity", "characteristic responders", "needs gap", "case finding", "patient selection", and "risk stratification".

Interventions Qualitative synthesis to identify themes for approaches to impactibility modelling.

Results – Of 1,244 records identified, 20 were eligible for inclusion. Identified themes were health conditions amenable to care (n=6), propensity to succeed (PTS) modelling (n=8), and comparison or combination with clinical judgement (n=6). For health conditions, particularly ambulatory-care-sensitive conditions, changes in practice did not reduce admissions and sometimes increased them, with implementation noted as a possible issue. For PTS modelling, high costs and needs did not necessarily equate to high impactibility, and targeting a larger number of individuals with disorders associated with lower costs had more potential. PTS modelling seemed to improve accuracy in care planning, estimation of cost savings, engagement and/or care quality improvements. In the clinical judgment theme suggested a complementary role for models. A model used to identify patients appropriate for a proactive programme of multimorbid care management showed reasonable concordance with physicians (c-statistic 0.75). Another model showed 65% concordance between electronic health record scores and nurse and physician decisions when referring elderly hospitalised patients to a readmission prevention programme. However, as well as high models scores, healthcare professionals included factors such as eligibility for a nursing home, non-controlled conditions and need for social-services support or special equipment at home in judgements.

Conclusions The efficiency and equity of targeted preventive care guided by risk stratification could be augmented and personalised by impactibility modelling.

Keywords access to care; impactibility; personalised care; population health management; triple aim; propensity to succeed; amenability.

Strengths and limitations

- Limitation – comparing data was difficult due to widespread inconsistency in terminology.
- Limitation – the quality of the articles included in this review was not graded.
- Limitation – as this is a growing area of interest and few studies are available
- Strength – we were as inclusive as possible with types of article, including abstracts and grey literature.
- Strength – to make the findings most applicable to PHM, we excluded studies of specific diseases.

Introduction

The triple aim, in which the goals of improving the individual experience of care, improving the health of populations, and reducing the per capita costs of care,[1] has become a popular healthcare objective. Risk stratification is one type of population health management (PHM) tool used by health system managers to achieve the triple aim[2–5] and identifies groups that are at high risk of poor outcomes so that they can be offered preventive care aimed at lowering this risk. For instance, care in accident and emergency has high costs and a cohort of patients experience frequent attendances, making this cohort a potential target for increased preventive spending. However, within this high-risk cohort, some individuals may be labelled as being "beyond help" because they their attendance is perceived by clinicians to be non-preventable (e.g., because of age, sex, or chronic conditions, including alcohol or drug abuse).[2,3] For these individuals, preventive care interventions will have little or no effect and they will continue to be at risk of so-called triple-fail events (in this case accident and emergency attendances), which are harmful, costly, and result in poor patient satisfaction.[4,6–9]

While risk stratification models may accurately predict which individuals are at risk of future adverse health outcomes, such as readmission risk or 1-year mortality risk,[2–5] their use has not consistently led to improvements in health outcomes across the population.[10] Calculating and understanding the probability of a particular outcome for an individual may not be enough for health care professionals to intervene in the most efficient way to delay or prevent that outcome or divert the course of a disease, and often needs to be supported by additional information to determine the most accurate or appropriate model.[11] Furthermore, as many risk stratification models predict future adverse health outcomes through current or previous healthcare activity and use a limited number of variables,[12–15] they may miss out on valuable additional information that could better direct resources to patients amenable to benefit.[9,16]

Lewis[6] found that impactibility was being assessed by many healthcare systems for PHM, reflecting a growing recognition that not all high-risk patients will benefit from preventive care. He described the ideal impactibility model as one that "would use information about the differential effects of a specific preventive intervention offered at random to patients and controls, so as to identify the characteristics of the 'perfect patient' for that preventive program". However, suitable data are rarely available in real-world records. Instead, he found that models were being formulated in three main classes: "(1) giving priority to patients with diseases that are particularly amenable to preventive care; (2) excluding patients who are least likely to respond to preventive care; or (3) identifying the form of preventive care best matched to each patient's characteristics". While such impactibility models have considerable potential to improve the efficiency of preventive care delivery, certain approaches could increase health inequalities if used indiscriminately without catering to individual needs.[6] The aim of this current study was to describe how and in what contexts impactibility modelling has been implemented or assessed in PHM from 2010 up to 2020.

Methods

A systematic literature review was carried out to identify all papers published between January 2010 and May 2020. The Ovid search platform was used to search four relevant databases: Embase Classic & Embase, Global Health, Healthcare Management Information Consortium, and Ovid MEDLINE. Additional searches for grey literature were performed in OpenGrey.

Search strategies were built iteratively, with relevant keywords and subject headings for each database added based on initial reviews of relevant publications. The final set of search terms (see supplementary information pp 1–28) included alternative spellings of impactibility and synonyms, including "intervenability", "amenability", and "propensity to succeed". We 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.

Database search results were exported to the systematic review software Covidence. Two reviewers (AO and SS) independently screened titles and abstracts for relevance and reviewed the full texts that specifically referenced analyses of amenability, impactibility, and propensity to succeed (PTS) in relation to future events. Papers that concerned youth offending, aimed to increase screening detection rates, and looked only at identifying individuals a high risk of a specific disease or health event were excluded. Full inclusion and exclusion criteria are shown in the supplementary information (pp 29–31). To achieve the widest possible overview of work in this emerging field, studies were not excluded based on assessment of methodological quality. Conflicts were discussed with a third reviewer (WS) at each review stage. A pragmatic forward citation search was subsequently conducted using PubMed for all articles included in the initial review round. These were added to Covidence, and the screening process was repeated. A targeted Google search (see supplementary information p 32) was conducted to identify any additional publications containing the term 'impactibility'.

Data extraction was performed by SS, HH, and WS. For studies describing impactibility models, information about country of implementation, data sources, population studied, intervention and any reported outcome measures were extracted into a data table. Qualitative synthesis was performed to assess themes and to group papers by approach to impactibility modelling.[17] Outcome measures, where reported, were not comparable across studies so meta-analysis was not considered to be appropriate.

Ethics Approval

As this as a systematic review of published literature and assessed data at the population level, ethnics approval was not required.

Results

Of 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. Thus, 20 studies related to the development, application, or validation of impactibility models for use in PHM and were included in the review (**Figure 1**).

In the qualitative synthesis, we grouped papers under three themes representing different approaches to assessing impactibility: health conditions amenable to preventive care (n=6); PTS (n=8); and comparison or combination with clinical judgement (n=6; see supplementary information pp 33–43).

Health conditions amenable to preventive care

Several studies inferred participants' potential to benefit from preventive care based on the diagnosis of a specific health condition[18–21] or a multi-morbid cluster of health conditions.[22,23] Many of these studies specifically targeted people with ambulatory-care-sensitive conditions (ACSCs), including chronic obstructive pulmonary disease, chronic heart failure, and diabetes, for which evidence suggests that optimal management in the community should not result in unplanned hospital admission.[10,16,24,25] Preventive interventions (e.g. case management) that were targeted based on the presence of one or more ACSC did not consistently lead to reductions in hospital admissions or secondary care costs, and indeed, in some cases led to increases in emergency hospital admissions.[18–22] However, the success of these impactibility strategies may be hindered by ineffective implementation. In one of these studies, for example, the authors indicated that the targeted intervention was not effectively integrated into primary care practice during the observation period.[21]

Propensity to succeed

PTS modelling is an analytical approach to identify traits associated with better engagement with or outcomes from particular preventive health intervention(s) – outcomes such as cost or care quality.[26–32] Of the eight studies identified that used this approach, three used PTS modelling in relation to specific case management interventions.[30–32] One model was developed explicitly for 'low-risk' participants to assess who would be most likely to benefit from a digital health platform.[28]

In these studies, PTS regression analyses were performed using various sociodemographic factors,[26–28,30–32] health status (e.g., presence of chronic conditions, prescription data, prior health resource utilisation, various health risk scores),[26–28,30–32] or previous programme engagement metrics.[28] One study found that high costs and high needs did not equate to high impactibility, as only small proportions of people with diseases that would be expected to have high burden had scores indicating high impactibility. The authors suggested that targeting a larger number of individuals with disorders associated with lower costs could improve impact substantially and that better predictors of impactibility might be medication adherence and historical healthcare resource utilisation that was unexplained by disease burden.[31]

Five of the identified studies reported the statistical validity of PTS models for projecting cost savings, improved engagement, and/or care quality improvements;[26–28,30,32] however, prospective or comparative outcome data on the use of these models in real-world situations were extremely limited in the literature. Two studies reported improved engagement (defined as enrolment of contacted participants) with case management interventions after implementation of a PTS model: Ozminkowski et al[32] reported an 11% increase in programme enrolment in the 9 months after implementation of a PTS model, compared with the 3 months prior. Hommer et al[29] likewise reported increased enrolment in a depression management programme but did not quantify the change.

Hsueh et al[33] evaluated the Behavioural Response Inference Framework (BRIeF), a machine learning impactibility model derived from a large observational dataset of care management records from a private healthcare network. They tested the ability of the model to predict individual-level behavioural responses to multiple interventions used in care planning. Input data included participants' personalised goal attainment history across 16 goals set in a program to reduce hospital readmissions after discharge for acute care. They covered a wide spectrum of care needs (e.g., tobacco cessation, knowledge of healthy eating, medication adherence, actions to resolve care gaps, and fall prevention) and were categorised as 'met', 'abandoned', 'not met' or 'open'. Data on goal attainment were extracted for 131 different care coordination activities in the categories referral, education, coordination, screening, coaching, or other tasks, that were classified as met or otherwise. The BRIeF model was applied to assess behavioural responses at the individual patient and population levels. Covariates used in the model were demographic information (e.g., age and gender), care programme context (e.g., program experience and days in the program), and the interactions between care managers and patients (e.g., the day of making the recorded call). The authors described the results of the model as 'promising', with the individual-level care planning strategy showing the greatest accuracy in terms of correct intervention recommendations outperforming a population-level care planning approach, where the one-size-fits-all approach reduces precision.

Comparison or combination with clinical judgement

We identified six impactibility models that – either formally or informally – incorporated a healthcare provider's opinion of whether an individual patient was likely to benefit from a particular preventive health intervention.[16,34–39] In one study, clinical judgement was applied as a final (filtering) step to estimate how care management would impact patients after they had undergone risk stratification by a predictive analytic tool.[40] Such a combined approached led to an increase in the average risk score for patients enrolled in care management.

Cohen et al[41] designed a predictive model to identify patients who would benefit from proactive muiltimorbid care management based on inclusion and exclusion criteria refined from a physician survey of 375 cases and on risk of future high costs based on data extracted from a health services database. Recommended reasons for exclusion due to risk for future high costs were active cancer, schizophrenia, dialysis, residence in nursing homes or long-term care facilities, and age 95 years or older. The model was used to assess 5,341 high-risk patients. Discriminatory power of the model before and after clinical exclusions was c-statistic 0.80 and 0.75, respectively. Age, number of chronic conditions, and healthcare utilisation were associated with high-risk of high-cost care. The authors concluded that the model had acceptable discriminatory power for identifying who would benefit from proactive care management even after the highest-risk patients were excluded.

HCPs consider a range of factors when assessing an individual's suitability for a preventive health intervention. These include perceived hospitalisation risk; feelings of sympathy or aversion towards the patient; and a judgement of the patient's willingness and ability to participate in the intervention.[16,38] HCPs also reported excluding patients from preventive healthcare interventions because of language barriers.[16]

Flaks-Manov et al[42] investigated whether risk scores for 30-day readmission from an electronic health records model were aligned with nurses' and physicians' perceived impactibility of a readmission prevention programme for hospitalized patients aged 65 years or older. The clinical and model decisions for 435 patients were concordant in 65% of cases. Among the remaining 35%, 19% with high model scores were not referred by healthcare professionals and 16% with low model scores were referred. Decision-tree analysis indicated that as well as high models scores, eligibility for a nursing home, having a condition not under control, need for social-services support and need for special equipment at home were statistically associated with referral. The authors concluded that better understanding is needed of whether combining perceptions and modelling could improve selection of patients.

Freund et al[43] assessed areas in which impactibility modelling might be helpful. They invited 12 primary-care physicians in ten practices to review records for 104 hospitalizations in 81 patients who had ACSCs and rate whether they felt each hospital admissions was avoidable. The doctors deemed 43 (41%) hospitalisations to be avoidable. Reasons fell into five main categories: system related (eg, unavailability of ambulatory services), physician related (eg, suboptimum monitoring), medical (eg, medication side effects), patient related (eg, delayed help-seeking), and social (eg, lack of social support). Further reasons were after-hours referral required in the absence of the treating physician, not using ambulatory services, patients' fears, cultural background, and language skills, medication errors, non-adherence to medication, and overprotective caregivers. In discussing implications for clinical practice and policy, it was recommended the risk stratification modelling would be enhanced by considering patients' social situation, medication adherence, and self-management capabilities and sharing responsibility across sectors.

Discussion

As health systems turn to data-led approaches to deliver the triple aim, many are finding that allocating resources based on risk alone is suboptimal. The evidence reviewed shows varying attempts to make these decision tools more impactful/effective and increase the probability of success of interventions by using additional insights to bridge the impactibility gap. Targeting patients for preventive care only based on health conditions amenable to preventive care does not necessarily lead to reductions in resource use and might even increase it. PTS modelling showed some promising results when broader information, such as sociodemographic factors medication adherence or previous programme engagement, was included. The accuracy of behavioural responses seems so far to be most accurate at the individual level, but more data on real-world outcomes is needed, as implementation could affect the PHM potential. Of note, congruence between modelling and HCP decisions was low, and better understanding is needed of how perceptions and data analysis affect one another.

This study had several limitations. Interpreting and comparing the data was difficult due to widespread inconsistency in terminology. Even at the most basic level, "high-risk individuals" was conflated with "those most likely to benefit" in some papers[26,44] despite evidence indicating that these can be highly separated groups.[5,31,42] The quality of the articles included in this review was not graded. However, as this is a growing area of interest and few studies are available, it is a strength of the study that we were as inclusive as possible. Owing to the substantial differences in approaches to categorising model outputs and in outcome measures and lack of reporting these in some studies, it was not possible to perform a quantitative analysis. Finally, in order to make the findings most applicable to PHM, we excluded studies of specific diseases. Of note, given the descriptive nature of this review, it was not registered and no protocol was published.

While risk stratification models may accurately predict which individuals are at risk of future adverse health outcomes, it also allows a healthcare system to estimate the average cost of triple fail events for the people within a risk stratum over a set period, allowing a budget cap for preventive care to be set. Nevertheless, the effects on improving health outcomes have not been consistent.[10] Impactibility modelling includes broader factors and suggests where, when, and how to target preventive resources in order to maximise the desired effect. People respond to treatment differently, and without an impactibility model, it is not possible to establish which individuals within a particular stratum of risk will respond well or poorly to the proposed preventive care intervention.

Allocating every person to a stratum and allocating resources solely based on risk may be inefficient, as not all patients will be amenable to the offered intervention (**Figure 2A**). Incorporating an impactibility model into the decision process provides an extra layer of information that could predict which individuals are most likely respond to preventive care (as a whole or by specific type) and allow weighted investment in these individuals (**Figure 2B**).

It is important, first, to acknowledge that not everyone requiring medical care has the potential to benefit from preventive interventions in a PHM sense, such as those with a terminal diagnosis or who are unable to engage with self-care. However, even people approaching the end of their life can benefit from targeted palliative interventions that optimise care quality and avoid unnecessary and costly hospitalisations.[45,46] Some of the conditions most likely to benefit from appropriate ambulatory preventive interventions are ACSCs, but in practice, targeting care management interventions at ACSCs as a whole seems not to have led to the reduced hospital care at a population level.[10,18–20] However, in the studies by Steventon et al,[18–20] the education interventions could have encouraged the use of primary care services and increased hospitalisation. As follow-up was short, a longer period of time might have yielded a positive effect on reducing hospital-based management. The study by Bardsley et al[10] was much longer term but and showed that trends differed for ACSCs, such as reduced hospital admissions for angina, CHF, and perforated/bleeding ulcers but increases for pyelonephritis and urinary tract infection and pneumonia. These trends seemed to follow wider, even international, trends, which highlights the need to consider how the population for assessment should be selected. There are many other possible reasons for differences in impact, including little health literacy, language barriers, mental-health challenges, behavioural or personality traits, and practicalities such as inflexible work or childcare constraints.[35,47–49] The challenge for PHM, therefore, is to identify which intervention(s) 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. We have termed this challenge the 'impactibility gap' (**Figure 3**).

HCPs routinely identify practical barriers that might hinder the potential success of a prescribed intervention, for instance through conversations with their patients. Depending on the quality and openness of the patient–provider relationship, clinicians may be able to access real-time soft intelligence about their patients that is not available to modellers.[43] However, this approach is subjective, involving perceptions at system, HCP, clinical, patient, and social levels,[16] highly resource intensive, and not always achievable through routine primary care interactions. The findings of Hsueh et al[33] suggest that impactibility modelling might be able to improve the individualisation of care management, even with a broad range of therapeutic options.

To optimise impactibility modelling, large amounts of data are needed on people's health behaviours, socioeconomic, clinical, and environmental status, and broader data where possible, such as genomic data. Many data are held by private companies but are not always accessible to or affordable for health system analysts. Completeness of data may affect modelling and, for example, are known to be less complete for people with higher levels of deprivation.[50] The different modelling approaches have various limitations and benefits (**Table 1**), which might further determine 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 objectiveness of decision-making in PHM.

Potential biases towards groups that are perceived as likely to respond well to treatment, which could exclude some of the most vulnerable groups, has been identified as an important potential limitation of using impactibility as a PHM tool.[6,37,54–57] Thus, it should be borne in mind that the purposes of considering impactibility PHM are to improve access and equity of care and avoid unnecessarily wasting resources on providing additional interventions that are costly and will not benefit the recipients. Resources should be directed towards closing gaps in the evidence[56] and using the knowledge to develop better-tailored approaches to more people in the lower-risk categories (**Figure 2**). 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,[58] 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.

To achieve the triple aim using predictive models will require those models to have broad insights on which to base predictions. Additionally, 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 they are less resource intensive to implement.

Conclusions

Impactibility builds on other key PHM concepts, such as risk stratification,[59] by assessing more qualitatively which people might benefit the most from certain health interventions and when proactive treatment might be appropriate (eg, preventive care before an adverse health event or a programme to prevent hospital readmission). Although limited research is so far available, it seems that impactibility models can augment access to and equity of care when coupled with clinical insights and provide an opportunity to personalise preventive care delivery. Using this approach, it should be possible achieve the triple aims of PHM[1] – simultaneously improving the individual experience of care, improving the health of populations, and reducing the per capita costs of care for populations. The areas most studied so far is PTS, but very few prospective or comparative outcome data from real-world settings are available, and this would be judicious to explore further. Potential confounding factors, such as model implementation, should be included in these studies. Additionally, better understanding of why hospital admissions for ACSCs have not been reduced as much as anticipated would be beneficial. Disease-focussed applications will be the subject of future research.

Author contributions

Andi Orlowski: conceptualisation, methodology, validation, formal analysis, writing – original draft, writing – review and editing. **Sally Snow**: methodology, formal analysis, data curation, writing – original draft, writing – review and editing. **Heather Humphreys**: formal analysis. **Wayne Smith**: formal analysis. **Rebecca Sian Jones**: methodology. **Rachel Ashton**: writing – review & editing. **Jackie Buck**: methodology. **Alex Bottle**: writing – review & editing.

Competing interests statement

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Data sharing statement

Data are available upon reasonable request.

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Patient and public involvements

It was not appropriate to involve patients or the public in the design, or conduct, or reporting, or dissemination plans of our research.

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Figure 1: PRISMA diagram

Figure 2: Use of impactibility modelling enhances identification of individuals most likely respond to preventive care and allows weighted resourcing

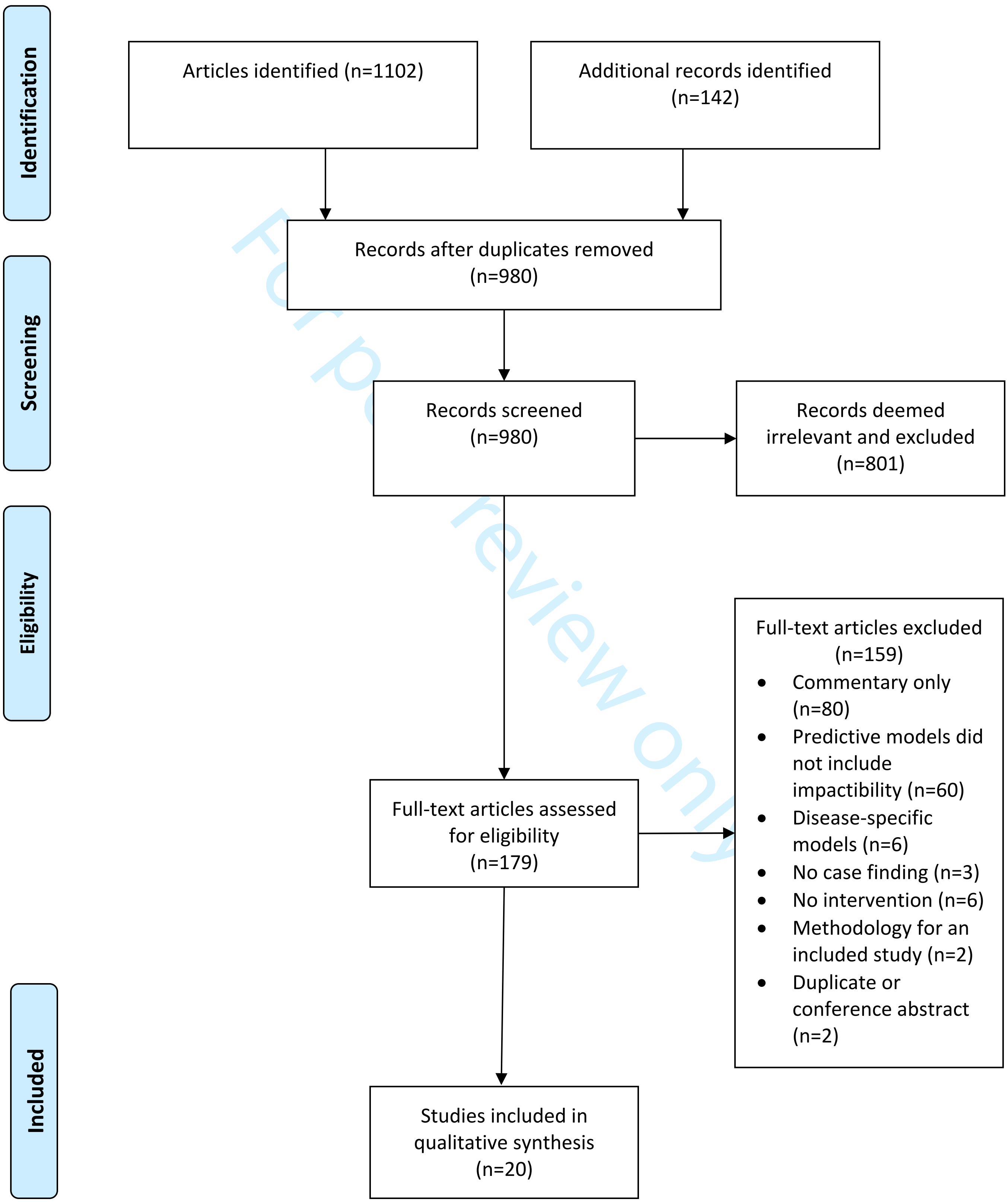
(A) Size of population at risk of unplanned event over a specific period of time (B) Highlighted population amenable to 3 possible interventions to reduce the number of unplanned events.

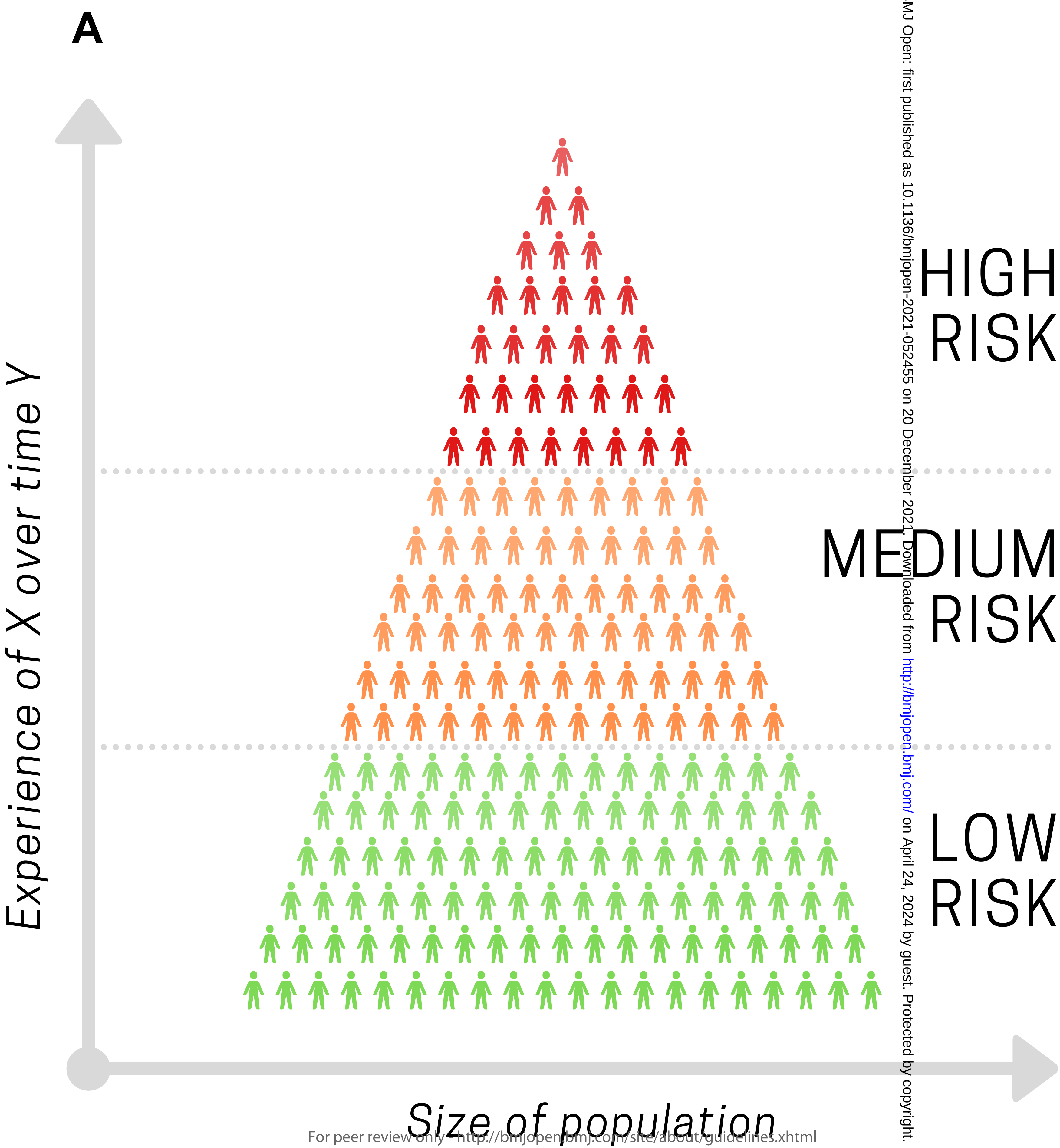
Figure 3: Use of impactibility modelling to increase the number of patients amenable to benefit

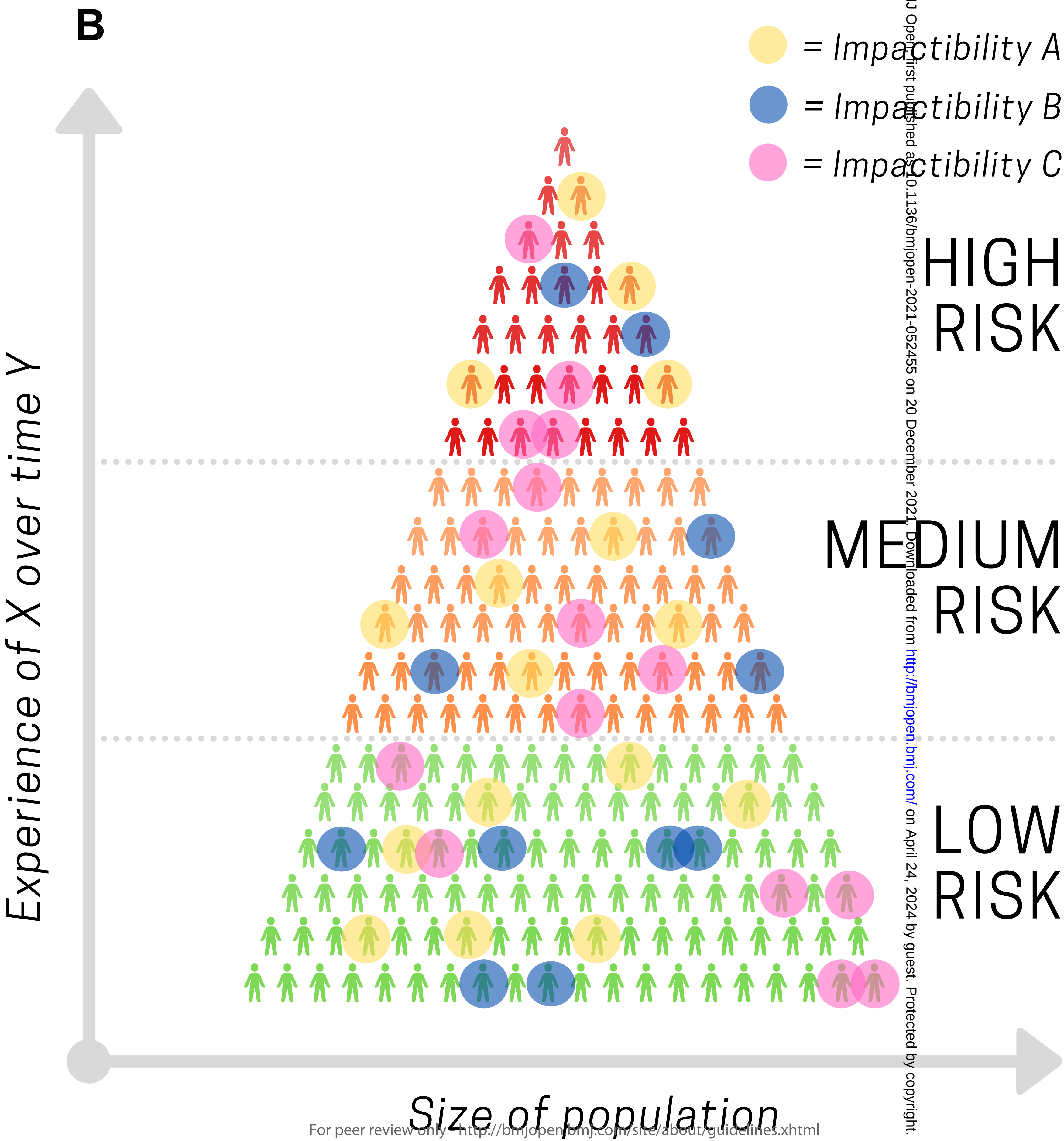
Table 1: Practical benefits and limitations of different approaches to determining impactibility

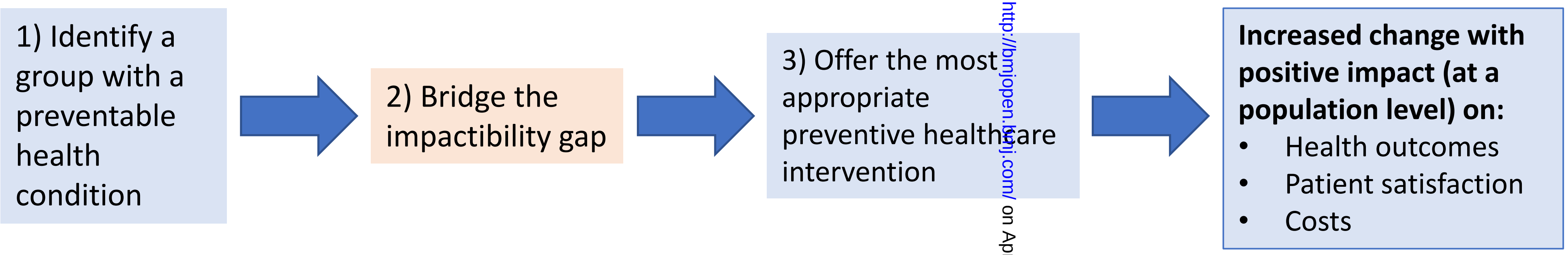
Approach	Benefits	Limitations
Health conditions amenable to preventive care	• Diagnosis data are readily available[18–21,23] • Programmes are relatively simple to model and implement[18–20,23] • May reduce inequalities, as preventable health conditions are more common in deprived communities[7]	Does not factor in psychosocial and behavioural variables, such as willingness or ability to engage with care.
Health needs/gap analysis	• Widely available data can be used to identify specific, evidence-based and scalable actions to address gaps in care[51,52] • May reduce inequalities, as preventable health conditions are more common in deprived communities[7] • Suitable data to assess gaps are rarely available in real-world records[6]	
Propensity to succeed models	• Identifies groups where an intervention is/is not likely to provide benefit, thereby is designed to avoid wasting resources where they are of no benefit[27–32]	Models would be enhanced by including educational, behavioural, psychological, social, economic and/or health information,[42] but data would need to be consistently recorded

Behavioural response models	• Care planning strategies are optimised at an individual and/or population level, based on previous behavioural responses to a range of potential interventions[33]	and accessible.
HCP's assessment of an individual's 'likelihood to benefit'	• Based on ad hoc, real-time information about capacity to access and engage with care[53,54] • HCPs may be able to predict future deterioration in "low risk" patients with relatively good current health status[36]	• Highly resource intensive • Relies on the quality and openness of the HCP-patient relationship, and the ability of the data to capture this[16,35–38] • May perpetuate biases or prejudices[7]


Identification
Screening
Eligibility
Included
Articles identified (n=1102)
Additional records identified (n=142)
Records after duplicates removed (n=980)
Records screened (n=980)
Records deemed irrelevant and excluded (n=801)
Full-text articles assessed for eligibility (n=179)
Full-text articles excluded (n=159)
• Commentary only (n=80)
• Predictive models did not include impactibility (n=60)
• Disease-specific models (n=6)
• No case finding (n=3)
• No intervention (n=6)
• Methodology for an included study (n=2)
• Duplicate or conference abstract (n=2)
Studies included in qualitative synthesis (n=20)


A
Experience of X over time Y
HIGH
RISK
MEDIUM
RISK
LOW
RISK
Size of population


B
= Impactibility A
= Impactibility B
= Impactibility C
HIGH RISK
MEDIUM RISK
LOW RISK
Experience of X over time Y
Size of population


1) Identify a group with a preventable health condition
2) Bridge the impactibility gap
3) Offer the most appropriate preventive healthcare intervention
Increased change with positive impact (at a population level) on:
• Health outcomes
• Patient satisfaction
• Costs

APPENDIX

Appendix Table S1: List of search strings

Database: Ovid MEDLINE(R) ALL <1946 to May 14, 2020>
Search Strategy:
----
1 impact?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9)
2 'propensity to succeed'.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6)
3 interven?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (3)
4 case finding.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4937)
5 casefinding.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (86)
6 Patient selection.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (83162)
7 Patient Selection/ (64332)
8 target* patient*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2387)

9 (target* adj2 segment*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (947)
10 case selection.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1810)
11 risk stratif*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (32437)
12 (predict* adj3 risk factor*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (7856)
13 risk factors/ (815581)
14 protective factor*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (21359)
15 protective factors/ (4040)
16 (risk adj2 population*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (34671)
17 susceptible population?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2135)
18 Vulnerable Populations/ (10281)
19 (risk adj2 analy*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (26586)
20 risk assess*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (298996)

21 Risk Assessment/mt, sn [Methods, Statistics & Numerical Data] (33887)
22 risk segment*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (101)
23 Health Status Indicators/ (23314)
24 (characterist* adj4 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (19693)
25 (characterist* adj3 nonrespon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (118)
26 (care adj3 sensitiv*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2767)
27 (receptiv* adj3 care).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (60)
28 (Likel* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9537)
29 (Likel* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1021)
30 (Likel* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9788)
31 (Likel* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (3232)
32 (Likel* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1163)
33 (Predict* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2225)
34 (Predict* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1508)
35 Predict* responder*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (192)
36 (Predict* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (13782)
37 (Probab* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (801)
38 (Probab* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (488)
39 (Probab* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6492)
40 (Probab* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2744)
41 (Probab* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1058)
42 (propensity adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (14)
43 (propensity adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (19)
44 (propensity adj2 respond*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (57)
45 (propensity adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (41)
46 (propensity adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (21)
47 (Potential* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (38647)
48 (Potential* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1341)
49 (Potential* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (11907)
50 (Potential* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2061)
51 (Potential* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (13813)
52 (Model* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1163)
53 (Model* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4006)
54 (Model* adj2 responder*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (71)
55 (Model* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2359)
56 "Patient acceptance of health care"/ (46068)
57 (predict* adj3 model*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (118731)
58 Adverse Outcome Pathways/ (83)
59 Markov Chains/ (14167)
60 logistic* model*.mp. (143517)
61 logistic models/ (137961)
62 population model*.mp. (3652)
63 Patient-Specific Modeling/ (969)
64 patient specific model*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1904)
65 ambulatory care sensitive condition?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (561)
66 Hospitalization/ (105786)
67 Patient Admission/ (24023)
68 Patient Readmission/ (16915)

69 preventive medicine.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (16812)
70 Preventive Medicine/ (11679)
71 preventive health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (17200)
72 Primary Prevention/ (18315)
73 secondary prevention/ (20153)
74 (early adj3 intervention*).mp. (37091)
75 Early Medical Intervention/ (2939)
76 Target* health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1545)
77 Target* healthcare.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (160)
78 (Target* adj3 care*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4252)
79 (prevent* adj3 intervention*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (40728)
80 (care adj3 management).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (26779)
81 population health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (12278)
82 Population Health/ (792)

83 Decision Support Systems, Clinical/ (7841)
84 Health Policy/ (65651)
85 Health* management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6159)
86 System? management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1650)
87 Patient care management/ (4035)
88 Public Health/mt, og, sn [Methods, Organization & Administration, Statistics & Numerical Data] (5126)
89 public health*.mp. (319968)
90 public health administration/ (15359)
91 health service? management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (411)
92 Models, Organizational/ (18878)
93 health care system?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (38577)
94 health* system?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (74494)
95 "Delivery of Health Care"/ (89529)
96 "Delivery of Health Care, Integrated"/ (12500)
97 Managed Care Programs/ (24211)
98 multidisciplinary service?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (204)
99 integrated service?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept

word, rare disease supplementary concept word, unique identifier, synonyms] (1229)
100 amen?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1110)
101 1 or 2 or 3 (18)
Annotation: Impactibility
102 4 or 5 (5020)
Annotation: Case finding
103 6 or 7 or 8 or 9 or 10 (88016)
Annotation: Patient selection
104 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 (1128808)
105 24 or 25 (19768)
Annotation: Characteristic response
106 26 or 27 (2827)
Annotation: Care sensitivity
107 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 or 56 (172438)
Annotation: Likeli to benefit
108 57 or 58 or 59 or 60 or 61 or 62 or 63 or 64 (275227)
109 65 or 66 or 67 or 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 (251550)
Annotation: Preventive healthcare
110 80 or 81 or 82 or 83 or 84 or 85 or 86 or 87 or 88 or 89 or 90 or 91 or 92 or 93 or 94 or 95 or 96 or 97 or 98 or 99 (614599)
Annotation: Population health management
111 109 and 110 (25971)
Annotation: Preventive health and population health management
112 109 or 110 (840178)
Annotation: Preventive healthcare or population health management
113 100 and 112 (27)
114 107 or 108 (439630)

115 102 and 114 (325)
116 111 and 115 (7)
117 103 and 114 (5324)
118 111 and 117 (35)
119 104 and 107 and 108 and 111 (26)
120 105 and 114 (975)
121 112 and 120 (84)
122 106 and 114 (278)
123 111 and 122 (39)
124 102 and 112 and 114 (102)
125 101 or 113 or 124 or 118 or 119 or 121 or 123 (329)

Database: HMIC Health Management Information Consortium <1979 to March 2020>
Search Strategy:
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1 impact?bility.mp. [mp=title, other title, abstract, heading words] (1)
2 'propensity to succeed'.mp. [mp=title, other title, abstract, heading words] (0)
3 interven?bility.mp. [mp=title, other title, abstract, heading words] (0)
4 case finding.mp. [mp=title, other title, abstract, heading words] (201)
5 casefinding.mp. [mp=title, other title, abstract, heading words] (3)
6 screening/ (3706)
7 Patient selection.mp. [mp=title, other title, abstract, heading words] (93)
8 Patient selection/ (47)
9 target* patient*.mp. [mp=title, other title, abstract, heading words] (81)
10 (target* adj2 segment*).mp. [mp=title, other title, abstract, heading words] (6)
11 case selection.mp. [mp=title, other title, abstract, heading words] (16)
12 (risk adj2 population*).mp. [mp=title, other title, abstract, heading words] (516)
13 exp "Risk adjusted monitors of outcome"/ (20)
14 exp vulnerability/ (1261)
15 susceptible population*.mp. [mp=title, other title, abstract, heading words] (10)

16 risk stratif*.mp. [mp=title, other title, abstract, heading words] (106)
17 (predict* adj3 risk factor*).mp. [mp=title, other title, abstract, heading words] (55)
18 risk factors/ (4430)
19 protective factor*.mp. [mp=title, other title, abstract, heading words] (144)
20 (risk adj2 analy*).mp. [mp=title, other title, abstract, heading words] (238)
21 risk assess*.mp. [mp=title, other title, abstract, heading words] (2572)
22 risk assessment/ (1859)
23 risk segment*.mp. [mp=title, other title, abstract, heading words] (1)
24 (characterist* adj4 respon*).mp. [mp=title, other title, abstract, heading words] (163)
25 (characterist* adj3 nonrespon*).mp. [mp=title, other title, abstract, heading words] (0)
26 (care adj3 sensitiv*).mp. [mp=title, other title, abstract, heading words] (196)
27 (receptiv* adj3 care).mp. [mp=title, other title, abstract, heading words] (1)
28 (Likel* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (183)
29 (Likel* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (38)
30 (Likel* adj2 respon*).mp. [mp=title, other title, abstract, heading words] (72)
31 (Likel* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (105)
32 (Likel* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (22)
33 (Predict* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (26)
34 (Predict* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (11)
35 Predict* responder*.mp. [mp=title, other title, abstract, heading words] (1)
36 (Predict* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (78)
37 (Probab* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (19)
38 (Probab* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (5)
39 (Probab* adj2 respon*).mp. [mp=title, other title, abstract, heading words] (19)
40 (Probab* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (10)
41 (Probab* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (10)
42 (propensity adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (0)
43 (propensity adj2 accept*).mp. [mp=title, other title, abstract, heading words] (0)
44 (propensity adj2 respon*).mp. [mp=title, other title, abstract, heading words] (4)
45 (propensity adj2 succe*).mp. [mp=title, other title, abstract, heading words] (0)

46 (propensity adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (1)
47 (Potential* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (882)
48 (Potential* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (23)
49 (Potential* adj2 respon*).mp. [mp=title, other title, abstract, heading words] (46)
50 (Potential* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (49)
51 (Potential* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (186)
52 (Model* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (41)
53 (Model* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (40)
54 (Model* adj2 responder*).mp. [mp=title, other title, abstract, heading words] (1)
55 (Model* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (75)
56 (predict* adj3 model*).mp. [mp=title, other title, abstract, heading words] (554)
57 exp Decision Support Systems/ (218)
58 logistic* model*.mp. (74)
59 population model*.mp. (22)
60 exp Computer aided decision making/ (29)
61 exp models/ (3243)
62 patient specific model*.mp. (0)
63 ambulatory care sensitive condition?.mp. [mp=title, other title, abstract, heading words] (45)
64 exp Ambulatory care/ (914)
65 exp Pre hospital care/ (49)
66 exp hospital admission/ (3371)
67 exp Hospitalisation/ (7032)
68 exp Health impact assessment/ (360)
69 exp Preventive Medicine/ (21451)
70 preventive medicine.mp. [mp=title, other title, abstract, heading words] (2305)
71 exp preventive medicine health services/ (210)
72 preventive health*.mp. [mp=title, other title, abstract, heading words] (228)
73 exp Health improvement programmes/ (237)
74 prevention/ (5896)
75 (early adj3 intervention*).mp. (749)

76 early intervention/ (0)
77 Target* health*.mp. [mp=title, other title, abstract, heading words] (120)
78 Target* healthcare.mp. [mp=title, other title, abstract, heading words] (12)
79 (Target* adj3 care*).mp. [mp=title, other title, abstract, heading words] (364)
80 (prevent* adj3 intervention*).mp. [mp=title, other title, abstract, heading words] (1001)
81 (care adj3 management).mp. [mp=title, other title, abstract, heading words] (2858)
82 population health*.mp. [mp=title, other title, abstract, heading words] (1085)
83 exp care management/ (500)
84 exp health policy/ (5647)
85 Health* management.mp. [mp=title, other title, abstract, heading words] (505)
86 System? management.mp. [mp=title, other title, abstract, heading words] (79)
87 public health*.mp. (16612)
88 exp public health/ (11196)
89 exp Health systems/ (44916)
90 health service? management.mp. [mp=title, other title, abstract, heading words] (5830)
91 health care system?.mp. [mp=title, other title, abstract, heading words] (3136)
92 health* system?.mp. [mp=title, other title, abstract, heading words] (7548)
93 multidisciplinary service?.mp. [mp=title, other title, abstract, heading words] (555)
94 integrated service?.mp. [mp=title, other title, abstract, heading words] (329)
95 amen?bility.mp. [mp=title, other title, abstract, heading words] (2)
96 1 or 2 or 3 (1)
Annotation: Impactibility
97 4 or 5 or 6 (3859)
Annotation: Case finding
98 7 or 8 or 9 or 10 or 11 (195)
Annotation: Patient selection
99 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 (8794)
Annotation: Risk stratification
100 24 or 25 (163)
Annotation: Characteristic response

101 26 or 27 (197)
Annotation: Care sensitivity
102 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 (1906)
Annotation: Likelihood of benefit
103 56 or 57 or 58 or 59 or 60 or 61 or 62 (4005)
Annotation: Modelling
104 63 or 64 or 65 or 66 or 67 or 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 77 or 78 or 79 or 80 (35800)
Annotation: Preventive health
105 81 or 82 or 83 or 84 or 85 or 86 or 87 or 88 or 90 or 91 or 92 or 93 or 94 (38931)
Annotation: Population health management
106 104 or 105 (69322)
107 104 and 105 (5409)
108 102 or 103 (5838)
109 97 and 108 (119)
110 106 and 109 (38)
111 98 and 108 (8)
112 99 and 108 (313)
113 107 and 112 (6)
114 100 and 108 (9)
115 101 and 108 (17)
116 95 or 96 or 110 or 111 or 113 or 114 or 115 (79)

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Search for: 84 or 96 or 99 or 100 or 102 or 104 or 105

Results: 163

Database: Global Health <1973 to 2020 Week 18>
Search Strategy:
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1 impact?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (4)
2 'propensity to succeed'.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1)
3 interven?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (0)
4 case finding.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1946)
5 casefinding.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (5)
6 Patient selection.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (611)
7 target* patient*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (283)
8 (target* adj2 segment*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (144)
9 case selection.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (88)
10 (risk adj2 population*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (11708)
11 susceptible population*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1174)
12 risk stratif*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2127)
13 (predict* adj3 risk factor*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1472)
14 protective factor*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (6071)
15 exp protective factors/ (279)
16 (risk adj2 analy*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (10280)
17 exp risk analysis/ (58968)

18 risk assess*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (63092)
19 risk segment*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (19)
20 (characterist* adj4 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2195)
21 (characterist* adj3 nonrespon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (18)
22 (care adj3 sensitiv*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (447)
23 (receptiv* adj3 care).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (10)
24 (Likel* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (982)
25 (Likel* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (281)
26 (Likel* adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1060)
27 (Likel* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (413)
28 (Likel* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (236)
29 (Predict* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (138)
30 (Predict* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (292)
31 Predict* responder*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (8)
32 (Predict* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1054)
33 (Probab* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (108)

34 (Probab* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (74)
35 (Probab* adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (800)
36 (Probab* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (198)
37 (Probab* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (183)
38 (propensity adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (0)
39 (propensity adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2)
40 (propensity adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (19)
41 (propensity adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (3)
42 (propensity adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (3)
43 (Potential* adj benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (4703)
44 (Potential* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (267)
45 (Potential* adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1196)
46 (Potential* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (302)
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48 (Model* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (185)

49 (Model* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (500)
50 (Model* adj2 responder*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (5)
51 (Model* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (619)
52 (predict* adj3 model*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (16099)
53 logistic* model*.mp. (2180)
54 population model*.mp. (497)
55 patient specific model*.mp. (4)
56 exp mathematical models/ (20591)
57 ambulatory care sensitive condition?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (133)
58 exp hospital admission/ (7087)
59 exp Preventive Medicine/ (5152)
60 preventive medicine.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (6066)
61 preventive health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1554)
62 prevention/ (24792)
63 (early adj3 intervention*).mp. (4352)
64 early intervention/ (0)
65 Target* health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (727)
66 Target* healthcare.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (44)
67 (Target* adj3 care*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (808)
68 (prevent* adj3 intervention*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers,

cabicodes] (13708)
69 (care adj3 management).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2707)
70 population health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (4811)
71 exp health policy/ (21123)
72 Health* management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2399)
73 System? management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (295)
74 public health*.mp. (263888)
75 exp public health/ (114710)
76 exp public health services/ (5031)
77 health service? management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (79)
78 health care system?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (7683)
79 health* system?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (22197)
80 multidisciplinary service?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (27)
81 integrated service?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (314)
82 amen?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (96)
83 animal*.mp. (2706683)
84 1 or 2 or 3 (5)
Annotation: Impactibility
85 4 or 5 (1950)
Annotation: Case finding
86 6 or 7 or 8 or 9 (1121)

Annotation: Patient selection
87 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 (90642)
Annotation: Risk stratification
88 20 or 21 (2208)
Annotation: Characteristic response
89 22 or 23 (457)
Annotation: Care sensitivity
90 24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 (16886)
Annotation: Likelihood benefit
91 52 or 53 or 54 or 55 or 56 (35958)
Annotation: Model
92 57 or 58 or 59 or 60 or 61 or 62 or 63 or 65 or 66 or 67 or 68 (56126)
Annotation: Preventive
93 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 or 79 or 80 or 81 (299016)
Annotation: Population
94 92 and 93 (8599)
95 92 or 93 (346543)
96 82 and 95 (15)
97 90 or 91 (52153)
98 85 and 97 (58)
99 95 and 98 (20)
100 86 and 97 (41)
101 87 and 97 (3893)
102 94 and 101 (42)
103 88 and 97 (82)
104 95 and 103 (17)
105 89 and 97 (25)
106 84 or 96 or 99 or 100 or 102 or 104 or 105 (163)

Ovid Technologies, Inc. Email Service

Search for: 104 or 116 or 118 or 121 or 123 or 125 or 128

Results: 320

Database: Embase Classic+Embase <1947 to 2020 May 14>
Search Strategy:
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1 impact?bility.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (12)
2 'propensity to succeed'.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (7)
3 interven?bility.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (2)
4 case finding.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (8308)
5 casefinding.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (200)
6 case finding/ (4164)
7 Patient selection.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (106833)
8 Patient selection/ (93046)
9 target* patient*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (4078)
10 (target* adj2 segment*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1381)
11 case selection.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug

manufacturer, device trade name, keyword, floating subheading word, candidate term word] (2699)
12 (risk adj2 population*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (170420)
13 high risk population/ (121003)
14 vulnerable population/ (16512)
15 susceptible population/ (1056)
16 risk stratif*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (58670)
17 (predict* adj3 risk factor*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (12148)
18 risk factor/ (1025885)
19 protective factor*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (24469)
20 protection/ (67132)
21 susceptible population*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3245)
22 risk stratif*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (58670)
23 (risk adj2 analy*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (95347)
24 risk assess*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (585434)
25 risk assessment/ (558053)
26 risk segment*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (137)
27 (characterist* adj4 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (26743)
28 (characterist* adj3 nonrespon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (147)
29 (care adj3 sensitiv*).mp. [mp=title, abstract, heading word, drug trade name, original title, device

manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3472)
30 (receptiv* adj3 care).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (85)
31 (Likel* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (14595)
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36 (Predict* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3898)
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51 (Potential* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1587)
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54 (Potential* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (18959)
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78 prevention/ (283203)
79 (early adj3 intervention*).mp. (64519)
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drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (6204)
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manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1356)
103 animal*.mp. (6389036)
104 1 or 2 or 3 (21)
Annotation: Impactibility
105 4 or 5 or 6 (8461)
Annotation: Case finding
106 7 or 8 or 9 or 10 or 11 (114598)
Annotation: Patient selection
107 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 (1764975)
Annotation: risk
108 27 or 28 (26841)
Annotation: Characteristic response
109 29 or 30 (3557)
Annotation: Care sensitivity
110 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 or 56 or 57 or 58 (176187)
Annotation: Likelihood of benefit
111 59 or 60 or 61 or 62 or 63 or 64 or 65 or 66 or 67 (189338)
Annotation: Predictive modelling
112 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 or 79 or 80 or 81 or 82 or 83 or 84 (1060770)
Annotation: Preventive healthcare
113 85 or 86 or 87 or 88 or 89 or 90 or 91 or 92 or 93 or 95 or 96 or 97 or 98 or 99 or 100 or 101 (840792)
114 112 or 113 (1821615)
115 112 and 113 (79947)
116 102 and 114 (51)
117 107 and 110 and 111 (877)
118 115 and 117 (30)
119 110 or 111 (360103)
Annotation: likely benefit or modelling
120 109 and 119 (192)

121	115 and 120 (37)
122	108 and 119 (948)
123	114 and 122 (66)
124	106 and 119 (4043)
125	115 and 124 (52)
126	105 and 119 (166)
127	115 and 126 (9)
128	105 and 114 and 119 (67)
129	104 or 116 or 118 or 121 or 123 or 125 or 128 (320)

Appendix Table S2: Full inclusion and exclusion criteria

		Yes	No
1	Does the title or abstract talk about amenability?	Continue	Go to 3
2	Is the paper about youth offending or amenability of specific diseases to treatment?	Exclude/STOP	Go to 4
3	Does the title or abstract talk about impactibility/ intervenability or 'propensity to succeed' modelling in a population health context?	Include/STOP	Continue
4	Is there an intervention that aims to prevent or ameliorate a future health event?	Continue	Exclude/STOP
6	Is the intervention solely aiming to increase screening programme detection rates?	Exclude/STOP	Continue
7	Does the study include case finding or selection of potential responders from the wider population?	Continue	Exclude/STOP
8	Is modelling limited to identifying subjects at 'high risk' of a disease or health event?	Exclude/STOP	Continue

9	Does the extended modelling identify subjects who may respond better to the intervention?	Include/STOP	Continue
10	Does the extended modelling identify subjects who are more likely to start and complete the intervention?	Include/STOP	Exclude/STOP

INCLUSION

- Papers that include Impactibility OR intervenability OR 'propensity to succeed' modelling OR Amenability in a population health context

OR

- Studies that include ALL of:
  1) an intervention that aims to prevent or ameliorate a future health event
  AND
  2) case finding OR selection of potential responders from the general population
  AND
  3) extended modelling that identifies subjects who may respond better to the intervention OR extended modelling that identifies subjects who are more likely to start and complete the intervention

EXCLUSION

- Amenability AND youth offending
- Amenability of specific diseases to treatment
- Modelling limited to identifying subjects at 'high risk' of a disease or health event
- Intervention solely aiming to increase diagnoses or screening programme detection rates

Definitions:

Case finding: a systematic or opportunistic process that identifies individuals (e.g. people with COPD) from a larger population for a specific purpose for example, 'Flu vaccination' https://www.england.nhs.uk/wp-content/uploads/2015/01/2015-01-20-CFRS-v0.14-FINAL.pdf

Intervention: A health intervention is an act performed for, with or on behalf of a person or population whose purpose is to assess, improve, maintain, promote or modify health, functioning or health conditions. https://www.who.int/classifications/ichi/en/

In medical terms this could be a drug treatment, surgical procedure, diagnostic test or psychological therapy. Examples of public health interventions could include action to help someone to be physically active or to eat a more healthy diet. Examples of social care interventions could include safeguarding or support for carers.
https://www.nice.org.uk/Glossary?letter=I

Appendix Table S3: Google search string

# results (2 November 2020)	
207	("impactability" OR "impactibility") AND (site:nhs.uk OR site:cdc.gov OR site:.ac.uk OR site:.gov.uk OR site:.edu OR site:.gov OR site:.ac.au OR site:.ac.ca OR site:elsevier.com OR site:researchgate.net) AND "case finding" AND (guide OR protocol OR process OR method)

Appendix Table S4: Studies of the development, validation or application of impactibility models included in the qualitative synthesis

Study Name/Ref			Population studied	Impactibility model	Results/author conclusions
Impactibility determined by presence of a health condition amenable to preventive intervention					
Buja et al. 2019	**Country**	Italy (Azienda ULSS4-Veneto local health unit)	Patients over 65 years, residing in the area served by. All patients had heart failure and "complex health care needs", as defined by Resource Utilization Band 4 or 5 (respectively high morbidity or very high morbidity) out of 5.	"Impactibility model" based on ACG (Adjusted Clinical Groups) created by identifying homogenous clinical subgroups of patients with **a high risk of at least 1 "preventable admission**" that may be addressed using case management	This will help policy makers develop ''tool kits'' for homogeneous groups of patients that improve health outcomes.
	Data source	Routinely collected administrative data			
	Intervention	Case management			
	Outcome measures	Hospital admission or readmission			
Guthrie et al. 2017	**Country**	UK	Patients with ACSCs who had "psychosocial risk factors for increased use of unscheduled care", including recent use of unscheduled care, depression, living alone or social stressors.	ACSC diagnosis	There was no evidence that this intervention impacted unscheduled care or was integrated into the practices.
	Data source	CHOICE: Choosing Health Options In Chronic Care Emergencies			
	Intervention	Low-intensity treatment for depression, coupled with social interventions.			
	Outcome measures	Unscheduled care over 12 months.			
McCormick 2012	**Country**	USA	Patients with cardiovascular ACSCs (congestive heart failure, angina, hypertension)	ACSC diagnosis	ACSC hospitalisations increased more in the intervention group than the control group over the intervention period. Therefore the intervention did not decrease the risk of avoidable hospitalisations.
	Data source	Acute hospital admission data			
	Intervention	Universal health insurance (vs a control group in states without universal health insurance)			
	Outcome measures	Hospital admissions			

Steventon et al. 2012	**Country**	UK (Cornwall, Kent, Newham)	Patients age 18 and over with a diagnosis of COPD, diabetes or heart failure, based on QoF register or confirmed diagnosis based on GP records or confirmation of disease status by a local clinician. Patients were not excluded for any other reasons	ACSC diagnosis	Telehealth was associated with lower mortality and emergency admission rates.
	Data source	HES data for England, mortality, (May 2008 to November 2009)			
	Intervention	Telehealth (vs usual care)			
	Outcome measures	Admission to hospital during a 12 month period; mortality			
Steventon et al. 2013	**Country**	UK (Birmingham OwnHealth)	Inclusion was restricted to patients with a recorded diagnosis of COPD, CHF, coronary heart disease or diabetes; a minimum level of disease severity in the past 15 months; age 18 or older; ability to communicate on the telephone; a recorded address and practice registration. Patients also had a history of inpatient or outpatient hospital use.	ACSC diagnosis augmented with clinical judgement of which patients were likely to benefit	The Birmingham OwnHealth telephone health coaching intervention did not lead to the expected reductions in hospital admissions or secondary care costs over 12 months, and could have led to increases.
	Data source	Primary care data (not specified)			
	Intervention	Telehealth (compared to usual care)			
	Outcome measures	Number of emergency hospital admissions over 12 months post-enrolment; hospital bed days; elective hospital admissions; outpatient attendances; secondary care costs.			
Steventon et al. 2016	**Country**	UK (North Yorkshire and York PCT)	Patients with ACSCs including COPD, CHF and diabetes	ACSC diagnosis	Telehealth intervention may have led to increases in emergency admissions. Authors recommend investing resources in other forms of preventive care for which an evidence base exists
	Data source				
	Intervention	Telehealth (vs usual care)			
	Outcome measures	Time to first emergency hospitalisation or death			
Impactibility based on propensity to succeed					

Dubard et al. 2018	**Country**	USA (North Carolina)	Medicaid beneficiaries who received some level of care management support and had at least 1 potentially preventable admission, readmission or ED visit in the year prior to initiation of case management. Patients were considered to have received care management support if they had at least 1 direct encounter with a care manager by phone or face to face.	Impactibility score developed using linear regression analysis. Independent variables: • Age, sex, race, ethnicity, disability status, foster care status • ED visit count, inpatient visit count • CRG weight • Presence of specific chronic conditions • Number of chronic conditions • Number of chronic medications filled • Number of acute medications filled • Total cost of care Derived variables include: • "Above expected potentially preventable costs" (AEPPC), which includes costs related to potentially preventable admissions, readmissions and ED visits • Monthly spending trajectory over the most recent 12 months • 2 indicators of	The coefficients from this model yielded the information required to build predictive models for prospective use. Model variables related to medication adherence and historical utilization unexplained by disease burden proved to be more important predictors of impactability than any given diagnosis or event, disease profile, or overall costs of care. This study helps highlight the difference between 'high-frequency/high-cost' users and 'highly-impactible' users, noting that there's a real difference between the two groups which makes traditional algorithms unhelpful.
	Data source	Administrative data available for the whole population (January 2010-May 2017) including eligibility and enrolment files; Medical and pharmacy claims paid by Medicaid and encounter claims from all managed care organisations; Disease burden categorised by hierarchical Clinical Risk Group (CRG)			
	Intervention	Care management (Community Care of North Carolina (CCNC), versus a control group receiving usual care			
	Outcome measures	Expected cost savings			

				adherence to chronic medications	
Hawkins et al. 2015	**Country**	USA (pilots in California, Florida, New York, North Carolina and Ohio)	Individuals with Medicare Supplement plans with multiple chronic health conditions who may benefit from additional care coordination and ancillary support. Patients are referred either directly from a provider or Nurse HealthLine, or data-driven referrals based on Hierarchical Condition Category risk score >3.74.	Propensity to succeed model based on logistic regression. Independent variables included: • dates and locations of service • indicators of the types of services, drugs, and procedures provided • AmeriLINK Data Sourcing system (generated by the KBM Group) to find information about socioeconomic status • Local supply of health care services in areas where qualified members lived was derived from the Dartmouth Atlas of Healthcare Outcome variables included medical expenditures per month based on Medicare data.	Given the low predictive ability of the quality of care model, the current HRCM program PTS prioritisation process employs only the engagement and financial success probabilities, which were summed into a combined PTS score. PTS models for engagement and financial savings were found to be statistically valid. The combined PTS score helped prioritise outreach to individuals who qualified for the HRCM program. "Using PTS models may help increase program engagement and financial success of care coordination programs."
	Data sources	United Healthcare (AARP Medicare Supplement plan provider) December 2008-December 2011.			
	Intervention	High-risk case management (HRCM) programme			
	Outcome measures	1) Engagement with the programme (yes/no) 2) Quality of care (yes/no), based on meeting 70% or more of the relevant clinical care guidelines Cost savings associated with the HRCM program			
Hommer et al. 2013	**Country**	USA (pilots in California, Florida, New York, North Carolina and Ohio)	Patients with depressive symptoms measured by PHQ-9 and AARP Medigap supplement insurance.	Propensity to succeed model based on characteristics of "engaged patients" compared with qualified but non-engaged patients.	This targeted approach incorporates demographic, socioeconomic and health status characteristics into a single measure that represents propensity to succeed. "These
	Data source	United Healthcare (AARP Medicare Supplement plan provider) combined with			

		inferred sociodemographic data (Dec 2009-Dec 2010)		Predictors of outcomes of interest included: • patient demographic • plan type • location • participation in other programmes • health status measures • various supply side measures	models allow for more efficient utilisation of health resources by refining targeting and outreach efforts to those most likely to be successful in the programme." Beginning in 2012, member outreach was modified to include PTS scoring, with authors suggesting that the programme has positively shifted quality and engagement.
	Intervention	Depression management programme			
	Outcome measures	Summary score based on engagement, cost (personal ROI >1) and quality outcomes (hospital readmission, EBM metrics)			
Hsueh et al. 2018	**Country**	USA	Patients recently discharged from an acute hospital admission and assigned to a transitional care programme with the objective of reducing hospital admissions.	Behavioural Response Inference Framework (BRIeF) Framework infers the goal attainment outcome of a target intervention from a large observational dataset and compares multiple interventions for effective goal attainment. Covariates include: • demographics (age, gender) • patient care programme context (programme experience, days in the programme) • interactions between care managers and patients (day of call) For each intervention, behavioural response was quantified as the likelihood of goal attainment after	Promising results of modelling using a test dataset demonstrate that the individual-level care planning strategies that are learned from practice by BRIeF, outperform population-level strategies, yielding significantly more accurate intervention recommendations for goal attainment.
	Data source	The GOAL dataset: care management records from a private not-for-profit healthcare network (Jan 2016 to Feb 17)			
	Intervention	131 care management interventions grouped into six categories: referral, education, coordination, other, coaching, screening			
	Outcome measures	Personalised goal attainment categorised as: education (e.g., post-discharge understanding); medication (e.g., adherence); reducing risk (e.g., resolve care gaps); self-care (e.g., heart failure home self-management); implementation (e.g. installing fall prevention facility), and others (e.g., obtaining accurate patient information).			

				implementing the target intervention.	
Mattie et al. 2019	**Country**	USA	Commercially insured, “low-risk” (not defined) population	A random forest machine learning model to categorise new patients as impactable versus not impactable based on cost savings with vs without a digital health intervention. The model was based on: • Administrative claims data • Age • Education level, employment status, income and poverty status inferred from zip code • Data derived from a patient-held mobile application.	The impactibility model reached an overall accuracy of 71.9%. “This demonstrates the potential to successfully target, based on impactibility, lower risk members of the population with a digital health intervention.
	Data source	Anonymised insurance claims data (June 2015 to May 2018) combined with inferred sociodemographic and patient-generated data			
	Intervention	Technology-enabled care management, delivered through a digital health platform **(Wellframe Inc)**, including a mobile app and clinician web dashboard.			
	Outcome measures	Expected cost savings			
Menard et al. 2018	**Country**	USA	Pregnant Medicaid beneficiaries	Maternal-Infant Impactibility Score: A weighted three-tier ‘impactibility’ model derived from the strength of association between lower birth weight and greater number of completed care tasks in pregnancy. Risk factors for pre-term birth were used to prioritise women to receive pregnancy care management.	The score effectively identifies women who will benefit most from pregnancy care management. “For every 100 women in Tier 1 who receive care management, 8 low birth weight outcomes can potentially be prevented.”
	Data source	Birth certificate pregnancy outcome data from the 2011-14 birth cohort.			
	Intervention	Pregnancy care management (North Carolina Pregnancy Medical Home Program)			
	Outcome measures	Low birth weight			
Osminkowski et al. 2015 (MyCarePath)	**Country**	USA	Individuals are qualified for MyCarePath either through direct or indirect referral. Indirect referrals use claims experience to	Propensity to succeed summary scores were calculated through logistic regression to generate	PTS models had higher specificity than sensitivity, suggesting they were better able to predict who would not participate/achieve

			calculate CMS Hierarchical Condition Category (HCC) score >3.74. Most individuals are age 65 and older, with a Medigap plan. Individuals may also be referred directly through their provider who “perceives a benefit” or nurses on a telephone advice line. *Note: individuals purchasing AARP Medigap insurance are asked to complete a health risk assessment after purchasing the plan. Answers to these questions may trigger referral to MyCarePath.*	predicted probability that a qualified individual: (1) participated in MyCarePath, (2) was managed in a way that was consistent with evidence based guidelines for treating their medical problems, and (3) was managed in a way that reduced the cost of their medical care and prescription pharmaceuticals. Independent variables included: • Demographic data • Health status • Medigap plan type • Healthcare supply • Location variables External consumer-generated variables have been studied but did not increase the model’s predictive ability.	cost savings/improve care quality. Comparing the 3 months prior to the implementation to the 9 months after implementation, the average number of new participants rose by 11%. "To date, program evaluations have reported positive returns on investment and improved quality of healthcare among program participants.”
Navratil-Strawn 2016	**Country**	USA	Patients covered by an AARP Medicare Supplement (Medigap) plan	Propensity to succeed modelling by means of logistic regression to identify characteristics associated with programme engagement. Model covariates included: • demographic measures (age, sex) • residential location: rural vs urban,	Propensity to succeed modelling was found to be "stable and valid" according to a K-fold cross-validation study. Authors suggest “PTS modelling may help to target and engage callers, thus increasing use of the Nurse Healthline and triage service.” “This in turn should lead to more efficient use of healthcare services and reduce unnecessary health care expenditures”
	Data sources	United Healthcare (AARP Medicare Supplement plan provider) combined with inferred sociodemographic data			
	Intervention	Telephone triage programme (Nurse HealthLine), compared to a 5% random sample of individuals in the AARP			

	Outcome measures	1) Utilisation of the Nurse Healthline 2) Triage engagement 3) Adherence to nurse recommendations		census region residence in 1 of 5 locations with other care coordination pilots ongoing • socioeconomic variables (zipcode level proxies of race and income) • health status (OptumInsight ImpactPro prospective risk score) • local supply of health services (hospital beds per 1000, primary care physicians and specialists per 100,000 residents) • Previous emergency healthcare use in 6 months (yes/no) • Time of call (weekday/weekend)	
Studies incorporating or comparing clinical judgement of impactibility					
Cohen C et al. 2015	**Country**	*Israel*	Exclusion criteria based on physician input were: active cancer, schizophrenia, dialysis, residence in nursing homes or long-term care facilities, and age 95 years or older.	Model based on the Adjusted Clinical Groups (ACG) predictive model risk scores for risk of future high costs, augmented with a survey of clinical considerations from six physicians	The c-statistic of the ACG model before and after exclusions applied was 0.80 and 0.75, respectively. After exclusion, the PPV for the 6% highest risk patients was 40%. High-risk patients' age, number of chronic conditions, and utilization were substantially higher than those of all other patients. This study shows that a validated predictive modeling tool provides
	Data source	Clalit Health Services' (managed care organization) database 2010-11			
	Intervention	Proactive care management			
	Outcome measures	Healthcare costs			

					acceptable discriminatory power for selecting multimorbid patients for participation in proactive care management, even after some of the highest risk patients are excluded because of priori clinical considerations.
Corbin et al. 2019	**Country**	USA	Outpatient primary care patients "at risk of hospitalisation in the next 12 months"	Clinical team assessment of the "potential of care to impact outcomes" of as an adjunct to a risk predictive model developed by EPIC, which identified 19 variables predictive of ED visits or hospitalisation in the next 12 months.	Average risk score of patients under care management increased from 33% to 40.4% over the first 2 months of the programme. Full results for other outcomes not yet available.
	Data source	Primary care database (not specified)			
	Intervention	High-risk care management			
	Outcome measures	1) Average risk score of patients under care management 2) ED visits 3) hospitalisation in the next 12 months			
Flaks-Manov et al. 2020	**Country**	*Israel*	Patients age 65 years and older who were hospitalized for at least 1 night in an internal medicine ward	Nurse and internal medicine physicians (in charge of direct patient care) assessment of impactibility, compared with a risk prediction model [Pre-admission readmission detection model (PREADM)]	Physician assessment of likelihood to benefit vs risk prediction model were 65% congruent, providing further evidence for a mismatch between being at high risk of hospital readmission and perceived impactibility
	Data source	HCP interview May 2016-June 2017			
	Intervention	Readmission prevention programme			
	Outcome measures	30-day hospital readmission			
Fleming et al. 2017	**Country**	USA	High cost "superutilizers" at two pubic urban safety-net hospitals	Physician assessment of patient engagement to determine "likelihood to benefit"	Providers considered 'likelihood to benefit' assessments to be highly challenging and oftentimes inaccurate, particularly because they understood low patient engagement to be the result of difficult socioeconomic conditions..."
	Data source	HCP interview conducted 2015 to 2016			
	Intervention	Complex care management			
	Outcome measures	HCP perception of high-risk participant engagement			

Freund et al. 2010, 2011, 2012, 2013	**Country**	Germany	Index condition: T2DM, COPD, asthma, CHF or late-life depression (age >60 years). Exclusion criteria: age under 18, dementia, palliative care, or nursing home residents, active cancer or dialysis	Family physician assessment of likelihood to benefit (vs risk predictive model)	Modelling (Case Smart Suite Germany (above 90th percentile) was more accurate than physician prediction at predicting risk of future hospitalisation. However, patients identified via PM had lower receptivity to care management programmes in the past. The authors recommend a combined approach between risk prediction and physician-determined impactibility.
	Data source/setting	[10 primary care practices in southwestern Germany]			
	Intervention	Case management			
	Outcome measures	Hospitalisation within 12 months			
Hudon et al. 2018	**Country**	Canada	Patients with at least 1 chronic disease, including diabetes, CV, respiratory, musculoskeletal or chronic pain, with "complex care needs whom family physicians felt could benefit from a case management intervention". Patients with serious cognitive problems were excluded.	Family physician's opinion of "likelihood to benefit"	The intervention "reduced psychological distress, but did not have any significant effect on patient activation"
	Data source	Pragmatic randomised controlled trial.			
	Intervention	VISAGES (Vulnerable Patients in Primary Care: Nurse Case management and Self-management support)			
	Outcome measures	Psychological distress, patient activation			
	Data source	Administrative claims data and health risk assessment from AARP Medicare Supplement Insurance Plan insured by UnitedHealthcare Insurance Company			
	Intervention	MyCarePath: high-risk case management care coordination program			

Outcome measures	1) Engaging in care coordination (yes/no) 2) Saving money once engaged Care quality (defined as meeting 70% pr more of relevant clinical care guidelines)

PRISMA 2020 Checklist

Bridging the impactibility gap in population health management: a systematic review

NB This study explores whether impactibility modelling is being used and does not statistically assess its effect on specific outcomes.

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title, p2, p5
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	P 2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	P 5
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	P 5
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	P 5–6
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	P 5
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	P5, appendix
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	P 5, appendix
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	P 5
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	P 5–6
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	P 5–6
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	N/A
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	N/A
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	P 6, appendix
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	N/A
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	N/A
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	N/A

PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	N/A
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	N/A
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	N/A
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	N/A
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	P 6, figure 1
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Figure 1
Study characteristics	17	Cite each included study and present its characteristics.	PP 6–9, appendix
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	N/A
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Appendix
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	PP 6–9
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	N/A
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	N/A
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	N/A
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	N/A
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	N/A
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	PP 9–10
	23b	Discuss any limitations of the evidence included in the review.	P 10
	23c	Discuss any limitations of the review processes used.	P 10
	23d	Discuss implications of the results for practice, policy, and future research.	PP 10–13
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	P 9
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	P 9
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	N/A
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	P 13
Competing	26	Declare any competing interests of review authors.	P 13

PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
interests			
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	P 13

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71

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Bridging the impactibility gap in population health management: a systematic review

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Bridging the impactibility gap in population health management: a systematic review

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Abstract

Objectives Assess whether impactibility modelling is being used to refine risk stratification for preventive health interventions.

Design Systematic review.

Setting Primary and secondary healthcare populations.

Papers Articles published from 2010 to 2020 on the use or implementation of impactibility modelling in population health management, reported with the terms "intervenability", "amenability", and "propensity to succeed" and associated with the themes "care sensitivity", "characteristic responders", "needs gap", "case finding", "patient selection", and "risk stratification".

Interventions Qualitative synthesis to identify themes for approaches to impactibility modelling.

Results – Of 1,244 records identified, 20 were eligible for inclusion. Identified themes were health conditions amenable to care (n=6), propensity to succeed (PTS) modelling (n=8), and comparison or combination with clinical judgement (n=6). For health conditions the theme amenable to care, changes in practice did not reduce admissions, particularly for ambulatory-care-sensitive conditions, and sometimes increased them, with implementation noted as a possible issue. For PTS modelling, high costs and needs did not necessarily equate to high impactibility and targeting a larger number of individuals with disorders associated with lower costs had more potential. PTS modelling seemed to improve accuracy in care planning, estimation of cost savings, engagement and/or care quality improvements. The clinical judgment theme suggested a complementary role for models. A model used to identify patients appropriate for a proactive programme of multimorbid care management showed reasonable concordance with physicians (c-statistic 0.75). Another model showed 65% concordance between electronic health record scores and nurse and physician decisions when referring elderly hospitalised patients to a readmission prevention programme. However, as well as high model scores, healthcare professionals included factors such as eligibility for a nursing home, non-controlled conditions and need for social-services support or special equipment at home in judgements.

Conclusions The efficiency and equity of targeted preventive care guided by risk stratification could be augmented and personalised by impactibility modelling.

Keywords access to care; impactibility; personalised care; population health management; triple aim; propensity to succeed; amenability.

Strengths and limitations

- Limitation – comparing data was difficult due to widespread inconsistency in terminology.
- Limitation – the quality of the articles included in this review was not graded.
- Limitation – this is a growing area of interest and few studies are available
- Strength – we were as inclusive as possible with types of article, including abstracts and grey literature.
- Strength – to make the findings most applicable to PHM, we excluded studies of specific diseases.

Introduction

The triple aim is targeted towards improving the individual experience of care, improving the health of populations, and reducing the per capita costs of care,[1] and has become a popular healthcare objective. Risk stratification is one type of population health management (PHM) tool used by health system managers to achieve the triple aim[2-5] and identifies groups that are at high risk of poor outcomes so that they can be offered preventive care aimed at lowering this risk. For instance, care in accident and emergency has high costs and a cohort of patients experience frequent attendances, making this cohort a potential target for increased preventive spending. However, within this high-risk cohort, some individuals may be labelled as being "beyond help" because they their attendance is perceived by clinicians to be non-preventable (e.g., because of age, sex, or chronic conditions, including alcohol or drug abuse).[2, 3] For these individuals, preventive care interventions will have little or no effect and they will continue to be at risk of so-called triple-fail events (in this case accident and emergency attendances), which are harmful, costly, and result in poor patient satisfaction.[4, 6-9]

While risk stratification models may accurately predict which individuals are at risk of future adverse health outcomes, such as readmission risk or 1-year mortality risk,[2-5] their use has not consistently led to improvements in health outcomes across the population.[10] Calculating and understanding the probability of a particular outcome for an individual may not be enough for health care professionals to intervene in the most efficient way to delay or prevent that outcome or divert the course of a disease, and often needs to be supported by additional information to determine the most accurate or appropriate model.[11] Furthermore, as many risk stratification models predict future adverse health outcomes through current or previous healthcare activity and use a limited number of variables,[12-15] they may miss out on valuable additional information that could better direct resources to patients amenable to benefit.[9, 16] Lewis[6] defined a different time of model – impactibility models – that are aimed at identifying the subset of at-risk patients for whom preventive care is expected to be successful.

Lewis[6] found that impactibility was being assessed by many healthcare systems for PHM, reflecting a growing recognition that not all high-risk patients will benefit from preventive care. He described the ideal impactibility model as one that "would use information about the differential effects of a specific preventive intervention offered at random to patients and controls, so as to identify the characteristics of the 'perfect patient' for that preventive program". However, suitable data are rarely available in real-world records.

Instead, he found that models were being formulated in three main classes: "(1) giving priority to patients with diseases that are particularly amenable to preventive care; (2) excluding patients who are least likely to respond to preventive care; or (3) identifying the form of preventive care best matched to each patient's characteristics". While such impactibility models have considerable potential to improve the efficiency of preventive care delivery, certain approaches could increase health inequalities if used indiscriminately without catering to individual needs.[6] The aim of this current study was to describe broadly how and in what contexts impactibility modelling has been implemented or assessed in PHMsince 2010. We defined impactibility as the identification of patients most likely to respond to care based not only quantitative but also on qualitative factors, and whose treatment would maximise the likelihood of achieving the triple aim. It was beyond the scope of this review to consider how impactibility modelling might affect management of individual diseases, heterogeneity in treatment effects, and different types of health system.

Methods

A systematic literature review was carried out to identify all papers published between January 2010 and May 2020. The Ovid search platform was used to search four relevant databases: Embase Classic & Embase, Global Health, Healthcare Management Information Consortium, and Ovid MEDLINE. Additional searches for grey literature were performed in OpenGrey.

Search strategies were built iteratively, with relevant keywords and subject headings for each database added based on initial reviews of relevant publications. The final set of search terms (see supplementary information pp 1–28) included alternative spellings of impactibility and synonyms, including "intervenability", "amenability", and "propensity to succeed". We 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.

Database search results were exported to the systematic review software Covidence. Two reviewers (AO and SS) independently screened titles and abstracts for relevance and reviewed the full texts that specifically referenced analyses of amenability, impactibility, and propensity to succeed (PTS) in relation to future events. Papers that concerned youth offending, aimed to increase screening detection rates, and looked only at identifying individuals at high risk of a specific disease or health event were excluded. Full inclusion and exclusion criteria are shown in the supplementary information (pp 29–31). To achieve the widest possible overview of work in this emerging field, studies were not excluded based on assessment of methodological quality. Conflicts were discussed with a third reviewer (WS) at each review stage. A pragmatic forward citation search was subsequently conducted using PubMed for all articles included in the initial review round. These were added to Covidence, and the screening process was repeated. A targeted Google search (see supplementary information p 32) was conducted to identify any additional publications containing the term 'impactibility'.

Data extraction was performed by SS, HH, and WS. For studies describing impactibility models, information about country of implementation, data sources, population studied, intervention and any reported outcome measures were extracted into a data table. Qualitative synthesis was performed to assess themes and to group papers by approach to impactibility modelling.[17] Outcome measures, where reported, were not comparable across studies so meta-analysis was not considered to be appropriate.

Ethics Approval

As this is as a systematic review of published literature and assessed data at the population level, ethics approval was not required.

Results

Of 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. Thus, 20 studies related to the development, application, or validation of impactibility models for use in PHM and were included in the review (**Figure 1**).

In the qualitative synthesis, we grouped papers under three themes representing different approaches to assessing impactibility: health conditions amenable to preventive care (n=6); PTS (n=8); and comparison or combination with clinical judgement (n=6; see supplementary information pp 33–43).

Health conditions amenable to preventive care

Several studies inferred participants' potential to benefit from preventive care if it is targeted after they have received a diagnosis of a specific health condition[18-21] or if they have a multi-morbid cluster of health conditions.[22, 23] Many of these studies specifically targeted people with ambulatory-care-sensitive conditions (ACSCs), including chronic obstructive pulmonary disease, chronic heart failure, and diabetes, for which evidence suggests that optimal management in the community should not result in unplanned hospital admission.[10, 16, 24, 25] Preventive interventions (e.g. case management) that were targeted based on the presence of one or more ACSC did not consistently lead to reductions in hospital admissions or secondary care costs, and indeed, in some cases led to increases in emergency hospital admissions.[18-22] However, the success of these impactibility strategies may be hindered by ineffective implementation. In one of these studies, for example, the authors indicated that the targeted intervention was not effectively integrated into primary care practice during the observation period.[21]

Propensity to succeed

PTS modelling is an analytical approach to identify traits associated with better engagement with or outcomes from particular preventive health intervention(s) – outcomes such as cost or care quality.[26-32] Of the eight studies identified that used this approach, three used PTS modelling in relation to specific case management interventions.[30-32] One model was developed explicitly for ‘low-risk’ participants to assess who would be most likely to benefit from a digital health platform.[28]

In these studies, PTS regression analyses were performed using various sociodemographic factors,[26-28, 30-32] health status (e.g., presence of chronic conditions, prescription data, prior health resource utilisation, various health risk scores),[26-28, 30-32] or previous programme engagement metrics.[28] One study found that high costs and high needs did not equate to high impactibility, as only small proportions of people with diseases that would be expected to have high burden had scores indicating high impactibility. The authors suggested that targeting a larger number of individuals with disorders associated with lower costs could improve impact substantially and that better predictors of impactibility might be medication adherence and historical healthcare resource utilisation that was unexplained by disease burden.[31]

Five of the identified studies reported the statistical validity of PTS models for projecting cost savings, improved engagement, and/or care quality improvements;[26-28, 30, 32] however, prospective or comparative outcome data on the use of these models in real-world situations were extremely limited in the literature. Two studies reported improved engagement (defined as enrolment of contacted participants) with case management interventions after implementation of a PTS model: Ozminkowski et al[32] reported an 11% increase in programme enrolment in the 9 months after implementation of a PTS model, compared with the 3 months prior. Hommer et al[29] likewise reported increased enrolment in a depression management programme but did not quantify the change.

Hsueh et al[33] evaluated the Behavioural Response Inference Framework (BRIeF), a machine learning impactibility model derived from a large observational dataset of care management records from a private healthcare network. They tested the ability of the model to predict individual-level behavioural responses to multiple interventions used in care planning. Input data included participants' personalised goal attainment history across 16 goals set in a program to reduce hospital readmissions after discharge for acute care. They covered a wide spectrum of care needs (e.g., tobacco cessation, knowledge of healthy eating, medication adherence, actions to resolve care gaps, and fall prevention) and were categorised as 'met', 'abandoned', 'not met' or 'open'. Data on goal attainment were extracted for 131 different care coordination activities in the categories referral, education, coordination, screening, coaching, or other tasks, that were classified as met or otherwise. The BRIeF model was applied to assess behavioural responses at the individual patient and population levels. Covariates used in the model were demographic information (e.g., age and gender), care programme context (e.g., program experience and days in the program), and the interactions between care managers and patients (e.g., the day of making the recorded call). The authors described the results of the model as 'promising', with the individual-level care planning strategy showing the greatest accuracy in terms of correct intervention recommendations outperforming a population-level care planning approach, where the one-size-fits-all approach reduces precision.

Comparison or combination with clinical judgement

We identified six impactibility models that – either formally or informally – incorporated a healthcare provider's opinion of whether an individual patient was likely to benefit from a particular preventive health intervention.[16, 34-39] In one study, clinical judgement was applied as a final (filtering) step to estimate how care management would impact patients after they had undergone risk stratification by a predictive analytic tool.[40] A predictive tool calculated a risk score for emergency department visits in the next 12 months based on 19 variables. Physicians then added information on medical and social factors that could alter the impact of care management. This combined improved identification of higher-risk patients, reflected by an increase in the average risk score for patients enrolled in care management from 33.4% to 40.4%.

Cohen et al[41] designed a predictive model to identify patients who would benefit from proactive multimorbid care management based on inclusion and exclusion criteria refined from a physician survey of 375 cases and on risk of future high costs based on data extracted from a health services database. Recommended reasons for exclusion due to risk for future high costs were active cancer, schizophrenia, dialysis, residence in nursing homes or long-term care facilities, and age 95 years or older. The model was used to assess 5,341 high-risk patients. Discriminatory power of the model before and after clinical exclusions was c-statistic 0.80 and 0.75, respectively. Age, number of chronic conditions, and healthcare utilisation were associated with high-risk of high-cost care. The authors concluded that the model had acceptable discriminatory power for identifying who would benefit from proactive care management even after the highest-risk patients were excluded.

HCPs consider a range of factors when assessing an individual's suitability for a preventive health intervention. These include perceived hospitalisation risk; feelings of sympathy or aversion towards the patient; and a judgement of the patient's willingness and ability to participate in the intervention.[16, 38] HCPs also reported excluding patients from preventive healthcare interventions because of language barriers.[16]

Flaks-Manov et al[42] investigated whether risk scores for 30-day readmission from an electronic health records model were aligned with nurses' and physicians' perceived impactibility of a readmission prevention programme for hospitalized patients aged 65 years or older. The clinical and model decisions for 435 patients were concordant in 65% of cases. Among the remaining 35%, 19% with high model scores were not referred by healthcare professionals and 16% with low model scores were referred. Decision-tree analysis indicated that as well as high models scores, eligibility for a nursing home, having a condition not under control, need for social-services support and need for special equipment at home were statistically associated with referral. The authors concluded that better understanding is needed of whether combining perceptions and modelling could improve selection of patients.

Freund et al[43] assessed areas in which impactibility modelling might be helpful. They invited 12 primary-care physicians in ten practices to review records for 104 hospitalizations in 81 patients who had ACSCs and rate whether they felt each hospital admissions was avoidable. The doctors deemed 43 (41%) hospitalisations to be avoidable. Reasons fell into five main categories: system related (eg, unavailability of ambulatory services), physician related (eg, suboptimum monitoring), medical (eg, medication side effects), patient related (eg, delayed help-seeking), and social (eg, lack of social support). Further reasons were after-hours referral required in the absence of the treating physician, not using ambulatory services, patients' fears, cultural background, and language skills, medication errors, non-adherence to medication, and overprotective caregivers. In discussing implications for clinical practice and policy, it was recommended the risk stratification modelling would be enhanced by considering patients' social situation, medication adherence, and self-management capabilities and sharing responsibility across sectors.

Discussion

Key findings

As health systems turn to data-led approaches to deliver the triple aim of improving individuals' experience of care and the health of populations while reducing per capita care costs,[1] many are finding that allocating resources based on risk stratification alone is suboptimal. Targeting patients for preventive care based only on health conditions amenable to preventive care does not necessarily lead to reductions in resource use and might even increase it, and recognition is growing that these goals will only be met if treatment is successful. This is the impactibility gap. Thus, rather than trying to identify patients by negative outcomes (eg, high cost of care, most severe disease), the importance of identifying patients in whom care options will be most effective is being realised. The evidence reviewed shows varying attempts to make prediction tools more impactful and effective by considering the probability of success of interventions. PTS modelling showed some of the most promising results when broader information, such as sociodemographic factors, medication adherence, or previous programme engagement, was included. The accuracy of predicting behavioural responses seems to be most accurate at the individual level, but more data on real-world outcomes are needed, as implementation could affect PHM potential. Of note, there was some incongruence between modelling and HCP decisions, and better understanding is needed of how perceptions and data analysis affect one another.

Risk stratification versus impactibility

Risk stratification models may accurately predict which individuals are at risk of future adverse health outcomes,[2-5] allowing resources to be allocated. However, allocation is inefficient because not all patients will be amenable to the offered intervention. A stratum cutoff risks not allocating care to people with lower risk who would be amenable and achieve better outcomes that those at higher risk.[44] Additionally, since risk is deemed equal for all people within a stratum, resources are also allocated equally (**Figure 2A**) and those for patients who refuse or do not respond to treatment cannot be reallocated to patients who will respond. Therefore, opportunities to maximise care for the most amenable people will be missed. Impactibility modelling provides an extra layer of information that can help predict where, to whom, when, and how to target preventive resources and allow weighting of investment (time, resources, and costs) towards these individuals, which can improve efficiency. As shown in **Figure 2B**, the likelihood of success for a given intervention is not necessarily determined by risk level, and individuals amenable to a specific intervention, due to their 'impactibility', can be found throughout the stratified population.

Types of models considered

The models described in the literature fell into three key themes: health conditions amenable to care, PTS, and models concerned with HCP input. In the first theme, we found that changes in practice did not reduce hospital admissions and care, and sometimes increased them.[10, 18-20] It was suggested in one study that suggested although input on organisational change from modelling was well accepted, it was not well integrated.[21] 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.[21] Bardsley et al[10] showed that different ACSCs follow different trends, possibly even at the national or international level, which highlights the need to consider how the population for assessment should be selected.[6]

The PTS models assessed in this review included a wide range of clinical, social, and behavioural factors mainly assessed by logistic regression to assess in whom treatment had been most successful (see supplementary information pp 33–43). Repeatedly, the results underscored that considering the highest levels of risk and treatment costs did not equate to high impactibility. For example, Dubard et al 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.[31] PTS modelling generally led to improved accuracy in care planning, estimation of cost savings, engagement, and/or care quality improvements. These finding support moving away from delineated risk groups towards continuous risk predictions.[44]

The clinical judgment theme suggested a complementary role for models. HCPs routinely identify practical barriers that might hinder the potential success of a prescribed intervention, for instance through conversations with their patients. Depending on the quality and openness of the patient–provider relationship, clinicians may be able to access real-time soft intelligence about their patients that is not available to modellers.[43] However, this approach is subjective, involving perceptions at system, HCP, clinical, patient, and social levels,[16] highly resource intensive, and not always achievable through routine primary care interactions. The findings of Hsueh et al[33] suggest that impactibility modelling might be able to improve the individualisation of care management, even with a broad range of therapeutic options.

Optimisation of impactibility modelling

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.[35, 45-48] The challenge for PHM, therefore, is to identify which intervention(s) 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 (**Figure 3**).

To optimise impactibility modelling, large amounts of data are needed on people's health behaviours, socioeconomic, clinical, and environmental status, and broader data where possible, such as genomic data. Many data are held by private companies but are not always accessible to or affordable for health system analysts. Completeness of data may affect modelling and, for example, are known to be less complete for people with higher levels of deprivation.[49] The different modelling approaches have various limitations and benefits (**Table 1**),[7, 16, 18-21, 23, 27-33, 35-38, 42, 50-53] which might further determine 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 objectiveness of decision-making in PHM.

Potential biases towards groups that are perceived as likely to respond well to treatment, which could exclude some of the most vulnerable groups, has been identified as an important potential limitation of using impactibility as a PHM tool.[6, 37, 53-56] Thus, it should be borne in mind that the purposes of considering impactibility PHM are to improve access and equity of care and avoid unnecessarily wasting resources on providing additional interventions that are costly and will not benefit the recipients. Resources should be directed towards closing gaps in the evidence[55] and using the knowledge to develop better-tailored approaches to more people, possibly in medium-risk and low-risk categories (**Figure 2**). 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,[57] 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.

To achieve the triple aim using predictive models will require those models to have broad insights on which to base predictions. Additionally, 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 they are less resource intensive to implement.

Study strengths and limitations

This study had several limitations. Interpreting and comparing the data was difficult due to widespread inconsistency in terminology. Even at the most basic level, "high-risk individuals" was conflated with "those most likely to benefit" in some papers[26, 58] despite evidence indicating that these can be highly separated groups.[5, 31, 42] The quality of the articles included in this review was not graded. However, as this is a growing area of interest and few studies are available, it is a strength of the study that we were as inclusive as possible. Owing to the substantial differences in approaches to categorising model outputs and in outcome measures and lack of reporting these in some studies, it was not possible to perform a quantitative analysis. Finally, in order to make the findings most applicable to PHM, we excluded studies of specific diseases. Of note, given the descriptive nature of this review, it was not registered and no protocol was published.

Conclusions

Impactibility builds on other key PHM concepts, such as risk stratification,[59] by assessing more qualitatively which people might benefit the most from certain health interventions and when proactive treatment might be appropriate (eg, preventive care before an adverse health event or a programme to prevent hospital readmission). It is important, to note that not everyone requiring medical care has the potential to benefit from preventive interventions in a PHM sense. Nevertheless, although limited research is available so far, it seems that impactibility models can augment access to and equity of care when coupled with clinical insights and provide an opportunity to personalise preventive care delivery. Using this approach, it should be possible achieve the triple aims[1] – simultaneously improving the individual experience of care, improving the health of populations, and reducing the per capita costs of care for populations. PTS models seem to improve accuracy of selection patients amenable to care, but very few prospective or comparative outcome data from real-world settings are available, and this would be judicious to explore further. Potential confounding factors, such as model implementation, the effects of biases and prejudices, accuracy and availability of relevant data, should be included in these studies. Additionally, better understanding of why hospital admissions for ACSCs have not been reduced as much as anticipated would be beneficial. Disease-focussed applications will be the subject of our future research.

Author contributions

Andi Orlowski: conceptualisation, methodology, validation, formal analysis, writing – original draft, writing – review and editing. **Sally Snow**: methodology, formal analysis, data curation, writing – original draft, writing – review and editing. **Heather Humphreys**: formal analysis. **Wayne Smith**: formal analysis. **Rebecca Sian Jones**: methodology. **Rachel Ashton**: writing – review & editing. **Jackie Buck**: methodology. **Alex Bottle**: writing – review & editing.

Competing interests statement

AB has received a research grant from Medtronic and his unit receives funding from Dr Foster, a wholly owned subsidiary of Telstra Health and healthcare information company. The other authors declare no competing interests.

Data sharing statement

Data are available upon reasonable request.

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Patient and public involvements

It was not appropriate to involve patients or the public in the design, or conduct, or reporting, or dissemination plans of our research.

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Figure 1: PRISMA diagram

Figure 2: Use of impactibility modelling enhances identification of individuals most likely respond to preventive care and allows weighted resourcing

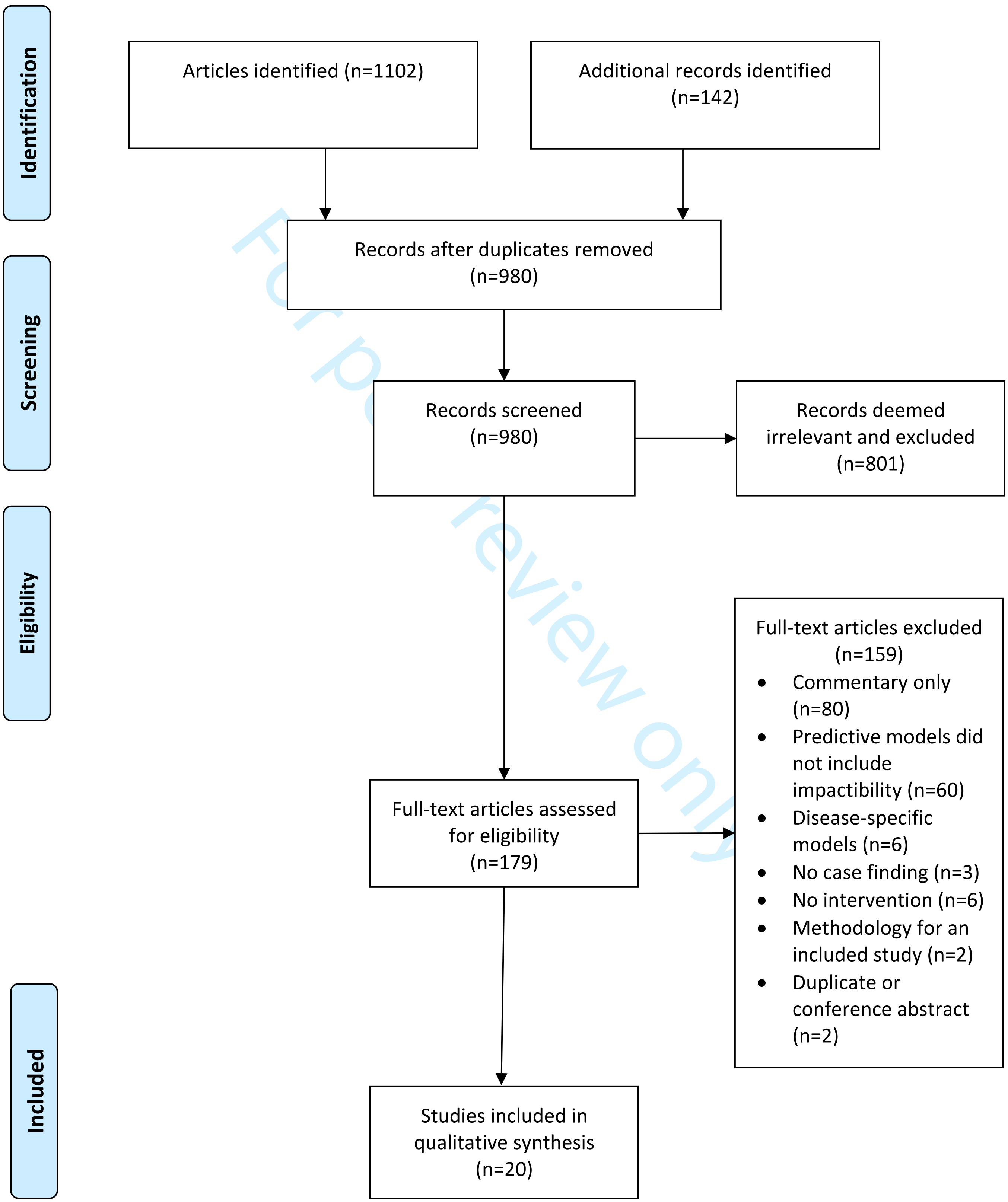
(A) Population with a given condition at risk of an outcome over a specific period of time, stratified by risk. (B) After impactibility analysis, different options can be targeted to the most amenable people. The numbers and positions of dots per intervention highlight that the likelihood of treatment success is not necessarily determined by risk level.

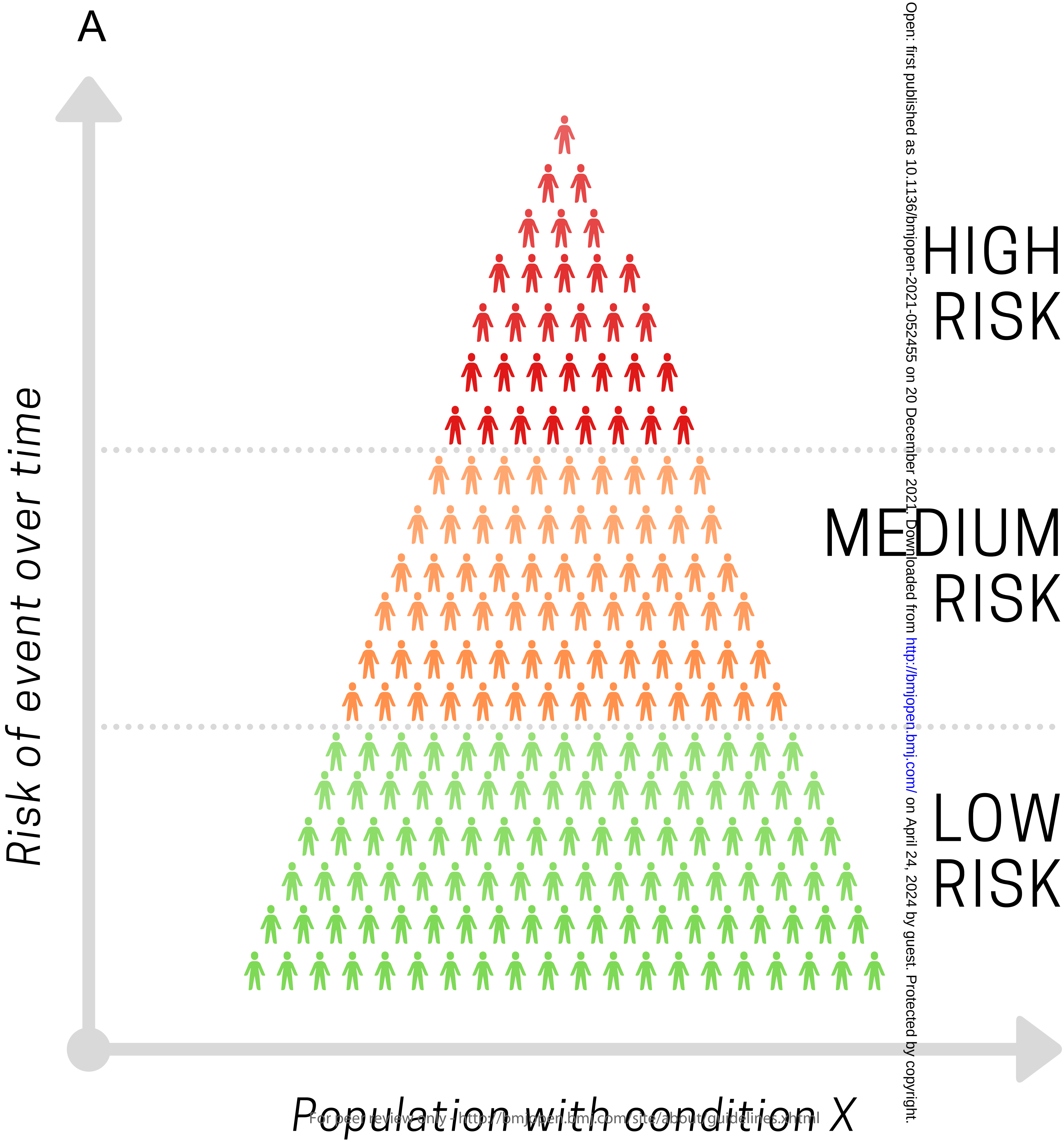
Figure 3: Use of impactibility modelling to increase the number of patients amenable to benefit

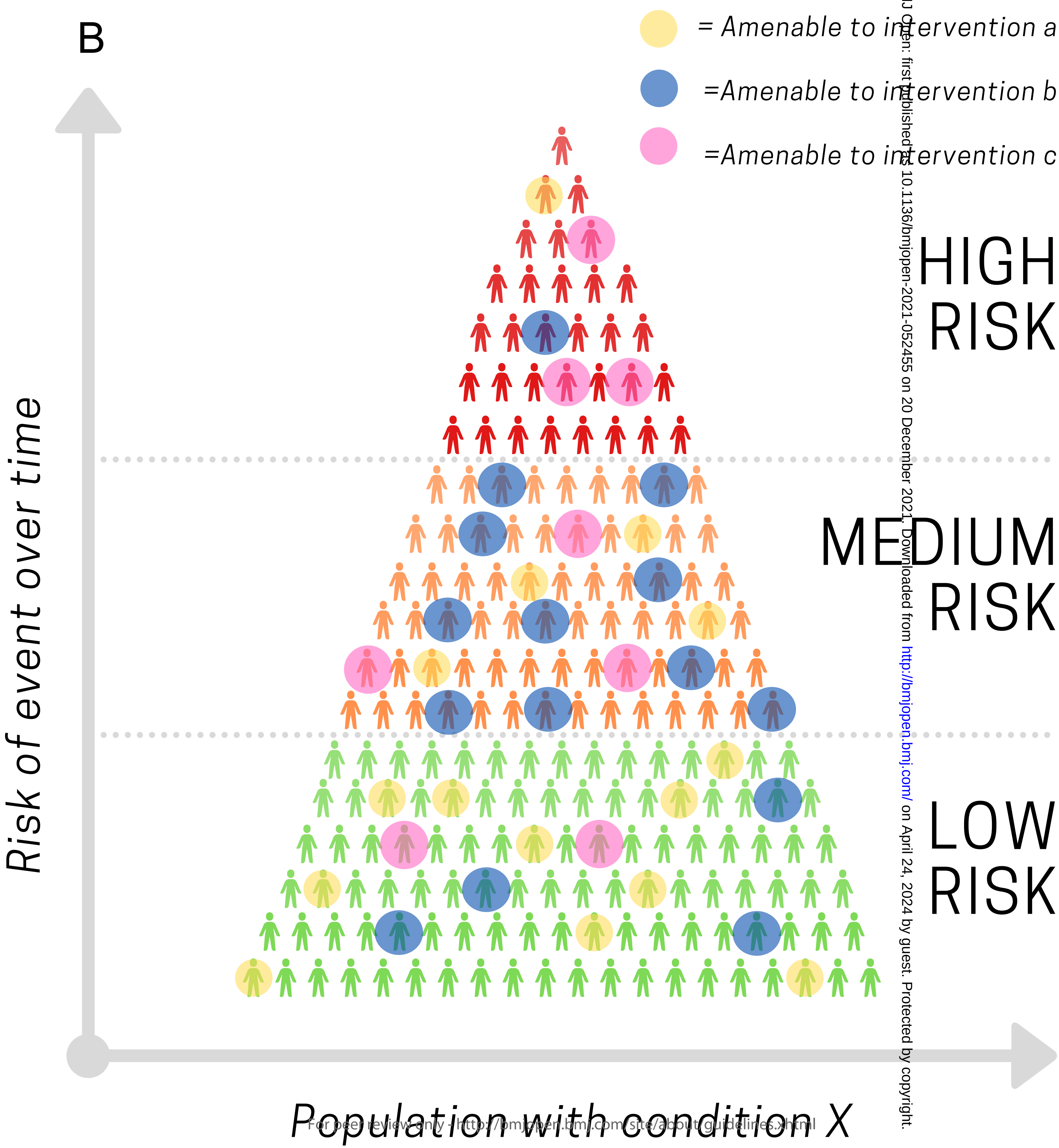
Table 1: Practical benefits and limitations of different approaches to determining impactibility

Approach	Benefits	Limitations
Health conditions amenable to preventive care (gap analysis)	• Diagnosis data are readily available[18-21, 23] • Programmes are relatively simple to model and implement[18-20, 23] • Widely available data can be used to identify specific, evidence-based and scalable actions to address gaps in care[50, 51] • May reduce inequalities, as preventable health conditions are more common in deprived communities[7]	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[6]
Propensity to succeed models, (behavioural response)	• Identifies groups where an intervention is/is not likely to provide benefit, thereby is designed to avoid wasting resources where they are of no benefit[27-32] • Care planning strategies are optimised at an individual and/or population level, based on previous behavioural responses to a range of potential interventions[33]	Models would be enhanced by including educational, behavioural, psychological, social, economic and/or health information,[42] 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[52, 53] • Health-care professionals may be able to predict future deterioration in "low risk" patients with relatively good current health status[36]	Highly resource intensive Relies on the quality and openness of the health-care-professional and patient relationship, and the ability of the data to capture this[16, 35-38] May perpetuate biases or prejudices[7]


Identification
Screening
Eligibility
Included
Articles identified (n=1102)
Additional records identified (n=142)
Records after duplicates removed (n=980)
Records screened (n=980)
Records deemed irrelevant and excluded (n=801)
Full-text articles assessed for eligibility (n=179)
Full-text articles excluded (n=159)
• Commentary only (n=80)
• Predictive models did not include impactibility (n=60)
• Disease-specific models (n=6)
• No case finding (n=3)
• No intervention (n=6)
• Methodology for an included study (n=2)
• Duplicate or conference abstract (n=2)
Studies included in qualitative synthesis (n=20)


A
HIGH
RISK
MEDIUM
RISK
LOW
RISK
Risk of event over time
Population with condition X


B
= Amenable to intervention a
=Amenable to intervention b
=Amenable to intervention c
HIGH RISK
MEDIUM RISK
LOW RISK
Risk of event over time
Population with condition X


1) Needs assessment (population segmentation)
2) Identify population with target health preventable health condition(s) or outcome(s)
3) Bridge the impactibility gap (eg, assessment by ACSC, propensity to succeed, or combined modelling and clinical input)
4) Case finding (eg, by risk and impactibility factors)
5) Offer most appropriate preventive intervention
Increased chance of achieving triple aim:
• Improved individual experience of care
• Improved population health
• Reduced costs per capita

APPENDIX

Appendix Table S1: List of search strings

Database: Ovid MEDLINE(R) ALL <1946 to May 14, 2020>
Search Strategy:
----
1 impact?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9)
2 'propensity to succeed'.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6)
3 interven?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (3)
4 case finding.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4937)
5 casefinding.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (86)
6 Patient selection.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (83162)
7 Patient Selection/ (64332)
8 target* patient*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2387)

9 (target* adj2 segment*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (947)
10 case selection.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1810)
11 risk stratif*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (32437)
12 (predict* adj3 risk factor*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (7856)
13 risk factors/ (815581)
14 protective factor*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (21359)
15 protective factors/ (4040)
16 (risk adj2 population*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (34671)
17 susceptible population?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2135)
18 Vulnerable Populations/ (10281)
19 (risk adj2 analy*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (26586)
20 risk assess*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (298996)

21 Risk Assessment/mt, sn [Methods, Statistics & Numerical Data] (33887)
22 risk segment*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (101)
23 Health Status Indicators/ (23314)
24 (characterist* adj4 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (19693)
25 (characterist* adj3 nonrespon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (118)
26 (care adj3 sensitiv*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2767)
27 (receptiv* adj3 care).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (60)
28 (Likel* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9537)
29 (Likel* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1021)
30 (Likel* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9788)
31 (Likel* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (3232)
32 (Likel* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1163)
33 (Predict* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2225)
34 (Predict* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1508)
35 Predict* responder*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (192)
36 (Predict* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (13782)
37 (Probab* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (801)
38 (Probab* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (488)
39 (Probab* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6492)
40 (Probab* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2744)
41 (Probab* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1058)
42 (propensity adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (14)

43 (propensity adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (19)

44 (propensity adj2 respond*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (57)

45 (propensity adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (41)

46 (propensity adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (21)

47 (Potential* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (38647)

48 (Potential* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1341)

49 (Potential* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (11907)

50 (Potential* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2061)

51 (Potential* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (13813)

52 (Model* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1163)
53 (Model* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4006)
54 (Model* adj2 responder*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (71)
55 (Model* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2359)
56 "Patient acceptance of health care"/ (46068)
57 (predict* adj3 model*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (118731)
58 Adverse Outcome Pathways/ (83)
59 Markov Chains/ (14167)
60 logistic* model*.mp. (143517)
61 logistic models/ (137961)
62 population model*.mp. (3652)
63 Patient-Specific Modeling/ (969)
64 patient specific model*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1904)
65 ambulatory care sensitive condition?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (561)
66 Hospitalization/ (105786)
67 Patient Admission/ (24023)
68 Patient Readmission/ (16915)

69 preventive medicine.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (16812)
70 Preventive Medicine/ (11679)
71 preventive health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (17200)
72 Primary Prevention/ (18315)
73 secondary prevention/ (20153)
74 (early adj3 intervention*).mp. (37091)
75 Early Medical Intervention/ (2939)
76 Target* health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1545)
77 Target* healthcare.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (160)
78 (Target* adj3 care*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4252)
79 (prevent* adj3 intervention*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (40728)
80 (care adj3 management).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (26779)
81 population health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (12278)
82 Population Health/ (792)

83 Decision Support Systems, Clinical/ (7841)
84 Health Policy/ (65651)
85 Health* management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6159)
86 System? management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1650)
87 Patient care management/ (4035)
88 Public Health/mt, og, sn [Methods, Organization & Administration, Statistics & Numerical Data] (5126)
89 public health*.mp. (319968)
90 public health administration/ (15359)
91 health service? management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (411)
92 Models, Organizational/ (18878)
93 health care system?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (38577)
94 health* system?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (74494)
95 "Delivery of Health Care"/ (89529)
96 "Delivery of Health Care, Integrated"/ (12500)
97 Managed Care Programs/ (24211)
98 multidisciplinary service?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (204)
99 integrated service?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept

word, rare disease supplementary concept word, unique identifier, synonyms] (1229)
100 amen?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1110)
101 1 or 2 or 3 (18)
Annotation: Impactibility
102 4 or 5 (5020)
Annotation: Case finding
103 6 or 7 or 8 or 9 or 10 (88016)
Annotation: Patient selection
104 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 (1128808)
105 24 or 25 (19768)
Annotation: Characteristic response
106 26 or 27 (2827)
Annotation: Care sensitivity
107 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 or 56 (172438)
Annotation: Likeli to benefit
108 57 or 58 or 59 or 60 or 61 or 62 or 63 or 64 (275227)
109 65 or 66 or 67 or 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 (251550)
Annotation: Preventive healthcare
110 80 or 81 or 82 or 83 or 84 or 85 or 86 or 87 or 88 or 89 or 90 or 91 or 92 or 93 or 94 or 95 or 96 or 97 or 98 or 99 (614599)
Annotation: Population health management
111 109 and 110 (25971)
Annotation: Preventive health and population health management
112 109 or 110 (840178)
Annotation: Preventive healthcare or population health management
113 100 and 112 (27)
114 107 or 108 (439630)

115 102 and 114 (325)
116 111 and 115 (7)
117 103 and 114 (5324)
118 111 and 117 (35)
119 104 and 107 and 108 and 111 (26)
120 105 and 114 (975)
121 112 and 120 (84)
122 106 and 114 (278)
123 111 and 122 (39)
124 102 and 112 and 114 (102)
125 101 or 113 or 124 or 118 or 119 or 121 or 123 (329)

Database: HMIC Health Management Information Consortium <1979 to March 2020>
Search Strategy:
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1 impact?bility.mp. [mp=title, other title, abstract, heading words] (1)
2 'propensity to succeed'.mp. [mp=title, other title, abstract, heading words] (0)
3 interven?bility.mp. [mp=title, other title, abstract, heading words] (0)
4 case finding.mp. [mp=title, other title, abstract, heading words] (201)
5 casefinding.mp. [mp=title, other title, abstract, heading words] (3)
6 screening/ (3706)
7 Patient selection.mp. [mp=title, other title, abstract, heading words] (93)
8 Patient selection/ (47)
9 target* patient*.mp. [mp=title, other title, abstract, heading words] (81)
10 (target* adj2 segment*).mp. [mp=title, other title, abstract, heading words] (6)
11 case selection.mp. [mp=title, other title, abstract, heading words] (16)
12 (risk adj2 population*).mp. [mp=title, other title, abstract, heading words] (516)
13 exp "Risk adjusted monitors of outcome"/ (20)
14 exp vulnerability/ (1261)
15 susceptible population*.mp. [mp=title, other title, abstract, heading words] (10)

16 risk stratif*.mp. [mp=title, other title, abstract, heading words] (106)
17 (predict* adj3 risk factor*).mp. [mp=title, other title, abstract, heading words] (55)
18 risk factors/ (4430)
19 protective factor*.mp. [mp=title, other title, abstract, heading words] (144)
20 (risk adj2 analy*).mp. [mp=title, other title, abstract, heading words] (238)
21 risk assess*.mp. [mp=title, other title, abstract, heading words] (2572)
22 risk assessment/ (1859)
23 risk segment*.mp. [mp=title, other title, abstract, heading words] (1)
24 (characterist* adj4 respon*).mp. [mp=title, other title, abstract, heading words] (163)
25 (characterist* adj3 nonrespon*).mp. [mp=title, other title, abstract, heading words] (0)
26 (care adj3 sensitiv*).mp. [mp=title, other title, abstract, heading words] (196)
27 (receptiv* adj3 care).mp. [mp=title, other title, abstract, heading words] (1)
28 (Likel* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (183)
29 (Likel* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (38)
30 (Likel* adj2 respon*).mp. [mp=title, other title, abstract, heading words] (72)
31 (Likel* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (105)
32 (Likel* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (22)
33 (Predict* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (26)
34 (Predict* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (11)
35 Predict* responder*.mp. [mp=title, other title, abstract, heading words] (1)
36 (Predict* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (78)
37 (Probab* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (19)
38 (Probab* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (5)
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40 (Probab* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (10)
41 (Probab* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (10)
42 (propensity adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (0)
43 (propensity adj2 accept*).mp. [mp=title, other title, abstract, heading words] (0)
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48 (Potential* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (23)
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50 (Potential* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (49)
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52 (Model* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (41)
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56 (predict* adj3 model*).mp. [mp=title, other title, abstract, heading words] (554)
57 exp Decision Support Systems/ (218)
58 logistic* model*.mp. (74)
59 population model*.mp. (22)
60 exp Computer aided decision making/ (29)
61 exp models/ (3243)
62 patient specific model*.mp. (0)
63 ambulatory care sensitive condition?.mp. [mp=title, other title, abstract, heading words] (45)
64 exp Ambulatory care/ (914)
65 exp Pre hospital care/ (49)
66 exp hospital admission/ (3371)
67 exp Hospitalisation/ (7032)
68 exp Health impact assessment/ (360)
69 exp Preventive Medicine/ (21451)
70 preventive medicine.mp. [mp=title, other title, abstract, heading words] (2305)
71 exp preventive medicine health services/ (210)
72 preventive health*.mp. [mp=title, other title, abstract, heading words] (228)
73 exp Health improvement programmes/ (237)
74 prevention/ (5896)
75 (early adj3 intervention*).mp. (749)

76 early intervention/ (0)
77 Target* health*.mp. [mp=title, other title, abstract, heading words] (120)
78 Target* healthcare.mp. [mp=title, other title, abstract, heading words] (12)
79 (Target* adj3 care*).mp. [mp=title, other title, abstract, heading words] (364)
80 (prevent* adj3 intervention*).mp. [mp=title, other title, abstract, heading words] (1001)
81 (care adj3 management).mp. [mp=title, other title, abstract, heading words] (2858)
82 population health*.mp. [mp=title, other title, abstract, heading words] (1085)
83 exp care management/ (500)
84 exp health policy/ (5647)
85 Health* management.mp. [mp=title, other title, abstract, heading words] (505)
86 System? management.mp. [mp=title, other title, abstract, heading words] (79)
87 public health*.mp. (16612)
88 exp public health/ (11196)
89 exp Health systems/ (44916)
90 health service? management.mp. [mp=title, other title, abstract, heading words] (5830)
91 health care system?.mp. [mp=title, other title, abstract, heading words] (3136)
92 health* system?.mp. [mp=title, other title, abstract, heading words] (7548)
93 multidisciplinary service?.mp. [mp=title, other title, abstract, heading words] (555)
94 integrated service?.mp. [mp=title, other title, abstract, heading words] (329)
95 amen?bility.mp. [mp=title, other title, abstract, heading words] (2)
96 1 or 2 or 3 (1)
Annotation: Impactibility
97 4 or 5 or 6 (3859)
Annotation: Case finding
98 7 or 8 or 9 or 10 or 11 (195)
Annotation: Patient selection
99 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 (8794)
Annotation: Risk stratification
100 24 or 25 (163)
Annotation: Characteristic response

101 26 or 27 (197)
Annotation: Care sensitivity
102 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 (1906)
Annotation: Likelihood of benefit
103 56 or 57 or 58 or 59 or 60 or 61 or 62 (4005)
Annotation: Modelling
104 63 or 64 or 65 or 66 or 67 or 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 77 or 78 or 79 or 80 (35800)
Annotation: Preventive health
105 81 or 82 or 83 or 84 or 85 or 86 or 87 or 88 or 90 or 91 or 92 or 93 or 94 (38931)
Annotation: Population health management
106 104 or 105 (69322)
107 104 and 105 (5409)
108 102 or 103 (5838)
109 97 and 108 (119)
110 106 and 109 (38)
111 98 and 108 (8)
112 99 and 108 (313)
113 107 and 112 (6)
114 100 and 108 (9)
115 101 and 108 (17)
116 95 or 96 or 110 or 111 or 113 or 114 or 115 (79)

Ovid Technologies, Inc. Email Service

Search for: 84 or 96 or 99 or 100 or 102 or 104 or 105

Results: 163

Database: Global Health <1973 to 2020 Week 18>
Search Strategy:
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1 impact?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (4)
2 'propensity to succeed'.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1)
3 interven?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (0)
4 case finding.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1946)
5 casefinding.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (5)
6 Patient selection.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (611)
7 target* patient*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (283)
8 (target* adj2 segment*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (144)
9 case selection.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (88)
10 (risk adj2 population*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (11708)
11 susceptible population*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1174)
12 risk stratif*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2127)
13 (predict* adj3 risk factor*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1472)
14 protective factor*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (6071)
15 exp protective factors/ (279)
16 (risk adj2 analy*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (10280)
17 exp risk analysis/ (58968)

18 risk assess*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (63092)
19 risk segment*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (19)
20 (characterist* adj4 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2195)
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24 (Likel* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (982)
25 (Likel* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (281)
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27 (Likel* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (413)
28 (Likel* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (236)
29 (Predict* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (138)
30 (Predict* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (292)
31 Predict* responder*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (8)
32 (Predict* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1054)
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34 (Probab* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (74)
35 (Probab* adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (800)
36 (Probab* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (198)
37 (Probab* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (183)
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39 (propensity adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2)
40 (propensity adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (19)
41 (propensity adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (3)
42 (propensity adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (3)
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48 (Model* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (185)

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53 logistic* model*.mp. (2180)
54 population model*.mp. (497)
55 patient specific model*.mp. (4)
56 exp mathematical models/ (20591)
57 ambulatory care sensitive condition?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (133)
58 exp hospital admission/ (7087)
59 exp Preventive Medicine/ (5152)
60 preventive medicine.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (6066)
61 preventive health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1554)
62 prevention/ (24792)
63 (early adj3 intervention*).mp. (4352)
64 early intervention/ (0)
65 Target* health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (727)
66 Target* healthcare.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (44)
67 (Target* adj3 care*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (808)
68 (prevent* adj3 intervention*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers,

cabicodes] (13708)
69 (care adj3 management).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2707)
70 population health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (4811)
71 exp health policy/ (21123)
72 Health* management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2399)
73 System? management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (295)
74 public health*.mp. (263888)
75 exp public health/ (114710)
76 exp public health services/ (5031)
77 health service? management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (79)
78 health care system?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (7683)
79 health* system?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (22197)
80 multidisciplinary service?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (27)
81 integrated service?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (314)
82 amen?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (96)
83 animal*.mp. (2706683)
84 1 or 2 or 3 (5)
Annotation: Impactibility
85 4 or 5 (1950)
Annotation: Case finding
86 6 or 7 or 8 or 9 (1121)

Annotation: Patient selection
87 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 (90642)
Annotation: Risk stratification
88 20 or 21 (2208)
Annotation: Characteristic response
89 22 or 23 (457)
Annotation: Care sensitivity
90 24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 (16886)
Annotation: Likelihood benefit
91 52 or 53 or 54 or 55 or 56 (35958)
Annotation: Model
92 57 or 58 or 59 or 60 or 61 or 62 or 63 or 65 or 66 or 67 or 68 (56126)
Annotation: Preventive
93 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 or 79 or 80 or 81 (299016)
Annotation: Population
94 92 and 93 (8599)
95 92 or 93 (346543)
96 82 and 95 (15)
97 90 or 91 (52153)
98 85 and 97 (58)
99 95 and 98 (20)
100 86 and 97 (41)
101 87 and 97 (3893)
102 94 and 101 (42)
103 88 and 97 (82)
104 95 and 103 (17)
105 89 and 97 (25)
106 84 or 96 or 99 or 100 or 102 or 104 or 105 (163)

Ovid Technologies, Inc. Email Service

Search for: 104 or 116 or 118 or 121 or 123 or 125 or 128

Results: 320

Database: Embase Classic+Embase <1947 to 2020 May 14>
Search Strategy:
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1 impact?bility.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (12)
2 'propensity to succeed'.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (7)
3 interven?bility.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (2)
4 case finding.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (8308)
5 casefinding.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (200)
6 case finding/ (4164)
7 Patient selection.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (106833)
8 Patient selection/ (93046)
9 target* patient*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (4078)
10 (target* adj2 segment*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1381)
11 case selection.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug

manufacturer, device trade name, keyword, floating subheading word, candidate term word] (2699)
12 (risk adj2 population*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (170420)
13 high risk population/ (121003)
14 vulnerable population/ (16512)
15 susceptible population/ (1056)
16 risk stratif*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (58670)
17 (predict* adj3 risk factor*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (12148)
18 risk factor/ (1025885)
19 protective factor*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (24469)
20 protection/ (67132)
21 susceptible population*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3245)
22 risk stratif*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (58670)
23 (risk adj2 analy*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (95347)
24 risk assess*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (585434)
25 risk assessment/ (558053)
26 risk segment*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (137)
27 (characterist* adj4 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (26743)
28 (characterist* adj3 nonrespon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (147)
29 (care adj3 sensitiv*).mp. [mp=title, abstract, heading word, drug trade name, original title, device

manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3472)
30 (receptiv* adj3 care).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (85)
31 (Likel* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (14595)
32 (Likel* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1390)
33 (Likel* adj2 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (14021)
34 (Likel* adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (4394)
35 (Likel* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1613)
36 (Predict* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3898)
37 (Predict* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1966)
38 Predict* responder*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (385)
39 (Predict* adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (19014)
40 (Probab* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1190)
41 (Probab* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (648)
42 (Probab* adj2 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (8877)
43 (Probab* adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3579)
44 (Probab* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device

manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1538)
45 (propensity adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (21)
46 (propensity adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (21)
47 (propensity adj2 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (141)
48 (propensity adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (67)
49 (propensity adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (26)
50 (Potential* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (53571)
51 (Potential* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1587)
52 (Potential* adj2 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (15605)
53 (Potential* adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (2679)
54 (Potential* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (18959)
55 (Model* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1562)
56 (Model* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (4879)
57 (Model* adj2 responder*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (144)
58 (Model* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3286)
59 (predict* adj3 model*).mp. [mp=title, abstract, heading word, drug trade name, original title, device

manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (155268)
60 adverse outcome pathway/ (358)
61 logistic* model*.mp. (11456)
62 population model*.mp. (10416)
63 information model/ (253)
64 process model/ (8488)
65 population model/ (7092)
66 markov chain/ (5170)
67 patient specific model*.mp. (1434)
68 ambulatory care sensitive condition?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (687)
69 ambulatory care/ (38902)
70 hospital readmission/ (62928)
71 hospital admission/ (194263)
72 hospitalization/ (376388)
73 hospital utilization/ (2228)
74 Preventive Medicine/ (28102)
75 preventive medicine.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (34859)
76 preventive health*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (33684)
77 preventive health service/ (28680)
78 prevention/ (283203)
79 (early adj3 intervention*).mp. (64519)
80 early intervention/ (24768)
81 Target* health*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1919)
82 Target* healthcare.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (213)
83 (Target* adj3 care*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer,

drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (6204)
84 (prevent* adj3 intervention*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (52335)
85 (care adj3 management).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (62219)
86 population health*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (14536)
87 population health management/ (117)
88 health care policy/ (192062)
89 population health/ (2476)
90 Health* management.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (7921)
91 System? management.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (959)
92 public health*.mp. (457567)
93 public health/ (187251)
94 public health service/ (74031)
95 health service? management.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (538)
96 health care system?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (138922)
97 integrated health care system/ (11078)
98 health* system?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (103788)
99 multidisciplinary service?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (406)
100 integrated service?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1673)
101 safety net hospital/ (2077)
102 amen?bility.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug

manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1356)
103 animal*.mp. (6389036)
104 1 or 2 or 3 (21)
Annotation: Impactibility
105 4 or 5 or 6 (8461)
Annotation: Case finding
106 7 or 8 or 9 or 10 or 11 (114598)
Annotation: Patient selection
107 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 (1764975)
Annotation: risk
108 27 or 28 (26841)
Annotation: Characteristic response
109 29 or 30 (3557)
Annotation: Care sensitivity
110 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 or 56 or 57 or 58 (176187)
Annotation: Likelihood of benefit
111 59 or 60 or 61 or 62 or 63 or 64 or 65 or 66 or 67 (189338)
Annotation: Predictive modelling
112 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 or 79 or 80 or 81 or 82 or 83 or 84 (1060770)
Annotation: Preventive healthcare
113 85 or 86 or 87 or 88 or 89 or 90 or 91 or 92 or 93 or 95 or 96 or 97 or 98 or 99 or 100 or 101 (840792)
114 112 or 113 (1821615)
115 112 and 113 (79947)
116 102 and 114 (51)
117 107 and 110 and 111 (877)
118 115 and 117 (30)
119 110 or 111 (360103)
Annotation: likely benefit or modelling
120 109 and 119 (192)

121 115 and 120 (37)
122 108 and 119 (948)
123 114 and 122 (66)
124 106 and 119 (4043)
125 115 and 124 (52)
126 105 and 119 (166)
127 115 and 126 (9)
128 105 and 114 and 119 (67)
129 104 or 116 or 118 or 121 or 123 or 125 or 128 (320)

Appendix Table S2: Full inclusion and exclusion criteria

		Yes	No
1	Does the title or abstract talk about amenability?	Continue	Go to 3
2	Is the paper about youth offending or amenability of specific diseases to treatment?	Exclude/STOP	Go to 4
3	Does the title or abstract talk about impactibility/ intervenability or 'propensity to succeed' modelling in a population health context?	Include/STOP	Continue
4	Is there an intervention that aims to prevent or ameliorate a future health event?	Continue	Exclude/STOP
6	Is the intervention solely aiming to increase screening programme detection rates?	Exclude/STOP	Continue
7	Does the study include case finding or selection of potential responders from the wider population?	Continue	Exclude/STOP
8	Is modelling limited to identifying subjects at 'high risk' of a disease or health event?	Exclude/STOP	Continue

9	Does the extended modelling identify subjects who may respond better to the intervention?	Include/STOP	Continue
10	Does the extended modelling identify subjects who are more likely to start and complete the intervention?	Include/STOP	Exclude/STOP

INCLUSION

- Papers that include Impactibility OR intervenability OR 'propensity to succeed' modelling OR Amenability in a population health context

OR

- Studies that include ALL of:
  1) an intervention that aims to prevent or ameliorate a future health event
  AND
  2) case finding OR selection of potential responders from the general population
  AND
  3) extended modelling that identifies subjects who may respond better to the intervention OR extended modelling that identifies subjects who are more likely to start and complete the intervention

EXCLUSION

- Amenability AND youth offending
- Amenability of specific diseases to treatment
- Modelling limited to identifying subjects at 'high risk' of a disease or health event
- Intervention solely aiming to increase diagnoses or screening programme detection rates

Definitions:

Case finding: a systematic or opportunistic process that identifies individuals (e.g. people with COPD) from a larger population for a specific purpose for example, 'Flu vaccination' https://www.england.nhs.uk/wp-content/uploads/2015/01/2015-01-20-CFRS-v0.14-FINAL.pdf

Intervention: A health intervention is an act performed for, with or on behalf of a person or population whose purpose is to assess, improve, maintain, promote or modify health, functioning or health conditions. https://www.who.int/classifications/ichi/en/

In medical terms this could be a drug treatment, surgical procedure, diagnostic test or psychological therapy. Examples of public health interventions could include action to help someone to be physically active or to eat a more healthy diet. Examples of social care interventions could include safeguarding or support for carers.
https://www.nice.org.uk/Glossary?letter=I

Appendix Table S3: Google search string

# results (2 November 2020)	
207	("impactability" OR "impactibility") AND (site:nhs.uk OR site:cdc.gov OR site:.ac.uk OR site:.gov.uk OR site:.edu OR site:.gov OR site:.ac.au OR site:.ac.ca OR site:elsevier.com OR site:researchgate.net) AND "case finding" AND (guide OR protocol OR process OR method)

Appendix Table S4: Studies of the development, validation or application of impactibility models included in the qualitative synthesis

Study Name/Ref			Population studied	Impactibility model	Results/author conclusions
Impactibility determined by presence of a health condition amenable to preventive intervention					
Buja et al. 2019	**Country**	Italy (Azienda ULSS4-Veneto local health unit)	Patients over 65 years, residing in the area served by. All patients had heart failure and "complex health care needs", as defined by Resource Utilization Band 4 or 5 (respectively high morbidity or very high morbidity) out of 5.	"Impactibility model" based on ACG created by identifying homogenous clinical subgroups of patients with **a high risk of at least 1 "preventable admission**" that may be addressed using case management	No statistical difference between algorithm and ACG risk scores. This will help policy makers develop ''tool kits'' for homogeneous groups of patients that improve health outcomes.
	Data source	Routinely collected administrative data			
	Aims	Case management by development of an impactibility model			
	Outcomes and measures	Predictive performance of algorithm to identify common sets of diseases most predictive for hospital admission or readmission compared with ACG risk scores.			
Guthrie et al. 2017	**Country**	UK	Patients with ACSCs who had "psychosocial risk factors for increased use of unscheduled care", including recent use of unscheduled care, depression, living alone or social stressors.	ACSC diagnosis	Depression was an important factor in unscheduled care use. However, there was no evidence that this intervention impacted unscheduled care as patients and HCPs seem unaware or unlikely to acknowledge the role of psychosocial factors and integration of tools might not have been complete.
	Data source	CHOICE: Choosing Health Options In Chronic Care Emergencies			
	Aims	Assess relationship between psychological morbidity and use of unscheduled care in people with long-term conditions by a literature review and prospective study of care use to develop a targeted intervention.			
	Outcomes and measures	Identification of factors that could reduce use of unscheduled care.			
McCormick 2012	**Country**	USA	Patients with cardiovascular ACSCs (congestive heart failure, angina, hypertension)	ACSC diagnosis	ACSC hospitalisations increased more in the intervention group than the control group over the intervention period.
	Data source	Acute hospital admission data			

	Aims	Difference-in-differences analysis of the impact of healthcare reforms aimed at improving access to care and coverage for preventable ACSCs.			Therefore the intervention did not decrease the risk of avoidable hospitalisations.
	Outcomes and measures	Hospital admission rates before and after reform versus control states without changes			
Steventon et al. 2012	**Country**	UK	Patients aged 18 and over with a diagnosis of COPD, diabetes, or heart failure, based on QOF register or confirmed diagnosis based on GP records or confirmation of disease status by a local clinician. Patients were not excluded for any other reasons	ACSC diagnosis	Logistic regression showed that telehealth was associated with lower hospital (OR 0.82, 95% CI 0.70–0.97, p=0.017) and Emergency (0.81, 0.65–1.00, p=0.046) admission rates and mortality (0.54, 0.39–0.75, p<0.001).
	Data source	HES data for England, mortality, (May 2008 to November 2009)			
	Aims	Assess the effects of home-based telehealth interventions			
	Outcomes and measures	Reductions in admission to hospital and mortality over 12 months versus usual care			
Steventon et al. 2013	**Country**	UK	Inclusion was restricted to patients with a recorded diagnosis of COPD, CHF, coronary heart disease or diabetes; a minimum level of disease severity in the past 15 months; age 18 or older; ability to communicate on the telephone; a recorded address and practice registration. Patients also had a history of inpatient or outpatient hospital use.	ACSC diagnosis augmented with clinical judgement of which patients were likely to benefit	Logistic regression showed that telephone health coaching intervention did not lead to the expected reductions in hospital admissions or secondary care costs over 12 months and could have led to increases.
	Data source	Primary care data (not specified)			
	Aims	Assess the effects of a personalised telephone health coaching service			
	Outcomes and measures	Reductions in number of emergency hospital admissions, hospital bed days, elective hospital admissions, outpatient attendances, and secondary care costs over 12 months versus usual care			
Steventon et al. 2016	**Country**	UK	Patients with ACSCs including COPD, CHF, and diabetes	ACSC diagnosis	Logistic regression showed that the telehealth intervention may have led to increased risk of emergency admission or death (adjusted HR 1.34, 95% CI 1.16–1.56,
	Data source	Hospital administrative data and linked telehealth referral data			
	Aims	Assess the effects of home-based telehealth management of existing			

		conditions by a monitoring centre in a rural setting			p<0.001). Authors recommend investing resources in other forms of preventive care for which an evidence base exists
	Outcomes and measures	Changes in time to first emergency hospitalisation or death versus usual care			
			Impactibility based on PTS		
Dubard et al. 2018	**Country**	USA (North Carolina)	Medicaid beneficiaries who received some level of care management support and had at least 1 potentially preventable admission, readmission or ED visit in the year prior to initiation of case management. Patients were considered to have received care management support if they had at least 1 direct encounter with a care manager by phone or face to face.	Impactibility score developed using linear regression analysis. Independent variables: • Age, sex, race, ethnicity, disability status, foster care status • ED visit count, inpatient visit count • CRG weight • Presence of specific chronic conditions • Number of chronic conditions • Number of chronic medications filled • Number of acute medications filled • Total cost of care Derived variables include: • “Above expected potentially preventable costs” (AEPPC), which includes costs related to potentially preventable	Model variables related to medication adherence and historical utilization unexplained by disease burden were more important predictors of impactibility than any given diagnosis or event, disease profile, or overall costs of care. Impactibility based targeting could lead to two to three times greater return on investment that risk stratification by high ED use or inpatient admissions and high-risk disorders This study helps highlight the difference between “high-frequency/high-cost” users and “highly impactible” users, noting that there's a real difference between the two groups which makes traditional algorithms unhelpful.
	Data source	Administrative data available for the whole population (January 2010-May 2017) including eligibility and enrolment files; Medical and pharmacy claims paid by Medicaid and encounter claims from all managed care organisations; Disease burden categorised by hierarchical Clinical Risk Group (CRG)			
	Aims	Development of an impactibility score to estimate intervention effects and achievable savings for community-based care management			
	Outcomes and measures	Multivariable modelling including costs various risk stratification strategies to build a predictive model of expected cost savings versus usual care			

				admissions, readmissions and ED visits • Monthly spending trajectory over the most recent 12 months • 2 indicators of adherence to chronic medications	
Hawkins et al. 2015	**Country**	USA (pilots in California, Florida, New York, North Carolina and Ohio)	Individuals with Medicare Supplement plans with multiple chronic health conditions who may benefit from additional care coordination and ancillary support. Patients are referred either directly from a provider or Nurse HealthLine, or data-driven referrals based on Hierarchical Condition Category risk score >3.74.	PTS model based on logistic regression. Independent variables included: • dates and locations of service • indicators of the types of services, drugs, and procedures provided • AmeriLINK Data Sourcing system (generated by the KBM Group) to find information about socioeconomic status • Local supply of health care services in areas where qualified members lived was derived from the Dartmouth Atlas of Healthcare	The score significantly improved the ability to identify patients most likely to engage with treatment and succeed (predicted success rate 0.761, 95% CI 0.754–0.764) and financial success probabilities (0.697, 0.665–0.707), but not quality of care. The validated score helped to prioritise outreach to efforts to maximise programme engagement and savings. "Using PTS models may help increase program engagement and financial success of care coordination programs."
	Data sources	United Healthcare (AARP Medicare Supplement plan provider) December 2008-December 2011.			
	Aims	Develop and validate a PTS score to support a high-risk-case management programme			
	Outcomes and measures	Identify among programme members those most likely to: 1) engage with the programme (yes/no) 2) receive the highest quality of care (meeting 70% or more of the relevant clinical care guidelines) and cost savings associated with the HRCM program			
Hommer et al. 2013	**Country**	USA	Patients with depressive symptoms measured by PHQ-9 and AARP Medigap supplement insurance.	PTS model based on characteristics of "engaged patients" compared with qualified but non-engaged patients.	The score enabled more efficient utilisation of health resources by refining targeting and outreach efforts to those
	Data source	United Healthcare (AARP Medicare Supplement plan provider) combined			

		with inferred sociodemographic data (Dec 2009-Dec 2010)		Predictors of outcomes of interest included: • patient demographics • plan type • location • participation in other programmes • health status measures • various supply side measures	most likely to be successful in the programme.
	Aims	Develop and validate a PTS score to support a depression management programme			
	Outcomes and measures	Changes in identification of patients likely to engage, individual-level costs (ROI >1) and health-care quality outcomes (hospital readmission, EBM metrics)			
Hsueh et al. 2018	**Country**	USA	Review of records of patients recently discharged from an acute hospital admission and assigned to a transitional care programme with the objective of reducing hospital admissions.	Goal attainment factors assessed by logistic regression include: • demographics (age, gender) • patient care programme context (programme experience, days in the programme) • interactions between care managers and patients (day of call) and fivefold cross validation on the task of predicting whether a goal would be achieved given the recommended intervention	Accuracy for goal attainment was greatest at the individual level (87.24%), outperforming population-level strategies (85.70%), and no planning (28.98%). “Increased patient behavioral understanding could potentially benefit augmented intelligence for care management decision support”
	Data source	The GOAL dataset: care management records from a private not-for-profit healthcare network (Jan 2016 to Feb 17)			
	Aims	Develop models of conditional probability distributions for individual-level effect estimation to enable recognition of behavioural responses that could affect care planning			
	Outcomes and measures	Improved likelihood of goal attainment, categorised as: education (e.g., post-discharge understanding); medication (e.g., adherence); reducing risk (e.g., resolve care gaps); self-care (e.g., heart failure home self-management); implementation (e.g. installing fall prevention facility), and others (e.g., obtaining accurate patient information) in an observational data set.			
Mattie et al. 2019	**Country**	USA		A random forest machine learning model to	The impactibility model reached an overall

	Data source	Anonymised insurance claims data (June 2015 to May 2018) combined with inferred sociodemographic and patient-generated data	Commercially insured, "low-risk" (not defined) population	categorise new patients as impactable versus not impactable based on cost savings with vs without a digital health intervention. The model was based on: • Administrative claims data • Age • Education level, employment status, income and poverty status inferred from zip code • Data derived from a patient-held mobile application.	accuracy of 71.9% (sensitivity 0.77 and specificity of 0.65) and is generalisable to assess the impactibility of any intervention. "This demonstrates the potential to successfully target, based on impactibility, lower risk members of the population with a digital health intervention.
	Aims	Develop machine learning models to identify patients most likely to benefit from a digital health intervention for care management			
	Outcomes and measures	Expected cost savings compared with no predictive intervention			
Menard et al. 2018	**Country**	USA	Pregnant Medicaid beneficiaries	Retrospective analysis of risk screen and care management data, matched to birth certificate pregnancy outcome data. Analysis of degree of low birthweight and number of completed care tasks led to creation of a three-tier score (highest score range = greatest risk reduction with higher number of face-to-face care management tasks)	The score effectively identified women who would benefit most from pregnancy care management (OR for highest score range 0.80, p<0.05) "For every 100 women in Tier 1 who receive care management, 8 low birthweight outcomes can potentially be prevented"
	Data source	Birth certificate pregnancy outcome data from the 2011-14 birth cohort			
	Aims	Development and validation of a pregnancy care management strategy to identify women most likely to benefit from pregnancy care management to reduce the rate of low birthweight			
	Outcomes and measures	Associations between low birthweight and number of completed care management tasks during pregnancy			
Ozminkowski et al. 2015 (MyCarePath)	**Country**	USA	Individuals are qualified for MyCarePath either through direct or indirect referral. Indirect referrals use claims experience to calculate CMS Hierarchical Condition	PTS summary scores were calculated through logistic regression to generate predicted probability that a qualified individual:	PTS models had higher specificity than sensitivity, suggesting they were better able to predict who would not participate/achieve cost
	Data source	Administrative claims data and health risk assessment from AARP Medicare Supplement Insurance Plan insured			

		by UnitedHealthcare Insurance Company	Category (HCC) score >3.74. Most individuals are age 65 and older, with a Medigap plan. Individuals may also be referred directly through their provider who "perceives a benefit" or nurses on a telephone advice line. *Note: individuals purchasing AARP Medigap insurance are asked to complete a health risk assessment after purchasing the plan. Answers to these questions may trigger referral to MyCarePath.*	(1) participated in MyCarePath, (2) was managed in a way that was consistent with evidence-based guidelines for treating their medical problems, and (3) was managed in a way that reduced the cost of their medical care and prescription pharmaceuticals. Independent variables included: • Demographic data • Health status • Medigap plan type • Healthcare supply • Location variables External consumer-generated variables have been studied but did not increase the model's predictive ability.	savings/improve care quality. Comparing the 3 months prior to the implementation to the 9 months after implementation, the average number of new participants rose by 11%. "To date, program evaluations have reported positive returns on investment and improved quality of healthcare among program participants."
	Aims	Describe how big and small data are used to support care coordination programmes			
	Outcomes and measures	Change in calculation of risk scores after implementation of PTS modelling was			
Navratil-Strawn 2016	**Country**	USA	Patients covered by an AARP Medicare Supplement (Medigap) plan	PTS modelling by means of logistic regression to identify characteristics associated with programme engagement. Model covariates included:	PTS modelling was found to be "stable and valid" according to a K-fold cross-validation study "PTS modelling may help to target and engage callers, thus increasing use
	Data sources	United Healthcare (AARP Medicare Supplement plan provider) combined with inferred sociodemographic data			
	Aims	Increase use of a nurse telephone triage programme			

	Outcomes and measures	Changes after PTS in 1) Utilisation of the Nurse Healthline 2) Triage engagement 3) Adherence to nurse recommendations Compared with no intervention		• demographic measures (age, sex) • residential location: rural vs urban, census region, residence in 1 of 5 locations with other care coordination pilots ongoing • socioeconomic variables (zip code level proxies of race and income) • health status (OptumInsight ImpactPro prospective risk score) • local supply of health services (hospital beds per 1000, primary care physicians and specialists per 100,000 residents) • Previous emergency healthcare use in 6 months (yes/no) • Time of call (weekday/weekend)	of the Nurse Healthline and triage service." "This in turn should lead to more efficient use of healthcare services and reduce unnecessary health care expenditures"
Studies incorporating or comparing clinical judgement of impactibility					
Cohen C et al. 2015	**Country**	Israel	Exclusion criteria based on physician input were: active cancer, schizophrenia, dialysis, residence in nursing homes or long-term care facilities, and age 95 years or older.	Model based on ACG predictive model risk scores for risk of future high costs, augmented with a survey of clinical considerations from six physicians	C-statistics for the model before and after exclusions applied were 0.80 and 0.75, respectively. After exclusion, the PPV for the 6% highest risk patients
	Data source	Clalit Health Services' (managed care organization) database 2010-11			
	Aims	Develop a patient selection process for muiltimorbid care management based on physician knowledge and predictive model risk scores			

	Outcomes and measures	Improve discriminatory power for selecting multimorbid patients most amenable to proactive management			was 40%. High-risk patients' age, number of chronic conditions, and utilization were substantially higher than those of all other patients. This study shows that a validated predictive modelling tool provides acceptable discriminatory power for selecting multimorbid patients for participation in proactive care management, even after some of the highest risk patients are excluded because of priori clinical considerations.
Corbin et al. 2019	**Country**	USA	Outpatient primary care patients "at risk of hospitalisation in the next 12 months"	Clinical team assessment of the "potential of care to impact outcomes" based on medical and social factors as an adjunct to a risk predictive model developed by EPIC, which identified 19 variables predictive of ED visits or hospitalisation in the next 12 months.	Validation showed an average C-statistic of 0.71. Average risk score of patients under care management increased from 33% to 40.4% over the first 2 months of the programme. Full results for other outcomes not yet available.
	Data source	Primary care database (not specified)			
	Aims	Develop and validate a patient selection tool to guide allocation of care management based on physician knowledge and predictive model risk scores			
	Outcomes and measures	Changes in 1) Average risk score of patients under care management 2) Number of ED visits 3) Number of hospitalisation in the next 12 months after introduction of tool			
Flaks-Manov et al. 2020	**Country**	Israel	Patients aged 65 years and older who were hospitalized for at least 1 night in an internal medicine ward	Nurse and internal medicine physicians (in charge of direct patient care) assessment of impactibility, compared with a risk prediction model	Physician assessment of likelihood to benefit vs risk prediction model showed 65% overlap, 19% of patients had high predicted risk scores but
	Data source	HCP interview May 2016-June 2017			
	Aims	Explore healthcare providers' perspectives of patients' characteristics associated with decisions about which patients should			

		be referred to readmission prevention programs			were not referred, and 16% had low predicted risk scores but were referred. There is a mismatch between being risk classification by modelling and perceived impactibility. Additional research is required to understand how combining modelled data with provider insights might improve the selection of patients
	Outcomes and measures	Identify similarities and differences in recommendations for referral to a readmission prevention program based on physicians' opinions and a risk prediction model			
Fleming et al. 2017	**Country**	USA	High cost "superutilizers" at two public urban safety-net hospitals	Physician assessment of patient engagement to determine "likelihood to benefit" determined through interviews and ethnographic research	Providers considered 'likelihood to benefit' assessments to be highly challenging and oftentimes inaccurate, particularly because they understood low patient engagement to be the result of difficult socioeconomic conditions..." Health-care professionals look for more subtle signs of engagement and considered fluctuating trajectories of engagement due to living circumstances
	Data source	HCP interview conducted 2015 to 2016			
	Aims	Investigate how health care providers describe engagement for high-cost patients requiring complex care management			
	Outcomes and measures	Assess accuracy of health-care professional and provider definitions and predictions of engagement in relation to socioeconomic status			
Freund et al. 2010, 2011, 2012, 2013	**Country**	Germany	Index condition: T2DM, COPD, asthma, CHF or late-life depression (age >60 years).	Family physician assessment of likelihood to benefit (vs risk predictive model)	Predictive modelling was numerically more accurate than physicians at predicting risk of future hospitalisation, but rates
	Data source/setting	10 primary care practices in southwestern Germany			

	Aims	Compare physician referrals with risk prediction based on insurance claims data	Exclusion criteria: age under 18, dementia, palliative care, or nursing home residents, active cancer or dialysis		for the latter increased over time and patients had better receptivity to care management programmes The authors recommend a combined approach between risk prediction and physician-determined impactibility.
	Outcomes and measures	Selection of patients for primary-care-based management of complex and chronic illness, assessed by: 1) Hospitalisation within 12 months 2) Mortality			
Hudon et al. 2018	**Country**	Canada	Patients with at least one chronic disease, including diabetes, CVD, respiratory, musculoskeletal or chronic pain, with "complex care needs whom family physicians felt could benefit from a case management intervention" and at least three ED visits or hospital admissions. Patients with serious cognitive problems were excluded.	Randomised control trial of intervention and thematic analysis of in-depth interviews	The intervention reduced psychological distress (OR 0.43, 95% CI 0.19–0.95, p= 0.04), but did not have any significant effect on patient activation Patients and spouses benefitted from the case management intervention, gaining a sense of security, and stakeholders noted better patient self-management of health “Case management is a promising avenue to improve outcomes among frequent users of health care with complex needs”
	Data source	V1SAGES (Vulnerable Patients in Primary Care: Nurse Case management and Self-management support)			
	Aims	Assess effects of case-management intervention on psychological distress and patient activation in frequent health-care users			
	Outcomes and measures	Effects of intervention on 1) Psychological distress 2) Patient activation Stakeholder’s perceptions of interventions			

Abbreviations: ACG=adjusted clinical groups. ACSCs=ambulatory care sensitive conditions. OR=odds ratio. PTS=propensity to succeed.

PRISMA 2020 Checklist

Bridging the impactibility gap in population health management: a systematic review

NB This study explores whether impactibility modelling is being used and does not statistically assess its effect on specific outcomes.

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title, p2, p5
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	P 2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	P 5
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	P 5
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	P 5–6
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	P 5
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	P5, appendix
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	P 5, appendix
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	P 5
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	P 5–6
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	P 5–6
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	N/A
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	N/A
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	P 6, appendix
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	N/A
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	N/A
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	N/A

PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	N/A
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	N/A
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	N/A
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	N/A
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	P 6, figure 1
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Figure 1
Study characteristics	17	Cite each included study and present its characteristics.	PP 6–9, appendix
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	N/A
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Appendix
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	PP 6–9
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	N/A
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	N/A
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	N/A
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	N/A
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	N/A
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	PP 9–10
	23b	Discuss any limitations of the evidence included in the review.	P 10
	23c	Discuss any limitations of the review processes used.	P 10
	23d	Discuss implications of the results for practice, policy, and future research.	PP 10–13
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	P 9
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	P 9
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	N/A
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	P 13
Competing	26	Declare any competing interests of review authors.	P 13

PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
interests			
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	P 13

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71

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Bridging the impactibility gap in population health management: a systematic review

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Abstract

Objectives Assess whether impactibility modelling is being used to refine risk stratification for preventive health interventions.

Design Systematic review.

Setting Primary and secondary healthcare populations.

Papers Articles published from 2010 to 2020 on the use or implementation of impactibility modelling in population health management, reported with the terms "intervenability", "amenability", and "propensity to succeed" and associated with the themes "care sensitivity", "characteristic responders", "needs gap", "case finding", "patient selection", and "risk stratification".

Interventions Qualitative synthesis to identify themes for approaches to impactibility modelling.

Results – Of 1,244 records identified, 20 were eligible for inclusion. Identified themes were "health conditions amenable to care" (n=6), "propensity to succeed (PTS) modelling" (n=8), and "comparison or combination with clinical judgement" (n=6). For the theme "health conditions amenable to care", changes in practice did not reduce admissions, particularly for ambulatory-care-sensitive conditions, and sometimes increased them, with implementation noted as a possible issue. For "PTS modelling", high costs and needs did not necessarily equate to high impactibility and targeting a larger number of individuals with disorders associated with lower costs had more potential. PTS modelling seemed to improve accuracy in care planning, estimation of cost savings, engagement and/or care quality improvements. The "comparison or combination with clinical judgment" theme suggested that models can reach reasonable to good discriminatory power to detect impactible patients. For instance, a model used to identify patients appropriate for proactive multimorbid care management showed good concordance with physicians (c-statistic 0.75). Another model employing electronic health record scores reached 65% concordance with nurse and physician decisions when referring elderly hospitalised patients to a readmission prevention programme. However, healthcare professionals consider much wider information that might improve or impede the likelihood of treatment impact, suggesting that complementary use of models might be optimum.

Conclusions The efficiency and equity of targeted preventive care guided by risk stratification could be augmented and personalised by impactibility modelling.

Keywords access to care; impactibility; personalised care; population health management; triple aim; propensity to succeed; amenability.

Strengths and limitations

- Limitation – comparing data was difficult due to widespread inconsistency in terminology.
- Limitation – the quality of the articles included in this review was not graded.
- Limitation – this is a growing area of interest and few studies are available to assess.
- Strength – we were as inclusive as possible with types of article, including abstracts and grey literature.
- Strength – to make the findings most applicable to PHM, we excluded studies of specific diseases.

Introduction

The triple aim is targeted towards improving the individual experience of care, improving the health of populations, and reducing the per capita costs of care,[1] and has become a popular healthcare objective. Risk stratification is one type of population health management (PHM) tool used by health system managers to achieve the triple aim[2-5] and identifies groups that are at high risk of poor outcomes so that they can be offered preventive care aimed at lowering this risk. For instance, care in accident and emergency has high costs and a cohort of patients experience frequent attendances, making this cohort a potential target for increased preventive spending. However, within this high-risk cohort, some individuals may be labelled as being "beyond help" because they their attendance is perceived by clinicians to be non-preventable (e.g., because of age, sex, or chronic conditions, including alcohol or drug abuse).[2, 3] For these individuals, preventive care interventions will have little or no effect and they will continue to be at risk of so-called triple-fail events (in this case accident and emergency attendances), which are harmful, costly, and result in poor patient satisfaction.[4, 6-9]

While risk stratification models may accurately predict which individuals are at risk of future adverse health outcomes, such as readmission risk or 1-year mortality risk,[2-5] their use has not consistently led to improvements in health outcomes across the population.[10] Calculating and understanding the probability of a particular outcome for an individual may not be enough for health care professionals to intervene in the most efficient way to delay or prevent that outcome or divert the course of a disease, and often needs to be supported by additional information to determine the most accurate or appropriate model.[11] Furthermore, as many risk stratification models predict future adverse health outcomes through current or previous healthcare activity and use a limited number of variables,[12-15] they may miss out on valuable additional information that could better direct resources to patients amenable to benefit.[9, 16] Lewis[6] defined a different type of model – impactibility models – that are aimed at identifying the subset of at-risk patients for whom preventive care is expected to be successful.

Lewis[6] found that impactibility was being assessed by many healthcare systems for PHM, reflecting a growing recognition that not all high-risk patients will benefit from preventive care. He described the ideal impactibility model as one that "would use information about the differential effects of a specific preventive intervention offered at random to patients and controls, so as to identify the characteristics of the 'perfect patient' for that preventive program". However, suitable data are rarely available in real-world records.

Instead, he found that models were being formulated in three main classes: "(1) giving priority to patients with diseases that are particularly amenable to preventive care; (2) excluding patients who are least likely to respond to preventive care; or (3) identifying the form of preventive care best matched to each patient's characteristics". While such impactibility models have considerable potential to improve the efficiency of preventive care delivery, certain approaches could increase health inequalities if used indiscriminately without catering to individual needs.[6] The aim of this current study was to describe broadly how and in what contexts impactibility modelling has been implemented or assessed in PHM since 2010. We defined impactibility as the identification of patients most likely to respond to care based not only quantitative but also on qualitative factors, and whose treatment would maximise the likelihood of achieving the triple aim. It was beyond the scope of this review to consider how impactibility modelling might affect management of individual diseases, heterogeneity in treatment effects, and different types of health programmes.

Methods

A systematic literature review was carried out to identify all papers published between January 2010 and May 2020. The Ovid search platform was used to search four relevant databases: Embase Classic & Embase, Global Health, Healthcare Management Information Consortium, and Ovid MEDLINE. Additional searches for grey literature were performed in OpenGrey.

Search strategies were built iteratively, with relevant keywords and subject headings for each database added based on initial reviews of relevant publications. The final set of search terms (see supplementary information pp 1–28) included alternative spellings of impactibility and synonyms, including "intervenability", "amenability", and "propensity to succeed". We 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.

Database search results were exported to the systematic review software Covidence. Two reviewers (AO and SS) independently screened titles and abstracts for relevance and reviewed the full texts that specifically referenced analyses of amenability, impactibility, and propensity to succeed (PTS) in relation to future events. Papers that concerned youth offending, aimed to increase screening detection rates, and looked only at identifying individuals at high risk of a specific disease or health event were excluded. Full inclusion and exclusion criteria are shown in the supplementary information (pp 29–31). To achieve the widest possible overview of work in this emerging field, studies were not excluded based on assessment of methodological quality. Conflicts were discussed with a third reviewer (WS) at each review stage. A pragmatic forward citation search was subsequently conducted using PubMed for all articles included in the initial review round. These were added to Covidence, and the screening process was repeated. A targeted Google search (see supplementary information p 32) was conducted to identify any additional publications containing the term 'impactibility'.

Data extraction was performed by SS, HH, and WS. For studies describing impactibility models, information about country of implementation, data sources, population studied, intervention and any reported outcome measures were extracted into a data table. Qualitative synthesis was performed to assess themes and to group papers by approach to impactibility modelling.[17] Outcome measures, where reported, were not comparable across studies so meta-analysis was not considered to be appropriate.

Ethics Approval

As this is a systematic review of published literature and assessed data at the population level, ethics approval was not required.

Results

Of 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. Thus, 20 studies related to the development, application, or validation of impactibility models for use in PHM and were included in the review (**Figure 1**).

In the qualitative synthesis, we grouped papers under three themes representing different approaches to assessing impactibility: health conditions amenable to preventive care (n=6); PTS (n=8); and comparison or combination with clinical judgement (n=6; see supplementary information pp 33–43).

Health conditions amenable to preventive care

Several studies inferred participants' potential to benefit from preventive care if it is targeted after they have received a diagnosis of a specific health condition[18-21] or if they have a multi-morbid cluster of health conditions.[22, 23] Many of these studies specifically targeted people with ambulatory-care-sensitive conditions (ACSCs), including chronic obstructive pulmonary disease, chronic heart failure, and diabetes, for which evidence suggests that optimal management in the community should not result in unplanned hospital admission.[10, 16, 24, 25] Preventive interventions (e.g. case management) that were targeted based on the presence of one or more ACSC did not consistently lead to reductions in hospital admissions or secondary care costs, and indeed, in some cases led to increases in emergency hospital admissions.[18-22] However, the success of these impactibility strategies may be hindered by ineffective implementation. In one of these studies, for example, the authors indicated that the targeted intervention was not effectively integrated into primary care practice during the observation period.[21]

Propensity to succeed

PTS modelling is an analytical approach to identify traits associated with better engagement with or outcomes from particular preventive health intervention(s) – outcomes such as cost or care quality.[26-32] Of the eight studies identified that used this approach, three used PTS modelling in relation to specific case management interventions.[30-32] One model was developed explicitly for 'low-risk' participants to assess who would be most likely to benefit from a digital health platform.[28]

In these studies, PTS regression analyses were performed using various sociodemographic factors,[26-28, 30-32] health status (e.g., presence of chronic conditions, prescription data, prior health resource utilisation, various health risk scores),[26-28, 30-32] or previous programme engagement metrics.[28] One study found that high costs and high needs did not equate to high impactibility, as only small proportions of people with diseases that would be expected to have high burden had scores indicating high impactibility. The authors suggested that targeting a larger number of individuals with disorders associated with lower costs could improve impact substantially and that better predictors of impactibility might be medication adherence and historical healthcare resource utilisation that was unexplained by disease burden.[31]

Five of the identified studies reported the statistical validity of PTS models for projecting cost savings, improved engagement, and/or care quality improvements;[26-28, 30, 32] however, prospective or comparative outcome data on the use of these models in real-world situations were extremely limited in the literature. Two studies reported improved engagement (defined as enrolment of contacted participants) with case management interventions after implementation of a PTS model: Ozminkowski et al[32] reported an 11% increase in programme enrolment in the 9 months after implementation of a PTS model, compared with the 3 months prior. Hommer et al[29] likewise reported increased enrolment in a depression management programme but did not quantify the change.

Hsueh et al[33] evaluated the Behavioural Response Inference Framework (BRIeF), a machine learning impactibility model derived from a large observational dataset of care management records from a private healthcare network. They tested the ability of the model to predict individual-level behavioural responses to multiple interventions used in care planning. Input data included participants' personalised goal attainment history across 16 goals set in a program to reduce hospital readmissions after discharge for acute care. They covered a wide spectrum of care needs (e.g., tobacco cessation, knowledge of healthy eating, medication adherence, actions to resolve care gaps, and fall prevention) and were categorised as 'met', 'abandoned', 'not met' or 'open'. Data on goal attainment were extracted for 131 different care coordination activities in the categories referral, education, coordination, screening, coaching, or other tasks, that were classified as met or otherwise. The BRIeF model was applied to assess behavioural responses at the individual patient and population levels. Covariates used in the model were demographic information (e.g., age and gender), care programme context (e.g., program experience and days in the program), and the interactions between care managers and patients (e.g., the day of making the recorded call). The authors described the results of the model as 'promising', with the individual-level care planning strategy showing the greatest accuracy in terms of correct intervention recommendations outperforming a population-level care planning approach, where the one-size-fits-all approach reduces precision.

Comparison or combination with clinical judgement

We identified six impactibility models that – either formally or informally – incorporated a healthcare provider's opinion of whether an individual patient was likely to benefit from a particular preventive health intervention.[16, 34-39] In one study, clinical judgement was applied as a final (filtering) step to estimate how care management would impact patients after they had undergone risk stratification by a predictive analytic tool.[40] A predictive tool calculated a risk score for emergency department visits in the next 12 months based on 19 variables. Physicians then added information on medical and social factors that could alter the impact of care management. This combined improved identification of higher-risk patients, reflected by an increase in the average risk score for patients enrolled in care management from 33.4% to 40.4%.

Cohen et al[41] designed a predictive model to identify patients who would benefit from proactive multimorbid care management based on inclusion and exclusion criteria refined from a physician survey of 375 cases and on risk of future high costs based on data extracted from a health services database. Recommended reasons for exclusion due to risk for future high costs were active cancer, schizophrenia, dialysis, residence in nursing homes or long-term care facilities, and age 95 years or older. The model was used to assess 5,341 high-risk patients. Discriminatory power of the model before and after clinical exclusions was c-statistic 0.80 and 0.75, respectively. Age, number of chronic conditions, and healthcare utilisation were associated with high-risk of high-cost care. The authors concluded that the model had acceptable discriminatory power for identifying who would benefit from proactive care management even after the highest-risk patients were excluded.

HCPs consider a range of factors when assessing an individual's suitability for a preventive health intervention. These include perceived hospitalisation risk; feelings of sympathy or aversion towards the patient; and a judgement of the patient's willingness and ability to participate in the intervention.[16, 38] HCPs also reported excluding patients from preventive healthcare interventions because of language barriers.[16]

Flaks-Manov et al[42] investigated whether risk scores for 30-day readmission from an electronic health records model were aligned with nurses' and physicians' perceived impactibility of a readmission prevention programme for hospitalized patients aged 65 years or older. The clinical and model decisions for 435 patients were concordant in 65% of cases. Among the remaining 35%, 19% with high model scores were not referred by healthcare professionals and 16% with low model scores were referred. Decision-tree analysis indicated that as well as high models scores, eligibility for a nursing home, having a condition not under control, need for social-services support and need for special equipment at home were statistically associated with referral. The authors concluded that better understanding is needed of whether combining perceptions and modelling could improve selection of patients.

Freund et al[43] assessed areas in which impactibility modelling might be helpful. They invited 12 primary-care physicians in ten practices to review records for 104 hospitalizations in 81 patients who had ACSCs and rate whether they felt each hospital admissions was avoidable. The doctors deemed 43 (41%) hospitalisations to be avoidable. Reasons fell into five main categories: system related (eg, unavailability of ambulatory services), physician related (eg, suboptimum monitoring), medical (eg, medication side effects), patient related (eg, delayed help-seeking), and social (eg, lack of social support). Further reasons were after-hours referral required in the absence of the treating physician, not using ambulatory services, patients' fears, cultural background, and language skills, medication errors, non-adherence to medication, and overprotective caregivers. In discussing implications for clinical practice and policy, it was recommended the risk stratification modelling would be enhanced by considering patients' social situation, medication adherence, and self-management capabilities and sharing responsibility across sectors.

Discussion

Key findings

As health systems turn to data-led approaches to deliver the triple aim of improving individuals' experience of care and the health of populations while reducing per capita care costs,[1] many are finding that allocating resources based on risk stratification alone is suboptimal. Targeting patients for preventive care based only on health conditions amenable to preventive care does not necessarily lead to reductions in resource use and might even increase it, and recognition is growing that these goals will only be met if treatment is successful. This is the impactibility gap. Thus, rather than trying to identify patients by negative outcomes (eg, high cost of care, most severe disease), the importance of identifying patients in whom care options will be most effective is being realised. The evidence reviewed shows varying attempts to make prediction tools more impactful and effective by considering the probability of success of interventions. PTS modelling showed some of the most promising results when broader information, such as sociodemographic factors, medication adherence, or previous programme engagement, was included. The accuracy of predicting behavioural responses seems to be most accurate at the individual level, but more data on real-world outcomes are needed, as implementation could affect PHM potential. Of note, there was some incongruence between modelling and HCP decisions, and better understanding is needed of how perceptions and data analysis affect one another.

Risk stratification versus impactibility

Risk stratification models may accurately predict which individuals are at risk of future adverse health outcomes,[2-5] allowing resources to be allocated. However, allocation is inefficient because not all patients will be amenable to the offered intervention. A stratum cutoff risks not allocating care to people with lower risk who would be amenable and achieve better outcomes that those at higher risk.[44] Additionally, since risk is deemed equal for all people within a stratum, resources are also allocated equally (**Figure 2A**) and those for patients who refuse or do not respond to treatment cannot be reallocated to patients who will respond. Therefore, opportunities to maximise care for the most amenable people will be missed. Impactibility modelling provides an extra layer of information that can help predict where, to whom, when, and how to target preventive resources and allow weighting of investment (time, resources, and costs) towards these individuals, which can improve efficiency. As shown in **Figure 2B**, the likelihood of success for a given intervention is not necessarily determined by risk level, and individuals amenable to a specific intervention, due to their 'impactibility', can be found throughout the stratified population.

Types of models considered

The models described in the literature fell into three key themes: "health conditions amenable to care", "PTS modelling", and "comparison or combination with clinical judgment". In the first theme, we found that changes in practice did not reduce hospital admissions and care, and sometimes increased them.[10, 18-20] It was suggested in one study that suggested although input on organisational change from modelling was well accepted, it was not well integrated.[21] 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.[21] Bardsley et al[10] showed that different ACSCs follow different trends, possibly even at the national or international level, which highlights the need to consider how the population for assessment should be selected.[6]

The PTS models assessed in this review included a wide range of clinical, social, and behavioural factors mainly assessed by logistic regression to assess in whom treatment had been most successful (see supplementary information pp 33–43). Repeatedly, the results underscored that considering the highest levels of risk and treatment costs did not equate to high impactibility. For example, Dubard et al 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.[31] PTS modelling generally led to improved accuracy in care planning, estimation of cost savings, engagement, and/or care quality improvements. These finding support moving away from delineated risk groups towards continuous risk predictions.[44]

The clinical judgment theme indicated that HCPs are routinely able to access real-time 'soft intelligence' about their patients that is not available to modellers.[43] However, this approach is subjective, involving perceptions at system, HCP, clinical, patient, and social levels,[16] 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 same information for two different patients might be affected by HCP sympathy or aversion, how well the patient is known, perceived patient characteristics or abilities (eg, willingness to participate, language skills, or cognitive status), and manageable care needs.[16] 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.[33]

Optimisation of impactibility modelling

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.[35, 45-48] The challenge for PHM, therefore, is to identify which intervention(s) 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 (**Figure 3**).

To optimise impactibility modelling, large amounts of data are needed on people's health behaviours, socioeconomic, clinical, and environmental status, and broader data where possible, such as genomic data. Many data are held by private companies but are not always accessible to or affordable for health system analysts. Completeness of data may affect modelling and, for example, are known to be less complete for people with higher levels of deprivation.[49] The different modelling approaches have various limitations and benefits (**Table 1**),[7, 16, 18-21, 23, 27-33, 35-38, 42, 50-53] which might further determine 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 objectiveness of decision-making in PHM.

Potential biases towards groups that are perceived as likely to respond well to treatment, which could exclude some of the most vulnerable groups, has been identified as an important potential limitation of using impactibility as a PHM tool.[6, 37, 53-56] Thus, it should be borne in mind that the purposes of considering impactibility PHM are to improve access and equity of care and avoid unnecessarily wasting resources on providing additional interventions that are costly and will not benefit the recipients. Resources should be directed towards closing gaps in the evidence[55] and using the knowledge to develop better-tailored approaches to more people, possibly in medium-risk and low-risk categories (**Figure 2**). 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,[57] 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.

To achieve the triple aim using predictive models will require those models to have broad insights on which to base predictions. Additionally, 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 they are less resource intensive to implement.

Study strengths and limitations

This study had several limitations. Interpreting and comparing the data was difficult due to widespread inconsistency in terminology. Even at the most basic level, "high-risk individuals" was conflated with "those most likely to benefit" in some papers[26, 58] despite evidence indicating that these can be highly separated groups.[5, 31, 42] The quality of the articles included in this review was not graded. However, as this is a growing area of interest and few studies are available, it is a strength of the study that we were as inclusive as possible. Owing to the substantial differences in approaches to categorising model outputs and in outcome measures and lack of reporting these in some studies, it was not possible to perform a quantitative analysis. Finally, in order to make the findings most applicable to PHM, we excluded studies of specific diseases. Of note, given the descriptive nature of this review, it was not registered and no protocol was published.

Conclusions

Impactibility builds on other key PHM concepts, such as risk stratification,[59] by assessing more qualitatively which people might benefit the most from certain health interventions and when proactive treatment might be appropriate (eg, preventive care before an adverse health event or a programme to prevent hospital readmission). It is important, to note that not all people requiring medical care have the potential to benefit from preventive interventions in a PHM sense. Nevertheless, although limited research is available so far, it seems that impactibility models can augment access to and equity of care when coupled with clinical insights and provide an opportunity to personalise preventive care delivery. Using this approach, it should be possible achieve the triple aims[1] – simultaneously improving the individual experience of care, improving the health of populations, and reducing the per capita costs of care for populations. PTS models seem to improve accuracy of selection patients amenable to care, but very few prospective or comparative outcome data from real-world settings are available, and this would be judicious to explore further. Potential confounding factors, such as model implementation, the effects of biases and prejudices, accuracy and availability of relevant data, should be included in these studies. Additionally, better understanding of why hospital admissions for ACSCs have not been reduced as much as anticipated would be beneficial. Disease-focussed applications will be the subject of our future research.

Author contributions

Andi Orlowski: conceptualisation, methodology, validation, formal analysis, writing – original draft, writing – review and editing. **Sally Snow**: methodology, formal analysis, data curation, writing – original draft, writing – review and editing. **Heather Humphreys**: formal analysis. **Wayne Smith**: formal analysis. **Rebecca Sian Jones**: methodology. **Rachel Ashton**: writing – review & editing. **Jackie Buck**: methodology. **Alex Bottle**: writing – review & editing.

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Data sharing statement

Data are available upon reasonable request.

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Patient and public involvements

It was not appropriate to involve patients or the public in the design, or conduct, or reporting, or dissemination plans of our research.

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Figure 1: PRISMA diagram

Figure 2: Use of impactibility modelling enhances identification of individuals most likely respond to preventive care and allows weighted resourcing

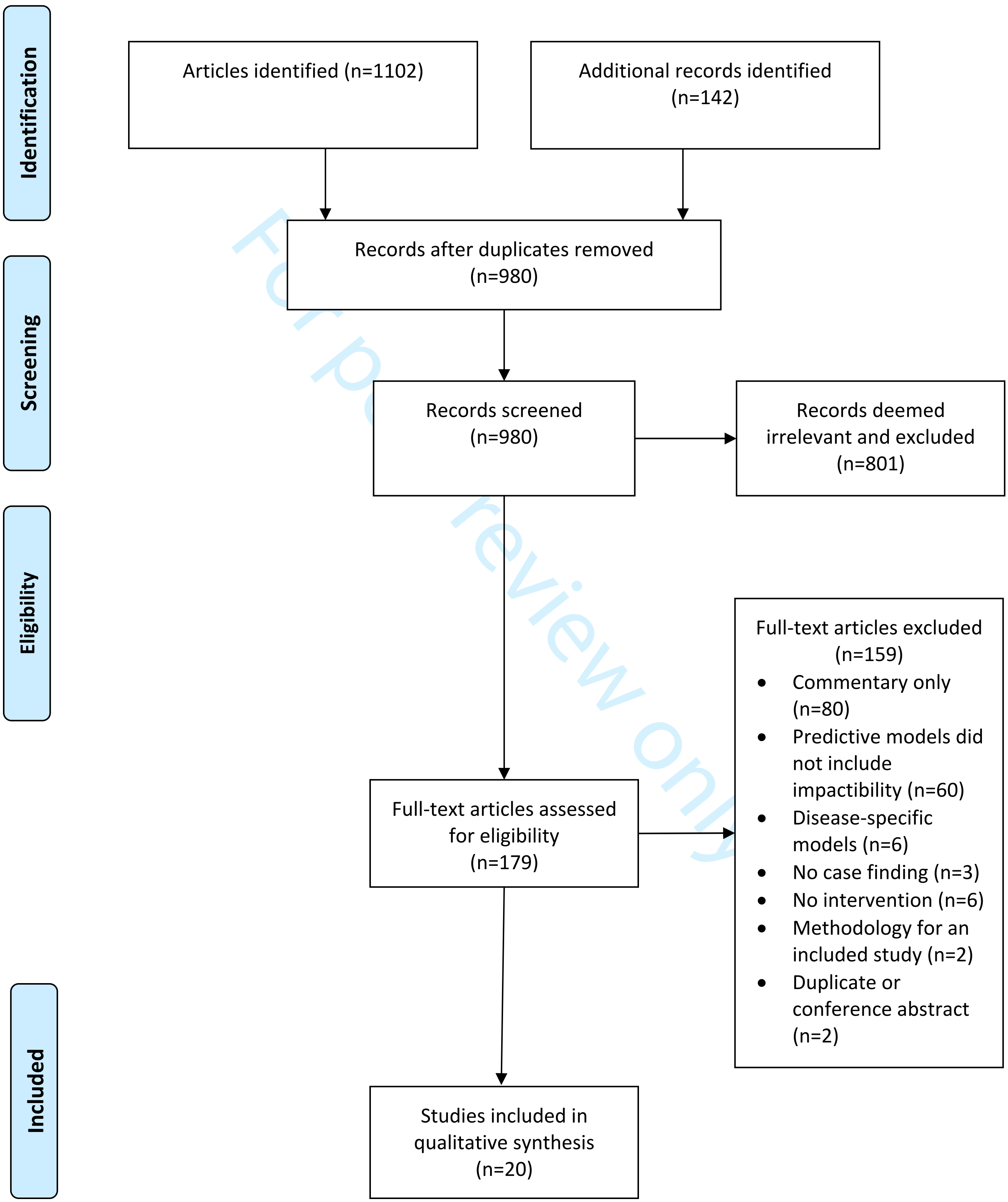
(A) Population with a given condition at risk of an outcome over a specific period of time, stratified by risk. (B) After impactibility analysis, different options can be targeted to the most amenable people. The numbers and positions of dots per intervention highlight that the likelihood of treatment success is not necessarily determined by risk level.

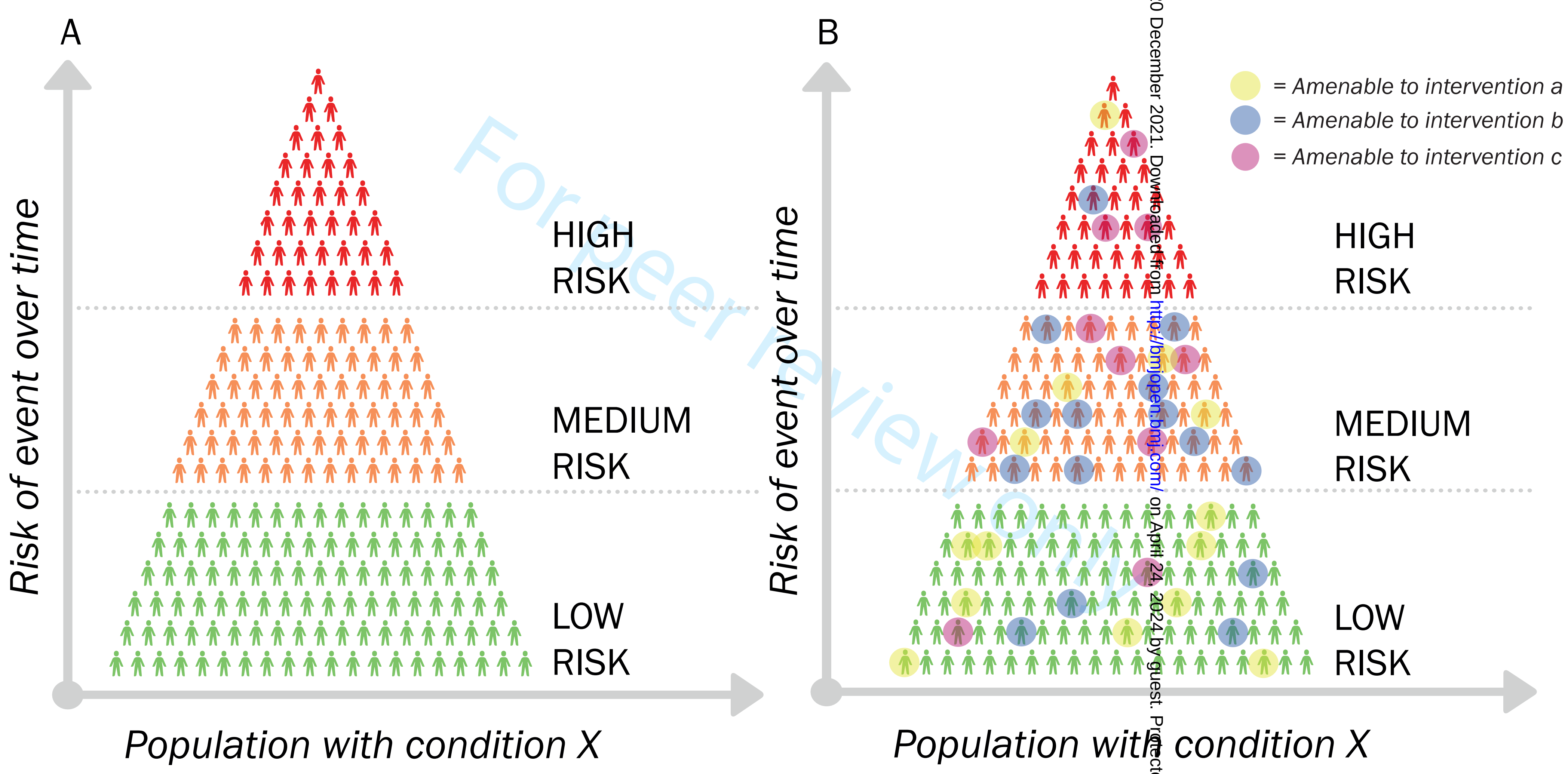
Figure 3: Use of impactibility modelling to increase the number of patients amenable to benefit

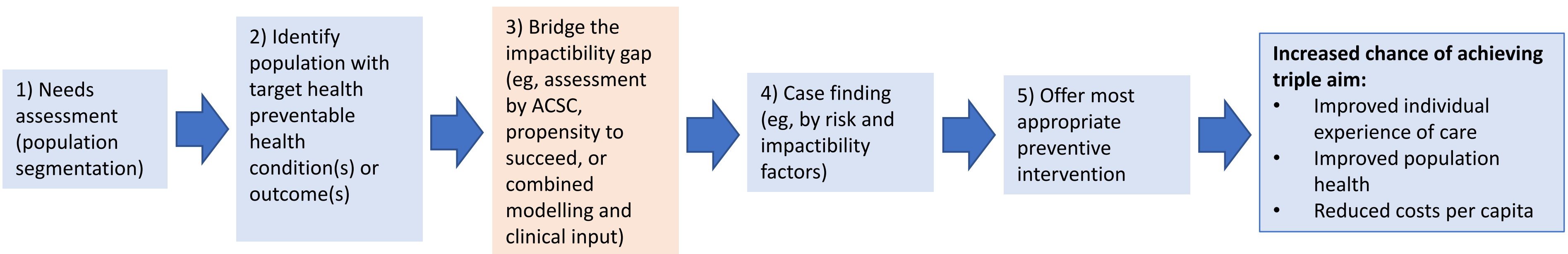
Table 1: Practical benefits and limitations of different approaches to determining impactibility

Approach	Benefits	Limitations
Health conditions amenable to preventive care (gap analysis)	• Diagnosis data are readily available[18-21, 23] • Programmes are relatively simple to model and implement[18-20, 23] • Widely available data can be used to identify specific, evidence-based and scalable actions to address gaps in care[50, 51] • May reduce inequalities, as preventable health conditions are more common in deprived communities[7]	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[6]
Propensity to succeed models, (behavioural response)	• Identifies groups where an intervention is/is not likely to provide benefit, thereby is designed to avoid wasting resources where they are of no benefit[27-32] • Care planning strategies are optimised at an individual and/or population level, based on previous behavioural responses to a range of potential interventions[33]	Models would be enhanced by including educational, behavioural, psychological, social, economic and/or health information,[42] 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[52, 53] • Health-care professionals may be able to predict future deterioration in "low risk" patients with relatively good current health status[36]	Highly resource intensive Relies on the quality and openness of the health-care-professional and patient relationship, and the ability of the data to capture this[16, 35-38] May perpetuate biases or prejudices[7]


Identification
Screening
Eligibility
Included
Articles identified (n=1102)
Additional records identified (n=142)
Records after duplicates removed (n=980)
Records screened (n=980)
Records deemed irrelevant and excluded (n=801)
Full-text articles excluded (n=159)
• Commentary only (n=80)
• Predictive models did not include impactibility (n=60)
• Disease-specific models (n=6)
• No case finding (n=3)
• No intervention (n=6)
• Methodology for an included study (n=2)
• Duplicate or conference abstract (n=2)
Full-text articles assessed for eligibility (n=179)
Studies included in qualitative synthesis (n=20)


A
Risk of event over time
HIGH
RISK
MEDIUM
RISK
LOW
RISK
Population with condition X
B
= Amenable to intervention a
= Amenable to intervention b
= Amenable to intervention c
Risk of event over time
HIGH
RISK
MEDIUM
RISK
LOW
RISK
Population with condition X


1) Needs assessment (population segmentation)
2) Identify population with target health preventable health condition(s) or outcome(s)
3) Bridge the impactibility gap (eg, assessment by ACSC, propensity to succeed, or combined modelling and clinical input)
4) Case finding (eg, by risk and impactibility factors)
5) Offer most appropriate preventive intervention
Increased chance of achieving triple aim:
Improved individual experience of care
Improved population health
Reduced costs per capita

APPENDIX

Appendix Table S1: List of search strings

Database: Ovid MEDLINE(R) ALL <1946 to May 14, 2020>
Search Strategy:
----
1 impact?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9)
2 'propensity to succeed'.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6)
3 interven?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (3)
4 case finding.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4937)
5 casefinding.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (86)
6 Patient selection.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (83162)
7 Patient Selection/ (64332)
8 target* patient*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2387)

9 (target* adj2 segment*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (947)
10 case selection.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1810)
11 risk stratif*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (32437)
12 (predict* adj3 risk factor*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (7856)
13 risk factors/ (815581)
14 protective factor*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (21359)
15 protective factors/ (4040)
16 (risk adj2 population*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (34671)
17 susceptible population?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2135)
18 Vulnerable Populations/ (10281)
19 (risk adj2 analy*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (26586)
20 risk assess*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (298996)

21 Risk Assessment/mt, sn [Methods, Statistics & Numerical Data] (33887)
22 risk segment*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (101)
23 Health Status Indicators/ (23314)
24 (characterist* adj4 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (19693)
25 (characterist* adj3 nonrespon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (118)
26 (care adj3 sensitiv*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2767)
27 (receptiv* adj3 care).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (60)
28 (Likel* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9537)
29 (Likel* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1021)
30 (Likel* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (9788)
31 (Likel* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (3232)
32 (Likel* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1163)
33 (Predict* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2225)
34 (Predict* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1508)
35 Predict* responder*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (192)
36 (Predict* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (13782)
37 (Probab* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (801)
38 (Probab* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (488)
39 (Probab* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6492)
40 (Probab* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2744)
41 (Probab* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1058)
42 (propensity adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (14)
43 (propensity adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (19)
44 (propensity adj2 respond*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (57)
45 (propensity adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (41)
46 (propensity adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (21)
47 (Potential* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (38647)
48 (Potential* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1341)
49 (Potential* adj2 respon*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (11907)
50 (Potential* adj2 succe*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2061)
51 (Potential* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (13813)
52 (Model* adj2 benefit*).mp. [mp=title, abstract, original title, name of substance word, subject heading word,

floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1163)

53 (Model* adj2 accept*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4006)

54 (Model* adj2 responder*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (71)

55 (Model* adj2 prevent*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (2359)

56 "Patient acceptance of health care"/ (46068)

57 (predict* adj3 model*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (118731)

58 Adverse Outcome Pathways/ (83)

59 Markov Chains/ (14167)

60 logistic* model*.mp. (143517)

61 logistic models/ (137961)

62 population model*.mp. (3652)

63 Patient-Specific Modeling/ (969)

64 patient specific model*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1904)

65 ambulatory care sensitive condition?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (561)

66 Hospitalization/ (105786)

67 Patient Admission/ (24023)

68 Patient Readmission/ (16915)

69 preventive medicine.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (16812)
70 Preventive Medicine/ (11679)
71 preventive health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (17200)
72 Primary Prevention/ (18315)
73 secondary prevention/ (20153)
74 (early adj3 intervention*).mp. (37091)
75 Early Medical Intervention/ (2939)
76 Target* health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1545)
77 Target* healthcare.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (160)
78 (Target* adj3 care*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (4252)
79 (prevent* adj3 intervention*).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (40728)
80 (care adj3 management).mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (26779)
81 population health*.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (12278)
82 Population Health/ (792)

83 Decision Support Systems, Clinical/ (7841)
84 Health Policy/ (65651)
85 Health* management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (6159)
86 System? management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1650)
87 Patient care management/ (4035)
88 Public Health/mt, og, sn [Methods, Organization & Administration, Statistics & Numerical Data] (5126)
89 public health*.mp. (319968)
90 public health administration/ (15359)
91 health service? management.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (411)
92 Models, Organizational/ (18878)
93 health care system?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (38577)
94 health* system?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (74494)
95 "Delivery of Health Care"/ (89529)
96 "Delivery of Health Care, Integrated"/ (12500)
97 Managed Care Programs/ (24211)
98 multidisciplinary service?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (204)
99 integrated service?.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept

word, rare disease supplementary concept word, unique identifier, synonyms] (1229)
100 amen?bility.mp. [mp=title, abstract, original title, name of substance word, subject heading word, floating sub-heading word, keyword heading word, organism supplementary concept word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms] (1110)
101 1 or 2 or 3 (18)
Annotation: Impactibility
102 4 or 5 (5020)
Annotation: Case finding
103 6 or 7 or 8 or 9 or 10 (88016)
Annotation: Patient selection
104 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 (1128808)
105 24 or 25 (19768)
Annotation: Characteristic response
106 26 or 27 (2827)
Annotation: Care sensitivity
107 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 or 56 (172438)
Annotation: Likeli to benefit
108 57 or 58 or 59 or 60 or 61 or 62 or 63 or 64 (275227)
109 65 or 66 or 67 or 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 (251550)
Annotation: Preventive healthcare
110 80 or 81 or 82 or 83 or 84 or 85 or 86 or 87 or 88 or 89 or 90 or 91 or 92 or 93 or 94 or 95 or 96 or 97 or 98 or 99 (614599)
Annotation: Population health management
111 109 and 110 (25971)
Annotation: Preventive health and population health management
112 109 or 110 (840178)
Annotation: Preventive healthcare or population health management
113 100 and 112 (27)
114 107 or 108 (439630)

115 102 and 114 (325)
116 111 and 115 (7)
117 103 and 114 (5324)
118 111 and 117 (35)
119 104 and 107 and 108 and 111 (26)
120 105 and 114 (975)
121 112 and 120 (84)
122 106 and 114 (278)
123 111 and 122 (39)
124 102 and 112 and 114 (102)
125 101 or 113 or 124 or 118 or 119 or 121 or 123 (329)

Database: HMIC Health Management Information Consortium <1979 to March 2020>
Search Strategy:
----
1 impact?bility.mp. [mp=title, other title, abstract, heading words] (1)
2 'propensity to succeed'.mp. [mp=title, other title, abstract, heading words] (0)
3 interven?bility.mp. [mp=title, other title, abstract, heading words] (0)
4 case finding.mp. [mp=title, other title, abstract, heading words] (201)
5 casefinding.mp. [mp=title, other title, abstract, heading words] (3)
6 screening/ (3706)
7 Patient selection.mp. [mp=title, other title, abstract, heading words] (93)
8 Patient selection/ (47)
9 target* patient*.mp. [mp=title, other title, abstract, heading words] (81)
10 (target* adj2 segment*).mp. [mp=title, other title, abstract, heading words] (6)
11 case selection.mp. [mp=title, other title, abstract, heading words] (16)
12 (risk adj2 population*).mp. [mp=title, other title, abstract, heading words] (516)
13 exp "Risk adjusted monitors of outcome"/ (20)
14 exp vulnerability/ (1261)
15 susceptible population*.mp. [mp=title, other title, abstract, heading words] (10)

16 risk stratif*.mp. [mp=title, other title, abstract, heading words] (106)
17 (predict* adj3 risk factor*).mp. [mp=title, other title, abstract, heading words] (55)
18 risk factors/ (4430)
19 protective factor*.mp. [mp=title, other title, abstract, heading words] (144)
20 (risk adj2 analy*).mp. [mp=title, other title, abstract, heading words] (238)
21 risk assess*.mp. [mp=title, other title, abstract, heading words] (2572)
22 risk assessment/ (1859)
23 risk segment*.mp. [mp=title, other title, abstract, heading words] (1)
24 (characterist* adj4 respon*).mp. [mp=title, other title, abstract, heading words] (163)
25 (characterist* adj3 nonrespon*).mp. [mp=title, other title, abstract, heading words] (0)
26 (care adj3 sensitiv*).mp. [mp=title, other title, abstract, heading words] (196)
27 (receptiv* adj3 care).mp. [mp=title, other title, abstract, heading words] (1)
28 (Likel* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (183)
29 (Likel* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (38)
30 (Likel* adj2 respon*).mp. [mp=title, other title, abstract, heading words] (72)
31 (Likel* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (105)
32 (Likel* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (22)
33 (Predict* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (26)
34 (Predict* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (11)
35 Predict* responder*.mp. [mp=title, other title, abstract, heading words] (1)
36 (Predict* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (78)
37 (Probab* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (19)
38 (Probab* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (5)
39 (Probab* adj2 respon*).mp. [mp=title, other title, abstract, heading words] (19)
40 (Probab* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (10)
41 (Probab* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (10)
42 (propensity adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (0)
43 (propensity adj2 accept*).mp. [mp=title, other title, abstract, heading words] (0)
44 (propensity adj2 respon*).mp. [mp=title, other title, abstract, heading words] (4)
45 (propensity adj2 succe*).mp. [mp=title, other title, abstract, heading words] (0)

46 (propensity adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (1)
47 (Potential* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (882)
48 (Potential* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (23)
49 (Potential* adj2 respon*).mp. [mp=title, other title, abstract, heading words] (46)
50 (Potential* adj2 succe*).mp. [mp=title, other title, abstract, heading words] (49)
51 (Potential* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (186)
52 (Model* adj2 benefit*).mp. [mp=title, other title, abstract, heading words] (41)
53 (Model* adj2 accept*).mp. [mp=title, other title, abstract, heading words] (40)
54 (Model* adj2 responder*).mp. [mp=title, other title, abstract, heading words] (1)
55 (Model* adj2 prevent*).mp. [mp=title, other title, abstract, heading words] (75)
56 (predict* adj3 model*).mp. [mp=title, other title, abstract, heading words] (554)
57 exp Decision Support Systems/ (218)
58 logistic* model*.mp. (74)
59 population model*.mp. (22)
60 exp Computer aided decision making/ (29)
61 exp models/ (3243)
62 patient specific model*.mp. (0)
63 ambulatory care sensitive condition?.mp. [mp=title, other title, abstract, heading words] (45)
64 exp Ambulatory care/ (914)
65 exp Pre hospital care/ (49)
66 exp hospital admission/ (3371)
67 exp Hospitalisation/ (7032)
68 exp Health impact assessment/ (360)
69 exp Preventive Medicine/ (21451)
70 preventive medicine.mp. [mp=title, other title, abstract, heading words] (2305)
71 exp preventive medicine health services/ (210)
72 preventive health*.mp. [mp=title, other title, abstract, heading words] (228)
73 exp Health improvement programmes/ (237)
74 prevention/ (5896)
75 (early adj3 intervention*).mp. (749)

76 early intervention/ (0)
77 Target* health*.mp. [mp=title, other title, abstract, heading words] (120)
78 Target* healthcare.mp. [mp=title, other title, abstract, heading words] (12)
79 (Target* adj3 care*).mp. [mp=title, other title, abstract, heading words] (364)
80 (prevent* adj3 intervention*).mp. [mp=title, other title, abstract, heading words] (1001)
81 (care adj3 management).mp. [mp=title, other title, abstract, heading words] (2858)
82 population health*.mp. [mp=title, other title, abstract, heading words] (1085)
83 exp care management/ (500)
84 exp health policy/ (5647)
85 Health* management.mp. [mp=title, other title, abstract, heading words] (505)
86 System? management.mp. [mp=title, other title, abstract, heading words] (79)
87 public health*.mp. (16612)
88 exp public health/ (11196)
89 exp Health systems/ (44916)
90 health service? management.mp. [mp=title, other title, abstract, heading words] (5830)
91 health care system?.mp. [mp=title, other title, abstract, heading words] (3136)
92 health* system?.mp. [mp=title, other title, abstract, heading words] (7548)
93 multidisciplinary service?.mp. [mp=title, other title, abstract, heading words] (555)
94 integrated service?.mp. [mp=title, other title, abstract, heading words] (329)
95 amen?bility.mp. [mp=title, other title, abstract, heading words] (2)
96 1 or 2 or 3 (1)
Annotation: Impactibility
97 4 or 5 or 6 (3859)
Annotation: Case finding
98 7 or 8 or 9 or 10 or 11 (195)
Annotation: Patient selection
99 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 (8794)
Annotation: Risk stratification
100 24 or 25 (163)
Annotation: Characteristic response

101 26 or 27 (197)
Annotation: Care sensitivity
102 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 (1906)
Annotation: Likelihood of benefit
103 56 or 57 or 58 or 59 or 60 or 61 or 62 (4005)
Annotation: Modelling
104 63 or 64 or 65 or 66 or 67 or 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 77 or 78 or 79 or 80 (35800)
Annotation: Preventive health
105 81 or 82 or 83 or 84 or 85 or 86 or 87 or 88 or 90 or 91 or 92 or 93 or 94 (38931)
Annotation: Population health management
106 104 or 105 (69322)
107 104 and 105 (5409)
108 102 or 103 (5838)
109 97 and 108 (119)
110 106 and 109 (38)
111 98 and 108 (8)
112 99 and 108 (313)
113 107 and 112 (6)
114 100 and 108 (9)
115 101 and 108 (17)
116 95 or 96 or 110 or 111 or 113 or 114 or 115 (79)

Ovid Technologies, Inc. Email Service

Search for: 84 or 96 or 99 or 100 or 102 or 104 or 105

Results: 163

Database: Global Health <1973 to 2020 Week 18>
Search Strategy:
----
1 impact?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (4)
2 'propensity to succeed'.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1)
3 interven?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (0)
4 case finding.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1946)
5 casefinding.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (5)
6 Patient selection.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (611)
7 target* patient*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (283)
8 (target* adj2 segment*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (144)
9 case selection.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (88)
10 (risk adj2 population*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (11708)
11 susceptible population*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1174)
12 risk stratif*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2127)
13 (predict* adj3 risk factor*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1472)
14 protective factor*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (6071)
15 exp protective factors/ (279)
16 (risk adj2 analy*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (10280)
17 exp risk analysis/ (58968)

18 risk assess*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (63092)
19 risk segment*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (19)
20 (characterist* adj4 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2195)
21 (characterist* adj3 nonrespon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (18)
22 (care adj3 sensitiv*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (447)
23 (receptiv* adj3 care).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (10)
24 (Likel* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (982)
25 (Likel* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (281)
26 (Likel* adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1060)
27 (Likel* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (413)
28 (Likel* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (236)
29 (Predict* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (138)
30 (Predict* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (292)
31 Predict* responder*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (8)
32 (Predict* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1054)
33 (Probab* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (108)

34 (Probab* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (74)
35 (Probab* adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (800)
36 (Probab* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (198)
37 (Probab* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (183)
38 (propensity adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (0)
39 (propensity adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2)
40 (propensity adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (19)
41 (propensity adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (3)
42 (propensity adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (3)
43 (Potential* adj benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (4703)
44 (Potential* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (267)
45 (Potential* adj2 respon*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1196)
46 (Potential* adj2 succe*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (302)
47 (Potential* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (3556)
48 (Model* adj2 benefit*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (185)

49 (Model* adj2 accept*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (500)
50 (Model* adj2 responder*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (5)
51 (Model* adj2 prevent*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (619)
52 (predict* adj3 model*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (16099)
53 logistic* model*.mp. (2180)
54 population model*.mp. (497)
55 patient specific model*.mp. (4)
56 exp mathematical models/ (20591)
57 ambulatory care sensitive condition?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (133)
58 exp hospital admission/ (7087)
59 exp Preventive Medicine/ (5152)
60 preventive medicine.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (6066)
61 preventive health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (1554)
62 prevention/ (24792)
63 (early adj3 intervention*).mp. (4352)
64 early intervention/ (0)
65 Target* health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (727)
66 Target* healthcare.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (44)
67 (Target* adj3 care*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (808)
68 (prevent* adj3 intervention*).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers,

cabicodes] (13708)
69 (care adj3 management).mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2707)
70 population health*.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (4811)
71 exp health policy/ (21123)
72 Health* management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (2399)
73 System? management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (295)
74 public health*.mp. (263888)
75 exp public health/ (114710)
76 exp public health services/ (5031)
77 health service? management.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (79)
78 health care system?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (7683)
79 health* system?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (22197)
80 multidisciplinary service?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (27)
81 integrated service?.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (314)
82 amen?bility.mp. [mp=abstract, title, original title, broad terms, heading words, identifiers, cabicodes] (96)
83 animal*.mp. (2706683)
84 1 or 2 or 3 (5)
Annotation: Impactibility
85 4 or 5 (1950)
Annotation: Case finding
86 6 or 7 or 8 or 9 (1121)

Annotation: Patient selection
87 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 (90642)
Annotation: Risk stratification
88 20 or 21 (2208)
Annotation: Characteristic response
89 22 or 23 (457)
Annotation: Care sensitivity
90 24 or 25 or 26 or 27 or 28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 (16886)
Annotation: Likelihood benefit
91 52 or 53 or 54 or 55 or 56 (35958)
Annotation: Model
92 57 or 58 or 59 or 60 or 61 or 62 or 63 or 65 or 66 or 67 or 68 (56126)
Annotation: Preventive
93 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 or 79 or 80 or 81 (299016)
Annotation: Population
94 92 and 93 (8599)
95 92 or 93 (346543)
96 82 and 95 (15)
97 90 or 91 (52153)
98 85 and 97 (58)
99 95 and 98 (20)
100 86 and 97 (41)
101 87 and 97 (3893)
102 94 and 101 (42)
103 88 and 97 (82)
104 95 and 103 (17)
105 89 and 97 (25)
106 84 or 96 or 99 or 100 or 102 or 104 or 105 (163)

Ovid Technologies, Inc. Email Service

Search for: 104 or 116 or 118 or 121 or 123 or 125 or 128

Results: 320

Database: Embase Classic+Embase <1947 to 2020 May 14>
Search Strategy:
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1 impact?bility.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (12)
2 'propensity to succeed'.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (7)
3 interven?bility.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (2)
4 case finding.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (8308)
5 casefinding.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (200)
6 case finding/ (4164)
7 Patient selection.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (106833)
8 Patient selection/ (93046)
9 target* patient*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (4078)
10 (target* adj2 segment*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1381)
11 case selection.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug

manufacturer, device trade name, keyword, floating subheading word, candidate term word] (2699)
12 (risk adj2 population*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (170420)
13 high risk population/ (121003)
14 vulnerable population/ (16512)
15 susceptible population/ (1056)
16 risk stratif*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (58670)
17 (predict* adj3 risk factor*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (12148)
18 risk factor/ (1025885)
19 protective factor*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (24469)
20 protection/ (67132)
21 susceptible population*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3245)
22 risk stratif*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (58670)
23 (risk adj2 analy*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (95347)
24 risk assess*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (585434)
25 risk assessment/ (558053)
26 risk segment*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (137)
27 (characterist* adj4 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (26743)
28 (characterist* adj3 nonrespon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (147)
29 (care adj3 sensitiv*).mp. [mp=title, abstract, heading word, drug trade name, original title, device

manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3472)
30 (receptiv* adj3 care).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (85)
31 (Likel* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (14595)
32 (Likel* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1390)
33 (Likel* adj2 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (14021)
34 (Likel* adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (4394)
35 (Likel* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1613)
36 (Predict* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3898)
37 (Predict* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1966)
38 Predict* responder*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (385)
39 (Predict* adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (19014)
40 (Probab* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1190)
41 (Probab* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (648)
42 (Probab* adj2 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (8877)
43 (Probab* adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3579)
44 (Probab* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device

manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1538)
45 (propensity adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (21)
46 (propensity adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (21)
47 (propensity adj2 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (141)
48 (propensity adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (67)
49 (propensity adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (26)
50 (Potential* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (53571)
51 (Potential* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1587)
52 (Potential* adj2 respon*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (15605)
53 (Potential* adj2 succe*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (2679)
54 (Potential* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (18959)
55 (Model* adj2 benefit*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1562)
56 (Model* adj2 accept*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (4879)
57 (Model* adj2 responder*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (144)
58 (Model* adj2 prevent*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (3286)
59 (predict* adj3 model*).mp. [mp=title, abstract, heading word, drug trade name, original title, device

manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (155268)
60 adverse outcome pathway/ (358)
61 logistic* model*.mp. (11456)
62 population model*.mp. (10416)
63 information model/ (253)
64 process model/ (8488)
65 population model/ (7092)
66 markov chain/ (5170)
67 patient specific model*.mp. (1434)
68 ambulatory care sensitive condition?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (687)
69 ambulatory care/ (38902)
70 hospital readmission/ (62928)
71 hospital admission/ (194263)
72 hospitalization/ (376388)
73 hospital utilization/ (2228)
74 Preventive Medicine/ (28102)
75 preventive medicine.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (34859)
76 preventive health*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (33684)
77 preventive health service/ (28680)
78 prevention/ (283203)
79 (early adj3 intervention*).mp. (64519)
80 early intervention/ (24768)
81 Target* health*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1919)
82 Target* healthcare.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (213)
83 (Target* adj3 care*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer,

drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (6204)
84 (prevent* adj3 intervention*).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (52335)
85 (care adj3 management).mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (62219)
86 population health*.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (14536)
87 population health management/ (117)
88 health care policy/ (192062)
89 population health/ (2476)
90 Health* management.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (7921)
91 System? management.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (959)
92 public health*.mp. (457567)
93 public health/ (187251)
94 public health service/ (74031)
95 health service? management.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (538)
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97 integrated health care system/ (11078)
98 health* system?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (103788)
99 multidisciplinary service?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (406)
100 integrated service?.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1673)
101 safety net hospital/ (2077)
102 amen?bility.mp. [mp=title, abstract, heading word, drug trade name, original title, device manufacturer, drug

manufacturer, device trade name, keyword, floating subheading word, candidate term word] (1356)
103 animal*.mp. (6389036)
104 1 or 2 or 3 (21)
Annotation: Impactibility
105 4 or 5 or 6 (8461)
Annotation: Case finding
106 7 or 8 or 9 or 10 or 11 (114598)
Annotation: Patient selection
107 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 (1764975)
Annotation: risk
108 27 or 28 (26841)
Annotation: Characteristic response
109 29 or 30 (3557)
Annotation: Care sensitivity
110 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 or 46 or 47 or 48 or 49 or 50 or 51 or 52 or 53 or 54 or 55 or 56 or 57 or 58 (176187)
Annotation: Likelihood of benefit
111 59 or 60 or 61 or 62 or 63 or 64 or 65 or 66 or 67 (189338)
Annotation: Predictive modelling
112 68 or 69 or 70 or 71 or 72 or 73 or 74 or 75 or 76 or 77 or 78 or 79 or 80 or 81 or 82 or 83 or 84 (1060770)
Annotation: Preventive healthcare
113 85 or 86 or 87 or 88 or 89 or 90 or 91 or 92 or 93 or 95 or 96 or 97 or 98 or 99 or 100 or 101 (840792)
114 112 or 113 (1821615)
115 112 and 113 (79947)
116 102 and 114 (51)
117 107 and 110 and 111 (877)
118 115 and 117 (30)
119 110 or 111 (360103)
Annotation: likely benefit or modelling
120 109 and 119 (192)

121	115 and 120 (37)
122	108 and 119 (948)
123	114 and 122 (66)
124	106 and 119 (4043)
125	115 and 124 (52)
126	105 and 119 (166)
127	115 and 126 (9)
128	105 and 114 and 119 (67)
129	104 or 116 or 118 or 121 or 123 or 125 or 128 (320)

Appendix Table S2: Full inclusion and exclusion criteria

		Yes	No
1	Does the title or abstract talk about amenability?	Continue	Go to 3
2	Is the paper about youth offending or amenability of specific diseases to treatment?	Exclude/STOP	Go to 4
3	Does the title or abstract talk about impactibility/ intervenability or 'propensity to succeed' modelling in a population health context?	Include/STOP	Continue
4	Is there an intervention that aims to prevent or ameliorate a future health event?	Continue	Exclude/STOP
6	Is the intervention solely aiming to increase screening programme detection rates?	Exclude/STOP	Continue
7	Does the study include case finding or selection of potential responders from the wider population?	Continue	Exclude/STOP
8	Is modelling limited to identifying subjects at 'high risk' of a disease or health event?	Exclude/STOP	Continue

9	Does the extended modelling identify subjects who may respond better to the intervention?	Include/STOP	Continue
10	Does the extended modelling identify subjects who are more likely to start and complete the intervention?	Include/STOP	Exclude/STOP

INCLUSION

- Papers that include Impactibility OR intervenability OR 'propensity to succeed' modelling OR Amenability in a population health context

OR

- Studies that include ALL of:
  1) an intervention that aims to prevent or ameliorate a future health event
  AND
  2) case finding OR selection of potential responders from the general population
  AND
  3) extended modelling that identifies subjects who may respond better to the intervention OR extended modelling that identifies subjects who are more likely to start and complete the intervention

EXCLUSION

- Amenability AND youth offending
- Amenability of specific diseases to treatment
- Modelling limited to identifying subjects at 'high risk' of a disease or health event
- Intervention solely aiming to increase diagnoses or screening programme detection rates

Definitions:

Case finding: a systematic or opportunistic process that identifies individuals (e.g. people with COPD) from a larger population for a specific purpose for example, 'Flu vaccination'
https://www.england.nhs.uk/wp-content/uploads/2015/01/2015-01-20-CFRS-v0.14-FINAL.pdf

Intervention: A health intervention is an act performed for, with or on behalf of a person or population whose purpose is to assess, improve, maintain, promote or modify health, functioning or health conditions. https://www.who.int/classifications/ichi/en/

In medical terms this could be a drug treatment, surgical procedure, diagnostic test or psychological therapy. Examples of public health interventions could include action to help someone to be physically active or to eat a more healthy diet. Examples of social care interventions could include safeguarding or support for carers.
https://www.nice.org.uk/Glossary?letter=I

Appendix Table S3: Google search string

# results (2 November 2020)	
207	("impactability" OR "impactibility") AND (site:nhs.uk OR site:cdc.gov OR site:.ac.uk OR site:.gov.uk OR site:.edu OR site:.gov OR site:.ac.au OR site:.ac.ca OR site:elsevier.com OR site:researchgate.net) AND "case finding" AND (guide OR protocol OR process OR method)

Appendix Table S4: Studies of the development, validation or application of impactibility models included in the qualitative synthesis

Study Name/Ref			Population studied	Impactibility model	Results/author conclusions
Impactibility determined by presence of a health condition amenable to preventive intervention					
Buja et al. 2019	**Country**	Italy (Azienda ULSS4-Veneto local health unit)	Patients over 65 years, residing in the area served by. All patients had heart failure and "complex health care needs", as defined by Resource Utilization Band 4 or 5 (respectively high morbidity or very high morbidity) out of 5.	"Impactibility model" based on ACG created by identifying homogenous clinical subgroups of patients with **a high risk of at least 1 "preventable admission**" that may be addressed using case management	No statistical difference between algorithm and ACG risk scores. This will help policy makers develop ''tool kits'' for homogeneous groups of patients that improve health outcomes.
	Data source	Routinely collected administrative data			
	Aims	Case management by development of an impactibility model			
	Outcomes and measures	Predictive performance of algorithm to identify common sets of diseases most predictive for hospital admission or readmission compared with ACG risk scores.			
Guthrie et al. 2017	**Country**	UK	Patients with ACSCs who had "psychosocial risk factors for increased use of unscheduled care", including recent use of unscheduled care, depression, living alone or social stressors.	ACSC diagnosis	Depression was an important factor in unscheduled care use. However, there was no evidence that this intervention impacted unscheduled care as patients and HCPs seem unaware or unlikely to acknowledge the role of psychosocial factors and integration of tools might not have been complete.
	Data source	CHOICE: Choosing Health Options In Chronic Care Emergencies			
	Aims	Assess relationship between psychological morbidity and use of unscheduled care in people with long-term conditions by a literature review and prospective study of care use to develop a targeted intervention.			
	Outcomes and measures	Identification of factors that could reduce use of unscheduled care.			
McCormick 2012	**Country**	USA	Patients with cardiovascular ACSCs (congestive heart failure, angina, hypertension)	ACSC diagnosis	ACSC hospitalisations increased more in the intervention group than the control group over the intervention period.
	Data source	Acute hospital admission data			

	Aims	Difference-in-differences analysis of the impact of healthcare reforms aimed at improving access to care and coverage for preventable ACSCs.			Therefore the intervention did not decrease the risk of avoidable hospitalisations.
	Outcomes and measures	Hospital admission rates before and after reform versus control states without changes			
Steventon et al. 2012	**Country**	UK	Patients aged 18 and over with a diagnosis of COPD, diabetes, or heart failure, based on QOF register or confirmed diagnosis based on GP records or confirmation of disease status by a local clinician. Patients were not excluded for any other reasons	ACSC diagnosis	Logistic regression showed that telehealth was associated with lower hospital (OR 0.82, 95% CI 0.70–0.97, p=0.017) and Emergency (0.81, 0.65–1.00, p=0.046) admission rates and mortality (0.54, 0.39–0.75, p<0.001).
	Data source	HES data for England, mortality, (May 2008 to November 2009)			
	Aims	Assess the effects of home-based telehealth interventions			
	Outcomes and measures	Reductions in admission to hospital and mortality over 12 months versus usual care			
Steventon et al. 2013	**Country**	UK	Inclusion was restricted to patients with a recorded diagnosis of COPD, CHF, coronary heart disease or diabetes; a minimum level of disease severity in the past 15 months; age 18 or older; ability to communicate on the telephone; a recorded address and practice registration. Patients also had a history of inpatient or outpatient hospital use.	ACSC diagnosis augmented with clinical judgement of which patients were likely to benefit	Logistic regression showed that telephone health coaching intervention did not lead to the expected reductions in hospital admissions or secondary care costs over 12 months and could have led to increases.
	Data source	Primary care data (not specified)			
	Aims	Assess the effects of a personalised telephone health coaching service			
	Outcomes and measures	Reductions in number of emergency hospital admissions, hospital bed days, elective hospital admissions, outpatient attendances, and secondary care costs over 12 months versus usual care			
Steventon et al. 2016	**Country**	UK	Patients with ACSCs including COPD, CHF, and diabetes	ACSC diagnosis	Logistic regression showed that the telehealth intervention may have led to increased risk of emergency admission or death (adjusted HR 1.34, 95% CI 1.16–1.56,
	Data source	Hospital administrative data and linked telehealth referral data			
	Aims	Assess the effects of home-based telehealth management of existing			

		conditions by a monitoring centre in a rural setting			p<0.001). Authors recommend investing resources in other forms of preventive care for which an evidence base exists
	Outcomes and measures	Changes in time to first emergency hospitalisation or death versus usual care			
		Impactibility based on PTS			
Dubard et al. 2018	**Country**	USA (North Carolina)	Medicaid beneficiaries who received some level of care management support and had at least 1 potentially preventable admission, readmission or ED visit in the year prior to initiation of case management. Patients were considered to have received care management support if they had at least 1 direct encounter with a care manager by phone or face to face.	Impactibility score developed using linear regression analysis. Independent variables: • Age, sex, race, ethnicity, disability status, foster care status • ED visit count, inpatient visit count • CRG weight • Presence of specific chronic conditions • Number of chronic conditions • Number of chronic medications filled • Number of acute medications filled • Total cost of care Derived variables include: • "Above expected potentially preventable costs" (AEPPC), which includes costs related to potentially preventable	Model variables related to medication adherence and historical utilization unexplained by disease burden were more important predictors of impactibility than any given diagnosis or event, disease profile, or overall costs of care. Impactibility based targeting could lead to two to three times greater return on investment that risk stratification by high ED use or inpatient admissions and high-risk disorders This study helps highlight the difference between "high-frequency/high-cost" users and "highly impactible" users, noting that there's a real difference between the two groups which makes traditional algorithms unhelpful.
	Data source	Administrative data available for the whole population (January 2010-May 2017) including eligibility and enrolment files; Medical and pharmacy claims paid by Medicaid and encounter claims from all managed care organisations; Disease burden categorised by hierarchical Clinical Risk Group (CRG)			
	Aims	Development of an impactibility score to estimate intervention effects and achievable savings for community-based care management			
	Outcomes and measures	Multivariable modelling including costs various risk stratification strategies to build a predictive model of expected cost savings versus usual care			

				admissions, readmissions and ED visits • Monthly spending trajectory over the most recent 12 months • 2 indicators of adherence to chronic medications	
Hawkins et al. 2015	**Country**	USA (pilots in California, Florida, New York, North Carolina and Ohio)	Individuals with Medicare Supplement plans with multiple chronic health conditions who may benefit from additional care coordination and ancillary support. Patients are referred either directly from a provider or Nurse HealthLine, or data-driven referrals based on Hierarchical Condition Category risk score >3.74.	PTS model based on logistic regression. Independent variables included: • dates and locations of service • indicators of the types of services, drugs, and procedures provided • AmeriLINK Data Sourcing system (generated by the KBM Group) to find information about socioeconomic status • Local supply of health care services in areas where qualified members lived was derived from the Dartmouth Atlas of Healthcare	The score significantly improved the ability to identify patients most likely to engage with treatment and succeed (predicted success rate 0.761, 95% CI 0.754–0.764) and financial success probabilities (0.697, 0.665–0.707), but not quality of care. The validated score helped to prioritise outreach to efforts to maximise programme engagement and savings. “Using PTS models may help increase program engagement and financial success of care coordination programs.”
	Data sources	United Healthcare (AARP Medicare Supplement plan provider) December 2008-December 2011.			
	Aims	Develop and validate a PTS score to support a high-risk-case management programme			
	Outcomes and measures	Identify among programme members those most likely to: 1) engage with the programme (yes/no) 2) receive the highest quality of care (meeting 70% or more of the relevant clinical care guidelines) and cost savings associated with the HRCM program			
Hommer et al. 2013	**Country**	USA	Patients with depressive symptoms measured by PHQ-9 and AARP Medigap supplement insurance.	PTS model based on characteristics of “engaged patients” compared with qualified but non-engaged patients.	The score enabled more efficient utilisation of health resources by refining targeting and outreach efforts to those
	Data source	United Healthcare (AARP Medicare Supplement plan provider) combined			

		with inferred sociodemographic data (Dec 2009-Dec 2010)		Predictors of outcomes of interest included: • patient demographics • plan type • location • participation in other programmes • health status measures • various supply side measures	most likely to be successful in the programme.
	Aims	Develop and validate a PTS score to support a depression management programme			
	Outcomes and measures	Changes in identification of patients likely to engage, individual-level costs (ROI >1) and health-care quality outcomes (hospital readmission, EBM metrics)			
Hsueh et al. 2018	**Country**	USA	Review of records of patients recently discharged from an acute hospital admission and assigned to a transitional care programme with the objective of reducing hospital admissions.	Goal attainment factors assessed by logistic regression include: • demographics (age, gender) • patient care programme context (programme experience, days in the programme) • interactions between care managers and patients (day of call) and fivefold cross validation on the task of predicting whether a goal would be achieved given the recommended intervention	Accuracy for goal attainment was greatest at the individual level (87.24%), outperforming population-level strategies (85.70%), and no planning (28.98%). "Increased patient behavioral understanding could potentially benefit augmented intelligence for care management decision support"
	Data source	The GOAL dataset: care management records from a private not-for-profit healthcare network (Jan 2016 to Feb 17)			
	Aims	Develop models of conditional probability distributions for individual-level effect estimation to enable recognition of behavioural responses that could affect care planning			
	Outcomes and measures	Improved likelihood of goal attainment, categorised as: education (e.g., post-discharge understanding); medication (e.g., adherence); reducing risk (e.g., resolve care gaps); self-care (e.g., heart failure home self-management); implementation (e.g. installing fall prevention facility), and others (e.g., obtaining accurate patient information) in an observational data set.			
Mattie et al. 2019	**Country**	USA		A random forest machine learning model to	The impactibility model reached an overall

	Data source	Anonymised insurance claims data (June 2015 to May 2018) combined with inferred sociodemographic and patient-generated data	Commercially insured, "low-risk" (not defined) population	categorise new patients as impactable versus not impactable based on cost savings with vs without a digital health intervention. The model was based on: • Administrative claims data • Age • Education level, employment status, income and poverty status inferred from zip code • Data derived from a patient-held mobile application.	accuracy of 71.9% (sensitivity 0.77 and specificity of 0.65) and is generalisable to assess the impactibility of any intervention. "This demonstrates the potential to successfully target, based on impactibility, lower risk members of the population with a digital health intervention.
	Aims	Develop machine learning models to identify patients most likely to benefit from a digital health intervention for care management			
	Outcomes and measures	Expected cost savings compared with no predictive intervention			
Menard et al. 2018	**Country**	USA	Pregnant Medicaid beneficiaries	Retrospective analysis of risk screen and care management data, matched to birth certificate pregnancy outcome data. Analysis of degree of low birthweight and number of completed care tasks led to creation of a three-tier score (highest score range = greatest risk reduction with higher number of face-to-face care management tasks)	The score effectively identified women who would benefit most from pregnancy care management (OR for highest score range 0.80, $p<0.05$) "For every 100 women in Tier 1 who receive care management, 8 low birthweight outcomes can potentially be prevented"
	Data source	Birth certificate pregnancy outcome data from the 2011-14 birth cohort			
	Aims	Development and validation of a pregnancy care management strategy to identify women most likely to benefit from pregnancy care management to reduce the rate of low birthweight			
	Outcomes and measures	Associations between low birthweight and number of completed care management tasks during pregnancy			
Ozminkowski et al. 2015 (MyCarePath)	**Country**	USA	Individuals are qualified for MyCarePath either through direct or indirect referral. Indirect referrals use claims experience to calculate CMS Hierarchical Condition	PTS summary scores were calculated through logistic regression to generate predicted probability that a qualified individual:	PTS models had higher specificity than sensitivity, suggesting they were better able to predict who would not participate/achieve cost
	Data source	Administrative claims data and health risk assessment from AARP Medicare Supplement Insurance Plan insured			

		by UnitedHealthcare Insurance Company	Category (HCC) score >3.74. Most individuals are age 65 and older, with a Medigap plan. Individuals may also be referred directly through their provider who “perceives a benefit” or nurses on a telephone advice line. *Note: individuals purchasing AARP Medigap insurance are asked to complete a health risk assessment after purchasing the plan. Answers to these questions may trigger referral to MyCarePath.*	(1) participated in MyCarePath, (2) was managed in a way that was consistent with evidence-based guidelines for treating their medical problems, and (3) was managed in a way that reduced the cost of their medical care and prescription pharmaceuticals. Independent variables included: • Demographic data • Health status • Medigap plan type • Healthcare supply • Location variables External consumer-generated variables have been studied but did not increase the model’s predictive ability.	savings/improve care quality. Comparing the 3 months prior to the implementation to the 9 months after implementation, the average number of new participants rose by 11%. "To date, program evaluations have reported positive returns on investment and improved quality of healthcare among program participants.”
	Aims	Describe how big and small data are used to support care coordination programmes			
	Outcomes and measures	Change in calculation of risk scores after implementation of PTS modelling was			
Navratil-Strawn 2016	**Country**	USA	Patients covered by an AARP Medicare Supplement (Medigap) plan	PTS modelling by means of logistic regression to identify characteristics associated with programme engagement. Model covariates included:	PTS modelling was found to be "stable and valid" according to a K-fold cross-validation study “PTS modelling may help to target and engage callers, thus increasing use
	Data sources	United Healthcare (AARP Medicare Supplement plan provider) combined with inferred sociodemographic data			
	Aims	Increase use of a nurse telephone triage programme			

	Outcomes and measures	Changes after PTS in 1) Utilisation of the Nurse Healthline 2) Triage engagement 3) Adherence to nurse recommendations Compared with no intervention		• demographic measures (age, sex) • residential location: rural vs urban, census region, residence in 1 of 5 locations with other care coordination pilots ongoing • socioeconomic variables (zip code level proxies of race and income) • health status (OptumInsight ImpactPro prospective risk score) • local supply of health services (hospital beds per 1000, primary care physicians and specialists per 100,000 residents) • Previous emergency healthcare use in 6 months (yes/no) • Time of call (weekday/weekend)	of the Nurse Healthline and triage service." "This in turn should lead to more efficient use of healthcare services and reduce unnecessary health care expenditures"
Studies incorporating or comparing clinical judgement of impactibility					
Cohen C et al. 2015	**Country**	Israel	Exclusion criteria based on physician input were: active cancer, schizophrenia, dialysis, residence in nursing homes or long-term care facilities, and age 95 years or older.	Model based on ACG predictive model risk scores for risk of future high costs, augmented with a survey of clinical considerations from six physicians	C-statistics for the model before and after exclusions applied were 0.80 and 0.75, respectively. After exclusion, the PPV for the 6% highest risk patients
	Data source	Clalit Health Services' (managed care organization) database 2010-11			
	Aims	Develop a patient selection process for muiltimorbid care management based on physician knowledge and predictive model risk scores			

	Outcomes and measures	Improve discriminatory power for selecting multimorbid patients most amenable to proactive management			was 40%. High-risk patients' age, number of chronic conditions, and utilization were substantially higher than those of all other patients. This study shows that a validated predictive modelling tool provides acceptable discriminatory power for selecting multimorbid patients for participation in proactive care management, even after some of the highest risk patients are excluded because of priori clinical considerations.
Corbin et al. 2019	**Country**	USA	Outpatient primary care patients "at risk of hospitalisation in the next 12 months"	Clinical team assessment of the "potential of care to impact outcomes" based on medical and social factors as an adjunct to a risk predictive model developed by EPIC, which identified 19 variables predictive of ED visits or hospitalisation in the next 12 months.	Validation showed an average C-statistic of 0.71. Average risk score of patients under care management increased from 33% to 40.4% over the first 2 months of the programme. Full results for other outcomes not yet available.
	Data source	Primary care database (not specified)			
	Aims	Develop and validate a patient selection tool to guide allocation of care management based on physician knowledge and predictive model risk scores			
	Outcomes and measures	Changes in 1) Average risk score of patients under care management 2) Number of ED visits 3) Number of hospitalisation in the next 12 months after introduction of tool			
Flaks-Manov et al. 2020	**Country**	Israel	Patients aged 65 years and older who were hospitalized for at least 1 night in an internal medicine ward	Nurse and internal medicine physicians (in charge of direct patient care) assessment of impactibility, compared with a risk prediction model	Physician assessment of likelihood to benefit vs risk prediction model showed 65% overlap, 19% of patients had high predicted risk scores but
	Data source	HCP interview May 2016-June 2017			
	Aims	Explore healthcare providers' perspectives of patients' characteristics associated with decisions about which patients should			

		be referred to readmission prevention programs			were not referred, and 16% had low predicted risk scores but were referred. There is a mismatch between being risk classification by modelling and perceived impactibility. Additional research is required to understand how combining modelled data with provider insights might improve the selection of patients
	Outcomes and measures	Identify similarities and differences in recommendations for referral to a readmission prevention program based on physicians' opinions and a risk prediction model			
Fleming et al. 2017	**Country**	USA	High cost "superutilizers" at two public urban safety-net hospitals	Physician assessment of patient engagement to determine "likelihood to benefit" determined through interviews and ethnographic research	Providers considered 'likelihood to benefit' assessments to be highly challenging and oftentimes inaccurate, particularly because they understood low patient engagement to be the result of difficult socioeconomic conditions..." Health-care professionals look for more subtle signs of engagement and considered fluctuating trajectories of engagement due to living circumstances
	Data source	HCP interview conducted 2015 to 2016			
	Aims	Investigate how health care providers describe engagement for high-cost patients requiring complex care management			
	Outcomes and measures	Assess accuracy of health-care professional and provider definitions and predictions of engagement in relation to socioeconomic status			
Freund et al. 2010, 2011, 2012, 2013	**Country**	Germany	Index condition: T2DM, COPD, asthma, CHF or late-life depression (age >60 years).	Family physician assessment of likelihood to benefit (vs risk predictive model)	Predictive modelling was numerically more accurate than physicians at predicting risk of future hospitalisation, but rates
	Data source/setting	10 primary care practices in southwestern Germany			

	Aims	Compare physician referrals with risk prediction based on insurance claims data	Exclusion criteria: age under 18, dementia, palliative care, or nursing home residents, active cancer or dialysis		for the latter increased over time and patients had better receptivity to care management programmes The authors recommend a combined approach between risk prediction and physician-determined impactibility.
	Outcomes and measures	Selection of patients for primary-care-based management of complex and chronic illness, assessed by: 1) Hospitalisation within 12 months 2) Mortality			
Hudon et al. 2018	**Country**	Canada	Patients with at least one chronic disease, including diabetes, CVD, respiratory, musculoskeletal or chronic pain, with "complex care needs whom family physicians felt could benefit from a case management intervention" and at least three ED visits or hospital admissions. Patients with serious cognitive problems were excluded.	Randomised control trial of intervention and thematic analysis of in-depth interviews	The intervention reduced psychological distress (OR 0.43, 95% CI 0.19–0.95, p= 0.04), but did not have any significant effect on patient activation Patients and spouses benefitted from the case management intervention, gaining a sense of security, and stakeholders noted better patient self-management of health "Case management is a promising avenue to improve outcomes among frequent users of health care with complex needs"
	Data source	V1SAGES (Vulnerable Patients in Primary Care: Nurse Case management and Self-management support)			
	Aims	Assess effects of case-management intervention on psychological distress and patient activation in frequent health-care users			
	Outcomes and measures	Effects of intervention on 1) Psychological distress 2) Patient activation Stakeholder's perceptions of interventions			

Abbreviations: ACG=adjusted clinical groups. ACSCs=ambulatory care sensitive conditions. OR=odds ratio. PTS=propensity to succeed.