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Synonyms in Health Services Research Methodology

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Abstract

There are often multiple discipline-specific terms for a given statistical concept, which can sow confusion in multidisciplinary teams or study sections if researchers are not aware of the synonyms from other disciplines. This article incorporates synonyms and a uniform definition of terminology related to study designs, elements of an equation, and types of bias. Greater multidisciplinary collaboration and exploration of new methods can be facilitated by this methods thesaurus.

Keywords

explanatory variables, quantitative methods, study design, synonyms, terminology

Health services research is a multidisciplinary field that draws on methodology from different social and biomedical sciences, including anthropology, biostatistics, economics, epidemiology, political science, psychology, sociology, and statistics. As a result, some quantitative methods used in health services research have unique terms that are universally understood but some methods have discipline-specific terms that are essentially synonyms. Researchers on multidisciplinary teams may misunderstand one another when discussing a study design or analytic issue if they are not aware of synonyms from other disciplines. Similar misunderstandings can arise during study section

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discussions. Misunderstandings or disagreements in these contexts can also arise because related methodology may have different assumptions or techniques.

Semantic misunderstandings can be resolved in a straightforward way by systematically defining and linking related terms from different disciplines. Greater awareness of synonyms for specific terms and the common definition for these synonyms can facilitate multidisciplinary communication and collaboration. The purpose of this article is to raise awareness of synonyms and a common definition for statistical terms related to study designs, elements of an equation, and types of bias commonly used by health services researchers.

New Contribution

This manuscript provides a comprehensive integration of synonyms and definitions for quantitative research methods terminology from disciplines in the social and health sciences. This article extends earlier work (Maciejewski, Diehr, Smith, & Hebert, 2002) on statistical methodology by including new terminology (e.g., mediation, moderation, field trial) and additional synonyms (e.g., hidden bias), discussing different types of explanatory variables, and providing a more thorough discussion of study designs and their purposes. In addition, we provide several specific examples to illustrate a statistical concept in practice and provide broad accessibility to researchers from different disciplines and with different research interests.

This article will be informative for three audiences. First, training programs in Schools of Public Health, Medicine, and Pharmacy may want to provide this "methods thesaurus" to their students, so they are aware of the range of terms used across disciplines to describe the same statistical concepts. Students may also find this "thesaurus" useful when integrating new methods from other disciplines into their existing toolkit. Second, multidisciplinary research teams may find this "methods thesaurus" useful when designing studies or statistical analyses with collaborators from different disciplines, so that a common understanding of terminology and concepts supports inclusiveness and avoids disciplinary turf battles that may arise due to vernacular. Third, researchers participating on study sections may find this article useful to ensure that methodological debates are based on technical issues and not misunderstanding of terminology.

Method

The sample of methods terms and synonyms was drawn from the prior article (Maciejewski et al., 2002) and from suggestions made by members of AcademyHealth's Methods Council who commissioned this work. Definitions and synonyms were searched in research methods textbooks listed in the Core Module Document generated from AcademyHealth's Core Library Project that was provided to us. The core module document was compiled in conjunction with the National Library of Medicine (http://www.nlm.nih.gov/nichsr/corelib/hsrmethods.html) by an expert panel of 9 librarians employed at think tanks, academic institutions, and government agencies, and an

expert panel of 10 academic experts in methodology from academic institutions across the country. The academic experts were from the fields of health economics, epidemiology, psychology, biostatistics, survey methods, qualitative methods, and psychometrics.

To ensure that a broad array of disciplines was represented, we obtained biostatistical, econometric, epidemiologic, general health services research, and psychology research methods textbooks. Additional terms were added as they were identified during the definition and synonym search process. Statistical terms were excluded if they related to qualitative research. The final definitions and synonyms were submitted to three economists, two biostatisticians, and one epidemiologist for review, and revisions were made based on their feedback.

Terminology for Elements of a Regression Equation

Researchers are familiar with the general expression of a regression equation that relates an outcome (indicated by Y on the left-hand side of Equation 1) to explanatory variables (indicated by T, X_1, and X_2 on the right-hand side). An outcome is defined as the levels of a certain characteristic in individuals, populations, or organizations that are determined by or associated with measurements of these individuals, populations, or organizations that are not predetermined by the investigator (Aday, Begley, Lairson, & Balkrishnan, 2004; Bowling & Ebrahim, 2005; Jewell, 2004; van Belle, Fisher, Heagerty, & Lumley, 2004). Outcomes typically examined in health services research include morbidity, mortality, quality of life, quality of care, access to care, patient satisfaction, health care utilization, expenditures, or efficiency. The subscript i in Equation (1) indicates that the patient is the unit of observation:

$$Y_i = \beta_0 + \beta_1 \cdot T_i + \beta_2 \cdot X_{1i} + \beta_3 \cdot X_{2i} + \beta_4 \cdot (T_i \cdot X_{1i}) + \varepsilon_i. \quad (1)$$

There are several synonyms for "outcome," namely Y_i in Equation (1), including dependent variable, explained variable, response variable, endogenous variable, left-hand side variable (because it is to the left of the equals sign), or regressand (Table 1). Outcomes can be continuously distributed or discrete. An outcome in some contexts can be an explanatory variable in other contexts (e.g., structural equation or causal modeling). For example, there have been many papers that examined the determinants of overweight and obesity in which obesity is the outcome variable. However, there is a burgeoning literature examining the association between obesity and health care expenditures (Arterburn, Maciejewski, & Tsevat, 2005; Finkelstein, Trogdon, Cohen, & Dietz, 2009), in which obesity is now the explanatory variable of interest.

Explanatory variables (i.e., T_i, X_{1i}, and X_{2i} in Equation 1) are defined as measurements of individuals, populations, or organizations that explain variation in the outcome (Daniel, 2005; Darlington, 1998; Mertens, 2005; van Belle et al., 2004). Explanatory variables may be experimentally manipulated or predetermined (Trochim, 2001; Vogt, 2005; Wooldridge, 2002). Examples of explanatory variables include whether a patient received a treatment or participated in a program; demographic or socioeconomic

Table 1. Definitions and Synonyms for Terms Describing Elements of a Regression

Statistical Term	Synonyms	Definition
Outcome	Dependent variable, response, endogenous variable, regressand, left-hand side variable, explained variable	The levels of a certain characteristic in individuals, populations, or organizations determined by (or associated with) measurements not predetermined by the investigator
Explanatory variable	Independent variables, predictor variables, control variables, regressor variables, regressors, covariates, exogenous variables, right-hand side variables	A measurement (or multiple measurements) of individuals, populations, organizations, or other relevant unit of analysis (possibly experimentally manipulated) that explains variation in the outcome
Regression coefficient	Beta, parameter estimate, slope, main effect, regression weight	The changes in the levels of the outcome that are associated with a one-unit change in an explanatory variable
Error term	Disturbance term, residual, white noise	An expression of the unmeasured explanatory variables that are related to the outcome

characteristics; characteristics of an individual's usual source of care, neighborhood, market area, state, or country. Synonyms for explanatory variables include independent variables, control variables, predictor variables, regressor variables, exogenous variables, regressors, right-hand side variables, or covariates (Table 1). The next section discusses explanatory variables in greater detail according to their purpose in the regression.

Each regression coefficient (indicated by β_1, β_2, β_3, β_4 in Equation 1) represents the change in the level of the outcome associated with a change in the level or presence of the explanatory variable. Synonyms for regression coefficient, including beta, parameter estimate, slope, main effect, or regression weight (Table 1). The error term (indicated by "ε_i" in Equation 1) represents random variation between subjects and may represent unmeasured explanatory variables that are related to the outcome (Pindyck & Rubinfeld, 1991; Wooldridge, 2003). Synonyms for the error term are listed in Table 1.

Specific Types of Explanatory Variables

The term *explanatory variable* is a general expression for specific types of measurements that are used in regression analysis to explain variation in an outcome. Each type of explanatory variable has a distinct purpose for being included in a regression model, based on its statistical meaning and its anticipated relationship to the outcome based on theory (Table 2).

Table 2. Definitions and Synonyms for Specific Types of Explanatory Variables

Main Statistical Term for Explanatory Variables			Subcategories of Statistical Terms		
Term	Synonyms	Definition	Term	Synonyms	Definition
Explanatory variable	Independent variable, predictor variable, regressor variable, regressor, covariate, exogenous variable, right-hand side variable	A condition or measurement (or multiple measurements) of individuals, populations, organizations, or other relevant unit of analysis (possibly experimentally manipulated) that potentially explains variation in the outcome			
Explanatory variables of interest	Independent variables of interest	Explanatory variables that are the subject of the primary research question or hypothesis	Treatment, intervention, exposure, program		A condition or state experienced by a study participant that may be experimentally manipulated by the scientist
Confounding variable	Confounder or confounding factor	A measurement that is associated with the explanatory variable of interest and with the outcome but is itself not a consequence of the explanatory variable of interest	Observed confounder	Observed confounding variable or factor	A measurement that is associated with the treatment and with the outcome, but is itself not a consequence of the explanatory variable of interest
			Unobserved confounder	Omitted variable, hidden confounding, unobserved confounding variable or factor	A measurement *not* observable by the scientist that is associated with the treatment and with the outcome, but is itself not a consequence of the explanatory variable of interest

(continued)

Table 2. (continued)

Main Statistical Term for Explanatory Variables			Subcategories of Statistical Terms		
Term	Synonyms	Definition	Term	Synonyms	Definition
Control variable	Control, nuisance parameter	A measurement not experimentally manipulated by the scientist that is associated with the outcome, but unassociated with the explanatory variable of interest, which is included in the regression to improve overall model fit to the data and precision of other parameter estimates			
Moderator	Moderating variable, effect modifier, qualifier variable, interaction term	An independent variable that causes the magnitude of effect of a treatment on an outcome to differ according to the level of this explanatory variable			
Mediator	Intervening variable, contingent variable, intermediate factor	An explanatory variable (*A*) that determines the impact of an another explanatory variable (*B*) on the outcome, because it lies on the causal pathway between explanatory variable (*B*) and the outcome			

The explanatory variable of interest or independent variable of interest is the explanatory variable related to the outcome that addresses the primary research question or hypothesis (Petrie & Sabin, 2005). This explanatory variable of interest may be a predetermined subject characteristic (e.g., race), a condition or state that a subject has chosen (e.g., enrollment in a specific health plan), a condition or state the subject finds himself in that is beyond the control of the scientist (e.g., newly diagnosed with diabetes), or a condition or state that is experimentally manipulated by the scientist in a randomized trial (Table 2; Bowling & Ebrahim, 2005; Rothman & Greenland, 1998; Trochim, 2001). Explanatory variables of interest may also be referred to as treatment, intervention, program, or exposure variables (indicated by T in Equation 1). For example, the purpose of a randomized trial is to examine whether outcomes differ between patients randomized to either treatment or control conditions and the treatment variable is the explanatory variable of interest. If treatment and control groups that were similar (on average) at baseline realize outcome differences at follow-up, then this is evidence of a treatment effect.

The second type of explanatory variable—a confounding variable—is a measurement that is associated with both the variable of interest and outcome, but is itself not a consequence of the explanatory variable of interest (Bowling & Ebrahim, 2005; Greenland, 1998; Hosmer & Lemeshow, 2004; Jewell, 2004; Selvin, 2004; Young, 2005). In some cases, unmeasured confounding can arise from measurement error. For example, an analysis might control for whether a patient has heart failure (HF) or not, but this simple indicator belies the wide range of HF severity. This error in the measurement of HF severity may be correlated with an independent variable of interest, and thus confound an estimation of the relationship between the variable of interest and the outcome. Synonyms for a confounding variable include confounder or confounding factor (Table 2). For example, age has been argued to be a confounder in the relationship between obesity and mortality in nonelderly individuals because obesity and the probability of death increase with age (Flegal, Graubard, Williamson, & Gail, 2005; Flegal, Williamson, Pamuk, & Rosenberg, 2004). Failure to properly adjust for the confounding effect of age (by including X_{1i} in Equation 1) can result in incorrect inferences about the deaths attributed to obesity. If all relevant confounders are observed by the scientist because they are known and explicitly measured, these confounders are referred to as observed confounders that can be controlled in the regression analysis or by other methods (e.g., matching or propensity scores). Synonyms for observed confounders are observed confounding variable or observed confounding factor. If all relevant confounders are not known or are known but not measured, then there exist unobserved confounders. In many observational studies, there are also unobserved confounders that greatly complicate the task of estimating the true relationship between treatment and outcome. A confounder that is often unobserved in claims data–based observational studies is patient functional status or severity of disease. Synonyms for unobserved confounders are omitted variables, unobserved confounding variable, unobserved confounding factor, or hidden confounder.

The third type of explanatory variable, referred to as a control variable (represented by X_{2i} in Equation 1) is a factor associated with the outcome, but unassociated with the explanatory variable of interest, not experimentally manipulated by the scientist, and not related to the treatment. Control variables are included in regression models because they can improve precision of the other parameter estimates and the overall fit of the model to the data (Armitage, Berry, & Matthews, 2002). Synonyms for control variable include control and nuisance parameter.

A moderator, the fourth type of explanatory variable, has been defined as an explanatory variable not experimentally manipulated by the scientist that causes the magnitude of effect of a treatment on an outcome to differ according to the level of this independent variable (Aguinis, 2004; Bowling & Ebrahim, 2005; Hosmer & Lemeshow, 2000; Strom, 2000; Trochim, 2001; Wooldridge, 2003). A moderator should also temporally precede the explanatory variable that it modifies (Kraemer, Wilson, Fairburn, & Agras, 2002). A moderator has also been referred to as a moderating variable, an effect modifier, a qualifier variable, or an interaction term (indicated as the product of T and X_{1i} in Equation 1). For example, an analysis of the relationship between social support and medication adherence found that a patient's locus of control moderated the social support–adherence relationship. That is, the "effect of social support on subsequent medication adherence depends on beliefs about the controllability of one's health" (Voils, Steffens, Flint, & Bosworth, 2005; see Figure 1).

Finally, a mediator is an explanatory variable that at least partly explains the relationship between another explanatory variable and the outcome, typically the impact of treatment on the outcome, because it lies on the causal pathway between the explanatory variable and the outcome (Aguinis, 2004; Bowling & Ebrahim, 2005). An explanatory variable may be identified as a mediator and used as such based on the particular theory and variables in a specific example. For example, analyses of the relationship between stress and obesity have found that dietary restraint is an important mediator of this relationship (Roberts, Troop, Connan, Treasure, & Campbell, 2007). That is, increased stress has been shown to reduce dietary restraint, which leads to greater consumption and obesity. Thus, the impact of stress on obesity is mediated by the impact of stress on dietary restraint. Mediators have also been referred to as intervening variables, contingent variables, or intermediate factors. A mediator causes variation in the outcome and itself varies due to variation in explanatory variable, because the explanatory variable temporally precedes mediator (Kraemer et al., 2002; Kraemer, Kiernan, Essex, & Kupfer, 2006; Kraemer, Stice, Kazdin, Offord, & Kupfer, 2001).

For example, a study that evaluates the impact of weight loss treatment on quality of life in obese individuals has to consider the mediating role that weight loss plays in the relationship between weight loss treatment (e.g., exercise program, low-fat diet, medication, or surgery) and quality of life (see Figure 2A). Quality of life could be different between people who were randomized to receive treatment and people were randomized to not receive treatment. For example, engaging in weight loss treatment may make participants feel that they are gaining control over their weight and this improves

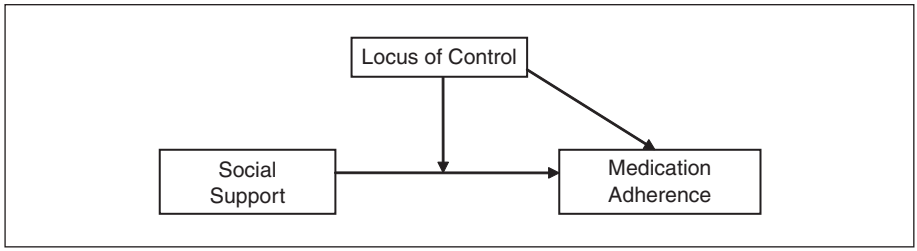

Figure 1. Moderation of locus of control in the social support–medication adherence relationship

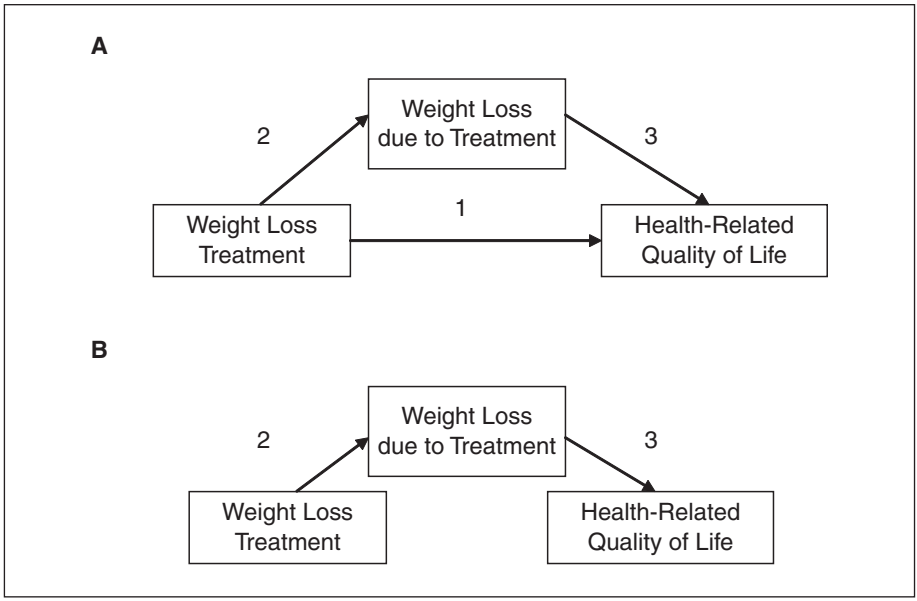

Figure 2. (A) Mediation of weight loss in the treatment–quality of life relationship and (B) full mediation of weight loss in the treatment–quality of life relationship

their quality of life, which is a direct effect of treatment. However, it could be the case that weight loss treatment does not affect quality of life directly (e.g., Path 1 is null), but indirectly through the impact of weight loss treatment on actual weight loss (Path 2) and the direct effect of weight loss on quality of life (Path 1). If this is the case, then the impact of weight loss treatment on quality of life is entirely due to the mediating impact of weight loss and the hypothesized relationship between treatment, weight loss, and quality of life changes from that illustrated in Figure 2A to the relationship in Figure 2B (Kraemer et al., 2001; Kraemer et al., 2002; Kraemer et al., 2006).

Terminology for Study Designs

Health services scientists conduct evaluations of individuals, families, health providers, health care organizations, neighborhoods, and health systems using a range of study designs that vary in their threats to internal and external validity (Campbell & Stanley, 1963; Donner & Klar, 2000; Murray, 1998; Piantadosi, 2005; Pocock, 1974; Rothman & Greenland, 1998; Shadish, Cook, & Campbell, 2002). Study designs can be partitioned according to the purpose of the study: (a) to provide a description of a population or condition, (b) to identify the association between an explanatory variable and an outcome, (c) to identify a causal effect of an intervention, treatment, or characteristic on an outcome, or (d) to enable synthesis of prior studies to develop an evidence base about a specific issue.

Well-designed experimental studies can be effective for identifying causal effects of treatment on an outcome. The researcher reduces the likelihood of unobserved confounding by randomly allocating subjects to either treatment or control. The researcher then manipulates a condition for subjects randomized to the treatment arm, takes outcome measurements on all subjects (e.g., patients) in both arms, and compares outcomes differences that result from the experimental manipulation (Campbell & Stanley, 1963; Rothman & Greenland, 1998). An experimental study is defined as a study in which subjects are randomized either to a condition or state that is manipulated by a scientist or to an alternative condition to ascertain what effect such manipulation has on the subjects (Shadish et al., 2002). Synonyms for experimental study include randomized study, randomized trial, randomized controlled trial (RCT), and field trial.

The RCT is considered the gold standard for identifying the unique impact of an experimentally manipulated treatment on an outcome (e.g., the impact of an antihypertensive medication on blood pressure control) because randomization provides reasonable assurance that treatment and control cohorts are balanced (on average) on observed and unobserved explanatory variables (Rothman & Greenland, 1998). If the only difference between the two experimental cohorts is the treatment they receive, then presumably the only cause of a change in the outcome can be the manipulated condition or state itself (Shadish et al., 2002).

Field trials randomize individuals at risk for developing a health condition to examine whether a treatment can prevent or delay the incidence of the health condition (Rothman & Greenland, 1998). For example, the Diabetes Prevention Program (DPP) was a large, multisite randomized trial that examined whether an oral medication (metformin) or a diet and exercise regimen could prevent or delay the onset of type 2 diabetes in individuals with impaired glucose tolerance, which put them at high risk for developing diabetes for the first time (Knowler et al., 2002).

For certain types of trials, the unit of randomization is not the patient but some larger aggregation of individuals. Community intervention trials randomize entire communities at risk for some condition to an intervention (Rothman & Greenland, 1998). Cluster randomized trials or group randomized trials randomize groups of individuals, such

as classrooms in schools or wards within hospitals, to an intervention to examine the impact of an intervention on an outcome (Murray, 1998; Rothman & Greenland, 1998). Cluster randomized trials are typically conducted because it is not feasible to deliver an intervention to some individuals within some larger unit but not others (e.g., an experimental change in the organization of a clinic affects all patients treated at the clinic), because the researcher is concerned that patients in the control group might be contaminated by social, organizational, or physical proximity to patients in the treatment group (e.g., the physician may be induced to change his prescribing practices for all his patients because of the recommendations he received from the care coordinator of his patient in a care management trial), or because a unit of analysis more aggregated than the individual is the natural unit of analysis. Patient-level and cluster-level experimental study designs have a common feature of randomizing subjects to an experimentally manipulated intervention and a common purpose of identifying the causal effect of the intervention.

RCTs may be challenging in some instances because it would be unethical to randomize patients to treatment or no treatment conditions or an RCT is infeasible because of cost, time, or practical difficulties. Quasi-experimental methods provide an alternative study design in these instances. Unlike experimental studies, quasi-experimental studies do not randomly allocate subjects to treatment and do not experimentally manipulate a treatment. Instead, subjects self-select or are assigned by a provider to a particular treatment. The purpose of quasi-experimental studies is to identify an association between a nonrandomly assigned or self-selected treatment and an outcome. Quasi-experimental studies identify the effect of a self-selected treatment on an outcome by comparing outcomes among those exposed to the treatment or condition with outcomes among those not exposed. This comparison can be based on an outcome assessment on a control group and/or a (preperiod) outcome assessment prior to treatment (Shadish et al., 2002). Quasi-experimental studies are also referred to as observational studies or nonexperimental studies (Table 3; Campbell & Stanley, 1963; Shadish et al., 2002). There are a variety of quasi-experimental designs that differ based on whether a control group is present, whether pretest measurements are taken, and whether measurements are taken once or repeated one or more times in the preperiod and/or postperiod. Quasi-experimental studies that have one measurement of self-selected treatment subjects and self-selected control subjects are only able to assess between-group differences in the outcome but not within-group differences over time. A frequently used quasi-experimental design for rare events is a case–control study in which subjects are identified on the basis of the presence or absence of the outcome to examine the association between an exposure and a rare event. For example, a study of the risk factors for bacterial pneumonia in HIV-positive patients used a case-control study to assess the association between smoking status and pneumonia (Tumbarello et al., 1998). On the other hand, cohort studies are studies of patients with a common characteristic at a single point in time in which measurements are conducted at multiple points in time. The collection of multiple measurements on subjects over two or more time periods enables an assessment of differences over time within a group

Table 3. Experimental and Quasi-Experimental Study Designs

Main Statistical Term for Explanatory Variables			Subcategories of Statistical Terms		
Term	Synonyms	Definition	Term	Synonyms	Definition
Experimental study	Randomized study, randomized trial, randomized controlled trial (RCT), field trial	A study in which subjects are randomized either to a condition or state that is manipulated by a scientist or to an alternative condition to ascertain what effect such manipulation has on the subjects	Group randomized trial	Cluster randomized trial	Randomization of groups of patients to an experimentally manipulated intervention
Quasi-experimental study	Nonexperimental study, observational study	A set of observations in which subjects are assigned to a condition or state in a nonrandom manner	Natural experiment		Studies in which there is a change in a situation, policy, or process that is not manipulated by the researcher or research
			Case–control study	Case–referent study	Studies in which subjects are identified on the basis of the presence or absence of the outcome to examine the association between an exposure and a rare event
			Cohort study	Panel data study, longitudinal cohort study	Studies of patients with a common characteristic at a single point in time in which measurements are conducted at multiple points in time
			Time series study		Studies in which a large series of observations made on the same variable consecutively over time, either on the same units of analysis or on different but similar units of analysis
			Cross-sectional time series study	Multiple cross-section study, time series of cross sections	Studies in which measurements are conducted on a cohort of subjects at multiple points in time, but the specific subjects that comprise the cohort change over time

(Fitzmaurice, Laird, & Ware, 2004; Greene, 2003; Jones & Wang, 1998; Machin & Campbell, 2005; Marczyk, DeMatteo, & Festinger, 2005; Vogt, 2005; Wooldridge, 2002). Cohort studies are often used to track patients with a specific medical condition to describe the incidence and natural history of that condition (Rothman & Greenland, 1998). Cohort studies are also referred to as panel data studies or longitudinal cohort studies.

A cohort study design commonly used in health services research is a natural experiment. A natural experiment is defined as a study in which there is a change in a situation, policy, or process that is not manipulated by the researcher or research (Shadish et al., 2002). For example, the introduction of Medicare Part D on January 1, 2006 created a natural experiment to examine how prescription drug coverage changes affected medication utilization (Yin et al., 2008). The effect of the introduction of Part D on medication utilization can be assessed by comparing the utilization of a cohort of Medicare beneficiaries prior to Part D with the utilization of this same cohort after the introduction of Part D. Causal inferences would be strengthened if it was possible to compare the experience of this "treatment" cohort to a cohort of patients who had no change in their medication benefits over the same time period.

There are two additional quasi-experimental study designs that involve repeated measurements of observations—time-series studies and cross-sectional time series studies. A time series study is "a large series of observations made on the same variable consecutively over time," which can be made on the same unit of analysis with repeated measurements (e.g., tracking annual rates of hospitalizations for Medicare beneficiaries to understand trends in influenza-related diseases; Greene, 2003; Hebert, McBean, & Kane, 2005; Kmenta, 1986; Shadish et al., 2002; Wooldridge, 2002). Time series studies are similar to cohort studies because multiple measurements are taken, but they are different from cohort studies because they track a single subject (e.g., a state, the nation, the Medicare program) over time, not multiple and individually identifiable subjects as in cohort studies. In a cross-sectional time-series study, measurements are conducted on a cohort of subjects at multiple points in time; however, the specific subjects within the cohort change over time. Cross-sectional, time-series studies have also been referred to as multiple cross-section study or a time series of cross sections. The general purpose of all of these quasi-experimental study designs is to identify an association between an exposure of interest and an outcome.

Studies in which measurements are taken on subjects at one point in time with or without a control group are referred to as cross-sectional studies (Fitzmaurice, Laird, & Ware, 2004; Machin & Campbell, 2005; Mertens, 2005; Rothman & Greenland, 1998; Young, 2005). The purpose of cross-sectional studies is to describe a population, condition, outcome, or treatment. A cross-sectional study is defined as a study in which measurements on multiple subjects (e.g., hospital discharge data on patients admitted in 1 month) is conducted at a single point in time, which may involve a single data set or multiple data sets. For example, a study of U.S. hospitals used a cross-sectional design to test the association between health network affiliation and financial performance of hospitals (Bazzoli, Chan, Shortell, & D'Aunno, 2000).

Table 4. Definitions and Synonyms for Descriptive Study Designs

Statistical Term	Synonyms	Definition
Cross-sectional study		Studies that conduct measurements on multiple subjects at a single point in time
Single case study	Case report	Studies of a single patient to describe manifestations, clinical course and prognosis
Case series		Studies of a consecutive group of subjects who have a common condition to describe manifestations, clinical course, and prognosis

A single case study can be used to describe manifestations, clinical course, and prognosis of a patient with a particular condition for the purpose of generating hypotheses. Single case studies have also been referred to as case reports (Rothman & Greenland, 1998). A case series is a summary of the manifestations, clinical course, and prognosis for a consecutive group of subjects who have a common condition, which can be useful in hypothesis generation (Table 4). A case study or a case series may also be conducted on organizations, such as a study that interviewed representatives of eight major integrated health systems and two large integrated medical groups to understand the types of capitation and contract support systems used in these systems (Bazzoli, Miller, & Burns, 2000).

Terminology for Types of Bias

Health services researchers conducting analyses in quasi-experimental studies typically have to consider two types of bias: (a) selection bias and (b) sample selection bias (Table 5). Selection bias is a "missing data" issue and sample selection bias is a "missing people" issue. Studies are subject to selection bias under three conditions: (a) when patients at different values of the explanatory variable of interest (e.g., patients in the treatment and control arms) are systematically different from one another, (b) when these systematic differences are also related to variations in the outcome, and (c) when these systematic differences are not captured in the available data and therefore represent unobserved confounders. As a result of selection bias, the estimated treatment effect is biased because it represents the effect of the treatment on the outcome and the impact of unobserved confounders on the outcome (Greene, 2003; Rothman & Greenland, 1998; Trochim, 2001).

Suppose there is a known confounder (X_5) that is unmeasured in a data set we have to model Equation (1). If this confounder (X_5) is unmeasured it becomes a part of the error term because we are unable to include it as a covariate as we would prefer. If the correlation between treatment (T) and X_5 is nonzero, the existence of this unobserved confounder greatly complicates the task of identifying the true relationship between treatment (represented in the parameter β_1) and the outcome (Y). There is a major body of research in the econometrics (Abadie & Imbens, 2006; Angrist,

Table 5. Definitions and Synonyms for Specific Types of Bias

Statistical Term	Synonyms	Definition
Sample selection bias	Self-selection bias, incidental truncation, response bias, nonresponse bias, informative missingness, missing not at random	Sample estimates that do not generalize to estimates for the population of interest because the study sample was not obtained from the population of interest by simple random sampling. Specific terms used to describe sample selection bias caused by attrition from a longitudinal study include attrition bias, and bias due to loss to follow-up
Selection bias	Endogeneity, omitted variables bias, unmeasured confounding, unobserved confounding, confounding by (contra-) indication, residual confounding, hidden selection bias	The estimated treatment effect estimate does not represent just the unique effect of treatment on an outcome, because a subset of confounders is missing and accounted for in the treatment effect estimate

Imbens, & Rubin, 1996; Bound, Jaeger, & Baker, 1995; Heckman & Hotz, 1989; LaLonde, 1986; Newhouse & McClellan, 1998), epidemiology (Greenland & Robins, 1986; Hernán & Robins, 2006; Pearl, 2000; Robins, Hernán, & Brumback, 2000; Robins, Mark, & Newey, 1992; Rotnitzky & Robins, 2003), and biostatistics (Rosenbaum, 1989; Rosenbaum & Rubin, 1983, 1984, 1985; Rubin, 1974, 1979) literature devoted to methods that attempt to address unobserved confounding.

Selection bias can also arise when observed variables are measured inaccurately, so that error in measuring the "true" concept induces an additional component of the error that is correlated with the treatment variable (Heckman, 1985). Last, selection bias can arise when observed variables are measured accurately but the functional form of these variables is misspecified. Selection bias has also been referred to as endogeneity, unobserved confounding, unmeasured confounding, residual confounding, hidden bias, and omitted variables bias.

Epidemiologic discussions of selection bias have described two variants of the general concept: (a) confounding by indication and (b) confounding by contraindication. Confounding by indication occurs when the association between an unobserved confounder (e.g., disease severity) and treatment has the same direction as the association between the unobserved confounder and the outcome. For example, more severe asthma makes patients ideal candidates for long-acting inhaled beta agonists but more severe asthma also puts patients at greater risk of death. Failure to account for asthma severity in an analysis of the impact of long-acting beta agonists on mortality would suggest that beta agonists put asthma patients at greater risk of death (e.g., "beta agonists

were killing people"; Slone, Shapiro, Miettinen, Finkle, & Stolley, 1979). In fact, beta agonists are protective against mortality, but the observed harmful effect is due to greater asthma severity. Confounding by contraindication occurs when an association between an unobserved confounder (e.g., disease severity) and treatment has the opposite direction as the association between the unobserved confounder and the outcome. For example, unobserved current smoking status confounds the body mass index (BMI) and mortality relationship. Because smoking lowers BMI and smoking increases mortality rates, the impact of BMI on mortality would be underestimated if smoking is not controlled (Lawlor, Hart, Hole, & Davey Smith, 2006; Manson, Stampfer, Hennekens, & Willett, 1987).

Sample selection bias, which is distinct from selection bias, occurs when a study sample under investigation represents a restricted, nonrandom segment of the population of interest because some individuals are not observed (Bowling & Ebrahim, 2005; Heckman, 1976, 1979, 1985; Winship & Mare, 1992; Wooldridge, 2002;). Hence, the earlier reference to sample selection bias as a "missing people" issue in which explanatory variables and outcomes are unobserved on a subset of subjects. Sample selection bias can also arise via attrition of a nonrandom group of patients because of disengagement from the study, moving out of the area, or death. Terms such as informative missingness, missing not at random, attrition bias, and bias due to loss to follow-up refer to this type of sample selection bias.

Finally, sample selection bias can occur in experimental studies and quasi-experimental studies if a nonrandom subset of a random sample provides data (e.g., a self-selected group of survey recipients do not respond to a survey) for evaluation (Gail, 1998). For example, the analysis of health care utilization obtained from claims data that adjusts for patient factors obtained from claims data and survey data will likely have to be estimated on a subsample of patients in the study who returned surveys. If the patients who returned surveys are different from the population measured in claims data, then sample selection bias exists due to nonrandom survey response. As a result of sample selection bias, the sample-based estimate of the relationship between an explanatory variable and outcome may be biased. Sample selection bias has also been referred to as self-selection bias, incidental truncation, or response bias.

Conclusion

The purpose of this article is to provide consistent definitions and a list of synonyms for statistical concepts commonly addressed in health services research. The article cannot address and resolve differences in assumptions or technical implementation of assumptions that exist between disciplinary methods, but those issues are beginning to be addressed in the theoretical and applied literature. Misunderstandings and conflicts that arise from fundamental mathematical and statistical differences of these sorts require a different focus than the semantic focus of this article. By providing a "methods thesaurus," this article can at least clarify semantic misunderstandings that are an important step in understanding and bridging technical differences.

If all terms describing the same statistical concept were understood by investigators conducting health services research, methodologists from different disciplines could spend less time being confused by each others' unique terminology and more time working on collaborative evaluation. Health services research training programs could advance toward this goal by making their doctoral students aware of the range of terms used by different disciplines to describe the same statistical concepts, as well the differences and similarities between the terms. In addition, health services research training programs could strengthen methods coursework to expose students to statistical methods available from different disciplines to address statistical challenges in health services research. Such training would foster investigations of the advantages and disadvantages of applying different statistical methods to address pressing health policy questions.

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