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1. **Distinguish between descriptive epidemiology and analytical epidemiology**
2. **Descriptive epidemiology**. Descriptive epidemiology aims to describe the distributions of diseases and determinants. It provides a way of organizing and analyzing these data to describe the variations in disease frequency among populations by geographical areas and over time (i.e., person, place, and time).

Descriptive [epidemiology](https://www.sciencedirect.com/topics/medicine-and-dentistry/cohort-effect) aims to describe the distributions of diseases and determinants. It provides a way of organizing and analyzing these data to describe the variations in disease frequency among populations by geographical areas and over time (i.e., person, place, and time). [Descriptive epidemiology](https://www.sciencedirect.com/topics/medicine-and-dentistry/descriptive-epidemiology) can thus generate hypotheses of etiologic research.

Ecologic study and cross-sectional study (see Chapter 4) are the most commonly applied in descriptive [epidemiologic studies](https://www.sciencedirect.com/topics/medicine-and-dentistry/cohort-effect). For example, the National Health and [Nutrition](https://www.sciencedirect.com/topics/medicine-and-dentistry/nutrition-physiology) Examination Survey is a cross-sectional study. In the study, participants’ health conditions, including the prevalence of CHD, heart failure, [stroke](https://www.sciencedirect.com/topics/medicine-and-dentistry/apoplexy), [diabetes](https://www.sciencedirect.com/topics/medicine-and-dentistry/diabetes-mellitus), and cancers, are measured through standard survey instruments.

Descriptive Epidemiology is used in reporting and presentation of health cases in a pie chart of in table forms, the below table show the weigh distribution at 18 years of age in Brazil.

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Weight distribution among 18-year-old young male sex (n = 2.194). Pelotas, Brazil, 2010

| **Weight at 18 years of age (in kg)** | | **Absolute frequency(n)** | | **Relative frequency (%)** | |
| --- | --- | --- | --- | --- | --- |
|  | 40.5 to 59.9 |  | 554 |  | 25.25 |
|  | 60.0 to 65.8 |  | 543 |  | 24.75 |
|  | 65.9 to 74.6 |  | 551 |  | 25.11 |
|  | 74.7 to 147.8 |  | 546 |  | 24.89 |
|  | **Total** |  | **2.194** |  | **100.00** |

This below tables show and summaries that due to help of descriptive epidemiology analysis, it could be very easy to report health status of the population in a very easy and understandable ways.

*Descriptive epidemiology* is very importance in searching for patterns by examining characteristics of person, place, & time. These characteristics are carefully considered when a disease outbreak occurs, because they provide **important** clues regarding the source of the outbreak.

1. **Analytic Epidemiology**: Analytic epidemiologic studies measure the association between a particular exposure and a disease, using information collected from individuals, rather than from the aggregate population. *Exposure* is defined broadly to include behavioral factors such as smoking or diet, environmental pollutants such as asbestos, personal characteristics such as obesity or tendency to sunburn, anthropometric measurements such as body mass index, and genetic traits and other measurable biologic factors that may affect cancer.

The two most common study designs in analytic epidemiology are cohort and case-control, depending on whether the subjects are first identified based on characteristics other than disease status (see below). Both approaches measure the association between a particular exposure and a given disease; both provide a stronger basis for inference than do descriptive studies alone

The end goal of both branches is to reduce the incidence of **health** events or diseases by understanding the risk factors for the **health** events or diseases. ... Frequency evaluates the rate of occurrence, and pattern helps **analytical** epidemiologists suggest risk factors.

2. **Write down and explain the mathematical expression of the following.**

I. **Incidence:** Incidence in epidemiology is a measure of the probability of occurrence of a given medical condition in a population within a specified period of time. Although sometimes loosely expressed simply as the number of new cases during some time period, it is better expressed as a proportion or a rate with a denominator.

Mathematically, incidence rate = x100 n

OR Incidence rate =

Where I= Number of new cases during follow-up

PT= Total time that diseases- free individuals in cohort are observed over the study period.

Synonyms: hazard rate, incidence density rate measures rapidity with which new cases occurring in a given population.

These mathematical calculations are based upon the population and it is multiplied by 100 percent of population rising to number of years presented by n

Where incidence density (ID|=

Incidence Density is a relative rate not proportional rate

ii. **Prevalence:** Prevalence is a measurement of all individuals affected by the disease at a particular time, whereas incidence is a measurement of the number of new individuals who contract a disease during a particular period of time.

Mathematically,

Prevalence =

1. Apart from Randomized trials, describe four (4) other epidemiological research designs

**Observational studies**

Observational studies include cross sectional, cohort, case-control, and ecological studies.

**CROSS SECTIONAL STUDIES**

In a cross sectional study, individuals with a defined disease, risk factor, or other condition of interest are identified at a point in time. The number of individuals with the condition divided by the total number in the population gives the prevalence (expressed as a proportion) of the condition in a defined population at that point in time. For example, many cross sectional studies have been conducted to estimate the prevalence of HIV infection in antenatal and genitourinary medicine clinics.

**COHORT STUDIES**

In cohort studies individuals are followed through time to monitor the natural history of a disease, to observe prognosis in relation to treatment, or to investigate aetiology. In the early days of the AIDS epidemic, several cohort studies provided vital information about the course of HIV infection—for example, the Multicenter AIDS Cohort Study. More recently, in the era of anti-HIV therapy, cohorts with continuous patient recruitment have made an important contribution to knowledge about the incubation period of infection and the impact of changes in therapy over time.

An example of a cohort study conducted to investigate etiology is provided by hepatitis B infection and liver cancer. To study the hypothesis that hepatitis B causes hepatocellular carcinoma, over 22 000 male Taiwanese civil servants, of whom 15% were hepatitis B surface antigen positive, were followed for approximately 9 years.At follow up, the death rate from hepatic cellular carcinoma was 98 times higher in HepBsAg positive men (the exposed group) than in HepBsAg negative men (the unexposed group), indicating an exceptionally strong association between HbsAg status and primary hepatocellular carcinoma. This example also illustrates how large cohort studies need to be if the outcome of interest is relatively rare. An alternative approach would be to do a case-control study.

**CASE-CONTROL STUDIES**

The distinctive feature of a case-control study is that individuals are selected according to disease or outcome status rather than exposure status. People with the disease or outcome of interest are selected as cases, and a suitable group of individuals without the disease are selected as controls. Returning to the example of liver cancer and hepatitis B, a case-control study could be conducted by recruiting cases with liver cancer and suitable controls who were free of liver cancer. The relative frequency (odds) of previous exposure to hepatitis B would then be compared between cases and controls. Another key feature of case-control studies is that inferences about the association between exposure and disease depend entirely on the exposure preceding the disease. For example, it would be impossible to conclude that hepatitis B causes liver cancer if the infection occurred after the cancer developed.

The case-control study has intuitive appeal as a means of investigating aetiology. It can be thought of as the logical extension of a case series. For example, it was a cluster of case reports of *Pneumocystis carinii* pneumonia and Kaposi's sarcoma in young, previously healthy, homosexual men that eventually prompted a national case-control study to seek explanations for these unusual presentations of immunodeficiency. The addition of a control group allows the frequency of exposure in cases to be expressed relative to people who are disease free. While it is perfectly logical to search for meaningful differences between comparable groups of people with and without the disease, the intuitive appeal of case-control studies belies a key problem—namely, how to select the most appropriate control group. This is the “Achilles heel” of the case-control study. Since the exposure has already happened, selecting controls who are more (or less) likely than the cases to have been exposed for reasons unrelated to the outcome of interest will result in a biased association (odds ratio) between exposure and disease. Unfortunately, there is no simple recipe for selecting the ideal control group. The potential biases specific to each research question need to be considered carefully before controls are defined and selected. Further discussion about selection of controls is beyond the scope of this article.

**ECOLOGICAL STUDIES**

Observational studies conducted at a population level rather than an individual level is called ecological studies. Differences in outcome between populations, or over time, are related to population characteristics that are thought to be risk (or preventive) factors. An example would be analysis of the decrease in Chlamydia infection and ectopic pregnancy over time in Sweden.[7](https://sti.bmj.com/content/76/4/244#ref-7) Although the findings may be causally linked, it is usually hard to explore alternative explanations within the limits of this study design. For this reason, results from ecological studies often serve as a basis for further investigation of individuals.

**Intervention studies (clinical trials)**

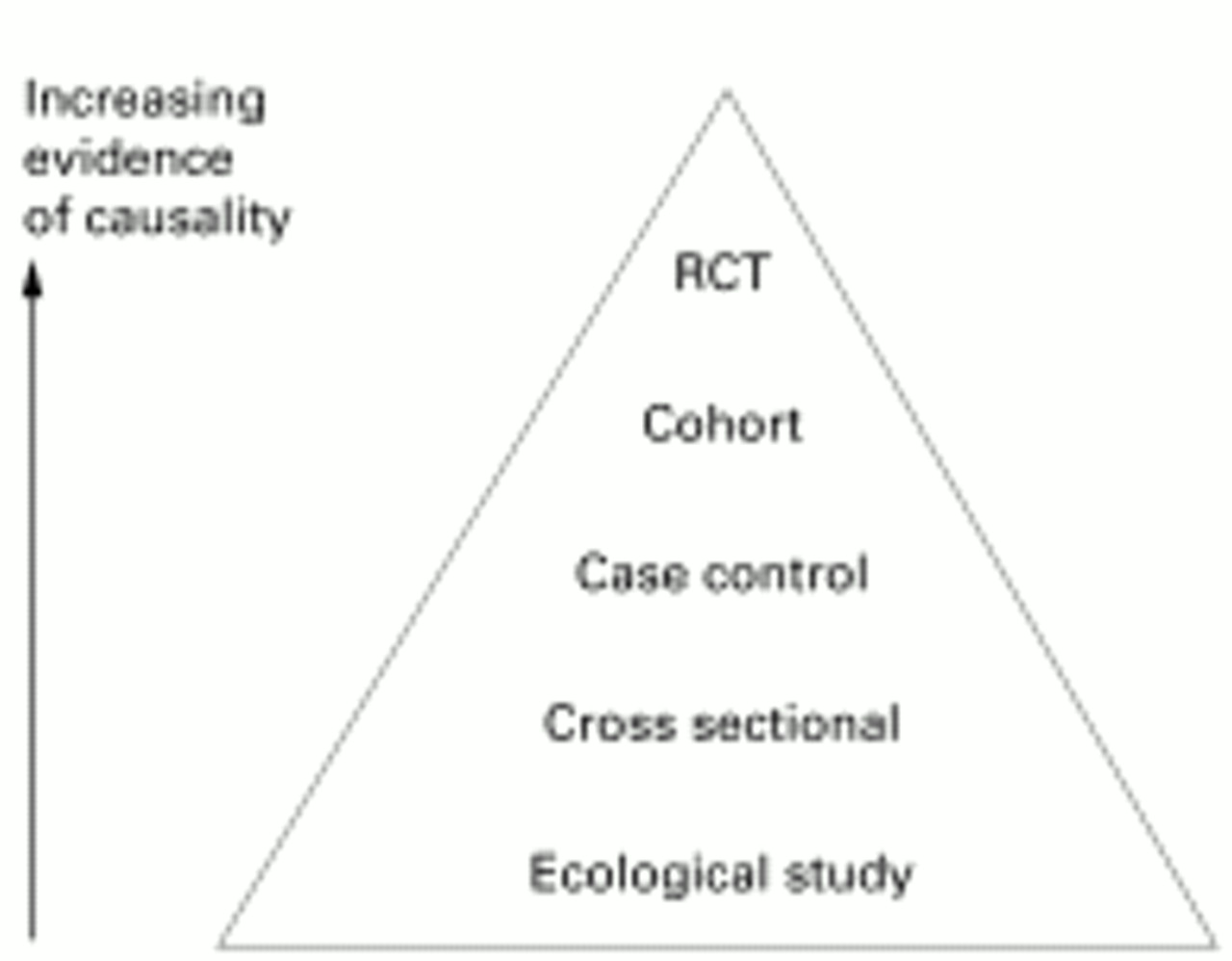
The accepted gold standard for the evaluation of a therapeutic or preventative intervention is the randomized control trial (RCT). The RCT has a distinct advantage over observational studies in terms of its potential to avoid selection bias. The key principle is randomization where, in the case of evaluating a single intervention against standard of care, patients are allocated to either the intervention under study (the experimental group) or to standard management (control group) by a pure chance process. The two groups are followed prospectively for a specified period of time and then compared in terms of an outcome measure specified at the outset. Bias and random error are two different obstacles to overcome in the reliable evaluation of the treatment effect—that is, the difference between the experimental and control groups in the study outcome. Bias in this context means any distortion of the study results in a particular direction as a consequence of a systematic difference between the two groups arising from an inappropriate design or conduct of the study. Random error is the play of chance leading to an inaccurate estimate of the treatment effect.

The most important design technique for avoiding bias is randomization. Randomization ensures that, within the limits of chance variation, there are no systematic differences between the two groups in known and unknown prognostic factors so that any difference in outcome can be reasonably attributed to the effect of the intervention. In addition, randomization provides a sound basis for the statistical analysis of the data. Functionally, the process of simple randomization is analogous to tossing a coin for each patient and allocating the patient to the intervention group if the result is heads and to the control group if tails. In practice, this is done by computer generated lists mimicking repeated coin tossing. Other techniques for avoiding bias include blinding where the clinician and/or the patient are made unaware of treatment allocation and the appropriate handling of non-adherence to allocated treatment and missing outcome measures in the analysis.

The uncertainty associated with a particular result of a trial is what we called “random error.” Chance can play a much greater part in determining trial results than many people realize. For example, in an RCT of a new antibiotic for the treatment of Chlamydia the observed cure rate in the patients allocated to the new antibiotic was 98% but the cure rate was only 90% in patients allocated to standard treatment. The question now is how confident should we be in concluding that the higher cure rate of the new antibiotic is real and not just the result of the characteristics of the patients who happened to be allocated to receive it?

Provided that the study is properly randomized and conducted, we can conclude that the observed superiority of the new antibiotic is either real or the result of random error —that is, chance. Randomization also allows us to quantify this random error and thereby provides ways of reducing our uncertainty in the results. The way to reduce random error is to recruit a sufficient number of patients in the trial. The larger the number of patients (the sample size) the less uncertainty and the more confidence we have in the trial result. Intuitively, we would have more confidence that the new antibiotic was genuinely superior if the trial had 500 patients than if it had only 50 patients. Later articles in this series will deal with how to work out how large a study should be and other design issues.

**Hierarchy of studies in determining causality**

Many studies are conducted to examine associations between exposures, or putative risk factors, and disease outcomes. Associations can arise through chance, through bias, or confounding, or they may indicate a causal relation. Distinguishing between these different explanations is a key objective of much research. The study designs described here differ in their ability  to indicate causality (fig 1)

4. Data from hospital records are one of the most important sources of information in

epidemiologic studies.

1. Outline the limitations of using hospital data.

**Number 1 (one of the most important): Avoid the averages**  
Most claims data sets are not normally distributed, so the averages do not provide relevant information. In most discussions today, employers evaluate the average cost of employees with specific conditions, e.g., diabetes or high blood pressure. This is a flawed approach because spending by employees with various chronic conditions is skewed, thus not really “average able.” For example, assume 90% of an employee population with diabetes is spending $10,000/year and 10% is spending $250,000/year; the average will be a meaningless $34,000/year. All too often, a wild goose chase ensues, when in fact the focus should be on the $250,000 cohort to understand why they were so much more expensive.

***See Also:*** [***Why Healthcare Costs Bleed Firms Dry***](http://insurancethoughtleadership.com/why-healthcare-costs-bleed-firms-dry/)

1. **Number 2: Follow the money**  
   A superior use of claims data is to look at distributions of spending. In most plans today, roughly 8% of enrollees are consuming 80% of plan dollars, and these 8% typically change every 12 to 18 months. (We still run into benefit managers who were unaware of that turnover.) The future belongs to micro-managing these “outliers,” rather than the 92% who spend only 20% of the dollars. If you study those outliers carefully, you will find that only about 7% of their spending possibly would have been preventable, and then only if they faithfully did what their doctors told them to do decades earlier. A cardiologist recently told me that, of the patients he has seen with a significant acute blockage, about 25% had no known health risks of any kind…no high blood pressure, cholesterol, diabetes, obesity, smoking, genetic predisposition, etc. As such, there is a component of randomness in terms of who gets blocked arteries. The same holds true for cancer. For the other 75%, their physicians have usually counseled them on the importance of exercise and nutrition and the dangers of tobacco use, but to no avail.

**Number 3: Realize the limitations for quality designations**  
yet another big error is trying to use claims data to determine the best-quality doctors. You had better be really, really talented to try that one. Why? We are in an era in which many doctors are making their “quality” and “outcomes” look better by referring their most complex and riskiest patients to someone else. (Much has been written about this.) On the other hand, there are highly effective doctors who take responsibility for their riskiest patients, but as a consequence score poorly on so-called “quality measures.” The real travesty is that the low-scoring doctors may be the most cost-effective and provide the best care.

**Number 4: Misdiagnoses are a real cost driver**  
another huge shortcoming of claims data is one that readers of [Cracking Health Costs](http://www.amazon.com/Cracking-Health-Costs-Companys-Employees/dp/1118636481/ref=sr_1_1?ie=UTF8&qid=1458598533&sr=8-1&keywords=cracking+health+costs) know about. Namely, a large number of patients with complex health problems are simply misdiagnosed – today, that’s about 20% of the outliers in benefit plans, accounting for 18% of claim dollars. Thus, you cannot rely on diagnoses in claims data, and you cannot tell who is getting diagnoses right or wrong – this takes detective work beyond claims data. [Click here for a good article](http://www.mayoclinicproceedings.org/article/S0025-6196%2814%2900245-6/fulltext) by the Mayo Clinic on rates of misdiagnoses. We have sent hundreds of people to the Mayo Clinic for second opinions and can verify by personal experience the truth in that article…same for other clinics we have used for employers. Our first rule in selecting a Center of Excellence is its success in correctly diagnosing patients with complex health problems. Huge amounts of claim dollars are spent on treatments or surgeries that are either completely erroneous or clearly suboptimal. An executive at a Fortune 100 company once said to me that the biggest quality failure in healthcare is to misdiagnose a patient…everything that follows harms the patient.

***See Also:*** [***To Go Big (Data), Try Starting Small***](http://insurancethoughtleadership.com/to-go-big-data-try-starting-small/)

**Number 5: Coding can affect the data analysis**  
during a data analysis for a very larger employer, with more than 250,000 covered lives, executives told me they had not paid for a solid organ transplant in a number of years. Based on their size, they should have been paying for about 25 a year. After further detective work, we discovered their consultant was using a DRG grouper that coded all transplants as ventilator cases…who knows why…but a huge error. The benefit team had no idea they were really paying for about 25 a year at an average cost over five years of about $1.5 million each.

**Number 6: Reversion to the mean**One thing we’ve learned from years of claims analysis of big companies’ benefit programs is that if you have enough life years of data, it all looks about the same, i.e., it reverts to the mean. If the workforce is comparatively older, they will have somewhat more high-cost claims.

b) **Describe the possible sources of error in interview surveys**

[**SPECIFICATION ERROR**](https://www.nap.edu/read/18605/chapter/1#a35)

For any survey, its intended purpose and concepts must be clearly defined in order for survey instruments and procedures to accurately translate those concepts into the collection of data. In surveys, specification error may occur when there is a mismatch between what the survey is measuring and what it is intended to measure.[5](https://www.nap.edu/read/18605/chapter/10#ch8_fn5) As defined by Biemer (2010, p. 31): “specification error pertains specifically to the problem of measuring the wrong concept in a survey, rather than measuring the right concept poorly.” This section examines a key concept associated with the NCVS to see if it is clearly defined and consistent between the survey’s purposes and processes.

[**NONRESPONSE ERROR**](https://www.nap.edu/read/18605/chapter/1#a34)

Nonresponse error in surveys arises from the inability to obtain a useful response to all survey items from the entire sample. A critical concern is when that nonresponse leads to biased estimates. Nonresponse bias is a product of the difference between respondents and nonrespondents on a particular measure and the size of the nonresponse population. A lower response rate increases the potential for greater nonresponse bias, but when the data are missing at random, a lower response rate will neither create nor increase nonresponse error.

[**MEASUREMENT ERROR**](https://www.nap.edu/read/18605/chapter/1#a36)

Measurement error includes a large family of errors that may occur when response on a survey results in the collection of inaccurate or incomplete information. In this section, the report discusses potential measurement errors on the NCVS associated with the respondent, the questionnaire, the mode of collection, and with the interviewer/respondent interaction. These issues are interrelated, and each has the potential to result in measurement error on the NCVS.

5. Explain the main determinants of health

Many factors combine together to affect the health of individuals and communities. Whether people are healthy or not, is determined by their circumstances and environment. To a large extent, factors such as where we live, the state of our environment, genetics, our income and education level, and our relationships with friends and family all have considerable impacts on health, whereas the more commonly considered factors such as access and use of health care services often have less of an impact.

#### The determinants of health include:

* the social and economic environment,
* the physical environment, and
* The person’s individual characteristics and behaviors.

The context of people’s lives determines their health, and so blaming individuals for having poor health or crediting them for good health is inappropriate. Individuals are unlikely to be able to directly control many of the determinants of health. These determinants—or things that make people healthy or not—include the above factors, and many others:

* *Income and social status* - higher income and social status are linked to better health. The greater the gap between the richest and poorest people, the greater the differences in health.
* *Education* – low education levels are linked with poor health, more stress and lower self-confidence.
* *Physical environment* – safe water and clean air, healthy workplaces, safe houses, communities and roads all contribute to good health. Employment and working conditions – people in employment are healthier, particularly those who have more control over their working conditions
* *Social support networks* – greater support from families, friends and communities is linked to better health. Culture - customs and traditions, and the beliefs of the family and community all affect health.
* *Genetics* - inheritance plays a part in determining lifespan, healthiness and the likelihood of developing certain illnesses. Personal behavior and coping skills – balanced eating, keeping active, smoking, drinking, and how we deal with life’s stresses and challenges all affect health.
* *Health services* - access and use of services that prevent and treat disease influences health
* *Gender* - Men and women suffer from different types of diseases at different ages.

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