Intended for healthcare professionals

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Practice Essentials

Evaluating the impact of healthcare interventions using routine data

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What you need to know

Assessing the impact of healthcare interventions is critical to inform future decisions

Compare observed outcomes with what you would have expected if the intervention had not been implemented

A wide range of routinely collected data is available for the evaluation of healthcare interventions

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evaluation of a health intervention. We highlight what to consider and discuss key concepts relating to design, analysis, implementation, and interpretation.

What are interventions, impacts, and impact evaluations?

A health intervention is a combination of activities or strategies designed to assess, improve, maintain, promote, or modify health among individuals or an entire population. Interventions can include educational or care programmes, policy changes, environmental improvements, or health promotion campaigns. Interventions that include multiple independent or interacting components are referred to as complex.[5] The impact of any intervention is likely to be shaped as much by the context (eg, communities, work places, homes, schools, or hospitals) in which it is delivered, as the details of the intervention itself.[6789]

An impact is a positive or negative, direct or indirect, intended or unintended change produced by an intervention. An impact evaluation is a systematic and empirical investigation of the effects of an intervention; it assesses to what extent the outcomes experienced by affected individuals were caused by the intervention in question, and what can be attributed to other factors such as other interventions, socioeconomic trends, and political or environmental conditions. Evaluations can be categorised as formative or summative (**table 1**).

Table 1
Impact evaluations

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Approaches such as the Plan, Do, Study, Act cycle[11], which is part of the Model for Improvement, a commonly used tool to test and understand small changes in quality improvement work[12] may be used to undertake formative evaluation.

With either type of evaluation, it is important to be realistic about how long it will take to see the intended effects. Assessment that takes place too soon risks incorrectly concluding that there was no impact. This might lead stakeholders to question the value of the intervention, when later assessment might have shown a different picture. For example, in a small case study of cost savings from proactively managing high risk patients, the costs of healthcare for the eligible intervention population initially increased compared with the comparison population, but after six months were consistently lower.[14]

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Formulate your evaluation questions using your understanding of the idea behind your intervention, the implementation challenges, and your knowledge of what data are available to measure outcomes. Review your theory of change or logic model[21,22] to understand what inputs and activities were planned, and what outcomes were expected and when. Once you have understood the intended causal pathway, consider the practical aspects of implementation, which include the barriers to change, unexpected changes by recipients or providers, and other influences not previously accounted for. Patient and public involvement (PPI) in setting the right question is strongly recommended for additional insights and meaningful results. For example, if evaluating the impact of case management, you could engage patients to understand what outcomes matter most to them. Healthcare leaders may emphasise metrics such as emergency admissions, but other aspects such as the experience of care might matter more to patients.[5,23]

What methods can be used to perform an impact evaluation?

Randomised control designs, where individuals are randomly selected to receive either an intervention or a control treatment, are often referred to as the “gold standard” of causal impact evaluation.[24] In large enough samples, the process of randomisation ensures a balance in observed and unobserved characteristics between treatment and control groups. However, while often suitable for assessing, for example, the safety and efficacy of medicines, these designs may be impractical, unethical, or irrelevant when assessing the impact of complex changes to health service delivery.

Observational studies are an alternative approach to estimate causal effects. They use the natural, or unplanned, variation in a population in relation to the exposure to an intervention, or the factors that affect its outcomes, to remove the consequences of a non-randomised selection process.[25] The idea is to mimic a randomised control design by ensuring treated and control groups are equivalent—at least in terms of *observed* characteristics. This can be achieved using a variety of well documented methods, including regression control and matching,[26] eg, propensity scoring[27] or genetic matching.[28] If the matching is successful at producing such groups, and there are also no differences in *unobserved* characteristics, then it can be assumed that the control group outcomes are representative of those that the treated group would have experienced if nothing had changed, ie, the counterfactual. For example, an evaluation of alternative elective surgical interventions for primary total hip replacement on osteoarthritis patients in England and Wales used genetic matching to compare patients across three different prosthesis groups, and reported that the most prevalent type of hip replacement was the least cost effective.[29]

Assessing similarity is only possible in relation to *observed* characteristics, and matching can result in biased estimates if the groups differ in relation to *unobserved* variables that are predictive of the outcome (confounders). It is rarely possible to eliminate this possibility of bias when conducting observational studies, meaning that the

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interventions.[41]

What's wrong with a simple before-and-after study?

Before-and-after studies compare changes in outcomes for the *same* group of patients at a single time point before and after receiving an intervention without reference to a control group. These differ from interrupted time series studies, which compare changes in outcomes for *successive* groups of patients before and after receiving an intervention (the interruption).

Before-and-after studies are useful when it is not possible to include an unexposed control group, or for hypothesis generation. However, they are inherently susceptible to bias since changes observed may simply reflect regression to the mean (any changes in outcomes that might occur naturally in the absence of the intervention), or influences or secular trends unrelated to the intervention, eg, changes in the economic or political environment, or a heightened public awareness of issues.

For example, a before-and-after study of the impact of a care coordination service for older people tracked the hospital utilisation of the same patients before and after they were accepted into the service. They found that the service resulted in savings in hospital bed days and attendances at the emergency department.[42] Reduced hospital utilisation could have reflected regression to the mean here rather than the effects of the intervention; for example, a patient could have had a specific health crisis before being invited to join the service and then reverted back to their previous state of health and hospital utilisation for reasons unconnected with the care coordination service.

Various tools are available to evaluate the risk of bias in non-randomised designs due to confounding and other potential biases.[43][44]

Where can I find suitable routine data?

Healthcare systems generate vast amounts of data as part of their routine operation. These datasets are often designed to support direct care, and for administrative purposes, rather than for research, and use of routinely collected data for evaluating changes in health service delivery is not without pitfalls. For example, any variation observed between geographical regions, providers, and sometimes individual clinicians may reflect real and important variations in the actual healthcare quality provided, but can also result from differences in measurement.[45] However, routine data can be a rich source of information on a large group of patients with different conditions across different geographical regions. Often, data have been collected for many years, enabling construction of individual patient histories describing healthcare utilisation, diagnoses, comorbidities, prescription of medication, and other treatments.

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Healthcare records can often be linked across different sources as a single patient identifier is commonly used across a healthcare system, eg, the use of an NHS number in the UK. Using a common pseudonym across different data sources can support linkage of pseudonymised records. Linking into publicly available sources of administrative data and surveys can further enrich healthcare records. Commonly used administrative data available for UK populations include measures of GP practice quality and outcomes from the Quality and Outcomes Framework (QOF),[52] deprivation, rurality, and demographics from the 2011 Census,[53] and patient experience from the GP Patient Survey.[54]

Are there any additional considerations?

It is essential to consider threats to validity when designing and evaluating an impact evaluation; validity relates to whether an evaluation is measuring what it is claiming to measure. See Rothman et al[55] for further discussion.

Internal validity refers to whether the effects observed are due to the intervention and not some other confounding factor. Selection bias, which results from the way in which subjects are recruited, or from differing rates of participation due, for example, to age, gender, cultural or socioeconomic factors, is often a problem in non-randomised designs. Care must be taken to account for such biases when interpreting the results of an impact evaluation. Sensitivity analyses should be performed to provide reassurance regarding the plausibility of causal inferences.

External validity refers to the extent to which the results of a study can be generalised to other settings. Understanding the societal, economic, health system, and environmental context in which an intervention is delivered, and which makes its impact unique, is critical when interpreting the results of evaluations, and considering whether they apply to your setting.[56] Descriptions of context should be as rich as possible.

Often, the impact of an intervention is likely to vary depending on the characteristics of patients. These can be usefully explored in subgroup analyses.[57]

Clear and transparent reporting using established guidelines (eg, STROBE[58] or TREND[59])to describe the intervention, study population, assignment of treatment, and control groups, and methods used to estimate impact should be followed. Limitations arising as a result of inherent biases, or validity, should be clearly acknowledged.

Around the world, many interventions designed to improve health and healthcare are under way. An evaluation is an essential part of understanding what impact these changes are having, for whom and in what circumstances, and

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- What types of routine data are collected about the care you deliver? Do you know how to access them and use them to evaluate care delivery?
- What resources are available to you to support impact evaluations for interventions?

Footnotes

- **Contributors** GMC, SC, ATW and AS designed the structure of the report. GMC wrote the first draft of the manuscript. SC wrote **table 2**. ATW wrote **table 3**. AS and GMC critically revised the manuscript for important intellectual content. All authors approved the final version of the manuscript.
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Use precise geolocation data. Actively scan device characteristics for identification. Store and/or access information on a device. Personalised advertising and content, advertising and content measurement, audience research and services development.

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