Epidemiology: Open Access

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Epidemiology in the Field

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The process of utilising epidemiological methods to safeguard or improve a population's health is known as applied epidemiology. Investigating communicable and non-communicable disease outbreaks, mortality and morbidity rates, and nutritional status, among other health indicators, is part of applied field epidemiology. The goal is to communicate the findings to those who can implement appropriate policies or disease control measures.

Humanitarian situation

In humanitarian crisis scenarios, surveillance and reporting of diseases and other health indicators is becoming increasingly challenging, putting the procedures used to submit the data at risk. According to one study, only half the nutrition surveys sampled from humanitarian contexts (42.4 per cent) accurately assessed the prevalence of malnutrition, and only one-third (35.3 per cent) of the surveys met the quality standards. Only 3.2 per cent of the mortality surveys passed the quality standards. The measurement and reporting of nutritional status and death rates is critical because they assist determine the severity of a crisis.

Vital registries are normally the most effective means to collect data; however they can be non-existent, unreliable, or inaccessible in humanitarian situations. As a result, mortality is frequently mismeasured using either prospective or retrospective demographic monitoring or mortality surveys. Prospective demographic surveillance necessitates a significant amount of manpower and is difficult to accomplish in a geographically dispersed population. Selection and reporting biases are common in retrospective mortality surveys. Other approaches are being developed, but they are not yet widely used [1, 2, 3, 4].

Precision and bias are two aspects of validity

In epidemiology, different domains have varied levels of validity. The ratio of false-positives (declared effects that are not correct) to false-negatives is one technique to measure the validity of findings (studies which fail to support a true effect). In the realm of genetic epidemiology, for example, candidate-gene research resulted in over 100 false-positive discoveries for every false-negative. Genome-wide associations, on the other hand, appear to be nearly the opposite, with just one false positive for every 100 or more erroneous negatives [5]. In genetic epidemiology, this ratio has improved over time as the discipline has adopted more stringent standards. Other epidemiological sectors, on the other hand, have not mandated such stringent reporting and, as a result, are far less dependable [5].

Random error

Random error is the outcome of sampling variability causing variations around a true value. The term "random error" refers to the fact that it is exactly that. It might happen while collecting, coding, transferring, or analysing data. Poorly written questions, a misunderstanding in interpreting an individual response from a particular respondent, or a typographical error during coding are all examples of random error. Random error has a temporary, inconsistent effect on measurement, and it is impossible to adjust for it.

In all sampling processes, there is random error. This is referred to as sampling error. Random error is measured by precision in epidemiological variables. Precision is inversely proportional to random error, therefore lowering random error means increasing precision. To highlight the precision of relative risk estimations, confidence intervals are calculated. The more precise the relative risk estimate, the narrower the confidence interval.

In an epidemiological investigation, there are two fundamental strategies to reduce random error. The first is to increase the study's sample size. To put it another way, broaden your study. The second goal is to lower the study's measurement variability. This could be accomplished by using a more accurate measuring instrument or by taking more measurements.

It's worth noting that increasing the sample size or number of measurements, or purchasing a more precise measuring gear, will almost always increase the study's expenditures. The balance between the need for acceptable precision and the practical issue of study cost is frequently difficult.

Systematic error

When there is a disparity between the true value (in the population) and the observed value (in the study) due to a factor other than sampling variability, it is called a systematic error or bias. If the pulse oximeter you're using is configured wrongly and adds two points to the true number each time a measurement is made, that's an example of systematic inaccuracy. Although the measuring device may be precise, it is not accurate. It is systematic since the fault occurs in every occasion. Your conclusions based on that information will still be erroneous. However, the mistake can be repeated in the future (e.g., by using the same mis-set instrument).

Another example of a systematic error is a coding error that impacts all responses for that particular inquiry.

The degree of systematic inaccuracy determines the study's validity. Validity is usually broken down into two parts:

Internal validity is determined by the degree of measurement error, which includes exposure, disease, and the relationships between these factors. Internal validity indicates that there is no measurement error and that inferences can be formed, at least as far as the persons under research are concerned.

The process of generalising the study's findings to the population from which the sample was collected is referred to as external validity (or even beyond that population to a more universal statement).

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This necessitates knowing which criteria are relevant (or not) to the generalisation. External validity plainly necessitates internal validity.

Selection bias

When study subjects are chosen or become a part of the study as a result of a third, unmeasured variable that is linked to both the exposure and the outcome of interest, selection bias develops [6]. For example, it has been consistently highlighted that the rates of research participation varies between cigarette smokers and non-smokers. (Sackett D references Seltzer et al., who found that 85 percent of nonsmokers and 67 percent of smokers responded to send questionnaires.) It's vital to remember that a difference in response does not equal bias unless it's accompanied by a systematic difference in outcome between the two groups.

Information bias

Bias resulting from systematic mistake in the assessment of a variable is known as information bias. Recall bias is an example of this. "In questioning mothers whose recent pregnancies had ended in foetal death or malformation (cases) and a matched group of mothers whose pregnancies ended normally (controls), it was found that 28 percent of the former, but only 20 percent of the latter, reported exposure to drugs that could not be substantiated either in earlier prospec. Recall bias most likely happened in this case as a result of women who had miscarriages having an apparent inclination to recall and hence report past exposures.

Confounding

Confounding has long been characterised as bias caused by the co-occurrence or mixing of effects of unrelated factors, known as confounders, with the main effect(s) of interest. Counterfactual effects are mentioned in a more current definition of confounding. When a result of interest, say Y=1 (as opposed to Y=0), is seen in a particular population A that is totally exposed (i.e. exposure X = 1 for every unit of the population), the risk of this happening is RA1. The risk that would have been seen if these identical people had not been exposed (i.e. X = 0 for every unit of the population) is known as the counterfactual or unobserved risk RA0. As a result, the true effect of exposure is: RA1 RA0 (if risk differences are of importance) or RA1/RA0 (if one is interested in relative risk). Because the counterfactual risk RA0 is unobservable, we use a second population B to approximate it, and we quantify the following relationships: RA1 RB0 or RA1/RB0. Confounding happens when RA0 RB0 in this case. (Note: In this example, the result and exposure variables are both binary.)

Confounding, unlike selection and information bias, is caused by true causal effects; hence some epidemiologists prefer to think of it separately from other types of bias [6].

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