# A Guide for Selecting Statistical Techniques for Analyzing Social Science Data

## Second Edition

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Institute for Social Research
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# PREFACE TO THE SECOND EDITION

This Guide is intended to help social scientists select from the vast array of statistical techniques a particular statistic or technique that can be appropriately applied in a given analysis. The Guide is addressed to practicing social scientists, data analysts, and graduate students who already have some knowledge of social science statistics and who want a systematic but highly condensed overview of many of the statistical techniques in current use and of the purposes for which each is intended.

The popularity of the first edition of the Guide leads us to hope that this substantially expanded and updated second edition will also prove useful. The original version of this Guide became available in 1971, was revised and formally published by the Institute for Social Research in 1974, and has subsequently been through four English-language printings. In addition, ISR has granted permission for editions in French (Laval University, Quebec) and Hebrew (University of Haifa). This second edition contains nearly all of the material that appeared in the first edition plus significant expansions: the number of statistical techniques included in the decision tree has been increased by almost 50 percent, with major additions being made to the coverage of multivariate analysis; a glossary that defines technical terms has been added; and Appendix B, which indicates where each statistic can be found in the output from computer software, now includes detailed information on sources in the OSIRIS, MIDAS, SPSS, SAS, and BMDP software systems. There has been a general updating throughout the Guide to incorporate many of the statistical and analytical developments of the past decade.

No guide could include all the statistics ever proposed as useful for social science data analysis and this Guide makes no claim to do so. Rather, it attempts to include—and functionally distinguish—those statistics and statistical techniques that are in common use in the social sciences, that receive significant attention in social science statistics texts, or that seem to have high potential usefulness. About 150 statistics or statistical techniques are included in this Guide.

The core of the Guide is the 28 pages of sequential questions-and-answers that lead the user to an appropriate technique. This is the "decision tree." Preceding the "tree" section is a short set of instructions about how to use the tree and some comments suggesting alternative strategies and certain cautions that should be kept in mind. Three appendices and a glossary follow the tree. Appendix A cites specific pages in a major reference where each statistic presented in the Guide is discussed and its means of computation is given. Appendix B identifies the programs in five major software systems and several special-purpose programs that compute given statistics. Appendix C covers some additional statistical techniques that were judged to be too new or too rarely used to merit inclusion in the decision-tree portion of the Guide but that seemed potentially useful for social science data analysis. The Guide concludes with a bibliography presenting the full reference for each cited book and article.

For assistance in the preparation of this Guide we are grateful to Christine Zupanovich and her colleagues in the ISR Word Processing Group, to Linda Stafford and her colleagues in the ISR Publishing Division, and to Eugene Leppanen and his colleagues in the University of Michigan Technical Illustration Unit. Preparation of the Guide has been partially supported by the Computer Support Group of ISR's Survey Research Center.

# INSTRUCTIONS AND COMMENTS ON THE USE OF THIS GUIDE

This Guide is intended to help a data analyst select statistics or statistical techniques appropriate for the purposes and conditions of a particular analysis.

To use this Guide, start with the question on page 3, choose one of the answers presented there, and then continue along the "branches" of the decision tree as instructed. Eventually you will arrive at a box that names a statistical technique and/or a statistical measure and/or a statistical test appropriate to your situation—if one was known to the authors. Many of the technical terms used in the Guide are defined in the Glossary that begins on page 63.

The typical box contains one statistical measure (in the portion outlined by solid lines) and one statistical test (in the dotted portion). In a few cases, several different measures, or several different tests, are presented in the same box. These are essentially equivalent from a functional point of view, and comments to help you choose among them may appear in an accompanying footnote. Sometimes a measure appears without an accompanying test if none seemed particularly appropriate, and sometimes a test is listed without any measure.

Some branches of the tree terminate in boxes that are empty. These indicate situations for which the authors knew of no appropriate technique—indeed, further statistical development may be needed. If an analysis is to be performed in such a case, it will be necessary to find an alternative sequence through the decision tree or to consult another source of information.

In many analysis situations it is possible to make alternative decisions about the nature of the variables, relationships, and/or goals, and these may result in the selection of alternative final boxes. It is always possible to use techniques that require less stringent assumptions than the ones originally considered. For example, measures or tests may be used that are appropriate for a weaker scale of measurement, or techniques appropriate for non-additive situations may be used even though the variables actually form an additive system. Note also that non-additive systems can sometimes be handled using an additive technique if an appropriate combination of variables (e.g., pattern variable, product variable) has been formed. Recall also that two-point nominal variables and ranks meet the definition of intervally scaled variables.

## Cautionary Comments

1. Weighted data, missing data, small sample sizes, complex sample designs, and capitalization on chance in fitting a statistical model are sources of potential problems in data analysis. The Guide does not deal with these complications. If one of these situations exists, the Guide should be used with caution. (See note 9 in Appendix C for a brief discussion

of sampling errors from complex samples.)

2. The statistical measures in the terminal boxes are descriptive of the particular sample being examined. For some statistical measures, the value obtained will also be a good estimate of the value in the population as a whole, whereas other statistics may underestimate (or overestimate) the population value. In general, the amount of bias is relatively small and sometimes adjustments can be made for it. These adjustments are discussed in some statistics texts (but not in this Guide). If a statistic is a biased estimator of the population value, it is marked in this Guide with an asterisk.

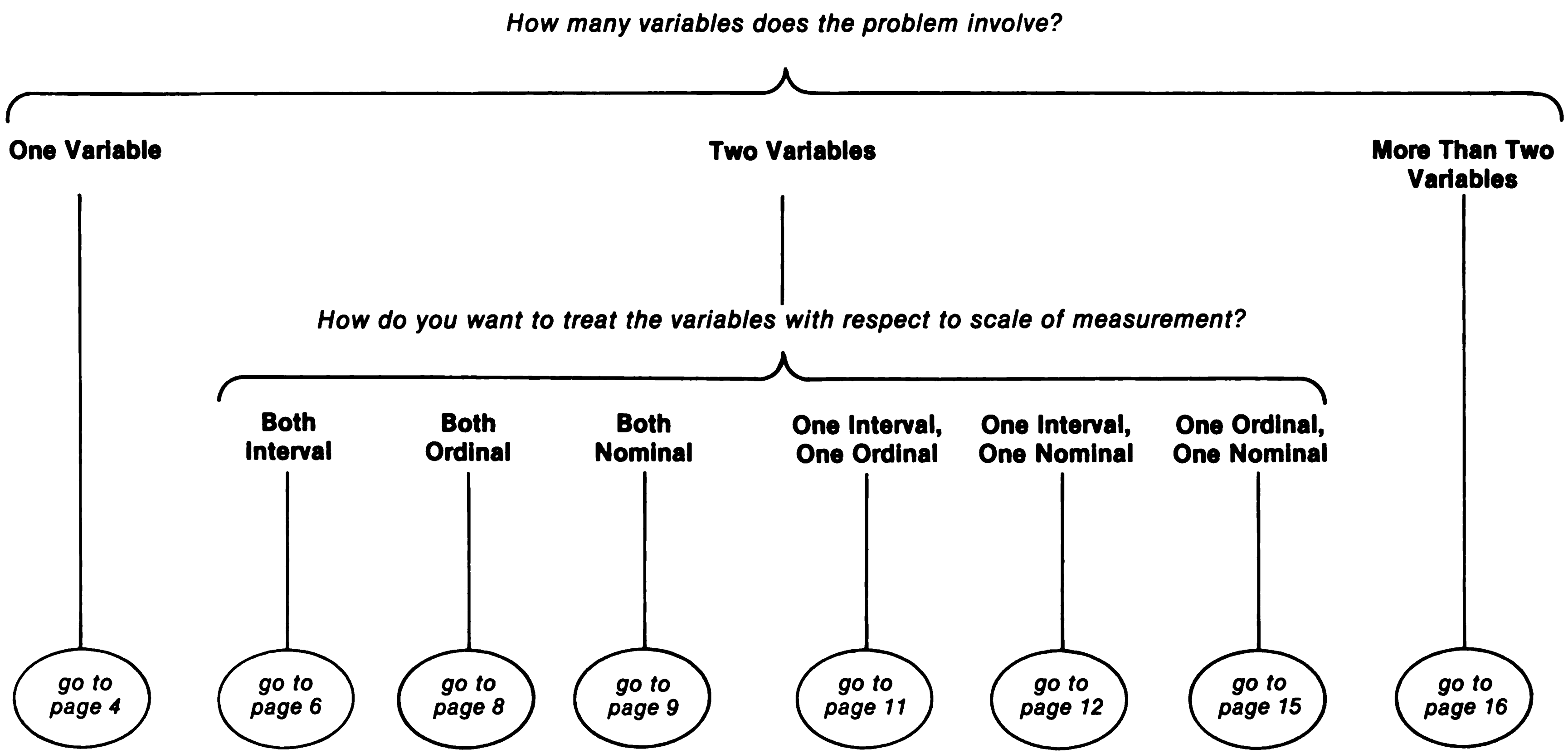
3. In principle, a confidence interval may be placed around any statistic. It is also possible to test the significance of the difference between values of a statistic calculated for two non-overlapping groups. These procedures are not indicated in the Guide but are discussed in standard textbooks.

4. The Guide does not explicitly consider possible transformations of the data such as bracketing, using logarithms, ranking, etc. Transformations may be used to simplify analysis or to bring data into line with assumptions. (For example, it is often possible to transform scores so that the transformed scores correspond to a normal distribution, constitute an interval scale, or relate linearly to another variable.) Occasionally, it may be wise to eliminate cases with extreme values. For guidance on selecting appropriate transformations, see Kruskal (1978).

5. Common assumptions for inferences based on techniques using one or more intervally scaled variables (particularly when the intervally scaled variable is a dependent variable) include the following: first, that the observations are independent, i.e., the selection of one case for inclusion in the sample does not affect the chances of any other case being included, and the value of a variable for one case in no way affects the value of the variable for any other case; second, that the observations are drawn from a population normally distributed on the intervally scaled variable(s); and third, if more than one variable is involved, that the intervally scaled variable(s) have equal variances within categories of the other variable(s), i.e., there is homogeneity of variance. Bivariate or multivariate normality is also sometimes assumed.

# THE DECISION TREE:
# QUESTIONS AND ANSWERS LEADING TO APPROPRIATE STATISTICS OR STATISTICAL TECHNIQUES

## STARTING POINT

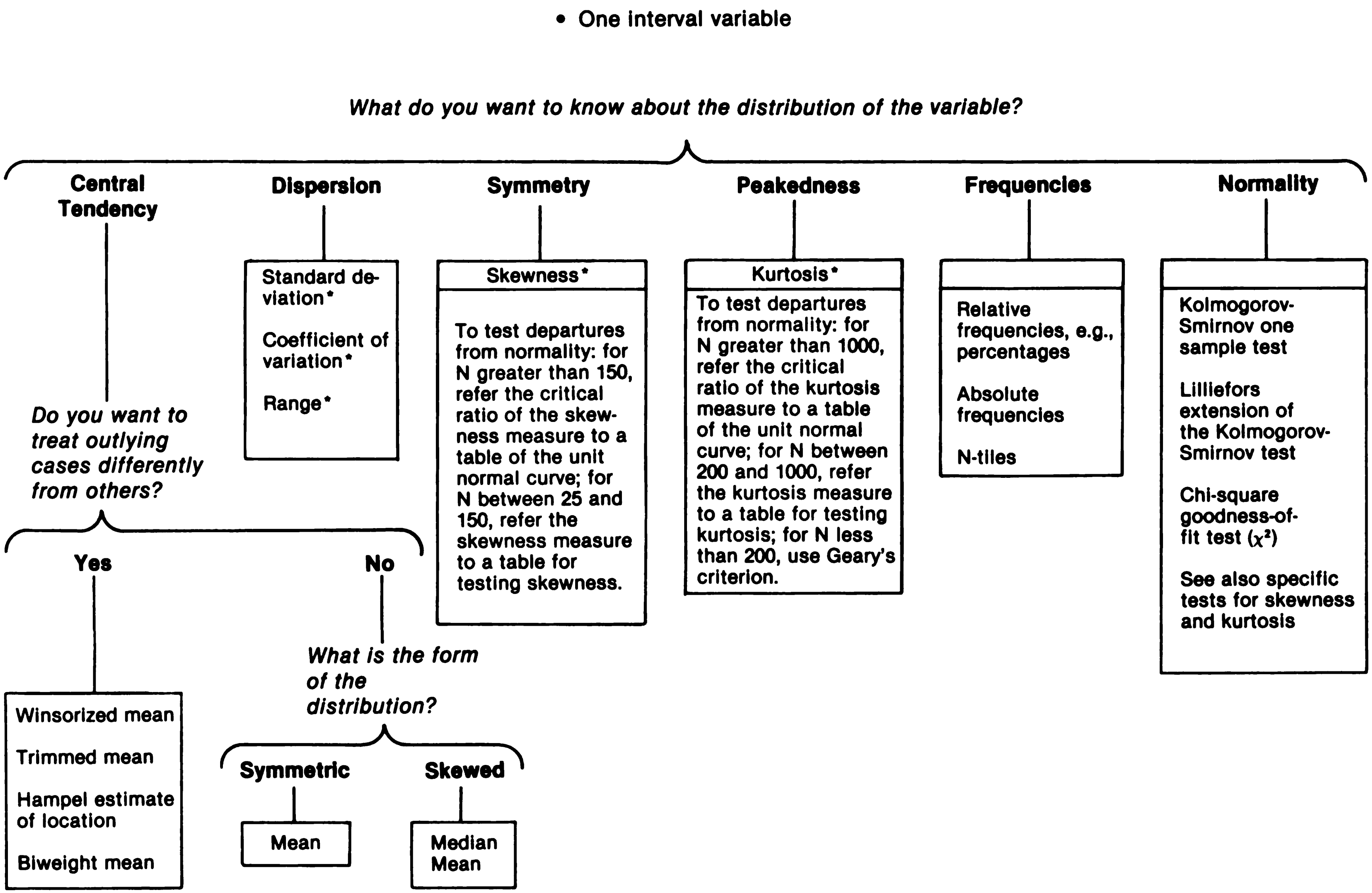


# ONE VARIABLE

*How do you want to treat the variable with respect to scale of measurement?*

- **Nominal**
  - *What do you want to know about the distribution of the variable?*
    - **Central Tendency**
      - Mode
    - **Dispersion**
      - Relative frequency of modal value or class
    - **Frequencies**
      - Relative frequencies, e.g., percentages
      - Absolute frequencies
- **Ordinal**
  - *What do you want to know about the distribution of the variable?*
    - **Central Tendency**
      - Median
    - **Dispersion**
      - Inter-quartile deviation
    - **Frequencies**
      - Relative frequencies, e.g., percentages
      - Absolute frequencies
      - N-tiles
- **Interval**
  - *go to page 5*

(continued from page 4)




* Biased estimator

# TWO INTERVAL VARIABLES

*Is a distinction made between a dependent and an independent variable?*

- **Yes** — *Do you want to treat the relationship as linear?*
  - **Yes** — Regression coefficient (b or beta, β)‡
    - F test† (F equals t²)
  - **No** — Coefficients from curvilinear regression (b or beta, β)‡,§
    - F test† (F equals t² for each coefficient)
- **No** — *Do you want to test whether the means on the two variables are equal?*
  - **Yes** — t test for paired observations†,**
  - **No** — *Do you want to treat the relationship as linear?*
    - **Yes** — *What do you want to measure?*
      - **Agreement** — *Should there be a penalty if the variables do not have the same distributions?*
        - **Yes** — Robinson's A; Intraclass correlation coefficient ($r_I$)*
          - F test†
        - **No** — Krippendorff's coefficient of agreement (r)
      - **Covariation** — go to page 7
    - **No**

* Biased estimator.

† The assumptions in note 5 on page 2 may apply.

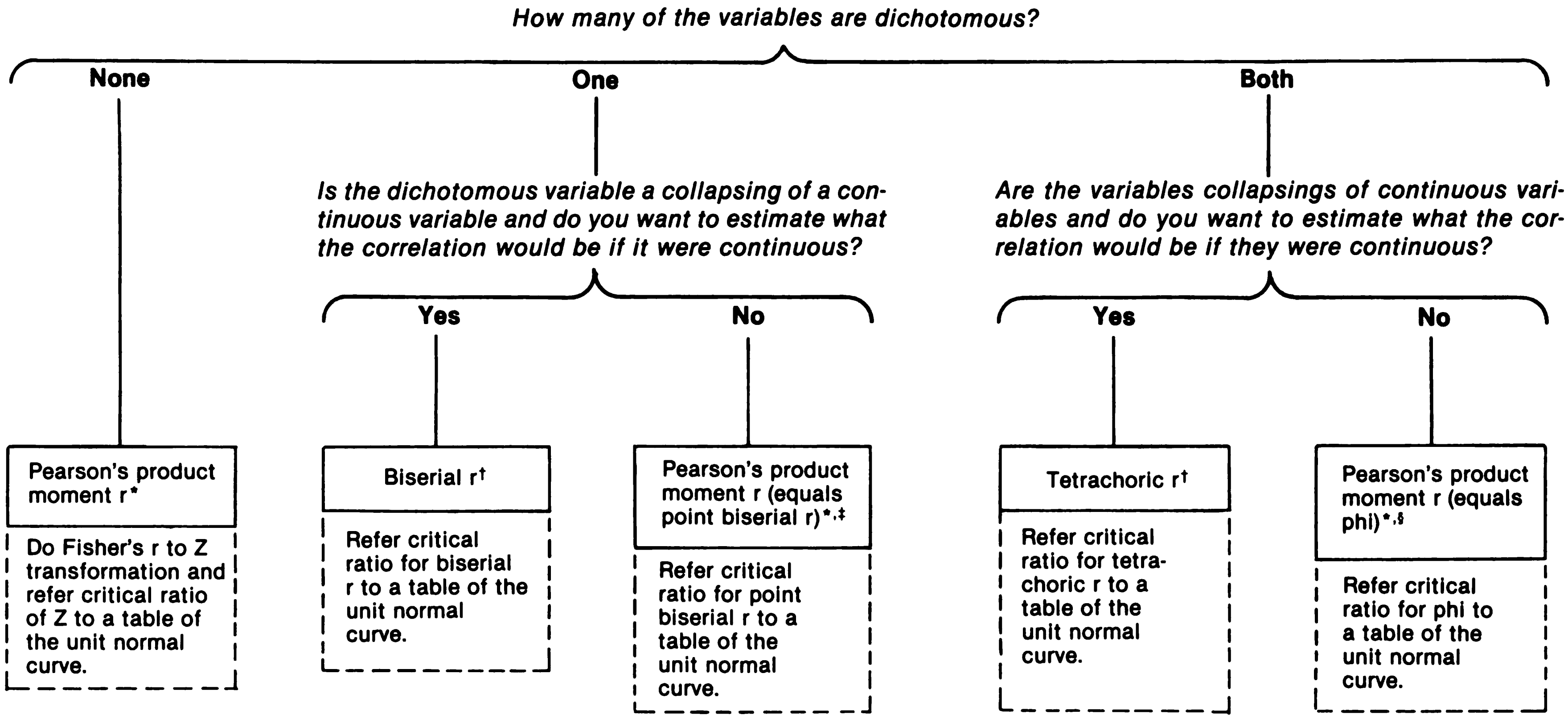
‡ Beta is a standardized version of b. See "standardized coefficient" in Glossary.

§ The type of curvilinear regression referred to here is also known as polynomial regression. See note 4 in Appendix C for further discussion.

**The t test for paired observations is appropriate for parallel measures from matched cases as well as for repeated measures on a single set of cases. See "matched samples" in Glossary.

(continued from page 6)

• Two interval variables • No distinction is made between a dependent and an independent variable • The relationship is to be treated as linear • Covariation is to be measured




* Biased estimator.

† Both the tetrachoric r and the biserial r depend on a strict assumption of the normality of the continuous variables that have been dichotomized. Furthermore, the sampling error for both coefficients is large when dichotomies are extreme. Nunnally (1978, pages 135–137) advises against the use of these coefficients.

‡ Pearson's r in this case is mathematically equivalent to a point biserial r; the tests are almost equivalent.

§ Pearson's r in this case is mathematically equivalent to phi (see page 9); the tests are almost equivalent.

# TWO ORDINAL VARIABLES

*Is a distinction made between a dependent and an independent variable?*

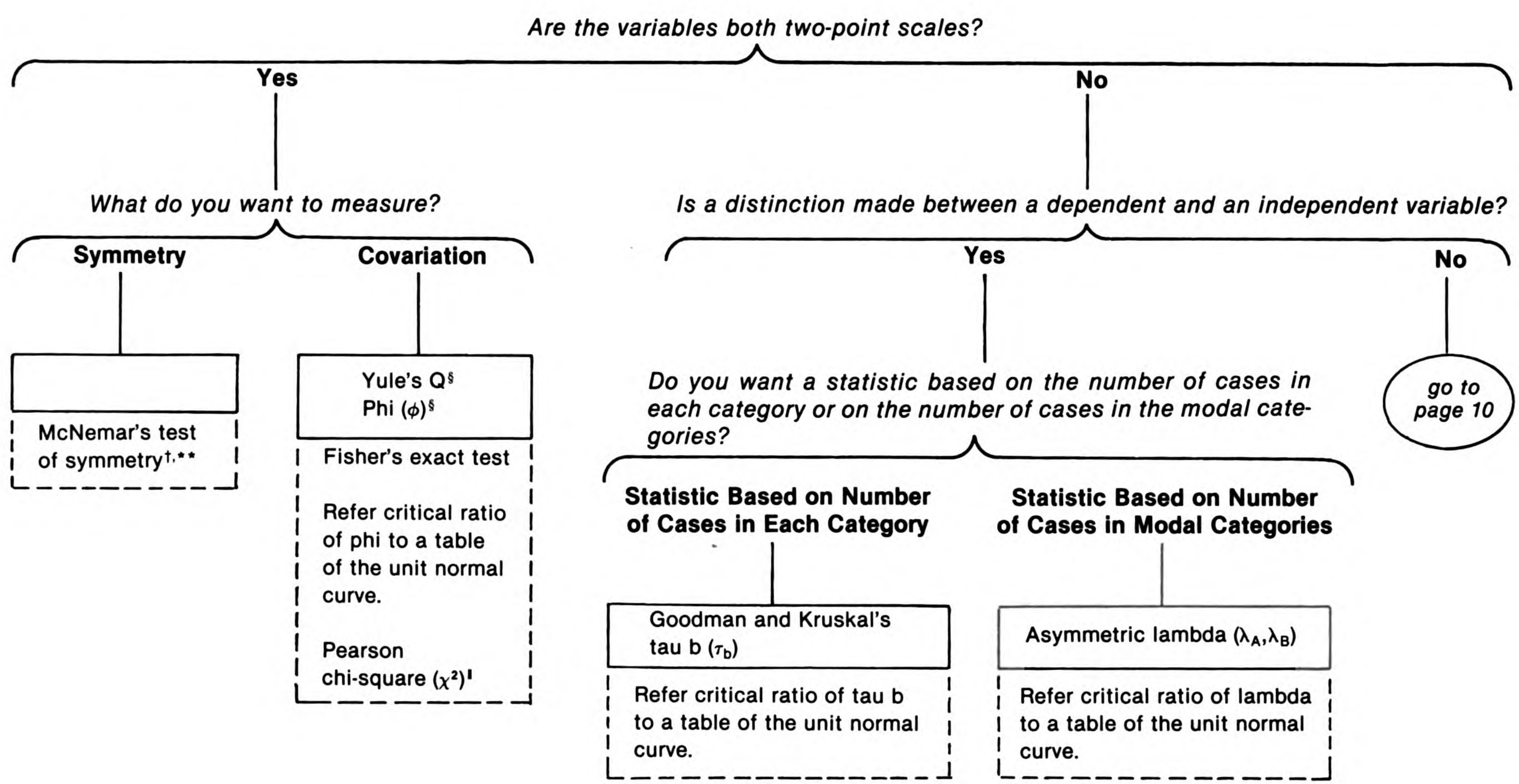
- **Yes**
  - Somers' d
    - For N greater than 10, refer the critical ratio of S to a table of the unit normal curve; for N less than or equal to 10, refer d to a table of critical values of S.
- **No**
  - *What do you want to measure?*
    - **Agreement**
      - †
    - **Covariation**
      - *Do you want to treat the ranks of the ordered categories as interval scales?*
        - **Yes**
          - Spearman's rho ($r_s$)*
            - When N is 10 or larger, refer the critical value of $r_s$ to a table of the t distribution; for N less than 10, refer $r_s$ to a table of critical values of $r_s$.
        - **No**
          - Kendall's tau a, tau b, or tau c ($\tau_a$, $\tau_b$, $\tau_c$)‡
          - Goodman and Kruskal's gamma ($\gamma$)‡
          - Kim's d‡
            - For N greater than 10 refer the critical ratio of S to a table of the unit normal curve; for N less than or equal to 10, refer these statistics to a table of critical values of S.

* Biased estimator.

† The data may be transformed to ranks and $r_I$ or Krippendorff's $\bar{r}$ used. See page 6.

‡ These statistics differ with respect to how they treat pairs of cases that fall in the same category on one or both of the variables. Except in extreme cases (i.e., where any of the statistics equals 0 or 1) the absolute value of gamma will be the highest of the five statistics, tau a will be the smallest, and tau b, tau c, and Kim's d will be intermediate. This ordering is because gamma ignores all ties (when present in the data—as is usually the case), whereas the other four statistics penalize for ties in the sense of reducing the absolute value of the statistic obtained. Unlike tau b and Kim's d, tau c can attain ±1 even if the two variables do not have the same number of categories. If there are no ties on either variable the five measures are identical. See Goodman and Kruskal (1954), Kendall (1970), Kendall and Stuart (1961), Stuart (1953), and Kim (1971).

# TWO NOMINAL VARIABLES




† In this case, McNemar's test of symmetry is equivalent to Cochran's Q.

§ In this case, Yule's Q is equivalent to Goodman and Kruskal's gamma and phi is equivalent to Pearson's product moment r. In general, Q will be higher in absolute value than phi because Q ignores pairs of cases which fall in the same category on one or both of the variables.

ǁ Pearson chi-squares can be corrected for continuity (Yate's correction) but this is controversial. See Camilli and Hopkins (1978).

** McNemar's test of symmetry is appropriate for parallel measures from matched cases as well as for repeated measures on a single set of cases. See "matched samples" in Glossary.

*(continued from page 9)*

• Two nominal variables • At least one of the variables is not a two-point scale • No distinction is made between a dependent and an independent variable

*What do you want to measure?*

- **Agreement**
  - *Should there be a penalty if the variables do not have the same distributions?*
    - **Yes** — Scott's coefficient of agreement, pi ($\pi$)
    - **No** — Cohen's agreement coefficients, kappas ($\kappa$'s)
      - Refer critical ratios for Cohen's $\kappa$'s to a table of the unit normal curve.
- **Symmetry**
  - McNemar's test of symmetry**
- **Covariation**
  - *Do you want a statistic based on the number of cases in each category or on the number of cases in the modal categories?*
    - **Statistic Based on Number of Cases in Each Category**
      - *Do you want a statistic whose upper limit varies with the number of categories and whose upper limit may be less than one?*
        - **Yes** — Contingency coefficient (C)
          - Pearson chi-square ($\chi^2$)'
        - **No** — Cramér's V
          - Pearson chi-square ($\chi^2$)'
    - **Statistic Based on Number of Cases in Modal Categories**
      - Symmetric lambda ($\lambda_{AB}$)
        - Refer critical ratio of symmetric lambda to a table of the unit normal curve.

' Pearson chi-squares can be corrected for continuity but this is controversial. See Bradley et al. (1979).

** McNemar's test of symmetry is appropriate for parallel measures from matched cases as well as for repeated measures on a single set of cases. See "matched samples" in Glossary.

## TWO VARIABLES: ONE INTERVAL, ONE ORDINAL

*Is the ordinal variable a two-point variable?*

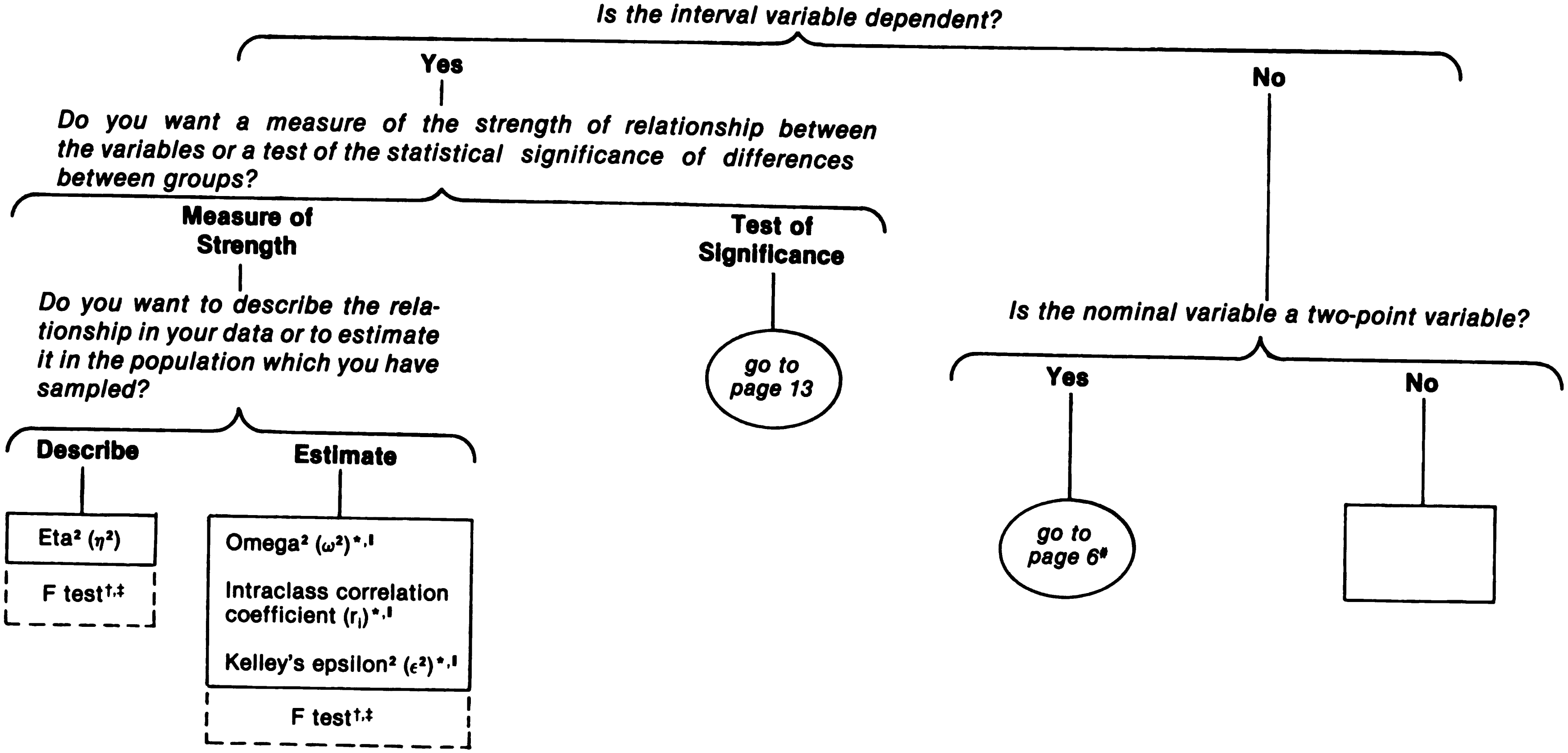
- **Yes**
  - *go to page 6#*
- **No**
  - *Do you want to treat the ordinal variable as if it were based on an underlying normally distributed interval variable?*
    - **Yes**
      - Jaspen's coefficient of multiserial correlation*,†
      - Do Fisher's r to Z transformation and refer critical ratio of Z to a table of the unit normal curve.
    - **No**
      - *Do you want to treat the ordinal variable as if it were a monotonic transformation of an underlying interval variable?*
        - **Yes**
          - Mayer and Robinson's $M_{yu}$*
          - Do Fisher's r to Z transformation and refer critical ratio of Z to a table of the unit normal curve.
        - **No**

* Biased estimator.

† Jaspen's coefficient is the product moment correlation between the interval variable and a transformation of the ordinal variable. The magnitude of this statistic is sensitive to the assumption of normality.

\# Any two-point variable meets the criteria for an intervally scaled variable.

# TWO VARIABLES: ONE INTERVAL, ONE NOMINAL




* Biased estimator.

† The assumptions in note 5 on page 2 may apply.

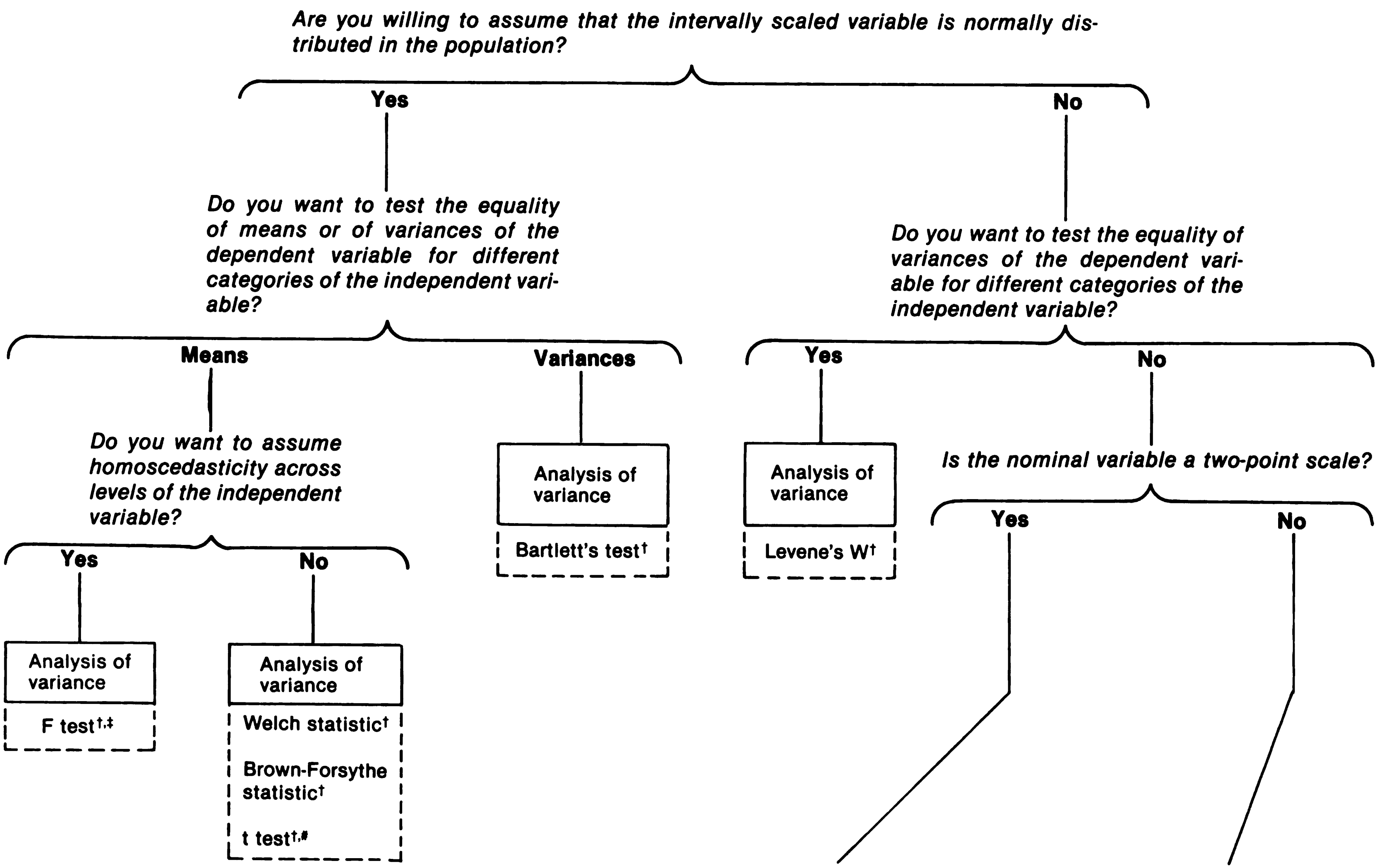
‡ If the nominal variable is a two-point scale, the t test is an alternative (because in such case F equals t²).

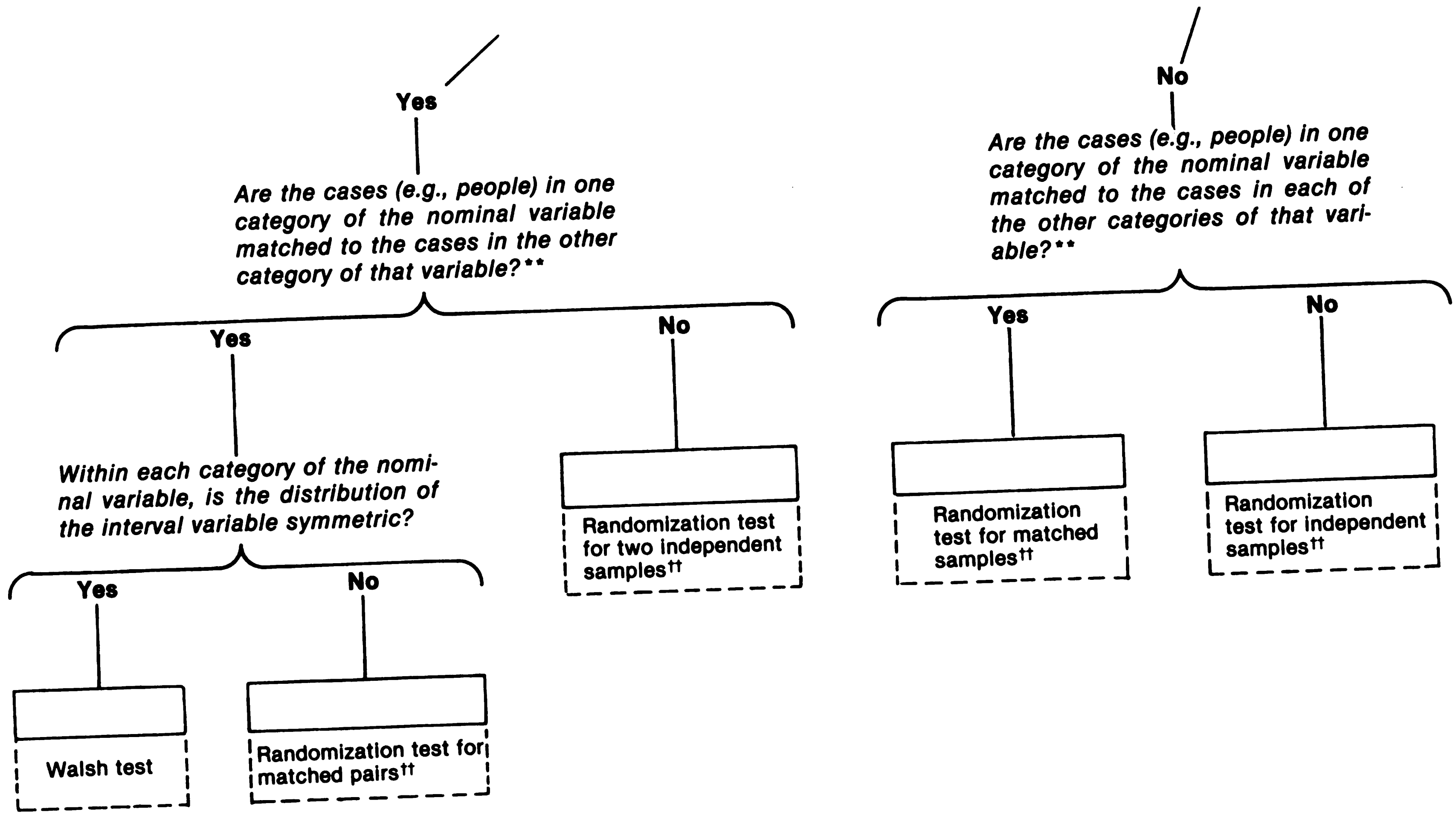
‖ Omega² applies to the fixed effects model, and the intraclass correlation coefficient applies to the random effects model. Thus omega² should be used if you want to make inferences only about the specific categories of the nominal variable which appear in the data, whereas the intraclass correlation coefficient should be used if you view the particular categories that appear in the data as a random sample from a larger set of potential categories and you want to make inferences about the total set of potential categories. (See Hays, 1973, page 525; Hays denotes the intraclass correlation as $\rho_I$ rather than $r_I$.) In most situations it is more appropriate to use the fixed effects model, i.e., omega². Kelley's epsilon² is used for exactly the same purpose as Hays' omega² but differs very slightly in computation. Hays' omega² was apparently developed independently of Kelley's earlier statistic. Kelley's epsilon² is precisely equivalent to eta², after eta² is adjusted for degrees of freedom. See Glass and Hakstian (1969), Kelley (1935), and Hays (1973; page 485).

\# Any two-point variable meets the criteria for an intervally scaled variable.

(continued from page 12)

• There are two variables, one interval and the other nominal • The interval variable is dependent • Statistical significance of differences between groups is to be tested






† The assumptions in note 5 on page 2 may apply.

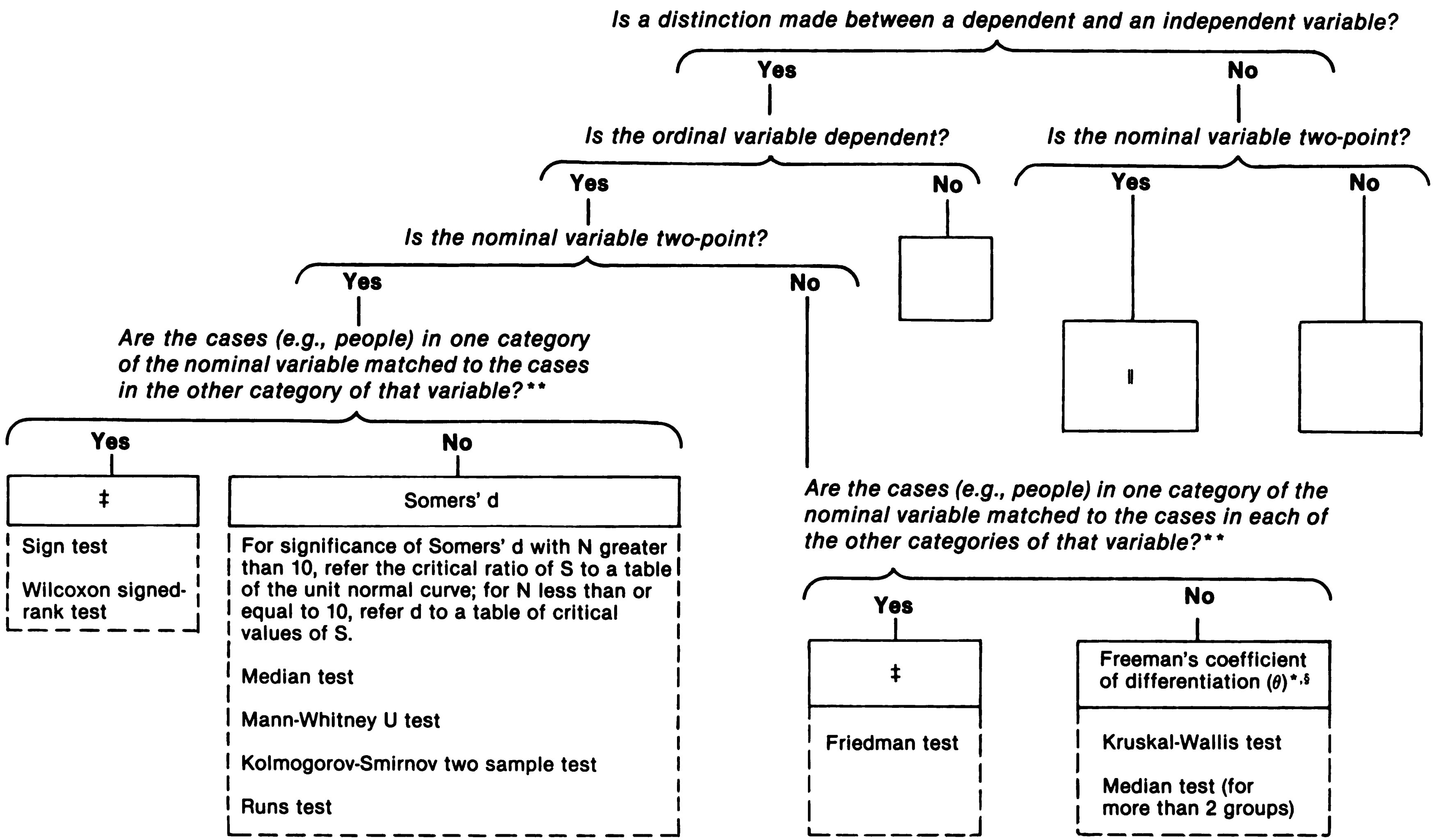
‡ If the nominal variable is a two-point scale, the t test is an alternative (because in such case F equals $t^2$).

# If the nominal variable is a two-point scale, a special form of the t test may be used. (See Hays, 1973, pp. 404 and 410.)

** See "matched samples" in Glossary.

†† In practice, randomization tests are usually only applied when the number of cases is very small. With larger N's the interval variable is generally treated as an ordinal variable.

## TWO VARIABLES: ONE ORDINAL, ONE NOMINAL




* Biased estimator.

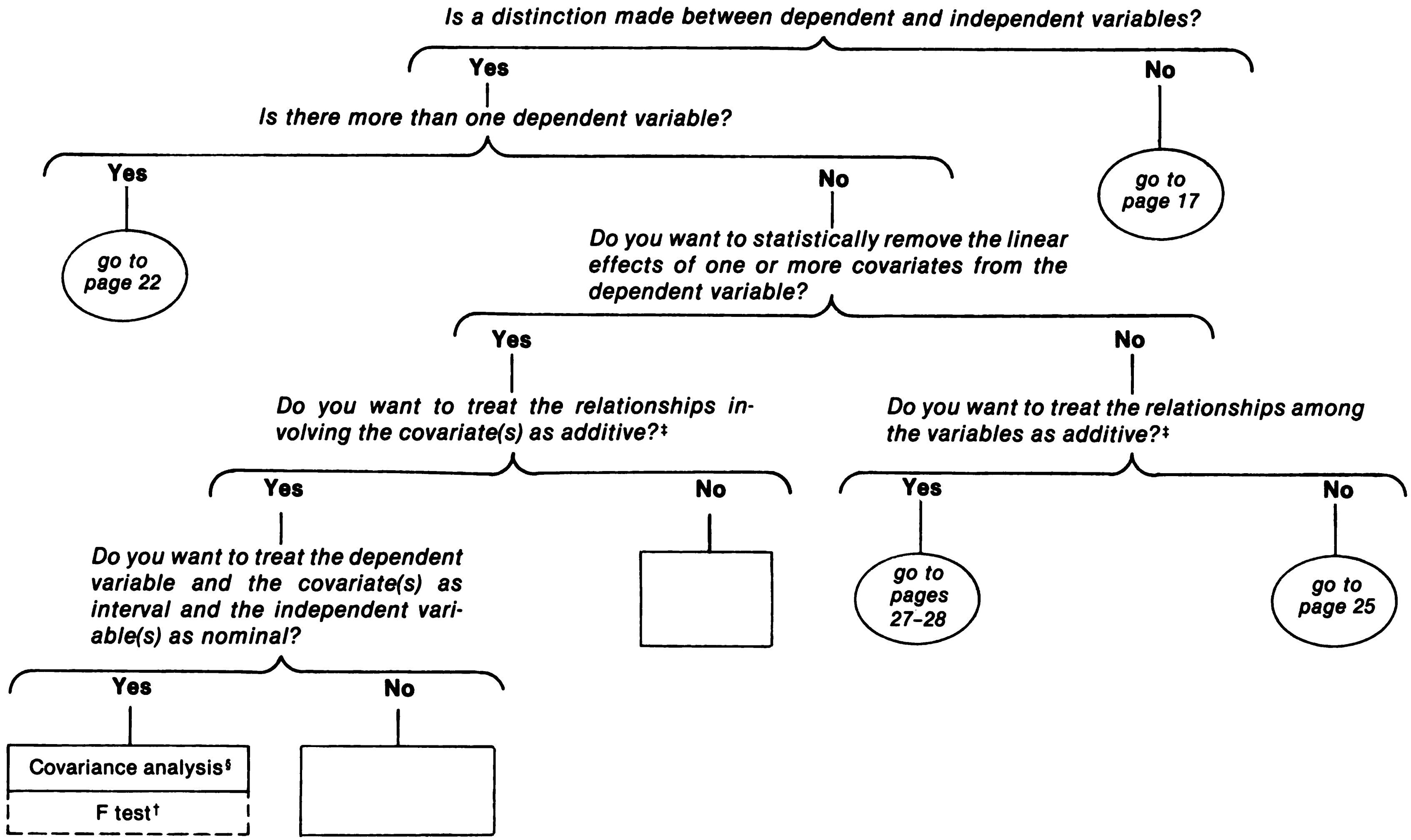
‡ Measures of strength of relationship that are appropriate for unmatched data can also be used descriptively here.

§ This coefficient implicitly orders the nominal categories. Given n nominal categories, there are n! values for Somers' d. Freeman's theta is equal to the highest of these d's.

ǁ The nominal variable may be treated as ordinal (in which case go to page 8) or as interval (in which case go to page 11).

** See "matched samples" in Glossary.

## MORE THAN TWO VARIABLES

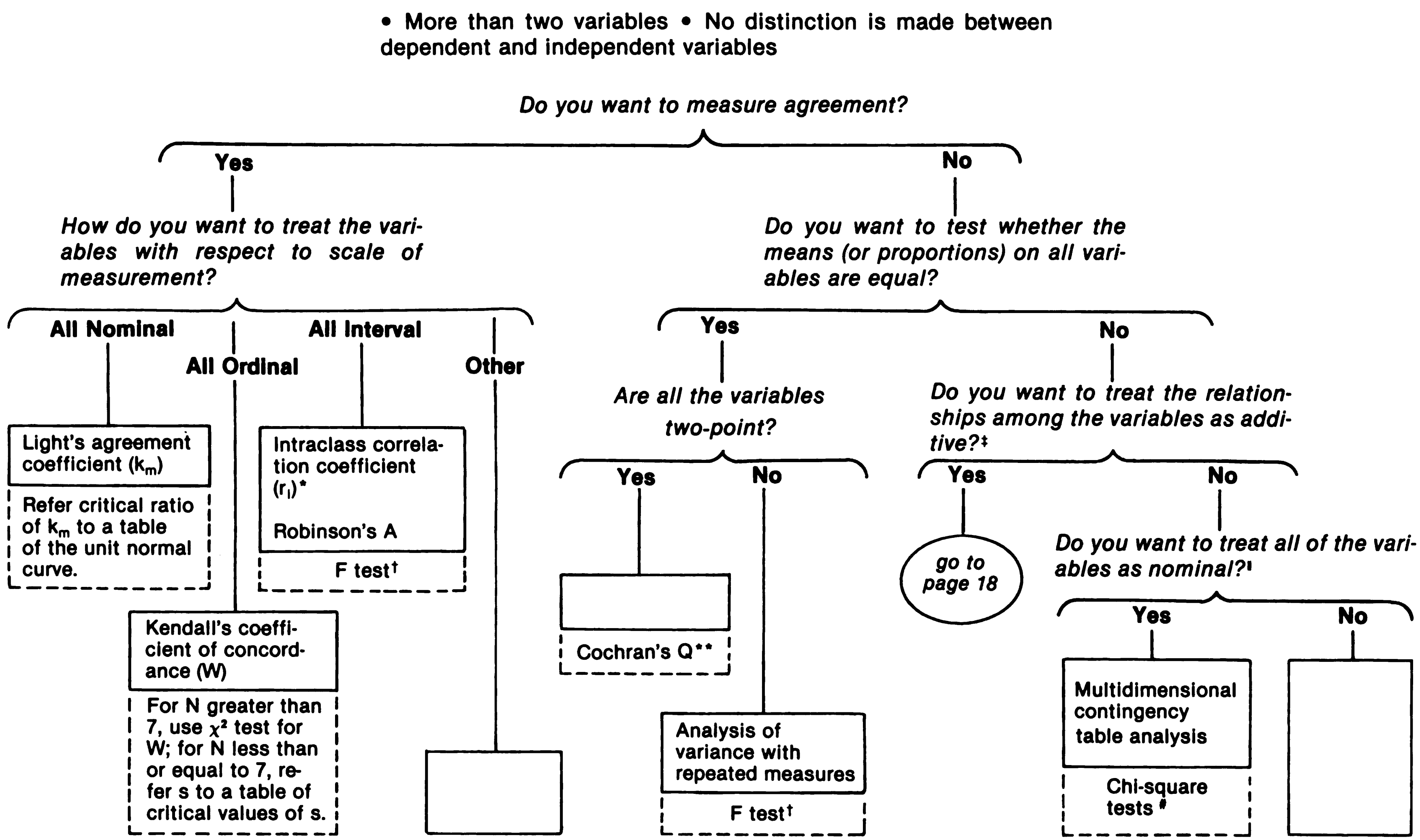



† The assumptions in note 5 on page 2 may apply.

‡ Nonadditivity can be represented within additive techniques by using a pattern variable or a product variable. Another possibility is to analyze subgroups separately. See Glossary.

§ Some analysis of covariance techniques assume statistical independence between all pairs of independent variables.

*(continued from page 16)*




* Biased estimator.

† The assumptions in note 5 on page 2 may apply.

‡ Nonadditivity can be represented within additive techniques by using a pattern variable or a product variable. Another possibility is to analyze subgroups separately. See Glossary.

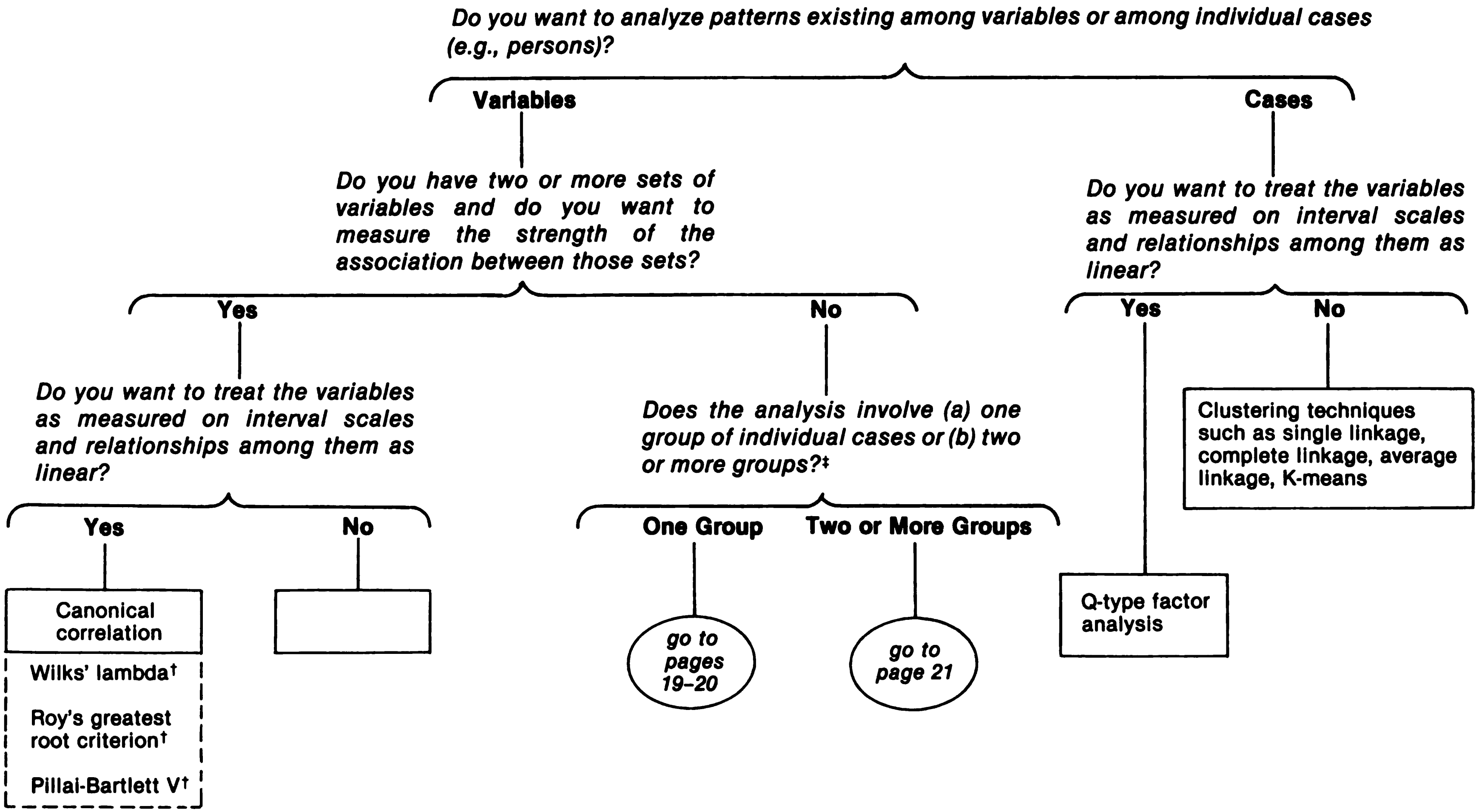
ǁ See note 3 in Appendix C.

\# There are various chi-square test statistics including Pearson, maximum likelihood, and Neyman.

** Cochran's Q is appropriate for parallel measures from matched cases as well as for repeated measures on a single set of cases. See "matched samples" in Glossary.

*(continued from page 17)*

• More than two variables • No distinction is made between dependent and independent variables • Relationships are to be treated as additive




† The assumptions in note 5 on page 2 may apply.

‡ "Two or more groups" may mean distinct sets of individuals, a set of individuals observed on two or more occasions, etc.

*(continued from page 18)*

• More than two variables • No distinction is made between dependent and independent variables • Relationships are to be treated as additive • Patterns among variables are to be analyzed • One group of individuals

*Do you want to explore covariation among the variables (e.g., to examine their relationships to underlying dimensions) or do you want to find clusters of variables that are more strongly related to one another than to the remaining variables?*

**Explore Covariation**

*Do you want to treat the variables as measured on interval scales and the relationships among them as linear?*[1]

**Yes**

*Do you want to explore the relationships among the set of variables or do you want to compare the pattern of the relationships with a prespecified pattern?*

**No**

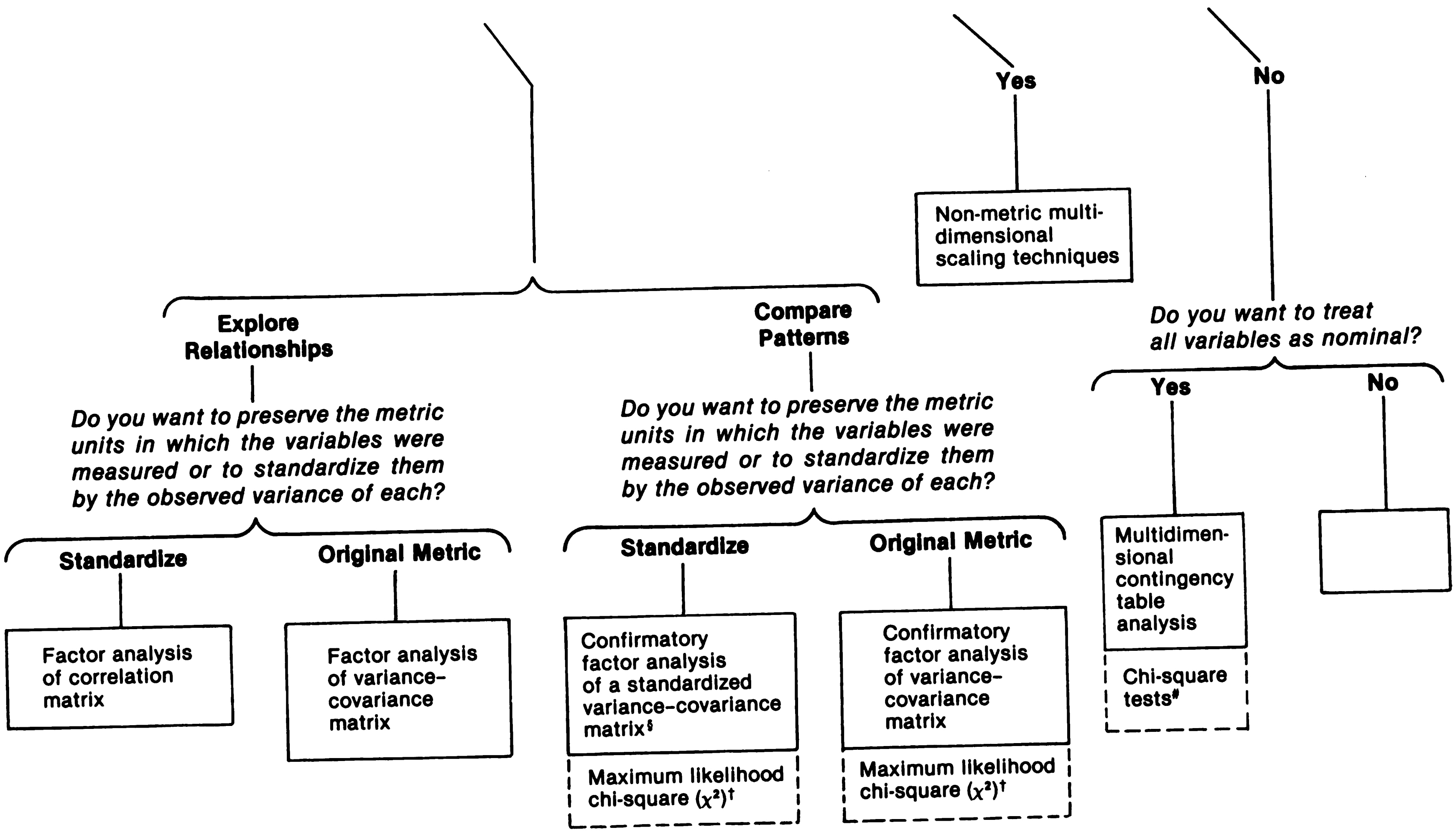
*Do you want to locate each of the variables in multidimensional space?*

**Yes**

**No**

**Find Clusters**

Clustering techniques such as single linkage, complete linkage, average linkage, K-means




† The assumptions in note 5 on page 2 may apply.

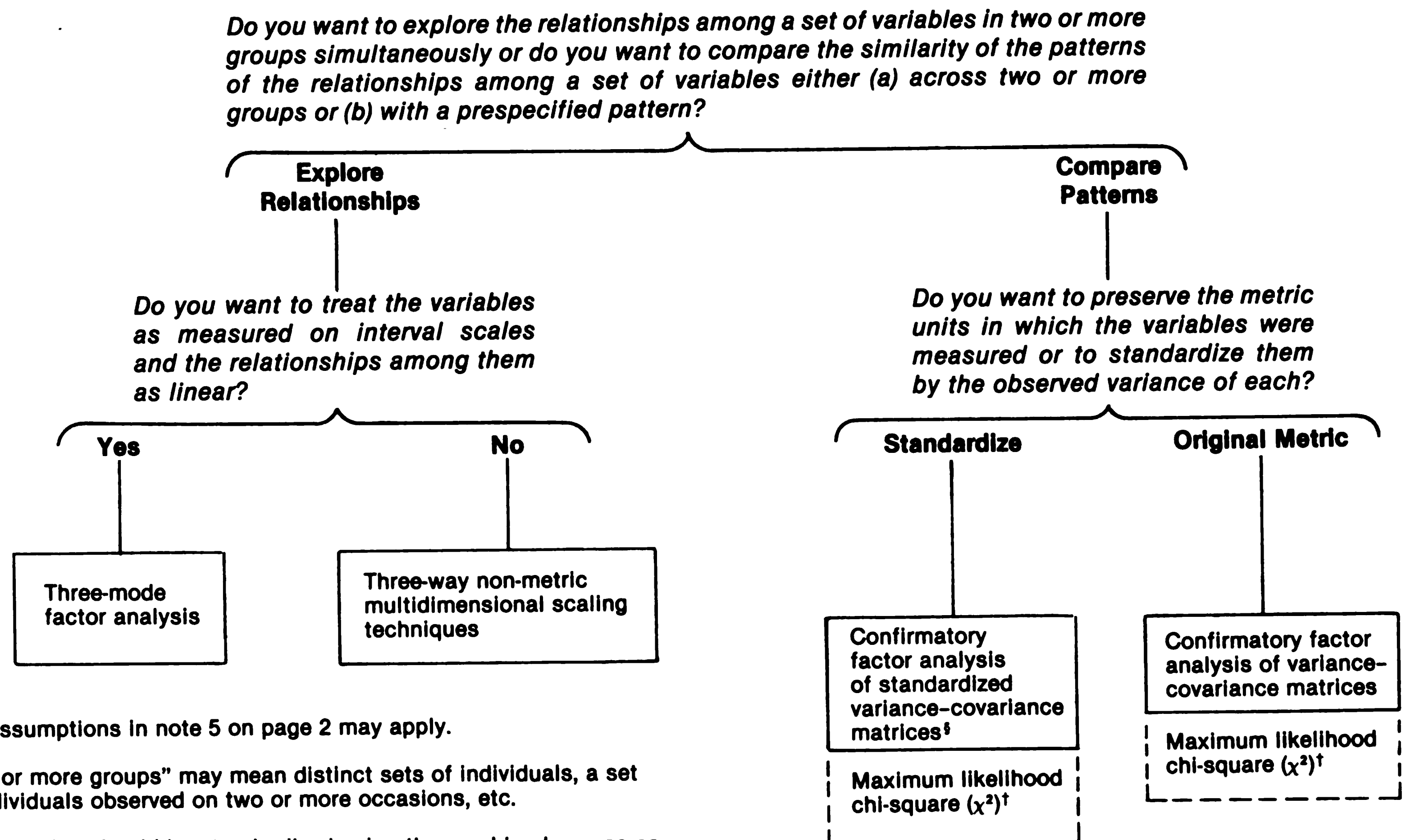
§ The variables should be standardized using the combined groups (i.e., the observed group and the prespecified pattern) as a reference. (Depending on the problem, this may or may not be equivalent to using the correlation matrix for the observed group.) See "standardized variable" in Glossary.

ǀ See note 3 in Appendix C.

# There are various chi-square test statistics including Pearson, maximum likelihood, and Neyman.

*(continued from page 18)*

• More than two variables • No distinction is made between dependent and independent variables • Relationships are to be treated as additive • Patterns among variables are to be analyzed • Two or more groups of individuals‡



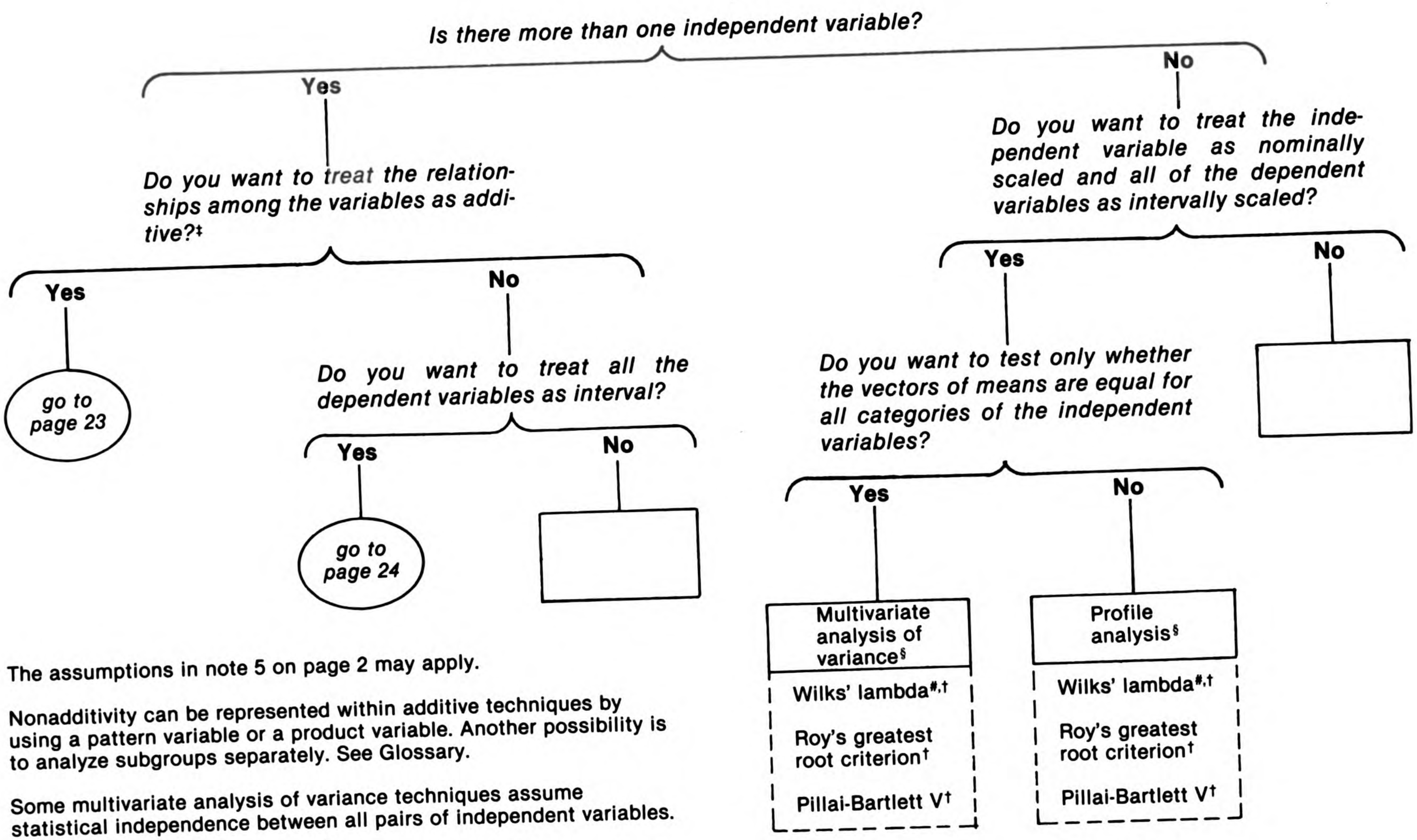

† The assumptions in note 5 on page 2 may apply.

‡ "Two or more groups" may mean distinct sets of individuals, a set of individuals observed on two or more occasions, etc.

§ The variables should be standardized using the combined groups as a reference group. (This is not the same as using the correlation matrices for the separate groups.) See "standardized variable" in Glossary.

*(continued from page 16)*

• More than two variables • A distinction is made between dependent and independent variables • There is more than one dependent variable




† The assumptions in note 5 on page 2 may apply.

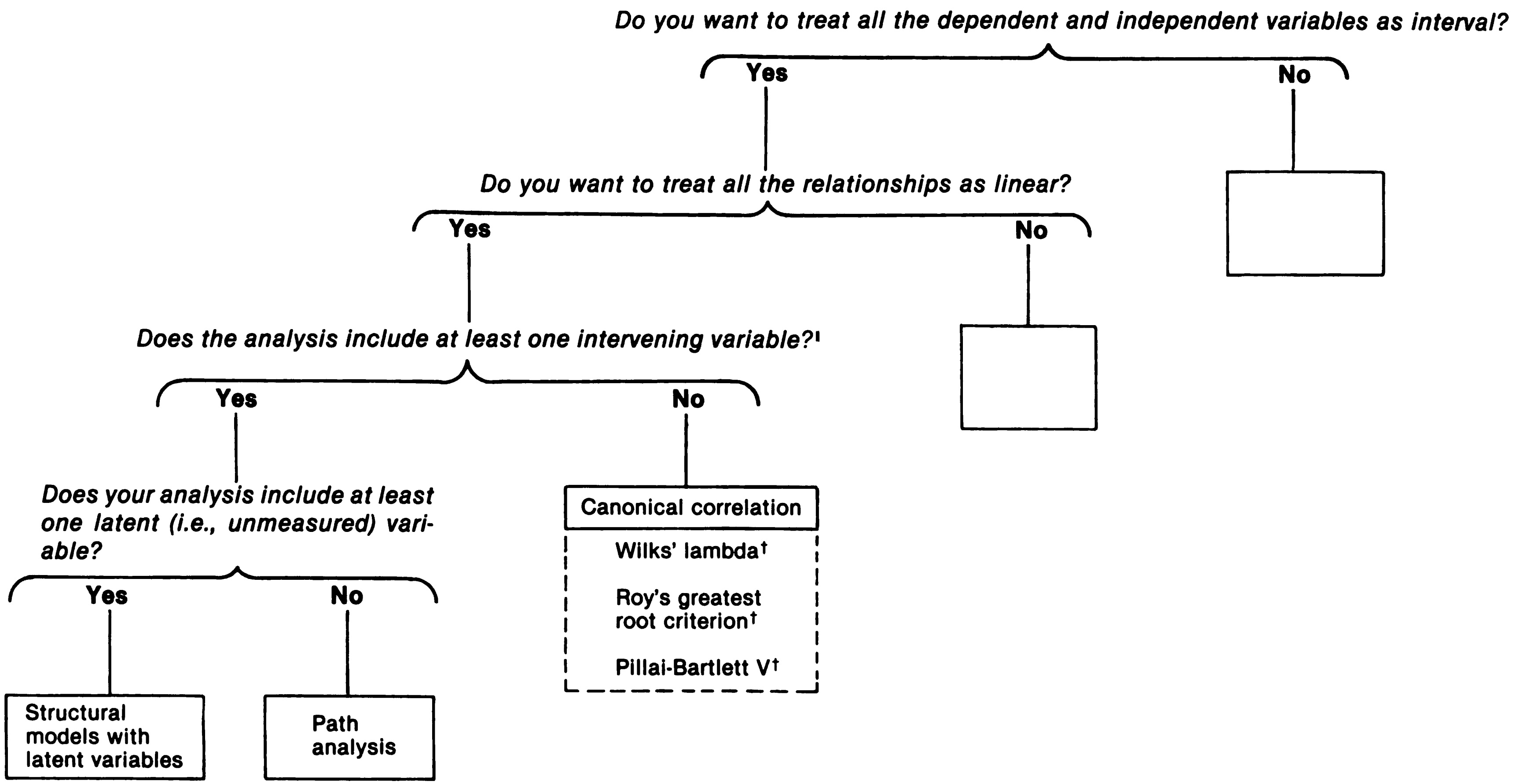
‡ Nonadditivity can be represented within additive techniques by using a pattern variable or a product variable. Another possibility is to analyze subgroups separately. See Glossary.

§ Some multivariate analysis of variance techniques assume statistical independence between all pairs of independent variables.

# If the independent variable is a two-point scale, Hotelling's $T^2$ is an alternative (because in such cases the $T^2$ test is equivalent to the $\Lambda$-test). Mahalanobis' $D^2$ is another alternative in such a case.

*(continued from page 22)*

• A distinction is made between dependent and independent variables • There is more than one dependent variable and more than one independent variable • Relationships among the variables are to be treated as additive




† The assumptions in note 5 on page 2 may apply.

ǀ See Glossary.

*(continued from page 22)*

• A distinction is made between dependent and independent variables • There is more than one dependent variable and more than one independent variable • Relationships among the variables are not to be treated as additive • All the dependent variables are interval

*Do you want to treat all the independent variables as nominal and test a set of prespecified relationships?*

**Yes**

Multivariate analysis of variance§

Wilks' lambda†

Roy's greatest root criterion†

Pillai-Bartlett V†

**No**

*Do you want to treat all the independent variables as nominal or ordinal and do you want to do an empirical search for strong relationships?*

**Yes**

Multivariate binary segmentation techniques

**No**

† The assumptions in note 5 on page 2 may apply.

§ Some multivariate analysis of variance techniques assume statistical independence between all pairs of independent variables.

*(continued from page 16)*

**• More than two variables • A distinction is made between dependent and independent variables • There is one dependent variable • No covariate is used to remove linear effects • Relationships among the variables are not to be treated as additive**

*Do you want to do an empirical search for strong relationships or to test a set of prespecified relationships?*

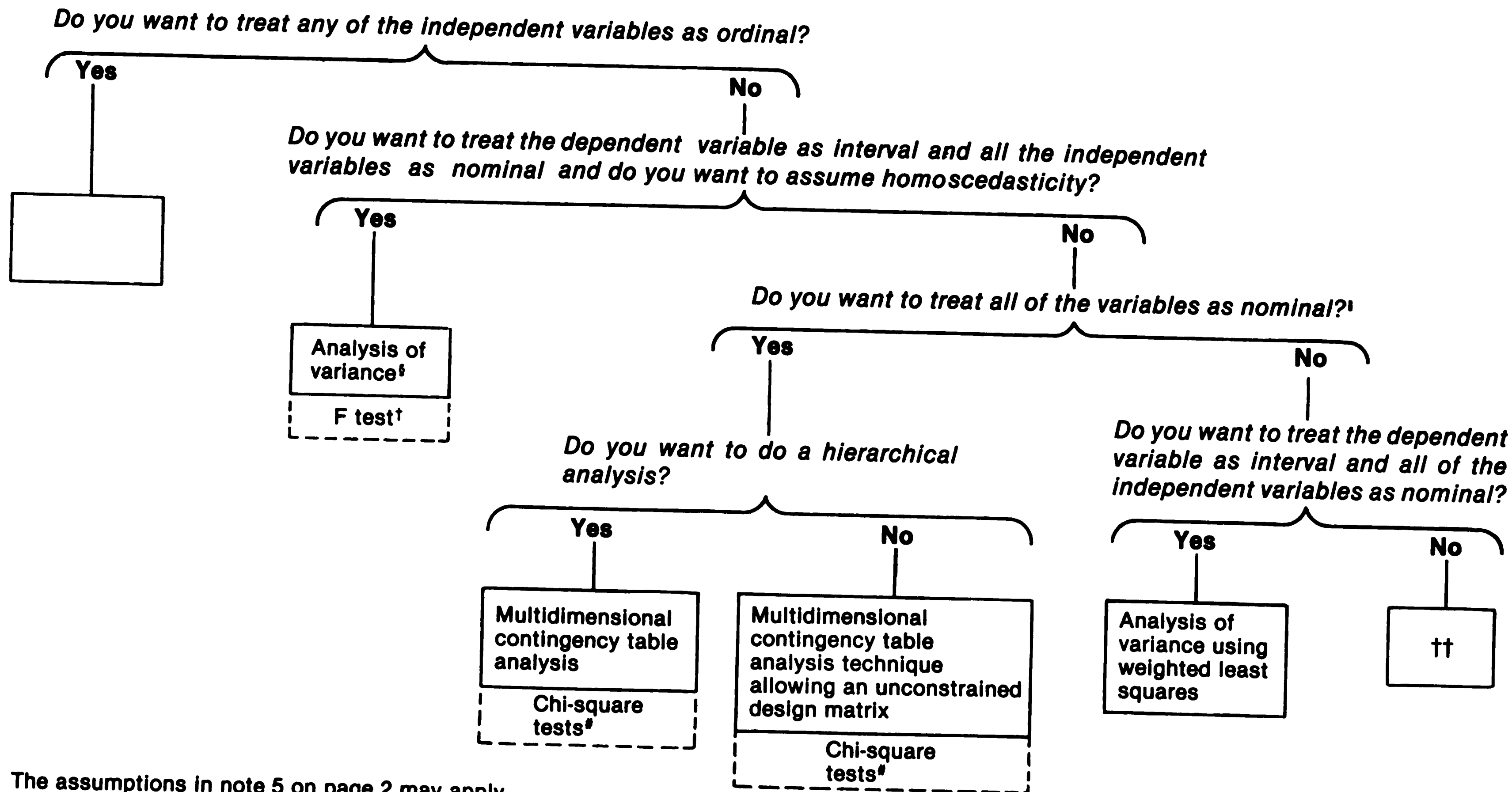
- **Search**
  - *How do you want to treat the variables with respect to scale of measurement?*
    - **Dependent: Nominal or Interval**
      **Independent: Nominal or Ordinal**
      - Binary segmentation techniques
    - **Other**
- **Test**
  - *Do you want to treat the dependent variable as ordinal?*
    - **Yes**
      - *Do you want to treat all the independent variables as nominal?*
        - **Yes**
          - Multidimensional contingency table analysis based on the cumulative logistic distribution‡
          - Chi-square tests#
        - **No**
    - **No**
      - *go to page 26*

‡ This technique depends on a strict assumption of the normality of the continuous variable which is represented by the ordinal dependent variable.

# There are various chi-square test statistics including Pearson, maximum likelihood, and Neyman.

*(continued from page 25)*

• More than two variables • A distinction is made between dependent and independent variables • There is one dependent variable • No covariate is used to remove linear effects • Relationships among the variables are not to be treated as additive • A set of prespecified relationships is to be tested • The dependent variable is not to be treated as ordinal




† The assumptions in note 5 on page 2 may apply.

§ Many analysis of variance techniques assume statistical independence between all pairs of independent variables.

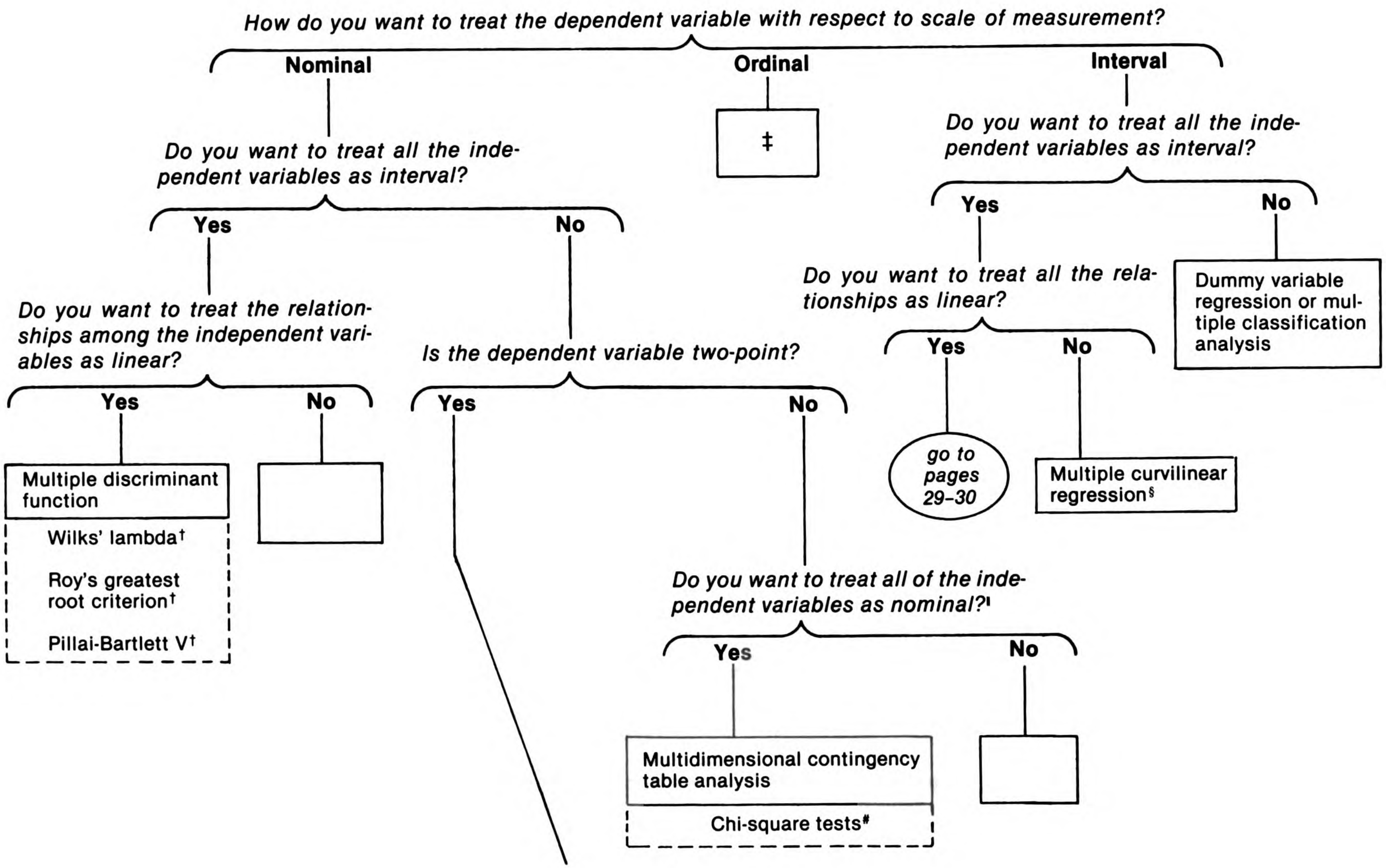
‖ See note 3 in Appendix C.

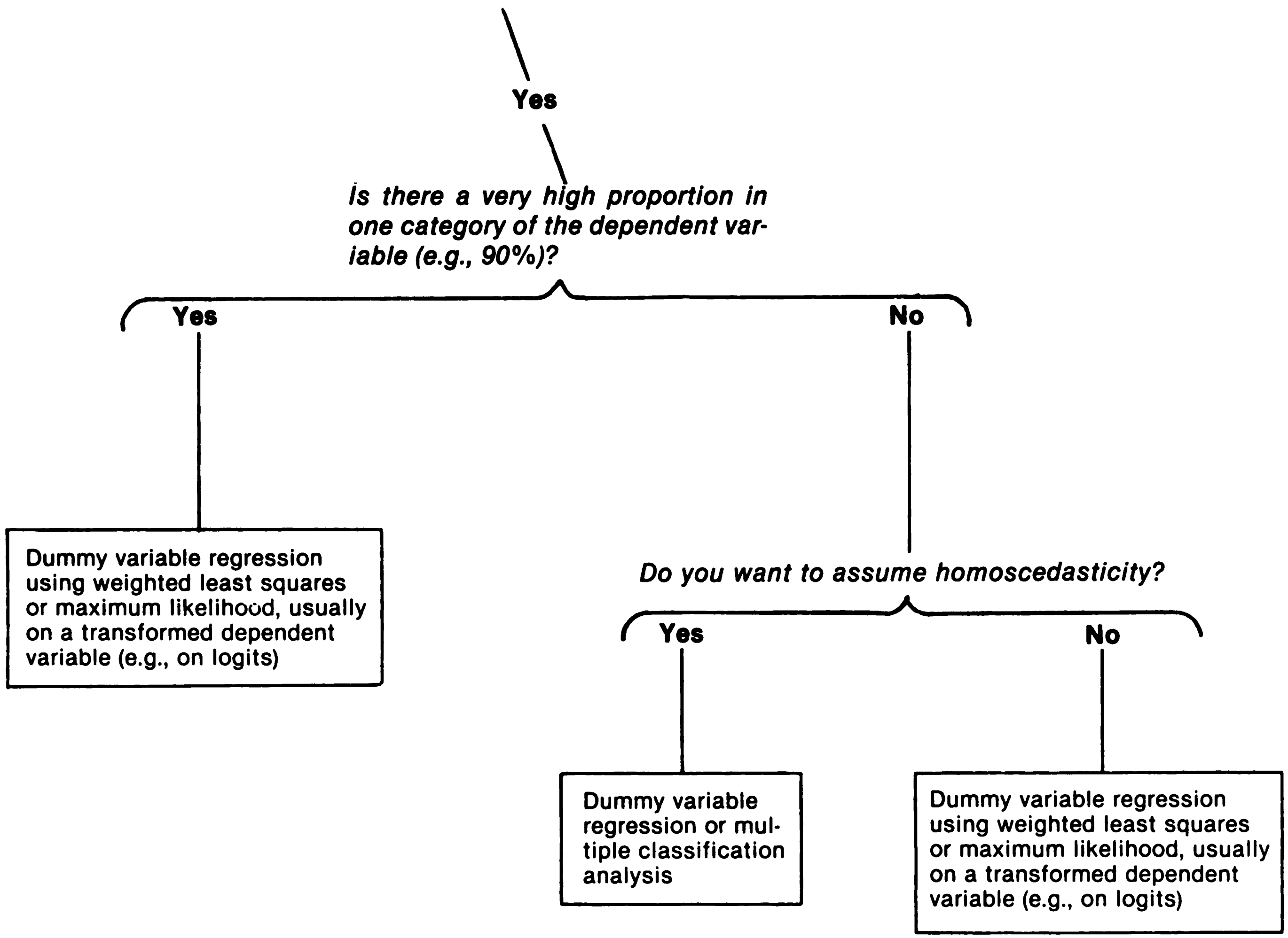
\# There are various chi-square test statistics including Pearson, maximum likelihood, and Neyman.

†† Multidimensional contingency table analysis using weighted least squares may be appropriate.

(continued from page 16)

• More than two variables • A distinction is made between dependent and independent variables • There is one dependent variable • No covariate is used to remove linear effects • Relationships among the variables are to be treated as additive






† The assumptions in note 5 on page 2 may apply.

‡ See note 1 in Appendix C.

§ The type of curvilinear regression referred to here is also known as polynomial regression. See note 4 in Appendix C for further discussion.

‖ See note 3 in Appendix C.

# There are various chi-square test statistics including Pearson, maximum likelihood, and Neyman.

*(continued from page 27)*

**• More than two variables • A distinction is made between dependent and independent variables • There is one dependent variable • No covariate is used to remove linear effects • Relationships among the variables are to be treated as additive and linear • All the variables are interval**

***Does the analysis include at least one intervening variable?***[1]

- **Yes** — ***Does the analysis include at least one latent (i.e., unmeasured) variable?***
  - **Yes** — Structural models with latent variables
  - **No** — Path analysis
- **No** — ***Do you want a single measure of the relationship between the dependent variable and all the independent variables taken together?***
  - **Yes** — Multiple correlation (multiple regression) ($R_{1\cdot 2,\ldots,k}$)
    - F test[†]
  - **No** — ***Do you want a statistic which assigns to each independent variable some of the explainable variance in the dependent variable which that independent variable shares with other independent variables?***
    - **Yes**
    - **No**

**Yes**

Regression coefficient (b or beta, $\beta$)‡

F test† (F equals $t^2$)

**No**

*Do you want a statistic that measures the additional proportion of the total variance in the dependent variable explainable by each independent variable, over and above what the other independent variables can explain?*§

**Yes**

Part correlation² $[r^2_{1(2\cdot3,\ldots,k)}]$*

F test (F equals $t^2$)†

**No**

*Do you want a statistic that measures the additional proportion of the total variance in the dependent variable explainable by each independent variable, over and above what the other independent variables can explain, expressed relative to the proportion of variance in the dependent variable unexplainable by the other independent variables?*

**Yes**

Partial correlation² $(r^2_{12\cdot3,\ldots,k})$*

Do Fisher's r to Z transformation and refer critical ratio of Z to a table of the unit normal curve.†

F test (F equals $t^2$)†

**No**

* Biased estimator.

† The assumptions in note 5 on page 2 may apply.

‡ Beta is a standardized version of b. See "standardized coefficient" in Glossary.

§ The additional proportion of the total variance explainable by a set of independent variables, over and above what the other independent variables can explain, can be measured by the difference between the $R^2$'s resulting from two separate multiple correlation analyses.

‖ See Glossary.

# APPENDIX A

## SOURCES OF FURTHER INFORMATION ABOUT STATISTICS APPEARING IN THIS GUIDE

A brief citation is given below for each statistic and statistical technique that appears in the Guide. A full entry for each cited work appears in the list of references.

**Page 4**

| | |
|---|---|
| Mode | McNemar, 1969, p. 14 |
| Distribution of relative frequencies | Blalock, 1979, p. 31 |
| Distribution of absolute frequencies | McNemar, 1969, p. 5 |
| Median | McNemar, 1969, p. 14 |
| Inter-quartile deviation | McNemar, 1969, p. 19 |
| N-tiles | McNemar, 1969, p. 19 |

**Page 5**

| | |
|---|---|
| Winsorized mean | Dixon and Massey, 1969, p. 330 |
| Trimmed mean | Andrews et al., 1972, p. 2B1 |
| Hampel estimate of location | Andrews et al., 1972, p. 2C3 |
| Biweight mean | Mosteller and Tukey, 1977, p. 205 |
| Mean | McNemar, 1969, p. 16 |
| Median | McNemar, 1969, p. 14 |
| Standard deviation | Hays, 1973, p. 238 |
| Coefficient of variation | Blalock, 1979, p. 84 |

| | |
|---|---|
| Range | McNemar, 1969, p. 19 |
| Skewness | McNemar, 1969, p. 25 |
| Critical ratio of skewness measure | Snedecor and Cochran, 1967, p. 86 |
| Table for testing skewness | Snedecor and Cochran, 1967, p. 552 |
| Kurtosis | McNemar, 1969, p. 25 |
| Critical ratio of kurtosis measure | Snedecor and Cochran, 1967, p. 86 |
| Table for testing kurtosis | Snedecor and Cochran, 1967, p. 552 |
| Geary's criterion for kurtosis | D'Agostino, 1970 |
| Distribution of relative frequencies | Blalock, 1979, p. 31 |
| Distribution of absolute frequencies | McNemar, 1969, p. 5 |
| N-tiles | McNemar, 1969, p. 19 |
| Kolmogorov-Smirnov one sample test | Siegel, 1956, p. 47 |
| Lilliefors test | Conover, 1971, p. 302 |
| Chi-square goodness-of-fit test | Hays, 1973, p. 725 |

**Page 6**

| | |
|---|---|
| Regression coefficient | Hays, 1973, pp. 623, 630 |
| F test for regression coefficient | Hays, 1973, p. 647 |
| Coefficient from curvilinear regression | Draper and Smith, 1966, p. 129; Hays, 1973, p. 675 |
| F test for coefficient from curvilinear regression | Hays, 1973, p. 680 |
| t test for paired observations | Hays, 1973, p. 424 |
| Robinson's A | Robinson, 1957 |
| Intraclass correlation cofficient | McNemar, 1969, p. 322 |
| F test for Robinson's A (translate to intraclass correlation coefficient and test as below) | McNemar, 1969, p. 322 |
| F test for intraclass correlation | McNemar, 1969, p. 322 |
| Krippendorff's $\bar{r}$ | Krippendorff, 1970, p. 143 |

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| | |
|---|---|
| Pearson's product moment r | Hays, 1973, p. 623 |

| | |
|---|---|
| Fisher's r to Z transformation and the critical ratio of Z | Hays, 1973, p. 662 |
| Biserial r | McNemar, 1969, p. 215; Nunnally, 1978, p. 135 |
| Critical ratio for biserial r | McNemar, 1969, p. 217 |
| Critical ratio for point biserial r | McNemar, 1969, p. 219 |
| Tetrachoric r | McNemar, 1969, p. 221; Nunnally, 1978, p. 136 |
| Critical ratio for tetrachoric r | McNemar, 1969, p. 223 |
| Critical ratio for phi | McNemar, 1969, p. 227 |

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| | |
|---|---|
| Somers' d | Somers, 1962 |
| Critical ratio of S | Kendall, 1970, p. 52 |
| Standard error of S, assuming ties | Kendall, 1970, p. 55 |
| Table of critical values of S, assuming ties | Harshbarger, 1971, p. 535 |
| Spearman's rho | Siegel, 1956, p. 202 |
| Critical ratio for Spearman's rho | Siegel, 1956, p. 212 |
| Table of critical values of rho | Siegel, 1956, p. 284 |
| Kendall's tau a | Kendall, 1970, p. 5 |
| Standard error of S, assuming no ties | Kendall, 1970, p. 51 |
| Table of critical values of S, assuming no ties | Kendall, 1970, p. 173 |
| Kendall's tau b | Kendall, 1970, p. 35 |
| Kendall's tau c | Kendall, 1970, p. 47 |
| Goodman and Kruskal's gamma | Hays, 1973, p. 800 |
| Kim's d | Kim, 1971, p. 899 |

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| | |
|---|---|
| McNemar's test of symmetry | Siegel, 1956, p. 63 (when both variables are two-point scales, McNemar's test of symmetry and McNemar's test for the significance of changes are equivalent); Bowker, 1948 |
| Yule's Q | Yule and Kendall, 1957, p. 30 |
| Phi | McNemar, 1969, p. 225 |

| | |
|---|---|
| Critical ratio of phi | McNemar, 1969, p. 227 |
| Fisher's exact test | Siegel, 1956, p. 96 |
| Pearson chi-square | Hays, 1973, p. 735 |
| Goodman and Kruskal's tau b | Blalock, 1979, p. 307 |
| Critical ratio of Goodman and Kruskal's tau b | Goodman and Kruskal, 1972, p. 417 |
| Asymmetric lambda | Hays, 1973, p. 747 |
| Critical ratio of lambda | Goodman and Kruskal, 1963, p. 316 |

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| | |
|---|---|
| Scott's coefficient of agreement | Krippendorff, 1970, p. 142 |
| Cohen's agreement coefficients (kappas) | Cohen, 1960; Cohen, 1968 |
| Critical ratio for Cohen's kappas | Fleiss, Cohen, and Everitt, 1969 |
| McNemar's test of symmetry | Bowker, 1948 |
| Contingency coefficient | Hays, 1973, p. 745 |
| Pearson chi-square | Hays, 1973, p. 730 |
| Cramér's V | Hays, 1973, p. 745 (Hays calls it Cramér's statistic); Srikantan, 1970 |
| Symmetric lambda | Hays, 1973, p. 749 |
| Critical ratio of symmetric lambda | Goodman and Kruskal, 1963, p. 321 |

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| | |
|---|---|
| Jaspen's coefficient of multiserial correlation | Freeman, 1965, p. 131 |
| Fisher's r to Z transformation and the critical ratio of Z | Hays, 1973, p. 662; Harshbarger, 1971, p. 395 |
| Mayer and Robinson's $M_{yu}$ | Mayer and Robinson, 1977 |
| Fisher's r to Z transformation and the critical ratio of Z | Mayer and Robinson, 1977; Hays, 1973, p. 662 |

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| | |
|---|---|
| $Eta^2$ | Hays, 1973, p. 683 |
| $Omega^2$ | Hays, 1973, p. 484 |
| Intraclass correlation coefficient | Hays, 1973, p. 535 |

| | |
|---|---|
| Kelley's epsilon² | Kelley, 1935; Glass and Hakstian, 1969 |
| F test for eta², omega², Kelley's epsilon², and intraclass correlation coefficient | Hays, 1973, p. 471 |

**Pages 13–14**

| | |
|---|---|
| Analysis of variance | Hays, 1973, p. 457 |
| F test for analysis of variance | Hays, 1973, p. 471 |
| Welch statistic | Brown and Forsythe, 1974a |
| Brown-Forsythe statistic | Brown and Forsythe, 1974a |
| t test | Hays, 1973, pp. 404, 410 |
| Bartlett's test | Kirk, 1969, p. 61 |
| Levene's W | Brown and Forsythe, 1974b |
| Walsh test | Siegel, 1956, p. 83 |
| Randomization test for matched pairs | Bradley, 1968, p. 76; Siegel, 1956, p. 88 |
| Randomization test for two independent samples | Bradley, 1968, p. 78; Siegel, 1956, p. 152 |
| Randomization test for matched samples | Bradley, 1968, p. 80 |
| Randomization test for independent samples | Bradley, 1968, p. 80 |

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| | |
|---|---|
| Sign test | Siegel, 1956, p. 68 |
| Wilcoxon signed-rank test | Siegel, 1956, p. 75 |
| Somers' d | Somers, 1962 |
| Critical ratio of S | Kendall, 1970, p. 52 |
| Standard error of S, assuming ties | Kendall, 1970, p. 55 |
| Table of critical values of S, assuming ties | Harshbarger, 1971, p. 535 |
| Median test | Siegel, 1956, p. 111 |
| Mann-Whitney U | Siegel, 1956, p. 116 |
| Kolmogorov-Smirnov two sample test | Siegel, 1956, p. 127 |
| Runs test | Siegel, 1956, p. 136 |
| Friedman test | Hays, 1973, p. 785 |

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|---|---|
| Freeman's coefficient of differentiation | Freeman, 1965, p. 112 |
| Kruskal-Wallis test | Siegel, 1956, p. 184 |
| Median test (for more than two groups) | Siegel, 1956, p. 179 |

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| | |
|---|---|
| Covariance analysis | Snedecor and Cochran, 1967, p. 419 |
| F test for covariance analysis | Snedecor and Cochran, 1967, p. 424 |

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| | |
|---|---|
| Light's agreement coefficient | Light, 1971 |
| Critical ratio of Light's agreement coefficient | Light, 1971 |
| Kendall's coefficient of concordance (W) | Siegel, 1956, p. 229 |
| Chi-square test for W | Siegel, 1956, p. 236 |
| Table of critical values of s in the Kendall coefficient of concordance | Siegel, 1956, p. 286 |
| Intraclass correlation coefficient | McNemar, 1969, p. 322 |
| Robinson's A | Robinson, 1957 |
| F test for intraclass correlation coefficient | McNemar, 1969, p. 322 |
| F test for Robinson's A (translate to intraclass correlation and test as above) | Robinson, 1957, p. 23;<br>McNemar, 1969, p. 322 |
| Cochran's Q | Siegel, 1956, p. 161 |
| Analysis of variance with repeated measures | McNemar, 1969, p. 338 |
| F test for analysis of variance with repeated measures | McNemar, 1969, p. 340 |
| Multidimensional contingency table analysis | Statistics Department, University of Chicago, 1973 (ECTA);<br>Landis et al., 1976 (GENCAT);<br>Fienberg, 1977 (General) |
| Chi-square tests | Fienberg, 1977, p. 36 (Pearson and maximum likelihood) |

**Page 18**

| | |
|---|---|
| Canonical correlation | Cooley and Lohnes, 1971, p. 168;<br>Harris, 1975, p. 132 |

| | |
|---|---|
| Wilks' lambda | Cooley and Lohnes, 1971, p. 175; Morrison, 1976, p. 222; Harris, 1975, p. 143 |
| Roy's greatest root criterion | Morrison, 1976, p. 178; Harris, 1975, pp. 103, 143 |
| Pillai-Bartlett V | Morrison, 1976, p. 223 |
| Q-type factor analysis | Overall and Klett, 1972, p. 201; Gorsuch, 1974, p. 279 |
| Clustering technqiues such as single linkage, complete linkage, average linkage, K-means | Sneath and Sokal, 1973 |

**Pages 19–20**

| | |
|---|---|
| Factor analysis of correlation matrix | Gorsuch, 1974 |
| Factor analysis of variance-covariance matrix | Gorsuch, 1974, p. 271 |
| Confirmatory factor analysis of a standardized variance-covariance matrix | Gorsuch, 1974, pp. 116, 166 (General); Sörbom and Jöreskog, 1976 (COFAMM) |
| Maximum likelihood chi-square | Gorsuch, 1974, pp. 118, 139; Sörbom and Jöreskog, 1976 (COFAMM) |
| Confirmatory factor analysis of variance-covariance matrix | Gorsuch, 1974, pp. 116, 166 (General); Sörbom and Jöreskog, 1976 (COFAMM) |
| Maximum likelihood chi-square | Gorsuch, 1974, pp. 118, 139; Sörbom and Jöreskog, 1976 (COFAMM) |
| Non-metric multidimensional scaling techniques | Kruskal and Wish, 1978 (General); Kruskal, 1964a, 1964b (MDSCAL); Guttman, 1968; Lingoes, Roskam, and Borg, 1979 (MINISSA); Young and Torgerson, 1976 (TORSCA); Takane, Young, and DeLeeuw, 1977 (ALSCAL); Kruskal, Young, and Seery, 1973 (KYST) |
| Multidimensional contingency table analysis | Statistics Department, University of Chicago, 1973 (ECTA); Landis et al., 1976 (GENCAT); Fienberg, 1977 (General) |
| Chi-square tests | Fienberg, 1977, p. 36 (Pearson and maximum likelihood) |
| Clustering techniques such as single linkage, complete linkage, average linkage, K-means | Sneath and Sokal, 1973 |

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| | |
|---|---|
| Three-mode factor analysis | Gorsuch, 1974, p. 283 |

| | |
|---|---|
| Three-way non-metric multidimensional scaling techniques | Kruskal and Wish, 1978, p. 60 (General); Carroll and Chang, 1970 (INDSCAL); Harshman, 1970 (PARAFAC); Lingoes and Borg, 1976 (PINDIS); Carroll, Pruzansky, and Kruskal, 1980 (CANDELINC); Ramsay, 1977 (MULTISCAL); Takane, Young, and DeLeeuw, 1977 (ALSCAL); Sands and Young, 1980 (ALSCOMP3) |
| Confirmatory factor analysis of standardized variance-covariance matrices | Gorsuch, 1974, pp. 116, 251 (General); Sörbom and Jöreskog, 1976 (COFAMM) |
| Maximum likelihood chi-square | Gorsuch, 1974, pp. 118, 139; Sörbom and Jöreskog, 1976 (COFAMM) |
| Confirmatory factor analysis of variance-covariance matrices | Gorsuch, 1974, pp. 116, 251 (General); Sörbom and Jöreskog, 1976 (COFAMM) |
| Maximum likelihood chi-square | Gorsuch, 1974, pp. 118, 139; Sörbom and Jöreskog, 1976 (COFAMM) |

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| | |
|---|---|
| Multivariate analysis of variance | Cooley and Lohnes, 1971, p. 223; Harris, 1975, p. 101; Bock and Haggard, 1968 |
| Wilks' lambda | Cooley and Lohnes, 1971, p. 175; Morrison, 1976, p. 222; Harris, 1975, p. 109; Olson, 1976 |
| Roy's greatest root criterion | Morrison, 1976, p. 178; Harris, 1975, pp. 103, 109; Olson, 1976 |
| Pillai-Bartlett V | Morrison, 1976, p. 223; Olson, 1976 |
| Profile analysis | Morrison, 1976, pp. 153, 205 |
| Wilks' lambda | Morrison, 1976, p. 222 |
| Roy's greatest root criterion | Morrison, 1976, p. 178 |
| Pillai-Bartlett V | Morrison, 1976, p. 223 |

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| | |
|---|---|
| Structural models with latent variables | Jöreskog and Sörbom, 1978 |
| Path analysis | Kerlinger and Pedhazur, 1973, p. 305 |
| Canonical correlation | Cooley and Lohnes, 1971, p. 168; Harris, 1975, p. 132 |

| | |
|---|---|
| Wilks' lambda | Cooley and Lohnes, 1971, p. 175;<br>Morrison, 1976, p. 222;<br>Harris, 1975, p. 143 |
| Roy's greatest root criterion | Morrison, 1976, p. 178;<br>Harris, 1975, pp. 103, 143 |
| Pillai-Bartlett V | Morrison, 1976, p. 223 |

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| | |
|---|---|
| Multivariate analysis of variance | Cooley and Lohnes, 1971, p. 223;<br>Harris, 1975, p. 118;<br>Bock and Haggard, 1968 |
| Wilks' lambda | Cooley and Lohnes, 1971, p. 175;<br>Morrison, 1976, p. 222;<br>Harris, 1975, p. 109; Olson, 1976 |
| Roy's greatest root criterion | Morrison, 1976, p. 178;<br>Harris, 1975, pp. 103, 109; Olson, 1976 |
| Pillai-Bartlett V | Morrison, 1976, p. 223; Olson, 1976 |
| Multivariate binary segmentation techniques | Gillo, 1972 (MAID); Gillo and Shelley, 1974 |

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| | |
|---|---|
| Binary segmentation techniques | Sonquist, Baker, and Morgan, 1974 (SEARCH, formerly known as AID) |
| Multidimensional contingency table analysis based on the cumulative logistic distribution | Bock, 1975, p. 541 (General);<br>Bock and Yates, 1973 (MULTIQUAL) |
| Chi-square tests | Bock, 1975, p. 518 (Pearson and maximum likelihood) |

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| | |
|---|---|
| Analysis of variance | McNemar, 1969, p. 325 |
| F test for analysis of variance | McNemar, 1969, p. 349 |
| Multidimensional contingency table analysis | Statistics Department, University of Chicago, 1973 (ECTA);<br>Fienberg, 1977 (General) |
| Chi-square tests | Fienberg, 1977, p. 36 (Pearson and maximum likelihood) |
| Multidimensional contingency table analysis technique allowing an unconstrained design matrix | Landis et al., 1976 (GENCAT) |

| | |
|---|---|
| Chi-square tests | Fienberg, 1977, p. 36 (Pearson and maximum likelihood) |
| Analysis of variance using weighted least squares | Draper and Smith, 1966, p. 77;<br>Rao, 1965, p. 178 |

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| | |
|---|---|
| Multiple discriminant function | Cooley and Lohnes, 1971, p. 243 |
| Wilks' lambda | Cooley and Lohnes, 1971, p. 248 |
| Roy's greatest root criterion | Morrison, 1976, p. 178;<br>Harris, 1975, pp. 103, 109 |
| Pillai-Bartlett V | Morrison, 1976, p. 223 |
| Dummy variable regression using weighted least squares or maximum likelihood | Draper and Smith, 1966, pp. 77, 134 (Weighted least squares—General);<br>DuMouchel, 1974, 1976 (Maximum likelihood—DREG);<br>Landis et al., 1967 (GENCAT) |
| Dummy variable regression or multiple classification analysis | Draper and Smith, 1966, p. 134;<br>Andrews et al., 1973;<br>Kerlinger and Pedhazur, 1973, p. 101 |
| Multidimensional contingency table analysis | Andrews and Messenger, 1973 (MNA);<br>Statistics Department, University of Chicago, 1973 (ECTA);<br>Landis et al., 1976 (GENCAT);<br>Fienberg, 1977 (General) |
| Chi-square tests | Fienberg, 1977, p. 36 (Pearson and maximum likelihood) |
| Multiple curvilinear regression | Neter and Wasserman, 1974, p. 273 |

**Pages 29–30**

| | |
|---|---|
| Structural models with latent variables | Jöreskog and Sörbom, 1978 |
| Path analysis | Kerlinger and Pedhazur, 1973, p. 305 |
| Multiple correlation | Hays, 1973, p. 707 |
| F test for multiple correlation | Hays, 1973, p. 709 |
| Regression coefficient | Hays, 1973, pp. 704, 708;<br>Kerlinger and Pedhazur, 1973, pp. 56, 61 |
| F test for regression coefficient | Kerlinger and Pedhazur, 1973, p. 66 |
| Part correlation | McNemar, 1969, p. 185 |
| F test for part correlation | McNemar, 1969, p. 321 |

| | |
|---|---|
| Partial correlation | McNemar, 1969, p. 183 |
| Fisher's r to Z transformation and the critical ratio of Z | McNemar, 1969, p. 185 |
| F test for partial correlation | McNemar, 1969, p. 185 |

# APPENDIX B

## PROGRAMS THAT COMPUTE STATISTICS LISTED IN THE GUIDE

For many of the statistics and statistical techniques that appear in the Guide, there exist one or more programs that calculate the statistic or use the technique. The entries in this Appendix are intended to guide the reader to an appropriate program or command. In some cases, the program or command listed provides a functional approximation to the indicated statistic (for example, many programs give probability values rather than critical ratios). An asterisk following a program name means that the statistic, while not printed, can be readily obtained or, in more complicated cases, that there is documentation in the User's Manual explaining how to obtain it.

In the following table, at least one program per column is cited for each entry whenever possible. If multiple programs could be cited, only the program or programs most frequently used for the particular purpose are listed. The appropriate program, command, or procedure was determined by a review of the published documentation for each system; it is therefore possible that some errors, particularly of omission, may have been made. It is important to note the dates of the documentation (see References) as program packages are constantly being improved and augmented.

| | OSIRIS | MIDAS | SPSS | SAS | BMDP | OTHER |
|---|---|---|---|---|---|---|
| **Page 4** | | | | | | |
| Mode | TABLES | HISTOGRAM ONEWAY | FREQUENCIES | UNIVARIATE | P2D | – |
| Distribution of relative frequencies | TABLES | HISTOGRAM ONEWAY | FREQUENCIES | UNIVARIATE CHART | P2D | – |
| Distribution of absolute frequencies | TABLES | HISTOGRAM ONEWAY | FREQUENCIES | UNIVARIATE CHART | P2D | – |
| Median | TABLES | DISTRIBUTION | FREQUENCIES | UNIVARIATE | P2D | – |
| Inter-quartile deviation | TABLES* | – | – | UNIVARIATE** | P2D | – |
| N-tiles | TABLES | DISTRIBUTION | – | UNIVARIATE | – | – |
| **Page 5** | | | | | | |
| Winsorized mean | – | – | – | – | P7D | – |
| Trimmed mean | – | – | – | – | P2D | – |
| Hampel estimate of location | – | – | – | – | P2D | – |
| Biweight mean | – | – | – | – | P2D | – |
| Mean | TABLES USTATS | DESCRIBE | CONDESCRIPTIVE FREQUENCIES | UNIVARIATE MEANS | P1D P2D | – |
| Median | TABLES | DISTRIBUTION | FREQUENCIES | UNIVARIATE | P2D | – |
| Standard deviation | TABLES USTATS | DESCRIBE | CONDESCRIPTIVE FREQUENCIES | UNIVARIATE MEANS | P1D P2D | – |
| Coefficient of variation | – | – | – | UNIVARIATE MEANS | P1D | – |

** SAS prints $Q_3 - Q_1$; our reference refers to $(Q_3 - Q_1)/2$.

| | OSIRIS | MIDAS | SPSS | SAS | BMDP | OTHER |
|---|---|---|---|---|---|---|
| Range | TABLES USTATS | DESCRIBE | CONDESCRIPTIVE FREQUENCIES | UNIVARIATE | P1D P2D | — |
| Skewness | TABLES | DESCRIBE | CONDESCRIPTIVE FREQUENCIES | UNIVARIATE MEANS | P2D | — |
| Critical ratio of skewness measure | — | — | — | — | P2D | — |
| Table for testing skewness | — | — | — | — | — | — |
| Kurtosis | TABLES | DESCRIBE | CONDESCRIPTIVE, FREQUENCIES | UNIVARIATE MEANS | P2D | — |
| Critical ratio of kurtosis measure | — | — | — | — | P2D | — |
| Table for testing kurtosis | — | — | — | — | — | — |
| Geary's criterion for kurtosis | — | — | — | — | — | — |
| Distribution of relative frequencies | TABLES | HISTOGRAM ONEWAY | FREQUENCIES | UNIVARIATE CHART | P2D | — |
| Distribution of absolute frequencies | TABLES | HISTOGRAM ONEWAY | FREQUENCIES | UNIVARIATE CHART | P2D | — |
| N-tiles | TABLES | DISTRIBUTION | — | UNIVARIATE | — | — |
| Kolmogorov-Smirnov one sample test | — | — | NPAR | — | — | — |
| Lilliefors test | — | ** | — | UNIVARIATE | — | — |
| Chi-square goodness-of-fit test | — | — | NPAR | FREQ | — | — |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Page 6** | | | | | | |
| Regression coefficient | REGRESSN | REGRESSION | REGRESSION† | GLM<br>REG | P1R<br>P4F | – |
| F test for regression coefficient | REGRESSN | REGRESSION | REGRESSION† | GLM<br>REG | P1R | – |
| Coefficient from curvilinear regression | – | POLY | REGRESSION*,†<br>ONEWAY | GLM | P5R | – |
| F test for coefficient from curvilinear regression | – | POLY | REGRESSION*,†<br>ONEWAY | GLM | P5R | – |
| t test for paired observations | – | PAIR | T-TEST | MEANS‡ | P3D | – |
| Robinson's A | – | – | – | – | – | – |
| Intraclass correlation coefficient | – | ANOVA* | – | – | – | – |
| F test for Robinson's A (translate to intraclass correlation coefficient and test as below) | – | – | – | – | – | – |
| F test for intraclass correlation coefficient | – | ANOVA | – | – | – | – |
| Krippendorff's r̄ | – | – | – | – | – | – |
| **Page 7** | | | | | | |
| Pearson's product moment r | MDC | CORRELATE<br>MCORR | PEARSON CORR<br>CROSSTABS | CORR | P8D<br>P4F | – |
| Fisher's r to Z transformation and the critical ratio of Z | MDC | CORRELATE<br>MCORR | PEARSON CORR<br>CROSSTABS | CORR | – | – |
| Biserial r | – | – | – | – | – | – |

** Requires a sequence of MIDAS commands. See Statistical Research Laboratory, 1976, page 274.

† All capabilities in SPSS REGRESSION are also available in NEW REGRESSION.

‡ Requires that the data analyzed be the differences between the paired observations.

| | OSIRIS | MIDAS | SPSS | SAS | BMDP | OTHER |
|---|---|---|---|---|---|---|
| Critical ratio for biserial r | – | – | – | – | – | – |
| Critical ratio for point biserial r | – | – | – | – | – | – |
| Tetrachoric r | – | – | – | – | P4F | – |
| Critical ratio for tetrachoric r | – | – | – | – | P4F | – |
| Critical ratio for phi | TABLES* | TWOWAY* | CROSSTABS* | FREQ* | P4F* | – |
| **Page 8** | | | | | | |
| Somers' d | – | – | CROSSTABS | FREQ | P4F | – |
| Critical ratio of S | TABLES | – | CROSSTABS<br>NONPAR CORR | FREQ | P4F | – |
| Standard error of S, assuming ties | – | – | – | – | – | – |
| Table of critical values of S, assuming ties | – | – | – | – | – | – |
| Spearman's rho | – | RCORR | NONPAR CORR | FREQ | P4F | – |
| Critical ratio for Spearman's rho | – | RCORR | NONPAR CORR | FREQ | P4F | – |
| Table of critical values for rho | – | – | – | – | – | – |
| Kendall's tau a | TABLES | – | NONPAR CORR | – | – | – |
| Standard error of S, assuming no ties | – | – | – | – | – | – |

| | | | | | | |
|---|---|---|---|---|---|---|
| Table of critical values of S, assuming no ties | – | – | – | – | – | – |
| Kendall's tau b | TABLES | RCORR TWOWAY | CROSSTABS | FREQ CORR | P4F | – |
| Kendall's tau c | TABLES | – | CROSSTABS | FREQ** | P4F** | – |
| Goodman and Kruskal's gamma | TABLES | RCORR TWOWAY | CROSSTABS | FREQ | P4F | – |
| Kim's d | – | – | – | – | | – |
| **Page 9** | | | | | | |
| McNemar's test of symmetry | – | TWOWAY | NPAR | – | P4F | – |
| Yule's Q | – | – | – | – | P4F | – |
| Phi | TABLES† | TWOWAY† | CROSSTABS | FREQ† | P4F | – |
| Critical ratio of phi | TABLES* | TWOWAY* | CROSSTABS* | FREQ* | P4F* | – |
| Fisher's exact test | – | TWOWAY | CROSSTABS | – | P4F | – |
| Pearson chi-square | TABLES | TWOWAY | CROSSTABS | FREQ | P4F | – |
| Goodman and Kruskal's tau b | – | TWOWAY | – | – | P4F | – |
| Critical ratio of Goodman and Kruskal's tau b | – | – | – | – | – | – |
| Asymmetric lambda | TABLES | TWOWAY | CROSSTABS | FREQ | P4F | – |
| Critical ratio of lambda | TABLES | – | – | FREQ | P4F | – |
| **Page 10** | | | | | | |
| Scott's coefficient of agreement | – | – | – | – | – | – |

** SAS and BMDP refer to this as Stuart's tau c.

† For two dichotomous variables, Cramér's V (in MIDAS, Cramér's phi) is equivalent to phi.

| | OSIRIS | MIDAS | SPSS | SAS | BMDP | OTHER |
|---|---|---|---|---|---|---|
| Cohen's agreement coefficients (kappas) | TABLES | — | — | — | — | — |
| Critical ratio for Cohen's kappas | TABLES | — | — | — | — | — |
| McNemar's test of symmetry | — | — | — | — | P4F | — |
| Contingency coefficient | TABLES | TWOWAY | CROSSTABS | FREQ | P4F | — |
| Pearson chi-square | TABLES | TWOWAY | CROSSTABS | FREQ | P4F | — |
| Cramér's V | TABLES | TWOWAY | CROSSTABS | FREQ | P4F | — |
| Symmetric lambda | TABLES | TWOWAY | CROSSTABS | FREQ | P4F | — |
| Critical ratio of symmetric lambda | TABLES | — | CROSSTABS | FREQ | P4F | — |
| **Page 11** | | | | | | |
| Jaspen's coefficient of multiserial correlation | — | — | — | — | — | — |
| Fisher's r to Z transformation and the critical ratio of Z | — | — | — | — | — | — |
| Mayer and Robinson's $M_{yu}$ | — | — | — | — | — | — |
| Fisher's r to Z transformation and the critical ratio of Z | — | — | — | — | — | — |
| **Page 12** | | | | | | |
| Eta$^2$ | ANOVA MCA | ANOVA | BREAKDOWN ANOVA | GLM ANOVA | — | — |

| | | | | | | |
|---|---|---|---|---|---|---|
| Omega$^2$ | — | — | — | GLM<br>ANOVA | — | — |
| Intraclass correlation coefficient | — | ANOVA* | — | GLM<br>ANOVA | — | — |
| Kelley's epsilon$^2$ | ANOVA**<br>MCA** | — | — | — | — | — |
| F test for eta$^2$, omega$^2$, Kelley's epsilon$^2$, and intraclass correlation coefficient | ANOVA | ANOVA | BREAKDOWN<br>ANOVA | GLM<br>ANOVA | P7D* | — |
| **Pages 13–14** | | | | | | |
| Analysis of variance | ANOVA | ANOVA | ANOVA<br>ONEWAY<br>BREAKDOWN<br>MANOVA | GLM<br>ANOVA | P1V<br>P7D | — |
| F test for analysis of variance | ANOVA | ANOVA | ANOVA<br>ONEWAY<br>BREAKDOWN<br>MANOVA | GLM<br>ANOVA | P1V<br>P7D | — |
| Welch statistic | — | — | — | — | P7D | — |
| Brown-Forsythe statistic | — | — | — | — | P7D | — |
| t test | — | — | T-TEST | T-TEST | P7D | — |
| Bartlett's test | — | ANOVA | ONEWAY<br>MANOVA | DISCRIM | P9D | — |
| Levene's W | — | — | — | — | P7D | — |
| Walsh test | — | — | — | — | — | — |
| Randomization test for matched pairs | — | — | — | — | — | — |
| Randomization test for two independent samples | — | — | — | — | — | — |
| Randomization test for matched samples | — | — | — | — | — | — |

** In OSIRIS, Kelley's epsilon$^2$ is labelled adjusted eta$^2$.

| | OSIRIS | MIDAS | SPSS | SAS | BMDP | OTHER |
|---|---|---|---|---|---|---|
| Randomization test for independent samples | – | – | – | – | – | – |
| **Page 15** | | | | | | |
| Sign test | TABLES* | RPAIR | NPAR | MRANK | P3S | – |
| Wilcoxon signed-rank test | TABLES* | RPAIR | NPAR | UNIVARIATE | P3S | – |
| Somers' d | – | – | CROSSTABS | FREQ | P4F | – |
| Critical ratio of S | TABLES | – | CROSSTABS | FREQ | P4F | – |
| Standard error of S, assuming ties | – | – | – | – | – | – |
| Table of critical values of S, assuming ties | – | – | – | – | – | – |
| Median test | – | TWOSAMPLE | NPAR | NPAR1WAY MRANK | – | – |
| Mann-Whitney U | TABLES | TWOSAMPLE | NPAR | NPAR1WAY MRANK | P3S | – |
| Kolmogorov-Smirnov two sample test | – | TWOSAMPLE | NPAR | – | – | – |
| Runs test | – | – | NPAR** | – | – | – |
| Friedman test | – | – | NPAR RELIABILITY | RANK* MRANK | P3S | – |
| Freeman's coefficient of differentiation | – | – | – | – | – | – |
| Kruskal-Wallis test | TABLES | KSAMPLE | NPAR | NPAR1WAY MRANK | P3S | – |
| Median test (for more than 2 groups) | – | KSAMPLE | NPAR | NPAR1WAY MRANK | – | – |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Page 16** | | | | | | |
| Covariance analysis | MANOVA | COVAR | ANOVA<br>MANOVA | GLM | P1V<br>P2V<br>P4V | – |
| F test for covariance analysis | MANOVA | COVAR | ANOVA<br>MANOVA | GLM | P1V<br>P2V<br>P4V | – |
| **Page 17** | | | | | | |
| Light's agreement coefficient | – | – | – | – | – | – |
| Critical ratio of Light's agreement coefficient | – | – | – | – | – | – |
| Kendall's coefficient of concordance (W) | – | RCORR | – | – | P3S | – |
| Chi-square test for W | – | RCORR | – | – | P3S | – |
| Table of critical values of s in the Kendall coefficient of concordance | – | – | – | – | – | – |
| Intraclass correlation coefficient | – | ANOVA* | – | – | – | – |
| Robinson's A | – | – | – | – | – | – |
| F test for intraclass correlation coefficient | – | ANOVA | – | – | – | – |
| F test for Robinson's A (translate to intraclass correlation and test as above) | – | – | – | – | – | – |
| Cochran's Q | – | – | NPAR<br>RELIABILITY | – | – | – |
| Analysis of variance with repeated measures | – | – | RELIABILITY<br>MANOVA | GLM<br>ANOVA | P2V<br>P4V | – |

** IN SPSS, this test is called Wald-Wolfowitz.

| | OSIRIS | MIDAS | SPSS | SAS | BMDP | OTHER |
|---|---|---|---|---|---|---|
| F test for analysis of variance with repeated measures | – | – | RELIABILITY ANOVA | GLM ANOVA | P2V P4V | – |
| Multidimensional contingency table analysis | – | – | – | FUNCAT | P4F | ECTA GENCAT |
| Chi-square tests | – | – | – | FUNCAT | P4F | ECTA GENCAT |
| **Page 18** | | | | | | |
| Canonical correlation | – | CANONICAL | CANCORR | CANCORR | P6M | – |
| Wilks' lambda | – | – | CANCORR | CANCORR | – | – |
| Roy's greatest root criterion | – | CANONICAL | – | CANCORR | – | – |
| Pillai-Bartlett V | – | – | – | CANCORR | – | – |
| Q-type factor analysis | FACTAN | FACTOR | FACTOR | FACTOR | P4M | – |
| Clustering techniques such as single linkage, complete linkage, average linkage, K-means | CLUSTER | CLUSTER | – | CLUSTER FASTCLUS | P2M PKM | – |
| **Pages 19–20** | | | | | | |
| Factor analysis of correlation matrix | FACTAN | FACTOR | FACTOR | FACTOR | P4M | – |
| Factor analysis of variance-covariance matrix | – | FACTOR | – | FACTOR | P4M | – |

| | | | | | | |
|---|---|---|---|---|---|---|
| Confirmatory factor analysis of a standardized variance-covariance matrix | – | ROTATE | – | – | – | COFAMM |
| Maximum likelihood chi-square | – | – | – | – | – | COFAMM |
| Confirmatory factor analysis of variance-covariance matrix | – | ROTATE | – | – | – | COFAMM |
| Maximum likelihood chi-square | – | – | – | – | – | COFAMM |
| Non-metric multidimensional scaling techniques | MINISSA | – | – | ALSCAL | – | MINISSA<br>MDSCAL<br>TORSCA<br>KYST<br>ALSCAL |
| Multidimensional contingency table analysis | – | – | – | FUNCAT | P4F | ECTA<br>GENCAT |
| Chi-square tests | – | – | – | FUNCAT | P4F | ECTA<br>GENCAT |
| Clustering techniques such as single linkage, complete linkage, average linkage, K-means | CLUSTER | CLUSTER | – | VARCLUS | P1M | – |
| **Page 21** | | | | | | |
| Three-mode factor analysis | – | – | – | – | – | – |
| Three-way non-metric multidimensional scaling techniques | – | – | – | ALSCAL | – | INDSCAL<br>PARAFAC<br>PINDIS<br>CANDELINC<br>MULTISCAL<br>ALSCAL<br>ALSCOMP3 |

| | OSIRIS | MIDAS | SPSS | SAS | BMDP | OTHER |
|---|---|---|---|---|---|---|
| Confirmatory factor analysis of standardized variance-covariance matrices | – | – | – | FACTOR | – | COFAMM |
| Maximum likelihood chi-square | – | – | – | FACTOR | – | COFAMM |
| Confirmatory factor analysis of variance-covariance matrices | – | – | – | FACTOR | – | COFAMM |
| Maximum likelihood chi-square | – | – | – | FACTOR | – | COFAMM |
| **Page 22** | | | | | | |
| Multivariate analysis of variance | MANOVA | MANOVA | MANOVA | GLM ANOVA | P4V | – |
| Wilks' lambda | MANOVA | – | MANOVA | GLM ANOVA | P4V | – |
| Roy's greatest root criterion | – | MANOVA | MANOVA | GLM ANOVA | P4V | – |
| Pillai-Bartlett V | – | – | MANOVA | GLM ANOVA | – | – |
| Profile analysis | – | PROFILE | MANOVA | GLM ANOVA | P4V | – |
| Wilks' lambda | – | – | MANOVA | GLM ANOVA | P4V | – |
| Roy's greatest root criterion | – | PROFILE | MANOVA | GLM ANOVA | P4V | – |
| Pillai-Bartlett V | – | – | MANOVA | GLM ANOVA | – | – |
| **Page 23** | | | | | | |
| Structural models with latent variables | – | – | – | – | – | LISREL |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Path analysis** | – | – | REGRESSION*,† | SYSREG | – | – |
| Canonical correlation | – | CANONICAL | CANCORR | CANCORR | P6M | – |
| Wilks' lambda | – | – | CANCORR | CANCORR | – | – |
| Roy's greatest root criterion | – | CANONICAL | – | CANCORR | – | – |
| Pillai-Bartlett V | – | – | – | CANCORR | – | – |
| **Page 24** | | | | | | |
| Multivariate analysis of variance | MANOVA | – | MANOVA | GLM ANOVA | P4V | – |
| Wilks' lambda | MANOVA | – | MANOVA | GLM ANOVA | P4V | – |
| Roy's greatest root criterion | – | – | MANOVA | GLM ANOVA | P4V | – |
| Pillai-Bartlett V | – | – | MANOVA | GLM ANOVA | – | – |
| Multivariate binary segmentation techniques | – | – | – | – | – | MAID |
| **Page 25** | | | | | | |
| Binary segmentation techniques | SEARCH** | – | – | – | – | – |
| Multidimensional contingency table analysis based on the cumulative logistic distribution | – | – | – | – | – | MULTIQUAL |
| Chi-square tests | – | – | – | – | – | MULTIQUAL |
| **Page 26** | | | | | | |
| Analysis of variance | – | – | ANOVA MANOVA | GLM ANOVA | P1V | – |

** Formerly known as AID.

† All capabilities in SPSS REGRESSION are also available in NEW REGRESSION.

| | OSIRIS | MIDAS | SPSS | SAS | BMDP | OTHER |
|---|---|---|---|---|---|---|
| F test for analysis of variance | – | – | ANOVA MANOVA | GLM ANOVA | P1V | – |
| Multidimensional contingency table analysis | – | – | – | FUNCAT | P4F | ECTA |
| Chi-square tests | – | – | – | FUNCAT | P4F | ECTA |
| Multidimensional contingency table analysis technique allowing an unconstrained design matrix | – | – | – | FUNCAT | – | GENCAT |
| Chi-square tests | – | – | – | FUNCAT | – | GENCAT |
| Analysis of variance using weighted least squares | – | – | – | GLM | P2V | – |
| **Pages 27–28** | | | | | | |
| Multiple discriminant function | – | DISCRIMINANT SEPARATE | DISCRIMINANT | DISCRIM CANDISC | P7M | – |
| Wilks' lambda | – | – | DISCRIMINANT | CANDISC | P7M | – |
| Roy's greatest root criterion | – | – | – | CANDISC | – | – |
| Pillai-Bartlett V | – | – | – | CANDISC | – | – |
| Dummy variable regression using weighted least squares or maximum likelihood | DREG | – | – | FUNCAT | P3R* PAR* | GENCAT |

| | | | | | | |
|---|---|---|---|---|---|---|
| Dummy variable regression or multiple classification analysis | REGRESSN* MCA | REGRESSION* SELECT* | REGRESSION*,† ANOVA | GLM* | P1R* | – |
| Multidimensional contingency table analysis | MNA | – | – | FUNCAT | P4F | ECTA GENCAT |
| Chi-square tests | – | – | – | FUNCAT | P4F | ECTA GENCAT |
| Multiple curvilinear regression | – | – | REGRESSION*,† MANOVA | GLM | P1R* | – |
| **Pages 29–30** | | | | | | |
| Structural models with latent variables | – | – | – | – | – | LISREL |
| Path analysis | – | – | REGRESSION*,† | SYSREG | – | – |
| Multiple correlation | REGRESSN | REGRESSION | REGRESSION† | GLM REG | P1R | – |
| F test for multiple correlation | REGRESSN | REGRESSION | REGRESSION† | GLM REG | P1R | – |
| Regression coefficient | REGRESSN | REGRESSION | REGRESSION† | GLM REG | P1R | – |
| F test for regression coefficient | REGRESSN | REGRESSION | REGRESSION† | GLM REG | P1R | – |
| Part correlation | REGRESSN** | REGRESSION | REGRESSION† | – | – | – |
| F test for part correlation | REGRESSN | REGRESSION | REGRESSION*,† | – | – | – |
| Partial correlation | PARTIALS REGRESSN | REGRESSION | PARTIAL CORR REGRESSION† | GLM REG | P6R | – |
| Fisher's r to Z transformation and the critical ratio of Z | – | – | – | – | – | – |
| F test for partial correlation | REGRESSN | REGRESSION | PARTIAL CORR REGRESSION† | GLM REG | – | – |

** The square of the part correlation is printed; it is labelled Marginal RSQD.

† All capabilities in SPSS REGRESSION are also available in NEW REGRESSION.

# APPENDIX C

## SOME NEW OR RARELY USED STATISTICAL TECHNIQUES

There are in the statistical literature many statistical techniques that are not included in this Guide for various reasons—they may be new and not yet well-known, or they may be old and seldom used. Some of these techniques are noted below.

**1. Multivariate analysis of ordinal data.**
Developing methods of multivariate analysis appropriate to the uniquely ordinal properties of ordinal scales, including constructing coefficients that measure multiple and partial association among ordinal measures, has been extensively discussed in the methodological literature of the 1970s but has proven to be a difficult problem. The issues are not yet resolved. Useful discussions of the problems, and references to other relevant literature, can be found in Blalock (1975), Kim (1975), and Mayer and Robinson (1977). From a practical standpoint, most analysts who desire to perform a multivariate analysis with ordinal measures disregard the uniquely ordinal aspects of their measures and treat them as either nominal scales or interval scales.

**2. Developments in nonmetric multidimensional scaling.**
Nonmetric multidimensional scaling has undergone considerable development and expansion in recent years through several distinct lines of methodological activity. One such line is yielding a variety of different algorithms for performing multidimensional mappings simultaneously for separate groups so as to generate information about how the groups differ. An early algorithm for this type of analysis, INDSCAL (Carroll and Chang, 1970), has now been complemented by several others that make fewer (or different) assumptions and that are in other ways more powerful and general. These include CANDELINC (Carroll, Puzansky, and Kruskal, 1980), PINDIS (Lingoes and Borg, 1976), MULTISCAL (Ramsay, 1977), ALSCOMP3 (Sands and Young, 1980), and ALSCAL (Takane, Young, and DeLeeuw, 1977). (In the decision tree, these are referred to as three-way nonmetric multidimensional scaling techniques.)

A second line of methodological investigation has focused on the statistical significance of the obtained fits—that is, the probability that the correspondence between the multidimensional scaling solution and the observed data could have been obtained purely by a random placement of a specified number of points in a space of given dimensionality; see Isaac and Poor (1974), Langeheine (1980), MacCallum and Cornelius (1977), Spence and Graef (1974), and Spence and Ogilvie (1973).

A third line of development has pursued "confirmatory" multidimensional scaling—the attempt to fit data to an existing structure; see Borg and Lingoes (1980), and Lingoes and Borg (1976).

**3. Developments in techniques for multidimensional contingency table analysis.**
Multidimensional contingency table analysis has been used mainly with nominal scales, but recent developments allow its use with interval scales that have a small number of categories. Because such applications are not yet common, use of multidimensional contingency table analysis with interval scales is not included in the decision tree portion of this Guide. For further information, see Fienberg (1977) and Landis et al. (1976).

**4. Polynomial regression and nonlinear regression.**
As used in this Guide, curvilinear regression refers to polynomial regression, a type of regression that is linear in its parameters but not in its variables (see Draper and Smith, 1966, page 129). This is different from a type of regression that is nonlinear in its parameters, usually referred to as nonlinear regression (see Draper and Smith, 1966, p. 263).

**5. Reduced variance regression techniques.**
When one is attempting to predict a dependent variable using two or more predictor variables, the appropriate weights to be applied to those predictor variables can be expected to show substantial variation from one random sample to another if the correlations among the predictor variables are high. Sometimes this is referred to as "instability" of coefficients that results from high multicollinearity among the predictor variables. In recent years there has been considerable discussion in the statistical literature about ways to achieve greater stability in regression coefficients by accepting certain biases. The underlying assumption is that it may be better to use coefficients that tend to be reasonably close to the ideal (population) value but that on average tend to come out slightly different from this value, rather than a coefficient that averages to the correct value over many samples but that in any one sample may be very far off. Although theoretically interesting, we believe these developments have not yet reached the point where most social science data analysts can routinely apply them and expect to obtain better results than would be produced by more traditional approaches. Useful discussions and reviews of biased estimation techniques (including, particularly, "ridge regression") have been provided by the following authors: Darlington (1978), Dempster, Schatzoff, and Wermuth (1977), Fennessey and d'Amico (1980), Rozeboom (1979), and Smith and Campbell (1980).

**6. Exploratory data analysis.**
"Exploratory data analysis" is a phrase associated with a collection of techniques proposed by Tukey (1977) that are intended to let the analyst explore a set of data while making minimal assumptions. Although based on well accepted statistical foundations, Tukey's terminology is nontraditional and his techniques are not yet widely used. Summaries of some of his key ideas can be found in Hartwig (1979) and Leinhardt and Wasserman (1978).

**7. Survival analysis.**
Techniques for survival analysis (i.e., the analysis of time intervals between events) are not included in the tree portion of this Guide because, at least in the past, their application in the social sciences has largely been restricted to specific disciplines, such as demography. It is possible, however, that these techniques could profitably be applied to problems encountered in other contexts, such as studies of residential and occupational mobility, completion of education, and retirement. Techniques to handle cases with incomplete data (censored data), data involving competing risks, covariates, and interactions have been developed. Texts that describe such techniques include Kalbfleisch and Prentice (1980) and Gross and Clark (1975).

**8. Information theory and the analysis of contingency tables.**
A measure of uncertainty, *H*, derived from information

theory, can be used to measure the degree of association between two or more nominal variables. (The coefficient of association is often called U.) More generally, information theory has been used to develop methods for analyzing multidimensional contingency tables. For details, see Gokhale and Kullback (1978).

**9. Sampling errors of statistics from complex designs.**

An assumption often required for the use of inferential statistics is that the observations are based on a simple random sample from some population. This assumption is required because the estimates of sampling error assume that each observation is independent of all others. Often, however, stratification or clustering is used instead of a simple random procedure, and this introduces non-independence among the observations. Two programs are available in the OSIRIS IV software package that can be used to estimate the sampling error of statistics from clustered or stratified samples: &PSALMS estimates the sampling error of means, and &REPERR estimates the sampling error of regression statistics.

**10. The polychoric correlation coefficient for two ordinal variables.**

It was pointed out in the Instructions and Comments section of this Guide that ordinally scaled variables may be transformed to ranks, and the transformed data then treated as intervally scaled. Another approach has been suggested for the case of two ordinal variables. This approach assumes that the ordinal variables have been generated from unobserved (latent) interval-scale variables with a bivariate-normal distribution. Then the "true" product-moment correlation is estimated by a measure called the polychoric correlation coefficient (Olsson, 1979, 1980). The polychoric coefficient is a generalization to polychotomies (scales with more than two points) of the tetrachoric coefficient, which is a similar measure used in the case of two dichotomous variables (see the cautionary footnote on page 7).

**11. Time series analysis.**

Generally, time series analysis uses regression techniques (often something other than ordinary least squares) to analyze or predict change. Economists have been the leaders among social scientists in developing this area, but other social scientists increasingly are finding time series analysis to be relevant to their analytic problems. The Guide does not include time series analysis—partly because the decision-tree approach does not lend itself well to the analysis of data of a special type (which is the case with time series data), and partly because time series analysis has not yet become widely used by social scientists (except economists). However, because several of the major software packages now include time series programs (BMDP, MIDAS, SAS, SPSS), increased use of these analytic techniques in the coming years seems likely. Introductions to time series analysis for social scientists can be found in Glass, Willson, and Gottman (1975), Hannan and Tuma (1979), and McCleary et al. (1980).

# GLOSSARY

ADDITIVE. A situation in which the best estimate of a dependent variable is obtained by simply adding together the appropriately computed effects of each of the independent variables. Additivity implies the absence of interactions. *See also* INTERACTION.

AGREEMENT. Agreement measures the extent to which two sets of scores (e.g., scores obtained from two raters) are identical. Agreement involves a more stringent matching of two variables than does covariation, which implicitly allows one to change the mean (by adding a constant) and/or to change the variance (by multiplying by a constant) for either or both variables before checking the match.

BIAS. The difference between the expected value of a statistic and the population value it is intended to estimate. *See* EXPECTED VALUE.

BIASED ESTIMATOR. A statistic whose expected value is not equal to the population value. *See* EXPECTED VALUE.

BIVARIATE NORMALITY. A particular form of distribution of two variables that has the traditional "bell" shape (but not all bell-shaped distributions are normal). If plotted in three-dimensional space, with the vertical axis showing the number of cases, the shape would be that of a three-dimensional bell (if the variances on both variables were equal) or a "fireman's hat" (if the variances were unequal). When perfect bivariate normality obtains, the distribution of one variable is normal for each and every value of the other variable. *See also* NORMAL DISTRIBUTION.

BRACKETING. The operation of combining categories or ranges of values of a variable so as to produce a small number of categories. Sometimes referred to as "collapsing" or "grouping."

CAPITALIZATION ON CHANCE. When one is searching for a maximally powerful prediction equation, chance fluctuations in a given sample act to increase the predictive power obtained; since data from another sample from the same population will show different chance fluctuations, the equation derived for one sample is likely to work less well in any other sample.

CAUSAL MODEL. An abstract quantitative representation of real-world dynamics (i.e., of the causal dependencies and other interrelationships among observed or hypothetical variables).

COMPLEX SAMPLE DESIGN. Any sample design that uses something other than simple random selection. Complex sample designs include multi-stage selection, and/or stratification, and/or clustering. For information on the calculation of sampling errors of statistics from complex designs, see note 9 in Appendix C.

COVARIATE. A variable that is used in an analysis to correct, adjust, or modify the scores on a dependent variable before those scores are related to one or more independent variables. For example, in an analysis of how demographic factors (age, sex, education, etc.) relate to wage rates, monthly earnings might first be adjusted to take account of (i.e., remove effects attributable to) number of hours worked, which in this example would be the covariate.

COVARIATION. Covariation measures the extent to which cases (e.g., persons) have the same relative positions on two variables. *See also* AGREEMENT.

DEPENDENT VARIABLE. A variable which the analyst is trying to explain in terms of one or more independent variables. The distinction between dependent and independent variables is typically made on theoretical grounds—in terms of a particular causal model or to test a particular hypothesis. Synonym: criterion variable.

DESIGN MATRIX. A specification, expressed in matrix format, of the particular effects and combinations of effects that are to be considered in an analysis.

DICHOTOMOUS VARIABLE. A variable that has only two categories. Gender (male/female) is an example. *See also* TWO-POINT SCALE.

DUMMY VARIABLE. A variable with just two categories that reflects only part of the information actually available in a more comprehensive variable. For example, the four-category variable Region (Northeast, Southeast, Central, West) could be the basis for a two-category dummy variable that would distinguish Northeast from all other regions. Dummy variables often come in sets so as to reflect all of the original information. In our example, the four-category region variable defines four dummy variables: (1) Northeast vs. all other; (2) Southeast vs. all other; (3) Central vs. all other; and (4) West vs. all other. Alternative coding procedures (which are equivalent in terms of explanatory power but which may produce more easily interpretable estimates) are effect coding and orthogonal coefficients.

EXPECTED VALUE. A theoretical average value of a statistic over an infinite number of samples from the same population.

HETEROSCEDASTICITY. The absence of homogeneity of variance. *See* HOMOGENEITY OF VARIANCE.

HIERARCHICAL ANALYSIS. As used on page 26 of the Guide, a hierarchical analysis is one in which inclusion of a higher order interaction term implies the inclusion of all lower order terms. For example, if the interaction of two independent variables is included in an explanatory model, then the main effects for both of those variables are also included in the model.

HOMOGENEITY OF VARIANCE. A situation in which the variance on a dependent variable is the same (homogeneous) across all levels of the independent variables. In analysis of variance applications, several statistics are available for testing the homogeneity assumption (see Kirk, 1968, page 61); in regression applications, a lack of homogeneity can be detected by examination of residuals (see Draper and Smith, 1966, page 86). In either case, a variance-stabilizing transformation may be helpful (see Kruskal, 1978, page 1052). Synonym: homoscedasticity. Antonym: heteroscedasticity.

HOMOSCEDASTICITY. *See* HOMOGENEITY OF VARIANCE.

INDEPENDENT VARIABLE. A variable used to explain a dependent variable. Synonyms: predictor variable, explanatory variable. *See also* DEPENDENT VARIABLE.

INTERACTION. A situation in which the direction and/or magnitude of the relationship between two variables depends on (i.e., differs according to) the value of one or more other variables. When interaction is present, simple additive techniques are inappropriate; hence, interaction is sometimes thought of as the absence of additivity. Synonyms: nonadditivity, conditioning effect, moderating effect, contingency effect. *See also* PATTERN VARIABLE, PRODUCT VARIABLE.

INTERVAL SCALE. A scale consisting of equal-sized units (dollars, years, etc.). On an interval scale the distance between any two positions is of known size. Results from analytic techniques appropriate for interval scales will be affected by any non-linear transformation of the scale values. *See also* SCALE OF MEASUREMENT.

INTERVENING VARIABLE. A variable which is postulated to be a predictor of one or more dependent variables, and simultaneously predicted by one or more independent variables. Synonym: mediating variable.

KURTOSIS. Kurtosis indicates the extent to which a distribution is more peaked or flat-topped than a normal distribution.

LINEAR. The form of a relationship among variables such that when any two variables are plotted, a straight line results. A relationship is linear if the effect on a dependent variable of a change of one unit in an independent variable is the same for all possible such changes.

MATCHED SAMPLES. Two (or more) samples selected in such a way that each case (e.g., person) in one sample is matched—i.e., identical within specified limits—on one or more preselected characteristics with a corresponding case in the other sample. One example of matched samples is having repeated measures on the same individuals. Another example is linking husbands and wives. Matched samples are different from independent samples, where such case-by-case matching on selected characteristics has not been assured.

MEASURE OF ASSOCIATION. A number (a statistic) whose magnitude indicates the degree of correspondence—i.e., strength of relationship—between two variables. An example is the Pearson product-moment correlation coefficient. Measures of association are different from statistical tests of association (e.g., Pearson chi-square, F test) whose primary purpose is to assess the probability that the strength of a relationship is different from some preselected value (usually zero). *See also* STATISTICAL MEASURE, STATISTICAL TEST.

MISSING DATA. Information that is not available for a particular case (e.g., person) for which at least some other information is available. This can occur for a variety of reasons, including a person's refusal or inability to answer a question, nonapplicability of a question, etc. For useful discussions of how to overcome problems caused by missing data in surveys see Hertel (1976) and Kim and Curry (1977).

MULTIVARIATE NORMALITY. The form of a distribution involving more than two variables in which the distribution of one variable is normal for each and every combination of categories of all other variables. See Harris (1975, page 231) for a discussion of multivariate normality. *See also* NORMAL DISTRIBUTION.

NOMINAL SCALE. A classification of cases which defines their equivalence and non-equivalence, but implies no quantitative relationships or ordering among them. Analytic techniques appropriate for nominally scaled variables are not affected by any one-to-one transformation of the numbers assigned to the classes. *See also* SCALE OF MEASUREMENT.

NONADDITIVE. Not additive. *See* ADDITIVE, INTERACTION.

NORMAL DISTRIBUTION. A particular form for the distribution of a variable which, when plotted, produces a "bell" shaped curve—symmetrical, rising smoothly from a small number of cases at both extremes to a large number of cases in the middle. Not all symmetrical bell-shaped distributions meet the definition of normality. See Hays (1973, page 296).

NORMALITY. *See* NORMAL DISTRIBUTION.

ORDINAL SCALE. A classification of cases into a set of ordered classes such that each case is considered equal to, greater than, or less than every other case. Analytic techniques appropriate for ordinally scaled variables are not affected by any monotonic transformation of the numbers assigned to the classes. *See also* SCALE OF MEASUREMENT.

OUTLYING CASE (OUTLIER). A case (e.g., person) whose score on a variable deviates substantially from the mean (or other measure of central tendency). Such cases can have disproportionately strong effects on statistics.

PATTERN VARIABLE. A nominally scaled variable whose categories identify particular combinations (patterns) of scores on two or more other variables. For example, a party-by-gender pattern variable might be developed by classifying people into the following six categories: (1) Republican males, (2) Independent males, (3) Democratic males, (4) Republican females, (5) Independent females, (6) Democratic females. A pattern variable can be used to incorporate interaction in multivariate analysis.

PRODUCT VARIABLE. An intervally scaled variable whose scores are equal to the product obtained when the values of two other variables are multiplied together. A product variable can be used to incorporate certain types of interaction in multivariate analysis.

RANKS. The position of a particular case (e.g., person) relative to other cases on a defined scale—as in "1st place," "2nd place," etc. Note that when the actual values of the numbers designating the relative positions (the ranks) are used in analysis they are being treated as an interval scale, not an ordinal scale. *See also* INTERVAL SCALE, ORDINAL SCALE.

SCALE OF MEASUREMENT. As used in this Guide, scale of measurement refers to the nature of the assumptions one makes about the properties of a variable; in particular, whether that variable meets the definition of nominal, ordinal, or interval measurement. *See also* NOMINAL SCALE, ORDINAL SCALE, INTERVAL SCALE.

SKEWNESS. Skewness is a measure of lack of symmetry of a distribution.

STANDARDIZED COEFFICIENT. When an analysis is performed on variables that have been standardized so that they have variances of 1.0, the estimates that result are known as standardized coefficients; for example, a regression run on original variables produces unstandardized regression coefficients known as b's, while a regression run on standardized variables produces standardized regression coefficients known as betas. (In practice, both types of coefficients can be estimated from the original variables.) Blalock (1967), Hargens (1976), and Kim and Mueller (1976) provide useful discussions on the use of standardized coefficients.

STANDARDIZED VARIABLE. A variable that has been transformed by multiplication of all scores by a constant and/or by the addition of a constant to all scores. Often these constants are selected so that the transformed scores have a mean of zero and a variance (and standard deviation) of 1.0.

STATISTICAL INDEPENDENCE. A complete lack of covariation between variables; a lack of association between variables. When used in analysis of variance or covariance, statistical independence between the independent variables is sometimes referred to as a balanced design.

STATISTICAL MEASURE. A number (a statistic) whose size indicates the magnitude of some quantity of interest—e.g., the strength of a relationship, the amount of variation, the size of a difference, the level of income, etc. Examples include means, variances, correlation coefficients, and many others. Statistical measures are different from statistical tests. *See also* STATISTICAL TEST.

STATISTICAL TEST. A number (a statistic) that can be used to assess the probability that a statistical measure deviates from some preselected value (often zero) by no more than would be expected due to the operation of chance if the cases (e.g., persons) studied were randomly selected from a larger population. Examples include Pearson chi-square, F test, t test, and many others. Statistical tests are different from statistical measures. *See also* STATISTICAL MEASURE.

TRANSFORMATION. A change made to the scores of all cases (e.g., persons) on a variable by the application of the same mathematical operation(s) to each score. (Common operations include addition of a constant, multiplication by a constant, taking logarithms, ranking, bracketing, etc.)

TWO-POINT SCALE. If each case is classified into one of two categories (e.g., yes/no, male/female, dead/alive), the variable is a two-point scale. For analytic purposes, two-point scales can be treated as nominal scales, ordinal scales, or interval scales.

WEIGHTED DATA. Weights are applied when one wishes to adjust the impact of cases (e.g., persons) in the analysis, e.g., to take account of the number of population units that each case represents. In sample surveys weights are most likely to be used with data derived from sample designs having different selection rates or with data having markedly different subgroup response rates.

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