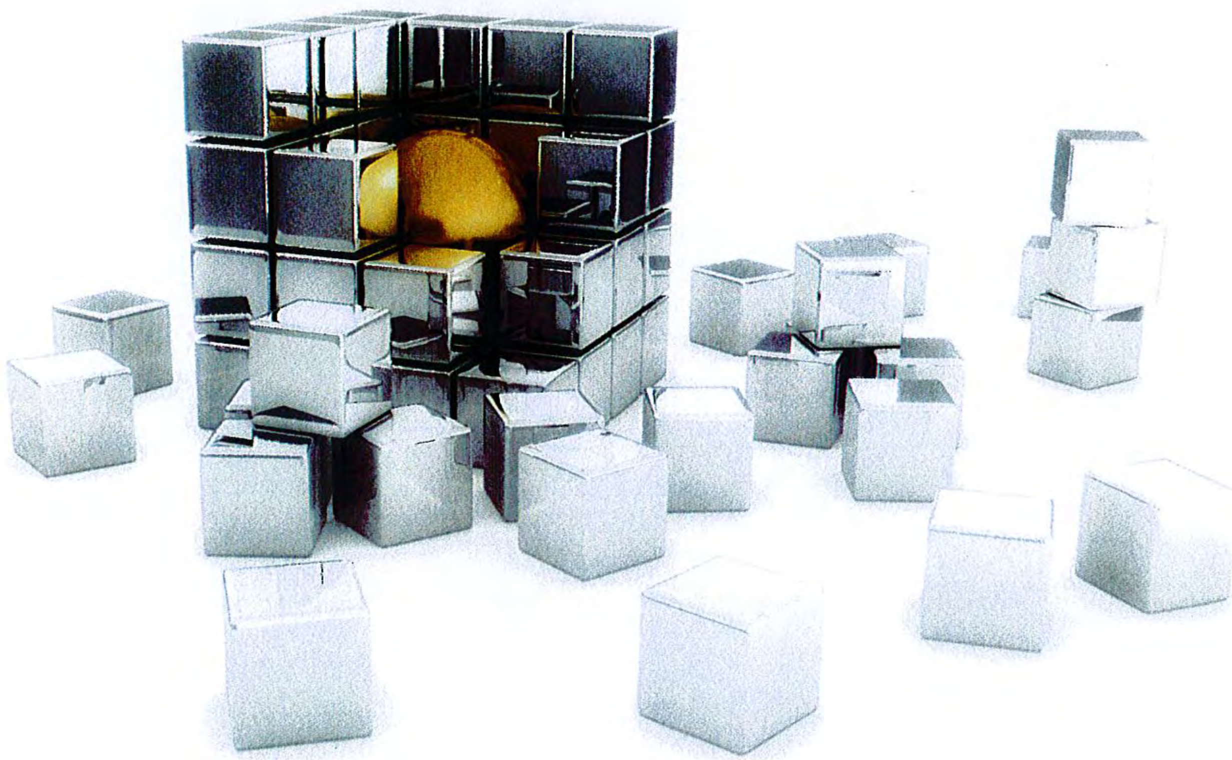
ENCYCLOPEDIA OF

RESEARCH DESIGN

VOLUME 1



EDITED BY
NEIL J. SALKIND

For information:

SAGE Publications, Inc.
2455 Teller Road
Thousand Oaks, California 91320
E-mail: order@sagepub.com

SAGE Publications Ltd..
1 Oliver's Yard
55 City Road
London EC1Y 1SP
United Kingdom

SAGE Publications India Pvt. Ltd.
B 1/I 1 Mohan Cooperative Industrial Area
Mathura Road, New Delhi 110 044
India

SAGE Publications Asia-Pacific Pte. Ltd.
33 Pekin Street #02-01
Far East Square
Singapore 048763

Printed in the United States of America.

Library of Congress Cataloging-in-Publication Data

Encyclopedia of research design/edited by Neil J. Salkind.
v. cm.
Includes bibliographical references and index.
ISBN 978-1-4129-6127-1 (cloth)
1. Social sciences—Statistical methods—Encyclopedias. 2. Social sciences—Research—Methodology—Encyclopedias.
I. Salkind, Neil J.

HA29.E525 2010
001.403—dc22 2010001779

This book is printed on acid-free paper.

10 11 12 13 14 10 9 8 7 6 5 4 3 2 1

Publisher:	Rolf A. Janke
Acquisitions Editor:	Jim Brace-Thompson
Editorial Assistant:	Michele Thompson
Developmental Editor:	Carole Maurer
Reference Systems Coordinators:	Leticia M. Gutierrez, Laura Notton
Production Editor:	Kate Schroeder
Copy Editors:	Bonnie Freeman, Liann Lech, Sheree Van Vreede
Typesetter:	C&M Digitals (P) Ltd.
Proofreaders:	Kristin Bergstad, Kevin Gleason, Sally Jaskold, Sandy Zilka
Indexer:	Virgil Diodato
Cover Designer:	Glenn Vogel
Marketing Manager:	Amberlyn McKay

the criteria used for measurement by the course instructor. However, one cannot assume that the difference between an A and a B is the same as the difference between a B and a C. Similarly, researchers might set up a Likert-type scale to measure level of satisfaction with one's job and assign a 5 to indicate *extremely satisfied*, 4 to indicate *very satisfied*, 3 to indicate *moderately satisfied*, and so on. A person who gives a rating of 5 feels more job satisfaction than a person who gives a rating of 3, but it has no meaning to say that one person has 2 units more satisfaction with a job than another has or exactly how much more satisfied one is with a job than another person is.

In addition to verbal descriptions, categorical variables are often presented visually using tables and charts that indicate the group frequency (i.e., the number of values in a given category). Contingency tables show the number of counts in each category and increase in complexity as more attributes are examined for the same object. For example, a car can be classified according to color, manufacturer, and model. This information can be displayed in a contingency table showing the number of cars that meet each of these characteristics (e.g., the number of cars that are white and manufactured by General Motors). This same information can be expressed graphically using a bar chart or pie chart. Bar charts display the data as elongated bars with lengths proportional to category frequency, with the category labels typically being the x-axis and the number of values the y-axis. On the other hand, pie charts show categorical data as proportions of the total value or as a percentage or fraction. Each category constitutes a section of a circular graph or "pie" and represents a subset of the 100% or fractional total. In the car example, if 25 cars out of a sample of 100 cars were white, then 25%, or one quarter, of the circular pie chart would be shaded, and the remaining portion of the chart would be shaded alternative colors based on the remaining categorical data (i.e., cars in colors other than white).

Specific statistical tests that differ from other quantitative approaches are designed to account for data at the categorical level. The only *measure of central tendency* appropriate for categorical variables at the nominal level is *mode* (the most frequent category or categories if there is more than one mode), but at the ordinal level, the median or point below which 50% of the scores fall is also used. The chi-square distribution is used for categorical data at the nominal level. Observed frequencies in each category are compared with the theoretical or expected frequencies. Types of correlation coefficients that use categorical data include point biserial; Spearman rho, in which both variables are at the ordinal level; and phi, in which both variables are dichotomous (e.g., boys vs. girls on a yes–no question). Categorical variables can also be used in various statistical analyses such as *t* tests, analysis of variance, multivariate analysis of variance, simple and multiple regression analysis, and discriminant analysis.

Karen D. Multon and Jill S. M. Coleman

See also Bar Chart; Categorical Data Analysis; Chi-Square Test; Levels of Measurement; Likert Scaling; Nominal Scale; Ordinal Scale; Pie Chart; Variable

Further Readings

Siegel, A. F., & Morgan, C. J. (1996). *Statistics and data analysis: An introduction* (2nd ed.). New York: Wiley.
Simonoff, J. S. (2003). *Analyzing categorical data.* New York: Springer.

Causal-Comparative Design

A causal-comparative design is a research design that seeks to find relationships between independent and dependent variables after an action or event has already occurred. The researcher's goal is to determine whether the independent variable affected the outcome, or dependent variable, by comparing two or more groups of individuals. There are similarities and differences between causal-comparative research, also referred to as *ex post facto research,* and both correlational and experimental research. This entry discusses these differences, as well as the benefits, process, limitations, and criticism of this type of research design. To demonstrate how to use causal-comparative research, examples in education are presented.

Comparisons With Correlational Research

Many similarities exist between causal-comparative research and correlational research. Both methods are useful when experimental research has been deemed impossible or unethical as the research design for a particular question. Both causal-comparative and correlational research designs attempt to determine relationships among variables, but neither allows for the actual manipulation of these variables. Thus, neither can definitively state that a true cause-and-effect relationship occurred between these variables. Finally, neither type of design randomly places subjects into control and experimental groups, which limits the generalizability of the results.

Despite similarities, there are distinct differences between causal-comparative and correlational research designs. In causal-comparative research, the researcher investigates the effect of an independent variable on a dependent variable by comparing two or more groups of individuals. For example, an educational researcher may want to determine whether a computer-based ACT program has a positive effect on ACT test scores. In this example, the researcher would compare the ACT scores from a group of students that completed the program with scores from a group that did not complete the program. In correlational research, the researcher works with only one group of individuals. Instead of comparing two groups, the correlational researcher examines the effect of one or more independent variables on the dependent variable within the same group of subjects. Using the same example as above, the correlational researcher would select one group of subjects who have completed the computer-based ACT program. The researcher would use statistical measures to determine whether there was a positive relationship between completion of the ACT program and the students' ACT scores.

Comparisons With Experimental Research

A few aspects of causal-comparative research parallel experimental research designs. Unlike correlational research, both experimental research and causal-comparative research typically compare two or more groups of subjects. Research subjects are generally split into groups on the basis of the independent variable that is the focus of the study. Another similarity is that the goal of both types of research is to determine what effect the independent variable may or may not have on the dependent variable or variables.

While the premises of the two research designs are comparable, there are vast differences between causal-comparative research and experimental research. First and foremost, causal-comparative research occurs after the event or action has been completed. It is a retrospective way of determining what may have caused something to occur. In true experimental research designs, the researcher manipulates the independent variable in the experimental group. Because the researcher has more control over the variables in an experimental research study, the argument that the independent variable caused the change in the dependent variable is much stronger. Another major distinction between the two types of research is random sampling. In causal-comparative research, the research subjects are already in groups because the action or event has already occurred, whereas subjects in experimental research designs are randomly selected prior to the manipulation of the variables. This allows for wider generalizations to be made from the results of the study.

Table 1 breaks down the causal-comparative, correlational, and experimental methods in reference to whether each investigates cause-effect and whether the variables can be manipulated. In addition, it notes whether groups are randomly assigned and whether the methods study groups or individuals.

When to Use Causal-Comparative Research Designs

Although experimental research results in more compelling arguments for causation, there are many times when such research cannot, or should not, be conducted. Causal-comparative research provides a viable form of research that can be conducted when other methods will not work. There are particular independent variables that are not capable of being manipulated, including gender, ethnicity, socioeconomic level, education level, and religious preferences. For instance, if researchers intend to examine whether ethnicity affects

Table 1 Comparison of Causal-Comparative, Correlational, and Experimental Research

Method	*Investigates Cause–Effect*	*Manipulates Variable*	*Randomly Assigns Participants to Groups*	*Involves Group Comparisons*	*Studies Groups or Individuals*	*Focus*	*Identifies Variables for Experimental Exploration*
Causal-comparative research	Yes	No (it already occurred)	No (groups formed prior to study)	Yes	Two or more groups of individuals and one independent variable	Focus on differences of variables between groups	Yes
Correlational research	No	No	No (only one group)	No	Two or more variables and one group of individuals	Focus on relationship among variables	Yes
Experimental research	Yes	Yes	Yes	Yes	Groups or individuals depending on design	Depends on design; focuses on cause/effect of variables	Yes

self-esteem in a rural high school, they cannot manipulate a subject's ethnicity. This independent variable has already been decided, so the researchers must look to another method of determining cause. In this case, the researchers would group students according to their ethnicity and then administer self-esteem assessments. Although the researchers may find that one ethnic group has higher scores than another, they must proceed with caution when interpreting the results. In this example, it might be possible that one ethnic group is also from a higher socioeconomic demographic, which may mean that the socioeconomic variable affected the assessment scores.

Some independent variables should not be manipulated. In educational research, for example, ethical considerations require that the research method not deny potentially useful services to students. For instance, if a guidance counselor wanted to determine whether advanced placement course selection affected college choice, the counselor could not ethically force some students to take certain classes and prevent others from taking the same classes. In this case, the counselor could still compare students who had completed advanced placement courses with those who had not, but causal conclusions are more difficult than with an experimental design.

Furthermore, causal-comparative research may prove to be the design of choice even when experimental research is possible. Experimental research is both time-consuming and costly. Many school districts do not have the resources to conduct a full-scale experimental research study, so educational leaders may choose to do a causal-comparative study. For example, the leadership might want to determine whether a particular math curriculum would improve math ACT scores more effectively than the curriculum already in place in the school district. Before implementing the new curriculum throughout the district, the school leaders might conduct a causal-comparative study, comparing their district's math ACT scores with those from a school district that has already used the curriculum. In addition, causal-comparative research is often selected as a precursor to experimental research. In the math curriculum example, if the causal-comparative study demonstrates that the curriculum has a positive effect on student math ACT scores, the school leaders may then choose to conduct a full experimental research study by piloting the curriculum in one of the schools in the district.

Conducting Causal Comparative Research

The basic outline for conducting causal comparative research is similar to that of other research

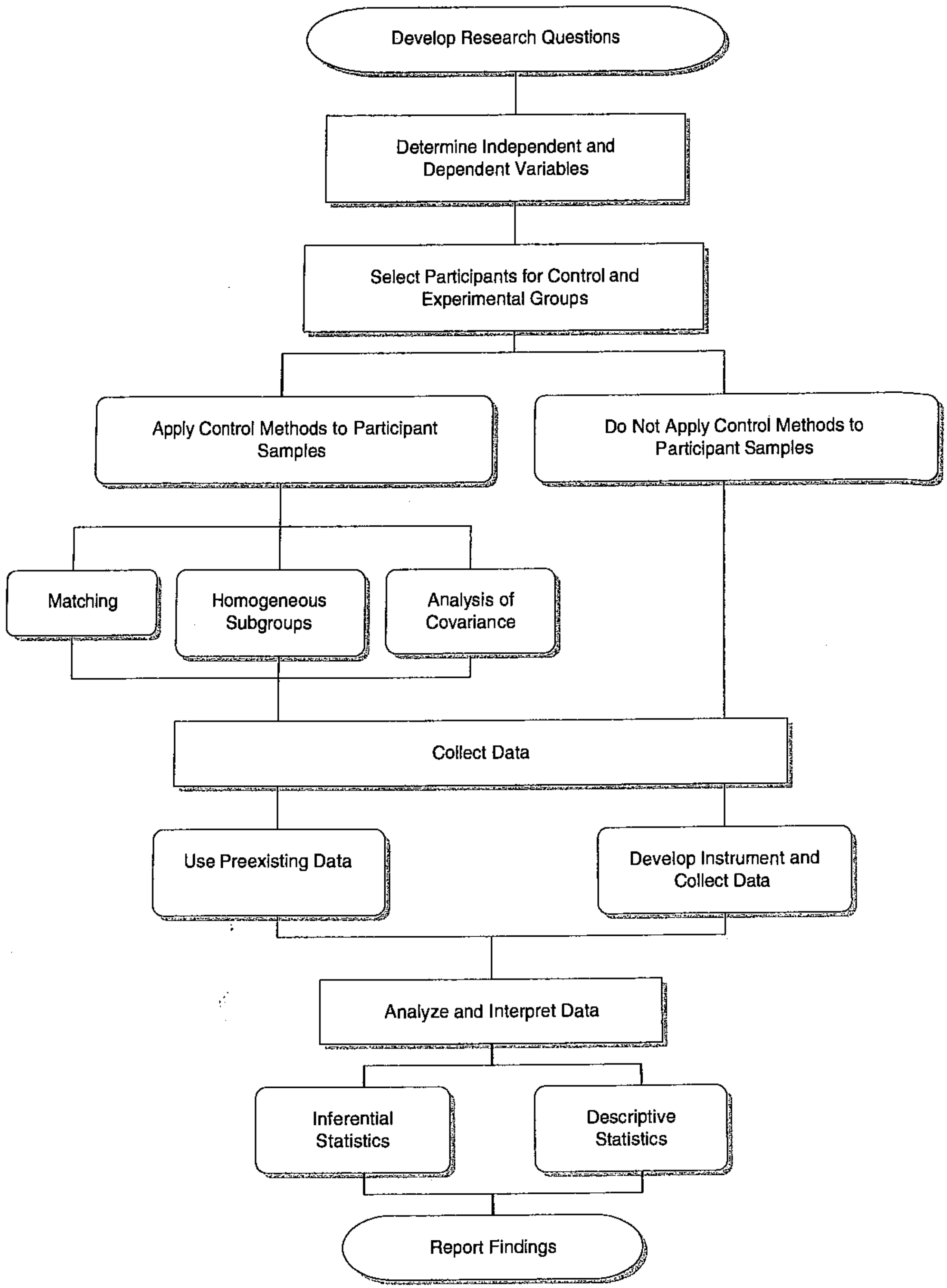


Figure 1 Flowchart for Conducting a Study

designs. Once the researcher determines the focus of the research and develops hypotheses, he or she selects a sample of participants for both an experimental and a control group. Depending on the type of sample and the research question, the researcher may measure potentially confounding variables to include them in eventual analyses. The next step is to collect data. The researcher then analyzes the data, interprets the results, and reports the findings. Figure 1 illustrates this process.

Determine the Focus of Research

As in other research designs, the first step in conducting a causal-comparative research study is to identify a specific research question and generate a hypothesis. In doing so, the researcher identifies a dependent variable, such as high dropout rates in high schools. The next step is to explore reasons the dependent variable has occurred or is occurring. In this example, several issues may affect dropout rates, including such elements as parental support, socioeconomic level, gender, ethnicity, and teacher support. The researcher will need to select which issue is of importance to his or her research goals. One hypothesis might be, "Students from lower socioeconomic levels drop out of high school at higher rates than students from higher socioeconomic levels." Thus, the independent variable in this scenario would be socioeconomic levels of high school students.

It is important to remember that many factors affect dropout rates. Controlling for such factors in causal-comparative research is discussed later in this entry. Once the researcher has identified the main research problem, he or she operationally defines the variables. In the above hypothesis, the dependent variable of high school dropout rates is fairly self-explanatory. However, the researcher would need to establish what constitutes lower socioeconomic levels and higher socioeconomic levels. The researcher may also wish to clarify the target population, such as what specific type of high school will be the focus of the study. Using the above example, the final research question might be, "Does socioeconomic status affect dropout rates in the Appalachian rural high schools in East Tennessee?" In this case, causal comparative would be the most appropriate method of research because the independent variable of socioeconomic status cannot be manipulated.

Because many factors may influence the dependent variable, the researcher should be aware of, and possibly test for, a variety of independent variables. For instance, if the researcher wishes to determine whether socioeconomic level affects a student's decision to drop out of high school, the researcher may also want to test for other potential causes, such as parental support, academic ability, disciplinary issues, and other viable options. If other variables can be ruled out, the case for socioeconomic level's influencing the dropout rate will be much stronger.

Participant Sampling and Threats to Internal Validity

In causal-comparative research, two or more groups of participants are compared. These groups are defined by the different levels of the independent variable(s). In the previous example, the researcher compares a group of high school dropouts with a group of high school students who have not dropped out of school. Although this is not an experimental design, causal-comparative researchers may still randomly select participants within each group. For example, a researcher may select every fifth dropout and every fifth high school student. However, because the participants are not randomly selected and placed into groups, internal validity is threatened. To strengthen the research design and counter threats to internal validity, the researcher might choose to impose the selection techniques of matching, using homogeneous subgroups, or analysis of covariance (ANCOVA), or both.

Matching

One method of strengthening the research sample is to select participants by matching. Using this technique, the researcher identifies one or more characteristics and selects participants who have these characteristics for both the control and the experimental groups. For example, if the researcher wishes to control for gender and grade level, he or she would ensure that both groups matched on these characteristics. If a male 12th-grade student is selected for the experimental group, then a male 12th-grade student must be selected for the control group. In this way the researcher is able to control these two extraneous variables.

Comparing Homogeneous Subgroups

Another control technique used in causal-comparative research is to compare subgroups that are clustered according to a particular variable. For example, the researcher may choose to group and compare students by grade level. He or she would then categorize the sample into subgroups, comparing 9th-grade students with other 9th-grade students, 10th-grade students with other 10th-grade students, and so forth. Thus, the researcher has controlled the sample for grade level.

Analysis of Covariance

Using the ANCOVA statistical method, the researcher is able to adjust previously disproportionate scores on a pretest in order to equalize the groups on some covariate (control variable). The researcher may want to control for ACT scores and their impact on high school dropout rates. In comparing the groups, if one group's ACT scores are much higher or lower than the other's, the researcher may use the technique of ANCOVA to balance the two groups. This technique is particularly useful when the research design includes a pretest, which assesses the dependent variable before any manipulation or treatment has occurred. For example, to determine the effect of an ACT curriculum on students, a researcher would determine the students' baseline ACT scores. If the control group had scores that were much higher to begin with than the experimental group's scores, the researcher might use the ANCOVA technique to balance the two groups.

Instrumentation and Data Collection

The methods of collecting data for a causal-comparative research study do not differ from any other method of research. Questionnaires, pretests and posttests, various assessments, and behavior observation are common methods for collecting data in any research study. It is important, however, to also gather as much demographic information as possible, especially if the researcher is planning to use the control method of matching.

Data Analysis and Interpretation

Once the data have been collected, the researcher analyzes and interprets the results. Although causal-comparative research is not true experimental research, there are many methods of analyzing the resulting data, depending on the research design. It is important to remember that no matter what methods are used, causal-comparative research does not definitively prove cause-and-effect results. Nevertheless, the results will provide insights into causal relationships between the variables.

Inferential Statistics

When using inferential statistics in causal-comparative research, the researcher hopes to demonstrate that a relationship exists between the independent and dependent variables. Again, the appropriate method of analyzing data using this type of statistics is determined by the design of the research study. The three most commonly used methods for causal-comparative research are the chi-square test, paired-samples and independent t tests, and analysis of variance (ANOVA) or ANCOVA.

Pearson's chi-square, the most commonly used chi-square test, allows the researcher to determine whether there is a statistically significant relationship between the experimental and control groups based on frequency counts. This test is useful when the researcher is working with nominal data, that is, different categories of treatment or participant characteristics, such as gender. For example, if a researcher wants to determine whether males and females learn more efficiently from different teaching styles, the researcher may compare a group of male students with a group of female students. Both groups may be asked whether they learn better from audiovisual aids, group discussion, or lecture. The researcher could use chi-square testing to analyze the data for evidence of a relationship.

Another method of testing relationships in causal-comparative research is to use independent or dependent t tests. When the researcher is comparing the mean scores of two groups, these tests can determine whether there is a significant difference between the control and experimental groups. The independent *t* test is used in research designs when no controls have been applied to the samples, while the dependent *t* test is appropriate for designs in which matching has been applied to the samples. One example of the use of *t* testing in causal-comparative research is to determine the significant difference in math course grades between two groups of elementary school students when one group has completed a math tutoring course. If the two samples were matched on certain variables such as gender and parental support, the dependent *t* test would be used. If no matching was involved, the independent *t* test would be the test of choice. The results of the *t* test allow the researcher to determine whether there is a statistically significant relationship between the independent variable of the math tutoring course and the dependent variable of math course grade.

To test for relationships between three or more groups and a continuous dependent variable, a researcher might select the statistical technique of one-way ANOVA. Like the independent *t* test, this test determines whether there is a significant difference between groups based on their mean scores. In the example of the math tutoring course, the researcher may want to determine the effects of the course for students who attended daily sessions and students who attended weekly sessions, while also assessing students who never attended sessions. The researcher could compare the average math grades of the three groups to determine whether the tutoring course had a significant impact on the students' overall math grades.

Limitations

Although causal-comparative research is effective in establishing relationships between variables, there are many limitations to this type of research. Because causal-comparative research occurs ex post facto, the researcher has no control over the variables and thus cannot manipulate them. In addition, there are often variables other than the independent variable(s) that may impact the dependent variable(s). Thus, the researcher cannot be certain that the independent variable caused the changes in the dependent variable. In order to counter this issue, the researcher must test several different theories to establish whether other variables affect the dependent variable. The researcher can reinforce the research hypothesis if he or she can demonstrate that other variables do not have a significant impact on the dependent variable.

Reversal causation is another issue that may arise in causal-comparative research. This problem occurs when it is not clear that the independent variable caused the changes in the dependent variable, or that a dependent variable caused the independent variable to occur. For example, if a researcher hoped to determine the success rate of an advanced English program on students' grades, he or she would have to determine whether the English program had a positive effect on the students, or in the case of reversal causation, whether students who make higher grades do better in the English program. In this scenario, the researcher could establish which event occurred first. If the students had lower grades before taking the course, then the argument that the course impacted the grades would be stronger.

The inability to construct random samples is another limitation in causal-comparative research. There is no opportunity to randomly choose participants for the experimental and control groups because the events or actions have already occurred. Without random assignment, the results cannot be generalized to the public, and thus the researcher's results are limited to the population that has been included in the research study. Despite this problem, researchers may strengthen their argument by randomly selecting participants from the previously established groups. For example, if there were 100 students who had completed a computer-based learning course, the researcher would randomly choose 20 students to compare with 20 randomly chosen students who had not completed the course. Another method of reinforcing the study would be to test the hypothesis with several different population samples. If the results are the same in all or most of the sample, the argument will be more convincing.

Criticisms

There have been many criticisms of causal-comparative research. For the most part, critics reject the idea that causal-comparative research results should be interpreted as evidence of causal relationships. These critics believe that there are too many limitations in this type of research to allow for a suggestion of cause and effect. Some critics are frustrated with researchers who hold that causal-comparative research provides stronger causal evidence than correlational research does. Instead, they maintain that neither type of research can produce evidence of a causal relationship, so neither is better than the other. Most of these critics argue that experimental research designs are the only method of research that can illustrate any type of causal relationships between variables. Almost all agree, however, that experimental designs potentially provide the strongest evidence for causation.

Ernest W. Brewer and Jennifer Kuhn

See also Cause and Effect; Correlation; Experimental Design; Ex Post Facto Study; Quasi-Experimental Designs

Further Readings

Fraenkel, J. R., & Wallen, N. E. (2009). *How to design and evaluate research in education.* New York: McGraw-Hill.

Gay, L. R., Mills, G. E., & Airasian, P. (2009). *Educational research: Competencies for analysis and applications.* Upper Saddle River, NJ: Pearson Education.

Lodico, M. G., Spaulding, D. T., & Voegtle, K. H. (2006). *Methods in educational research: From theory to practice.* San Francisco: Jossey-Bass.

Mertler, C. A., & Charles, C. M. (2005). *Introduction to educational research.* Boston: Pearson.

Suter, W. N. (1998). *Primer of educational research.* Boston: Allyn and Bacon.

Cause and Effect

Cause and effect refers to a relationship between two phenomena in which one phenomenon is the reason behind the other. For example, eating too much fast food without any physical activity leads to weight gain. Here eating without any physical activity is the "cause" and weight gain is the "effect." Another popular example in the discussion of cause and effect is that of smoking and lung cancer. A question that has surfaced in cancer research in the past several decades is, What is the effect of smoking on an individual's health? Also asked is the question, Does smoking cause lung cancer? Using data from observational studies, researchers have long established the relationship between smoking and the incidence of lung cancer; however, it took compelling evidence from several studies over several decades to establish smoking as a "cause" of lung cancer.

The term *effect* has been used frequently in scientific research. Most of the time, it can be seen that a statistically significant result from a linear regression or correlation analysis between two variables X and Y is explained as effect. Does X really cause Y or just relate to Y? The association (correlation) of two variables with each other in the statistical sense does not imply that one is the cause and the other is the effect. There needs to be a mechanism that explains the relationship in order for the association to be a causal one. For example, without the discovery of the substance nicotine in tobacco, it would have been difficult to establish the causal relationship between smoking and lung cancer. Tobacco companies have claimed that since there is not a single randomized controlled trial that establishes the differences in death from lung cancer between smokers and nonsmokers, there was no causal relationship. However, a cause-and-effect relationship is established by observing the same phenomenon in a wide variety of settings while controlling for other suspected mechanisms.

Statistical correlation (e.g., association) describes how the values of variable Y of a specific population are associated with the values of another variable X from the same population. For example, the death rate from lung cancer increases with increased age in the general population. The association or correlation describes the situation that there is a relationship between age and the death rate from lung cancer. *Randomized prospective studies* are often used as a tool to establish a causal effect. Time is a key element in causality because the cause must happen prior to the effect. Causes are often referred to as *treatments* or *exposures* in a study. Suppose a causal relationship between an investigational drug A and response Y needs to be established. Suppose Y_A represents the