A Guide for Selecting Statistical Techniques for Analyzing Social Science Data

Second Edition

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CONTENTS

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.

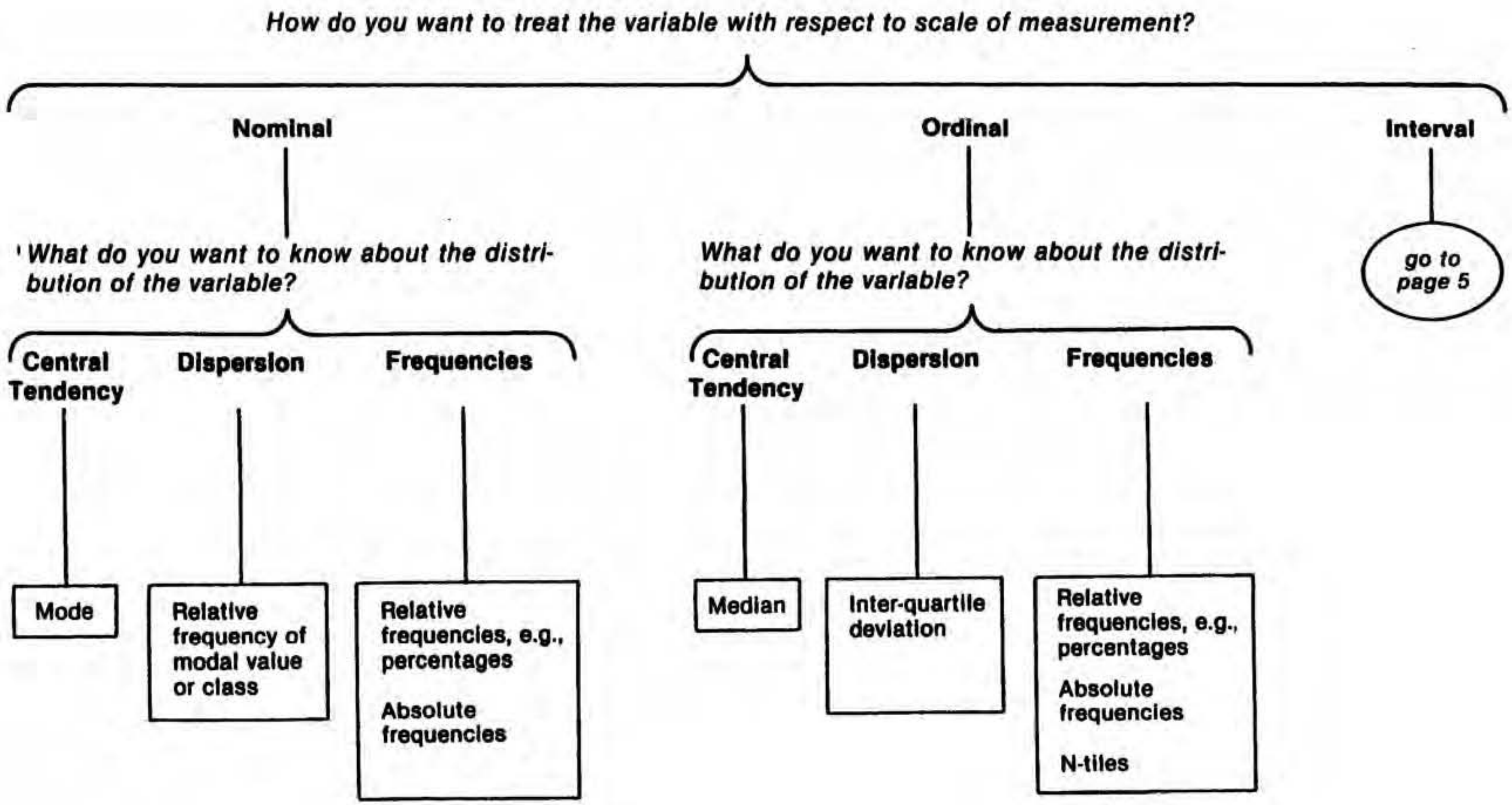
THE DECISION TREE:
QUESTIONS AND ANSWERS LEADING TO APPROPRIATE STATISTICS OR STATISTICAL TECHNIQUES

STARTING POINT

How many variables does the problem involve?

- **One Variable**
  - *go to page 4*
- **Two Variables**
  - *How do you want to treat the variables with respect to scale of measurement?*
    - **Both Interval**
      - *go to page 6*
    - **Both Ordinal**
      - *go to page 8*
    - **Both Nominal**
      - *go to page 9*
    - **One Interval, One Ordinal**
      - *go to page 11*
    - **One Interval, One Nominal**
      - *go to page 12*
    - **One Ordinal, One Nominal**
      - *go to page 15*
- **More Than Two Variables**
  - *go to page 16*

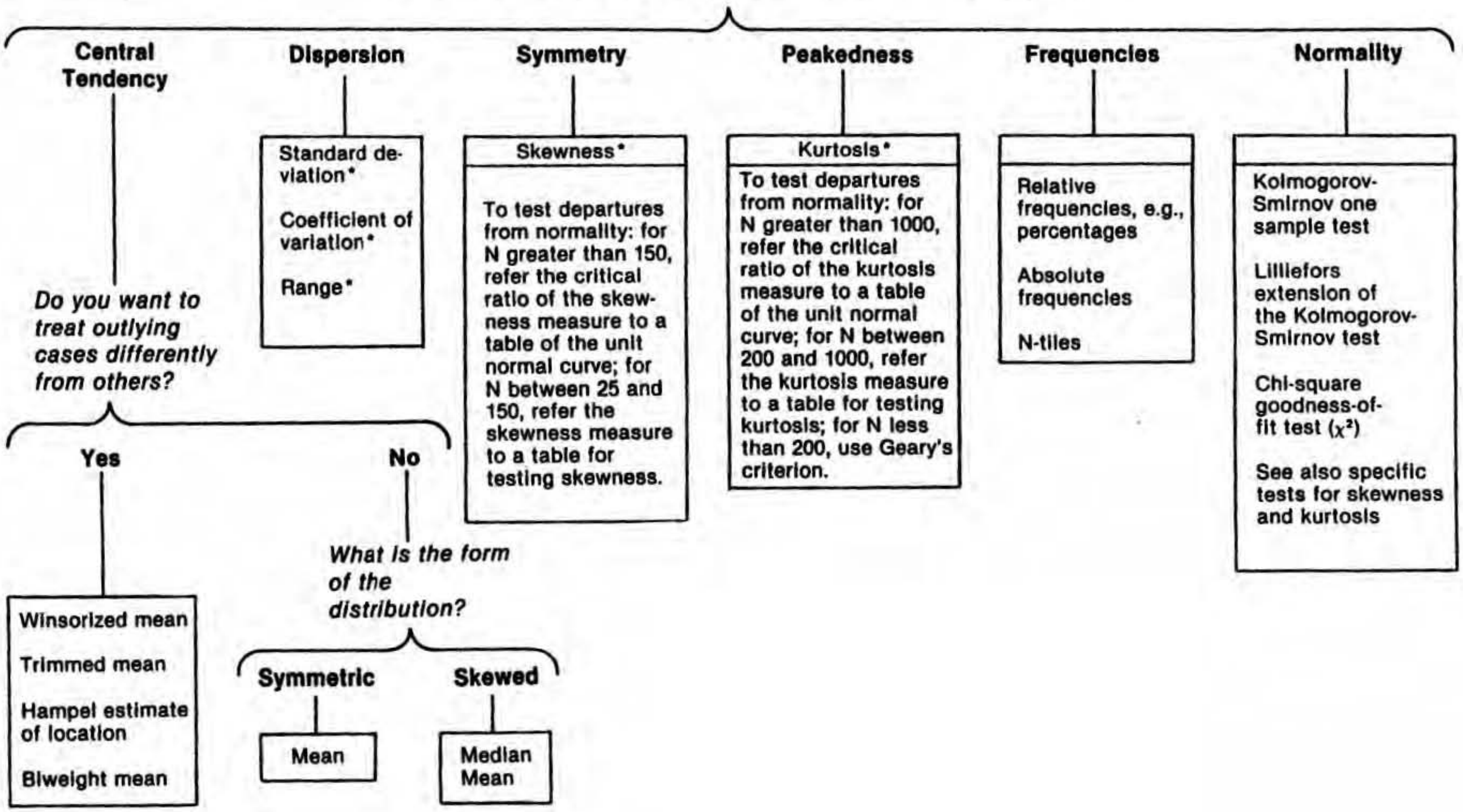
ONE VARIABLE



(continued from page 4)

- One interval variable

What do you want to know about the distribution of the variable?



*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 t^2)
    - **No**
      - Coefficients from curvilinear regression (b or beta, β)‡,§
      - F test† (F equals t^2 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 ($\bar{r}$)
            - **Covariation**
              - *go to page 7*
        - **No**

* Biased estimator.

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

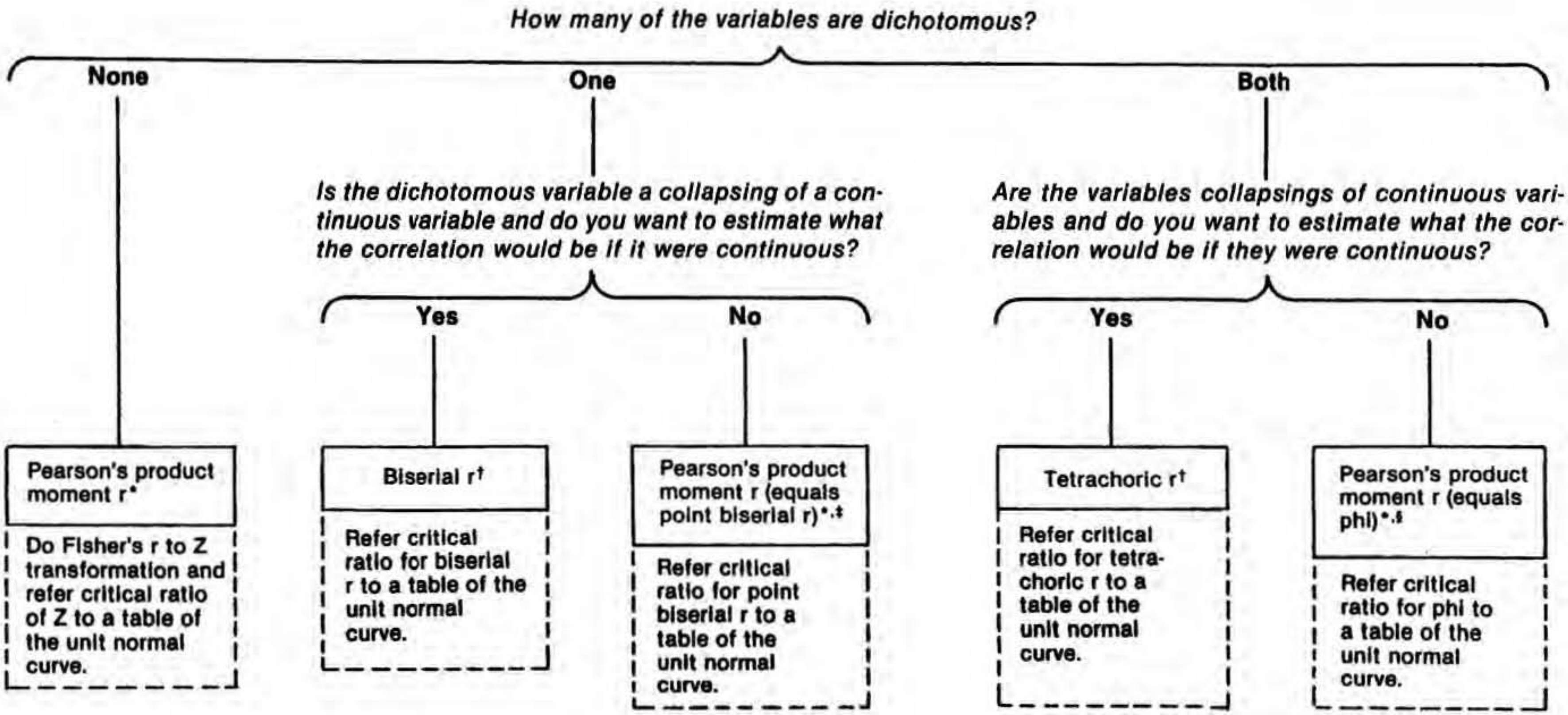
‡ Beta is a standardized version of b. See "standardized coefficient" in Glossary.

§ 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



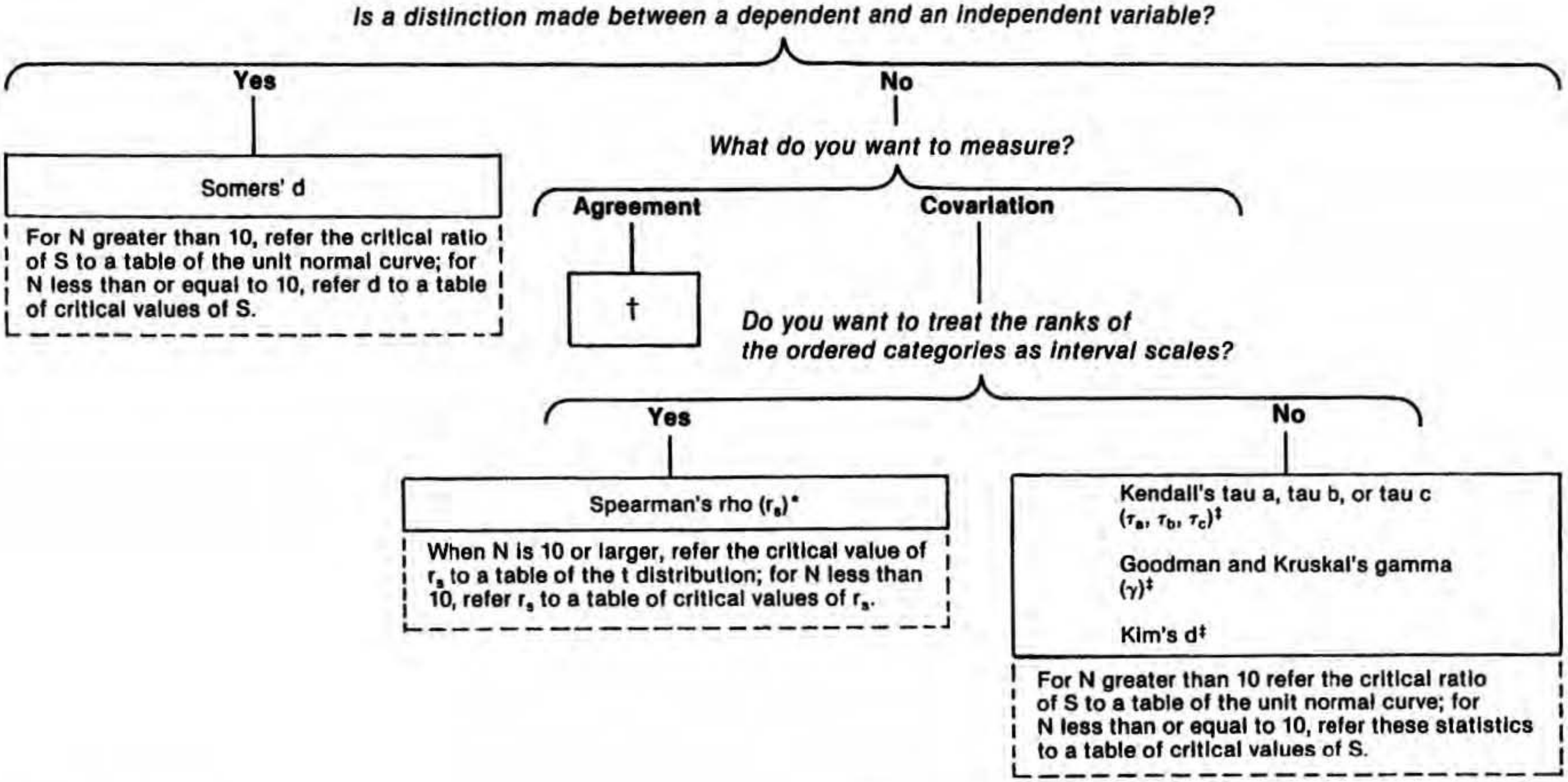
[*] Biased estimator.

[†] 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

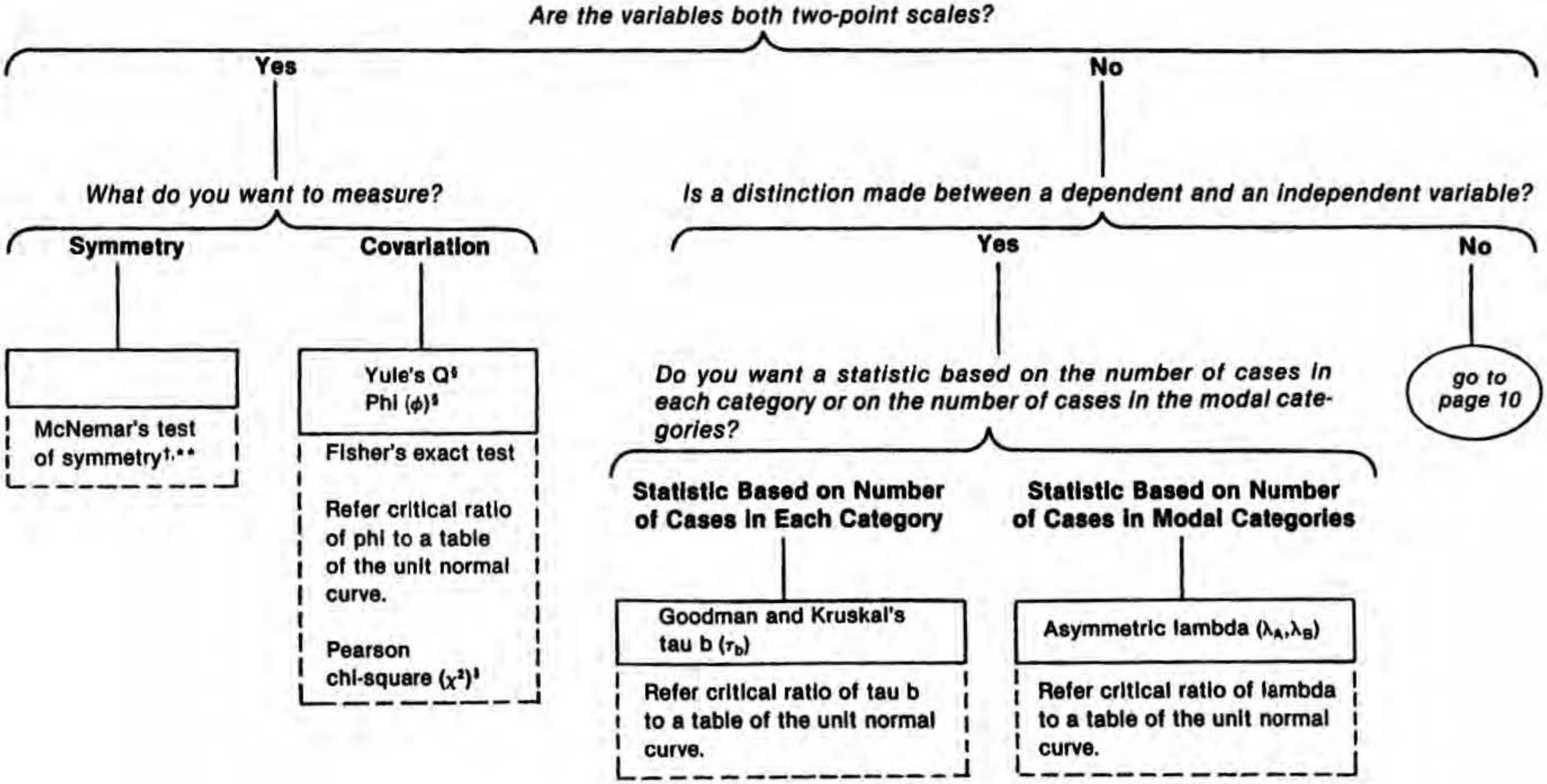


* Biased estimator.

† 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.

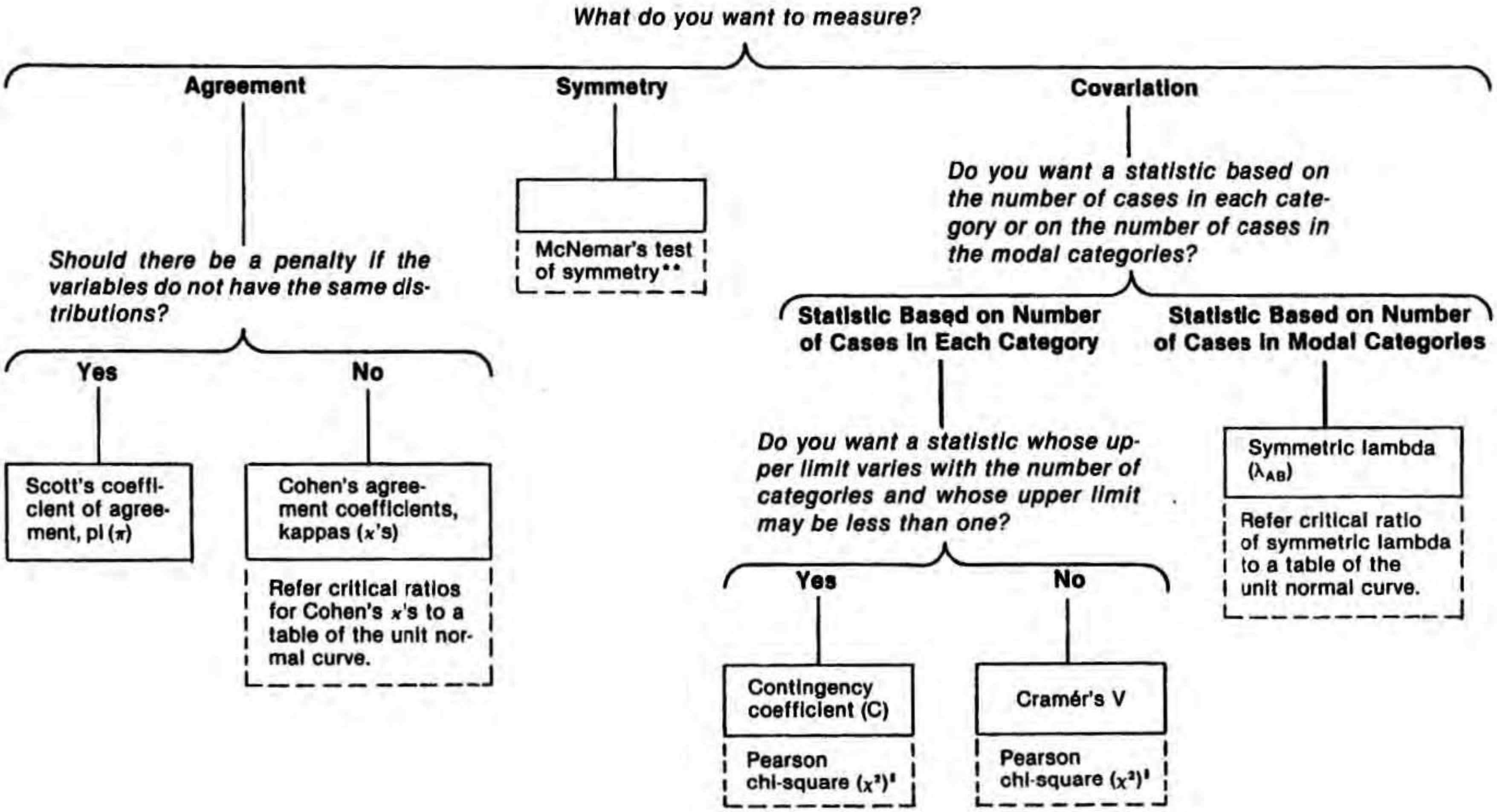
§ In this case, Yule's Q is equivalent to Goodman and Kruskal's gamma and phi is equivalent to Pearson's product moment r. In general, Q will be higher in absolute value than phi because Q ignores pairs of cases which fall in the same category on one or both of the variables.

‖ 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)

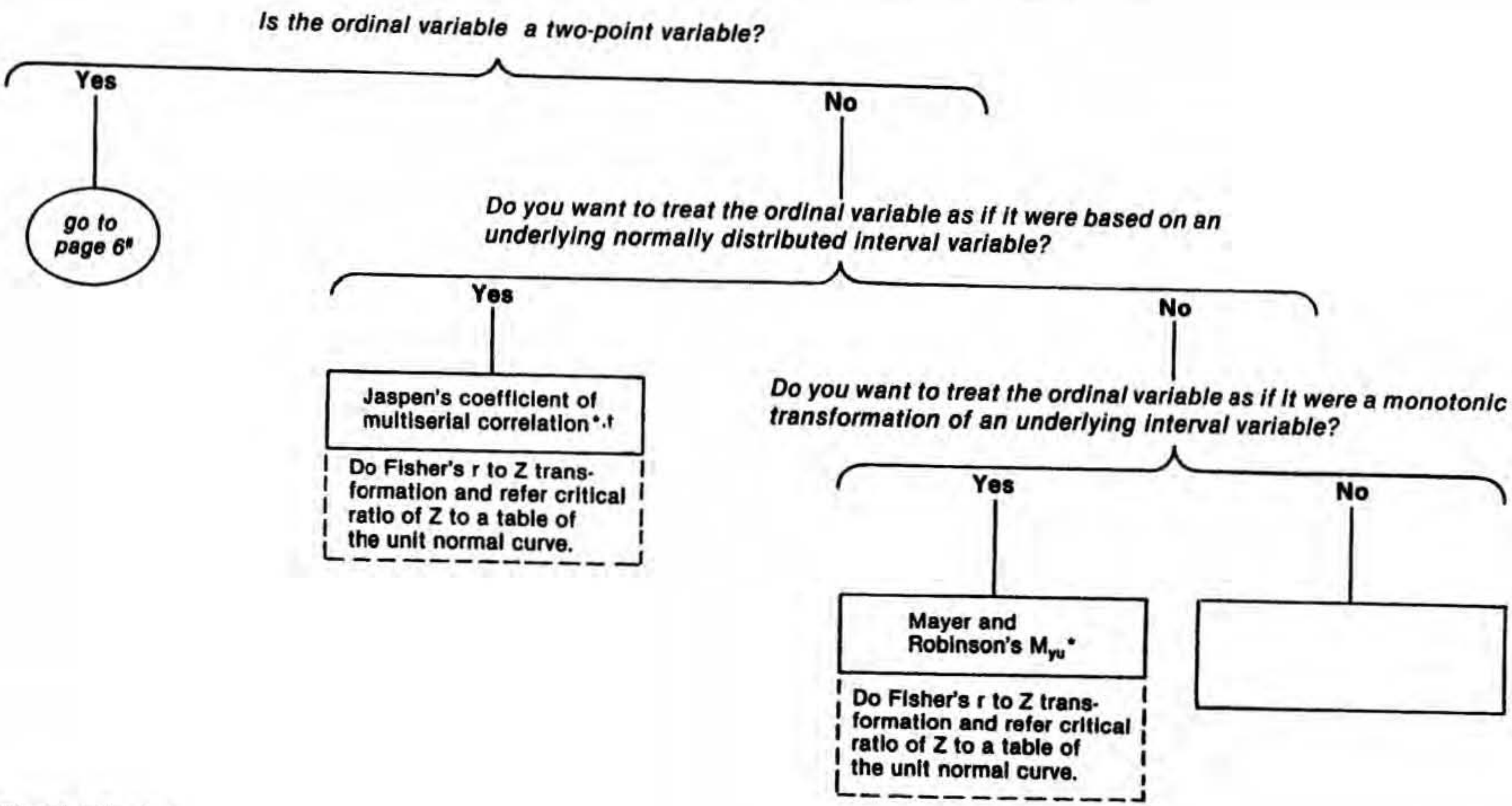
• Two nominal variables • At least one of the variables is not a two-point scale • No distinction is made between a dependent and an independent variable



* 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

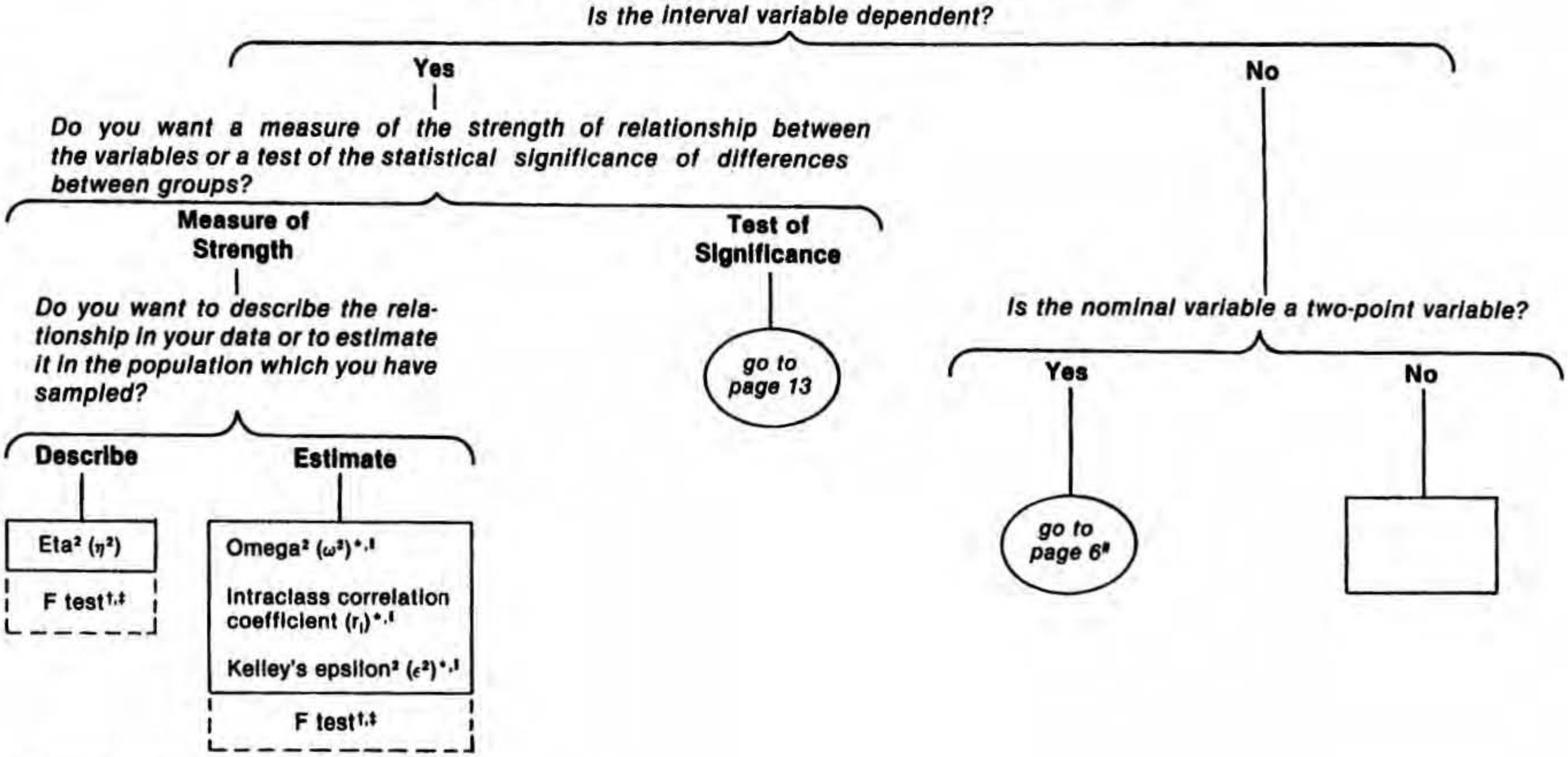


* Biased estimator.

† 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.

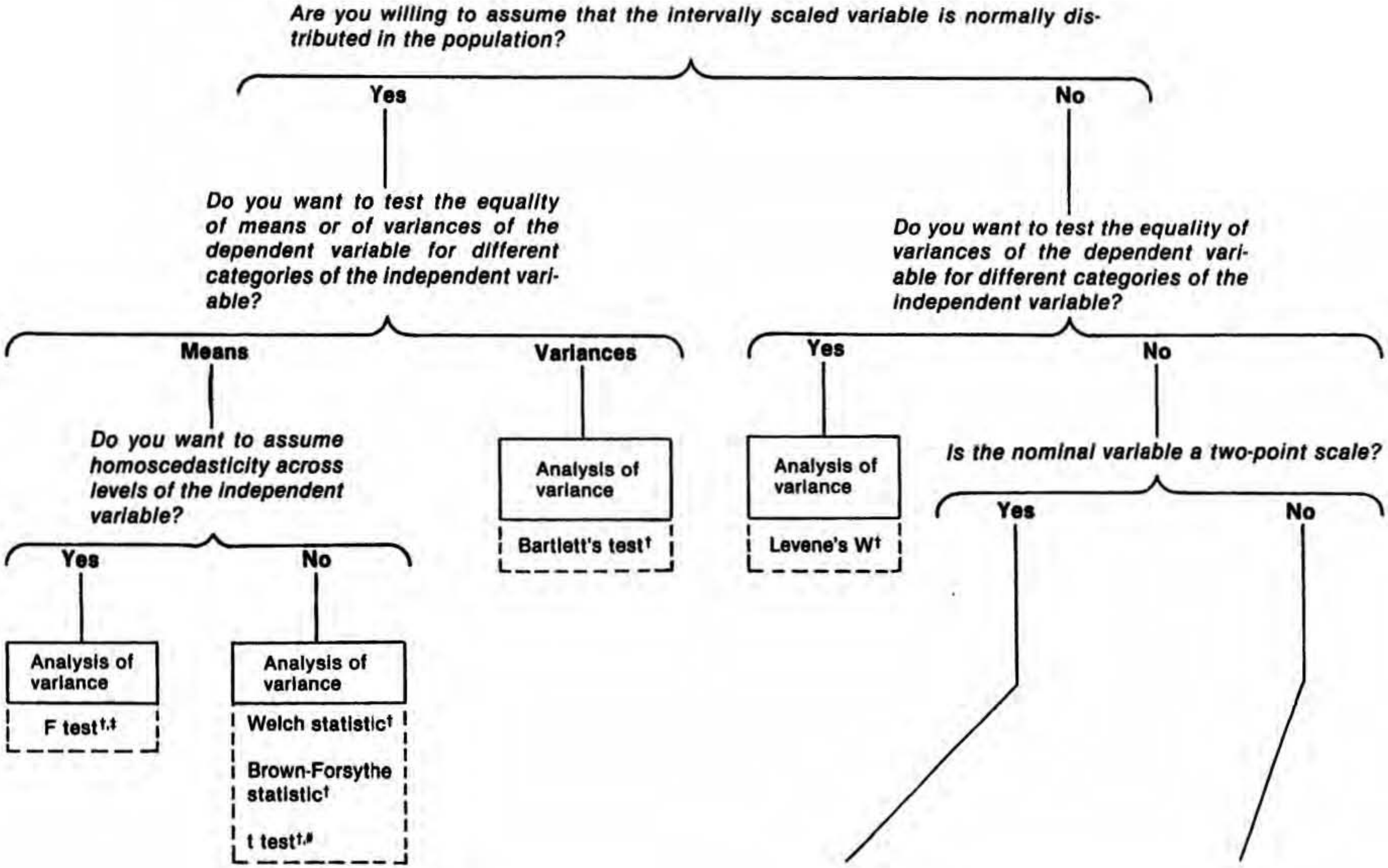
‡ If the nominal variable is a two-point scale, the t test is an alternative (because in such case F equals t^2).

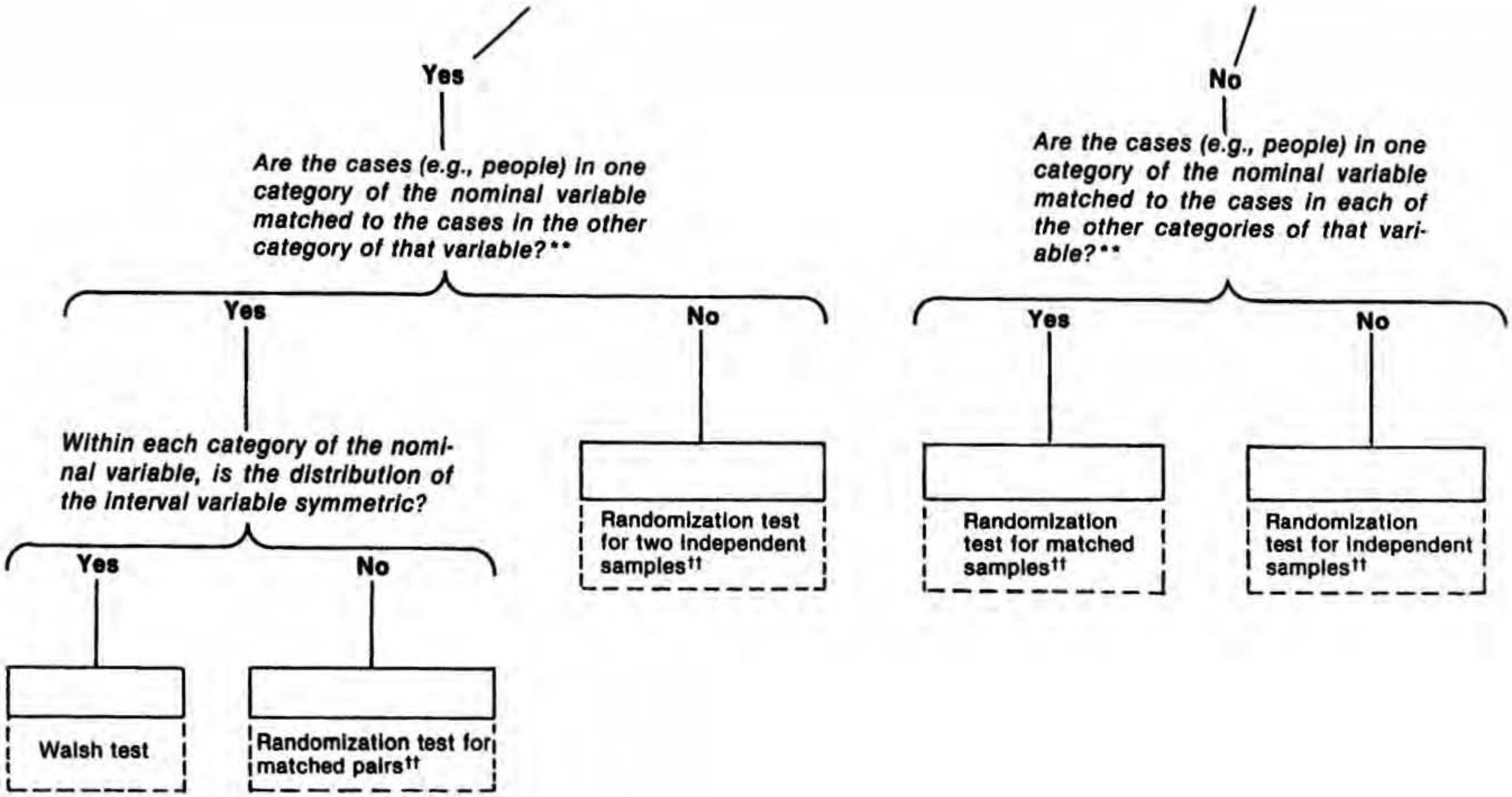
‖ Omega² applies to the fixed effects model, and the intraclass correlation coefficient applies to the random effects model. Thus omega² should be used if you want to make inferences only about the specific categories of the nominal variable which appear in the data, whereas the intraclass correlation 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 p_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.

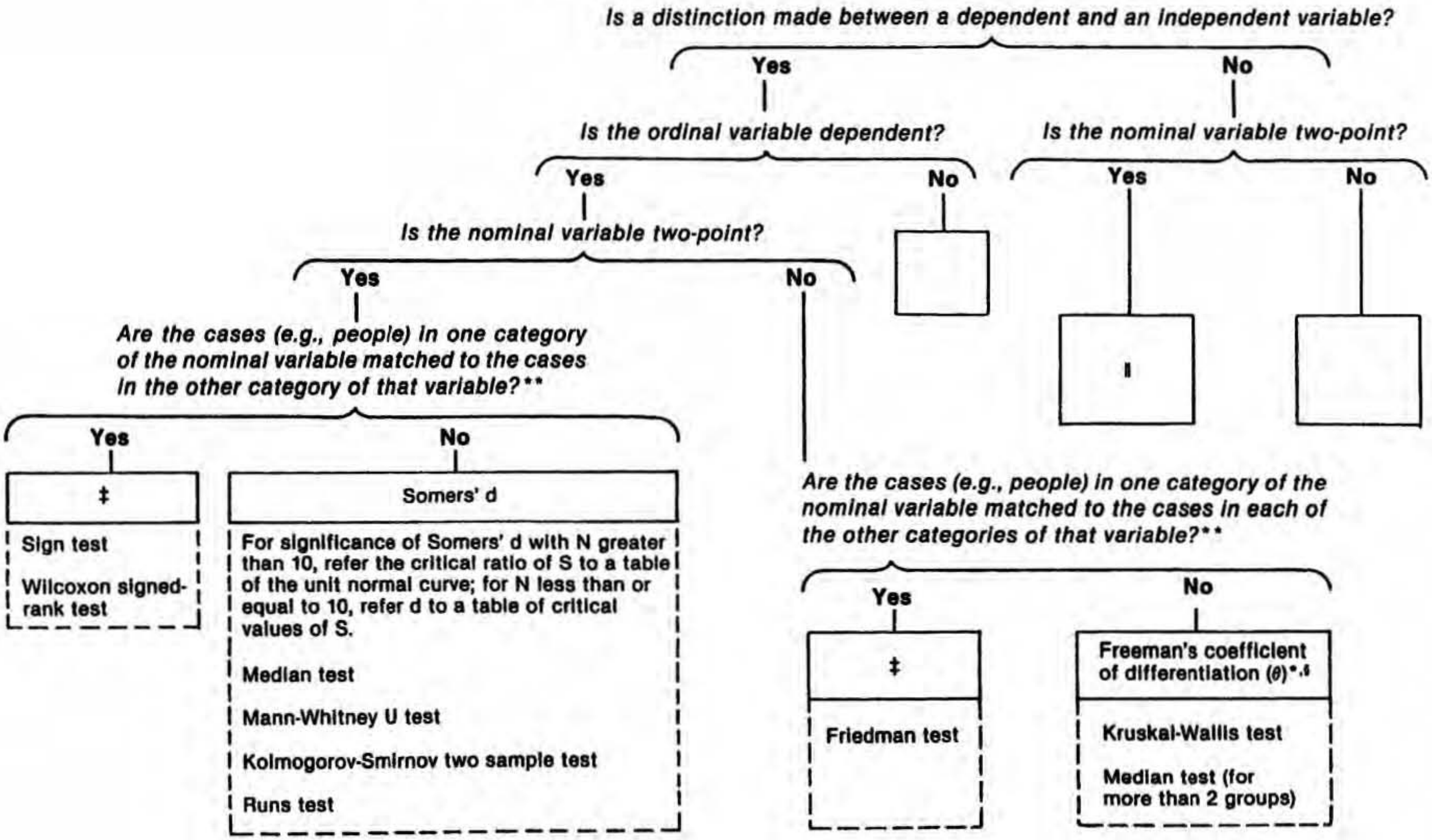
‡ If the nominal variable is a two-point scale, the t test is an alternative (because in such case F equals t^2).

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.

‖ 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

Is a distinction made between dependent and independent variables?

- **Yes**
  - *Is there more than one dependent variable?*
    - **Yes**
      - *go to page 22*
    - **No**
      - *Do you want to statistically remove the linear effects of one or more covariates from the dependent variable?*
        - **Yes**
          - *Do you want to treat the relationships involving the covariate(s) as additive?*[‡]
            - **Yes**
              - *Do you want to treat the dependent variable and the covariate(s) as interval and the independent variable(s) as nominal?*
                - **Yes**
                  - Covariance analysis[§]
                  - F test[†]
                - **No**
            - **No**
        - **No**
          - *Do you want to treat the relationships among the variables as additive?*[‡]
            - **Yes**
              - *go to pages 27–28*
            - **No**
              - *go to page 25*
- **No**
  - *go to page 17*

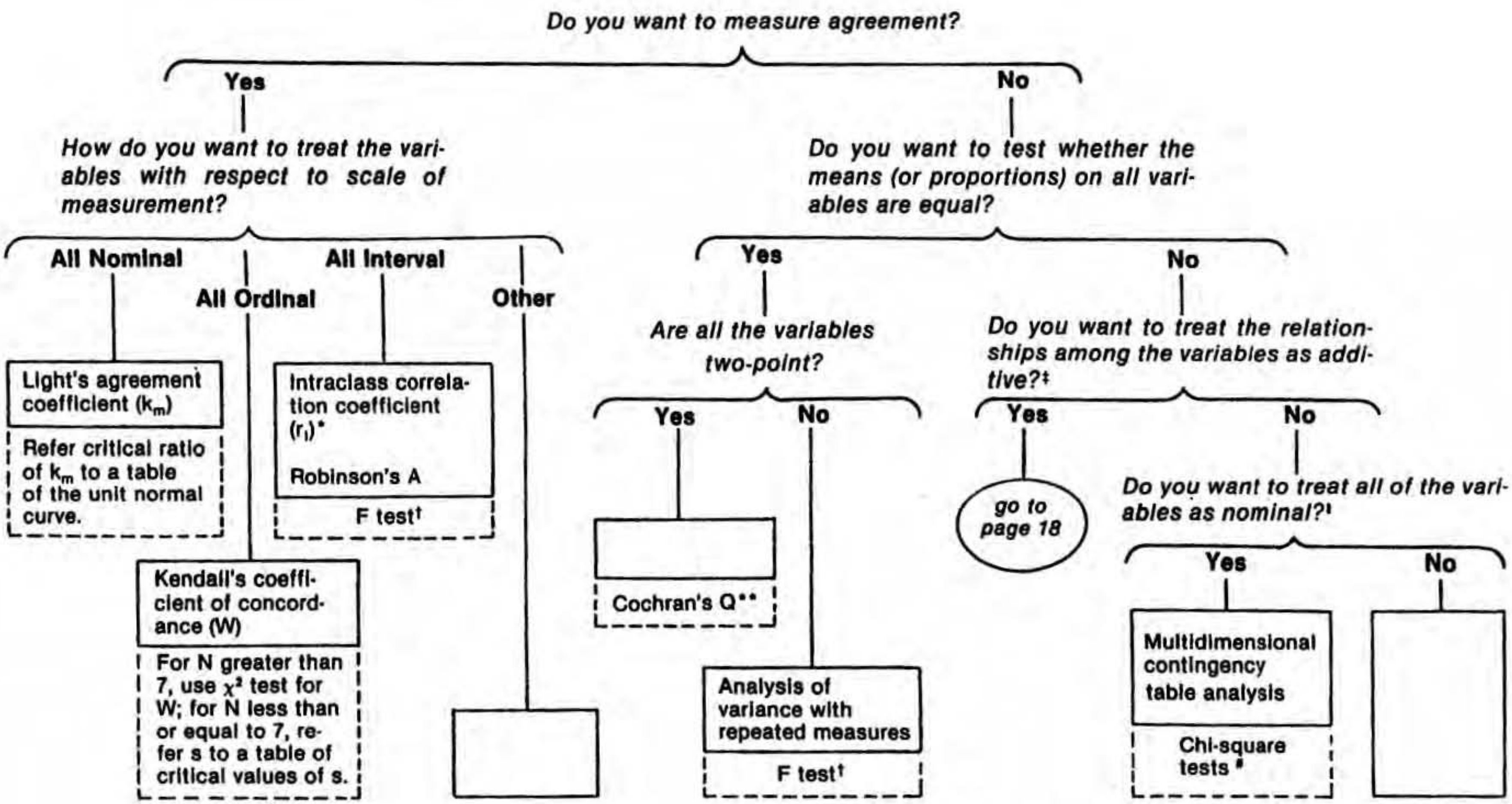
[†] The assumptions in note 5 on page 2 may apply.

[‡] 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)

• More than two variables • No distinction is made between dependent and independent variables



* 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.

' See note 3 in Appendix C.

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

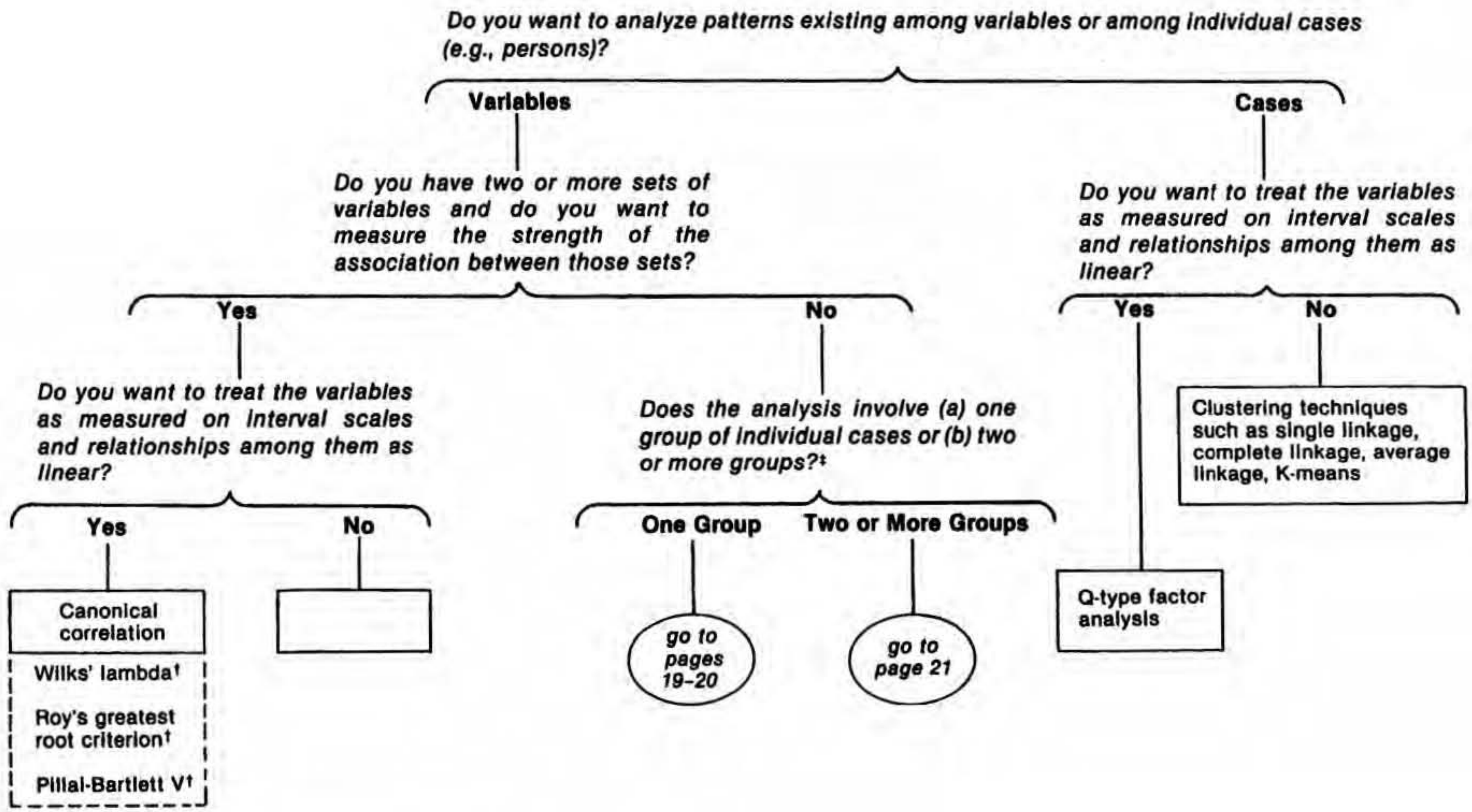
** Cochran's Q is appropriate for parallel measures from matched cases as well as for repeated measures on a single set of cases. See "matched samples" in Glossary.

to analyze subgroups separately. See Glossary.

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

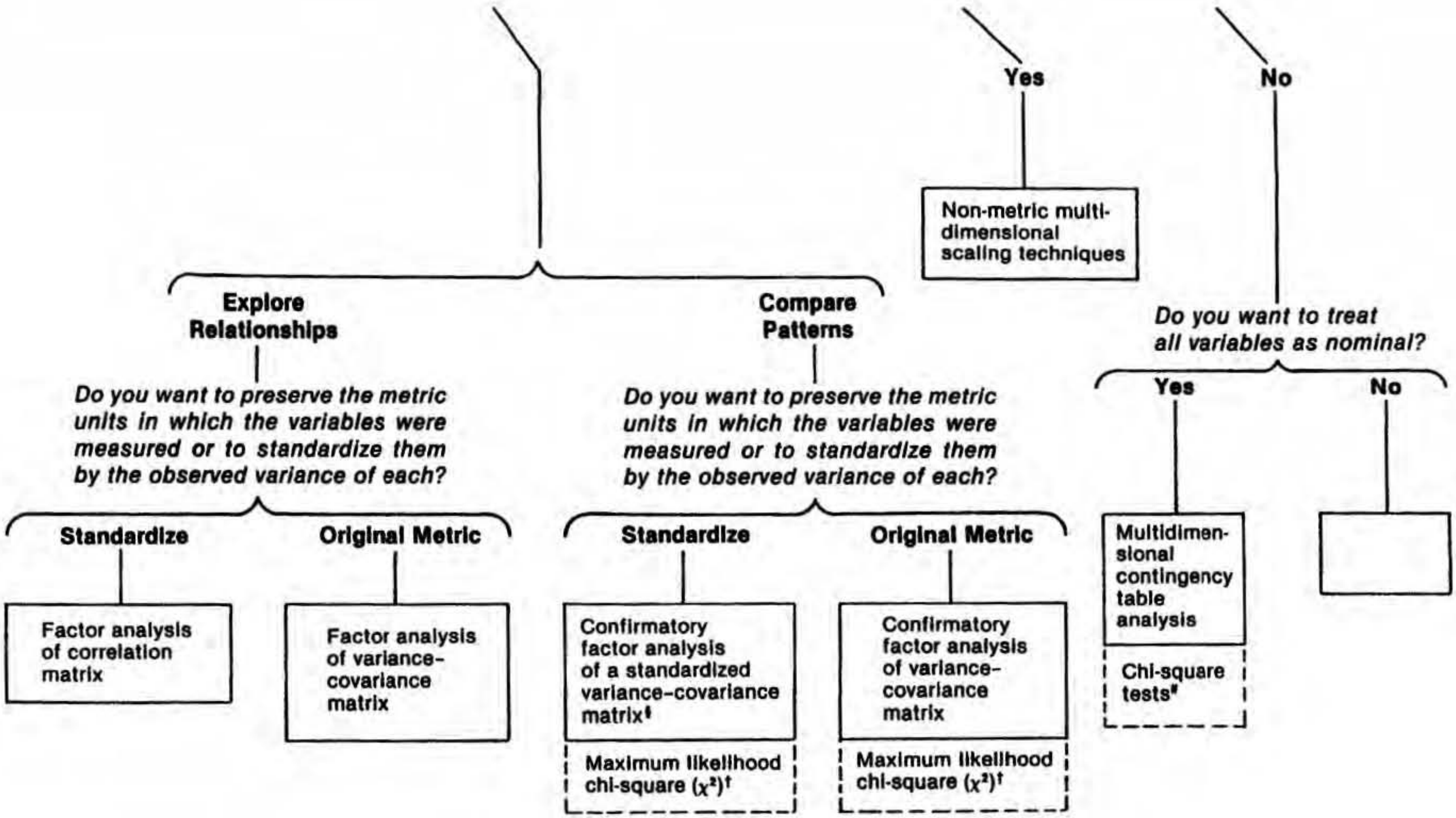
Do you want to locate each of the variables in multidimensional space?

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.

§ 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‡

Do you want to explore the relationships among a set of variables in two or more groups simultaneously or do you want to compare the similarity of the patterns of the relationships among a set of variables either (a) across two or more groups or (b) with a prespecified pattern?

Explore Relationships

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

Yes

Three-mode factor analysis

No

Three-way non-metric multidimensional scaling techniques

Compare Patterns

Do you want to preserve the metric units in which the variables were measured or to standardize them by the observed variance of each?

Standardize

Confirmatory factor analysis of standardized variance–covariance matrices§

Maximum likelihood chi-square (χ^2)†

Original Metric

Confirmatory factor analysis of variance–covariance matrices

Maximum likelihood chi-square (χ^2)†

† 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

Is there more than one independent variable?

- **Yes**
  - *Do you want to treat the relationships among the variables as additive?*‡
    - **Yes** — *go to page 23*
    - **No**
      - *Do you want to treat all the dependent variables as interval?*
        - **Yes** — *go to page 24*
        - **No**
- **No**
  - *Do you want to treat the independent variable as nominally scaled and all of the dependent variables as intervally scaled?*
    - **Yes**
      - *Do you want to test only whether the vectors of means are equal for all categories of the independent variables?*
        - **Yes** — Multivariate analysis of variance§
          - Wilks' lambda#,†
          - Roy's greatest root criterion†
          - Pillai-Bartlett V†
        - **No** — Profile analysis§
          - Wilks' lambda#,†
          - Roy's greatest root criterion†
          - Pillai-Bartlett V†
    - **No**

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

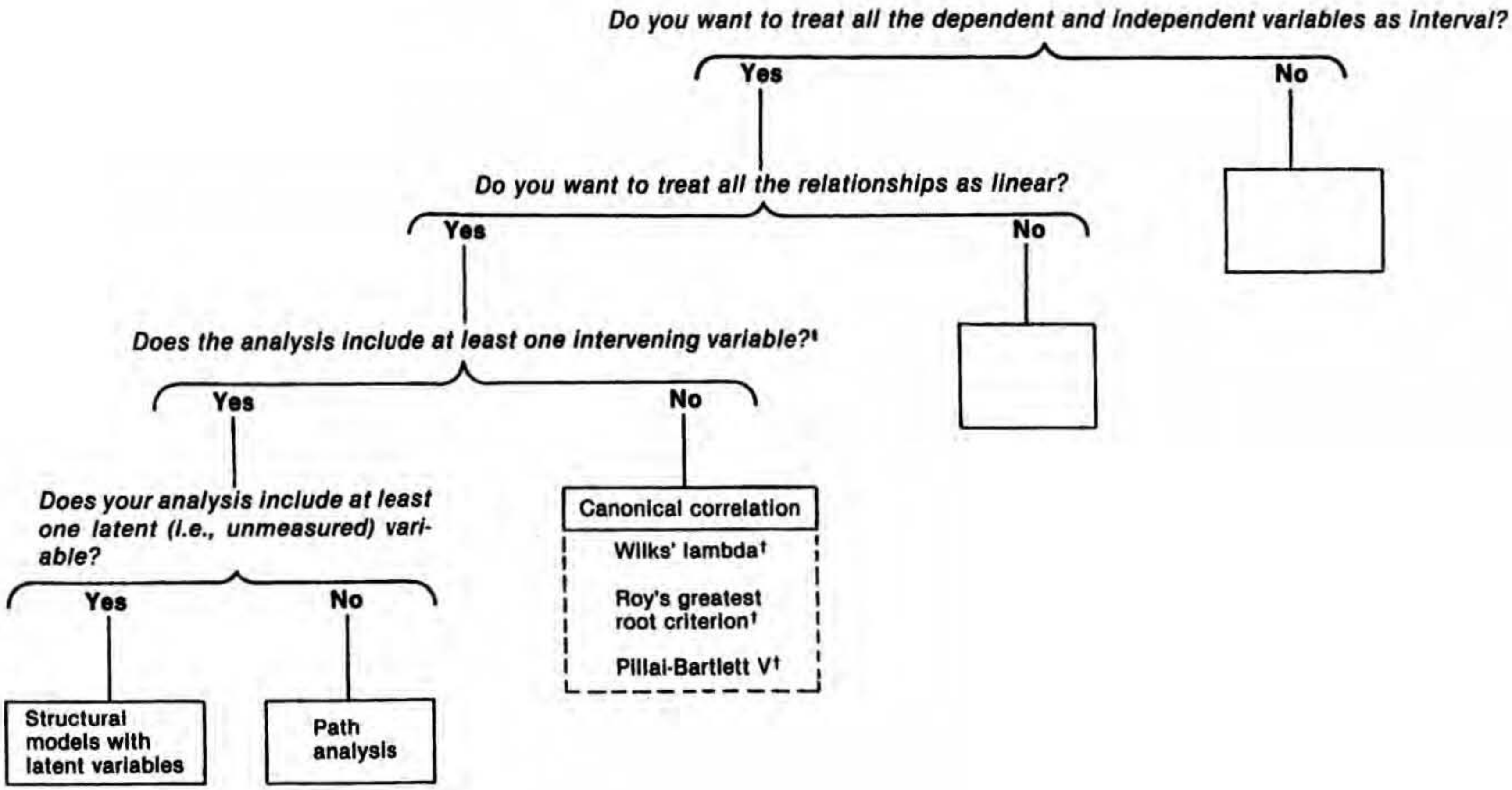
‡ Nonadditivity can be represented within additive techniques by using a pattern variable or a product variable. Another possibility is to analyze subgroups separately. See Glossary.

§ 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 Λ-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.

' 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?

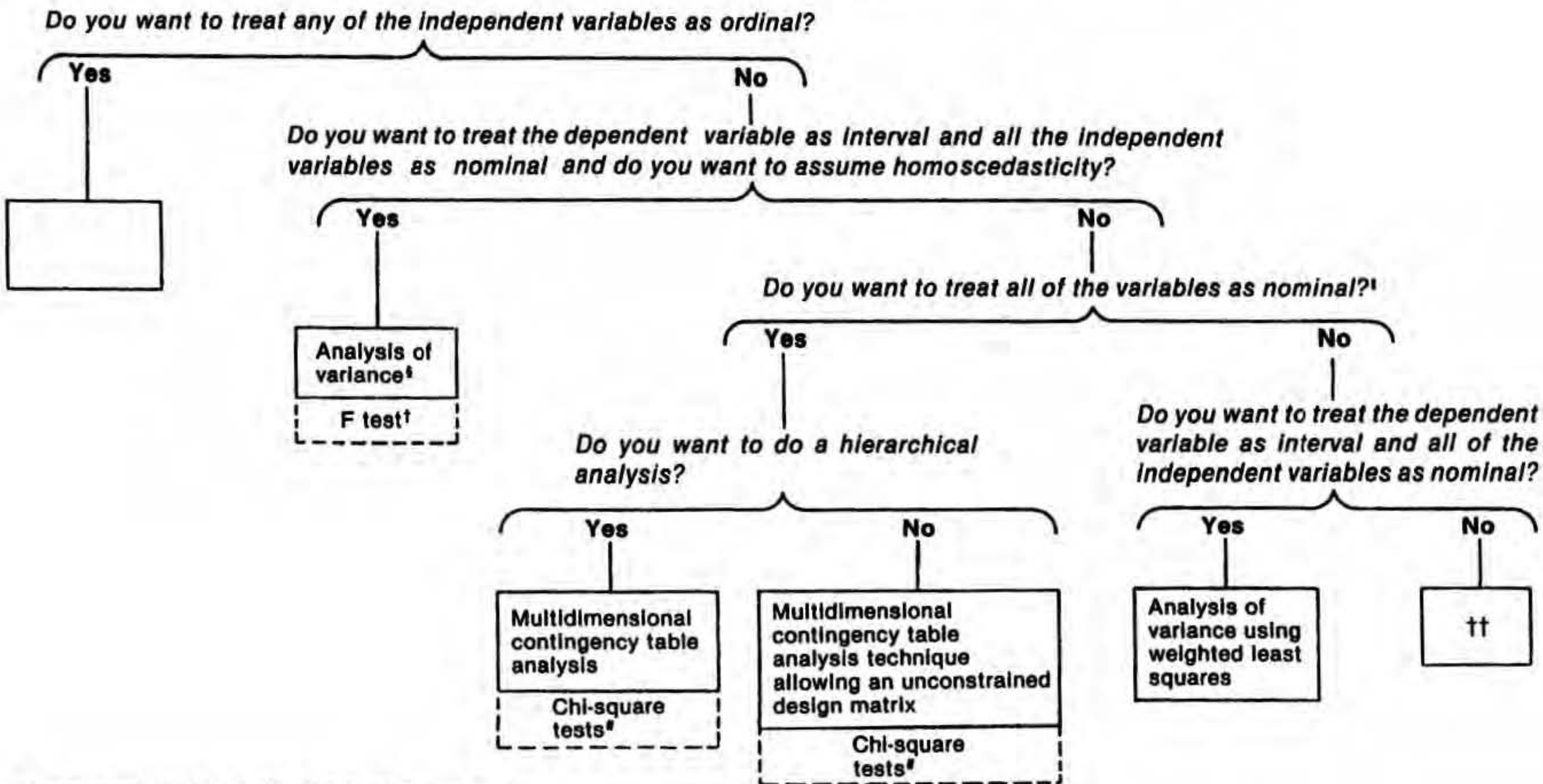
- **Search**
  - *How do you want to treat the variables with respect to scale of measurement?*
    - **Dependent: Nominal or Interval**
      Independent: Nominal or Ordinal
      - Binary segmentation techniques
    - **Other**
- **Test**
  - *Do you want to treat the dependent variable as ordinal?*
    - **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.

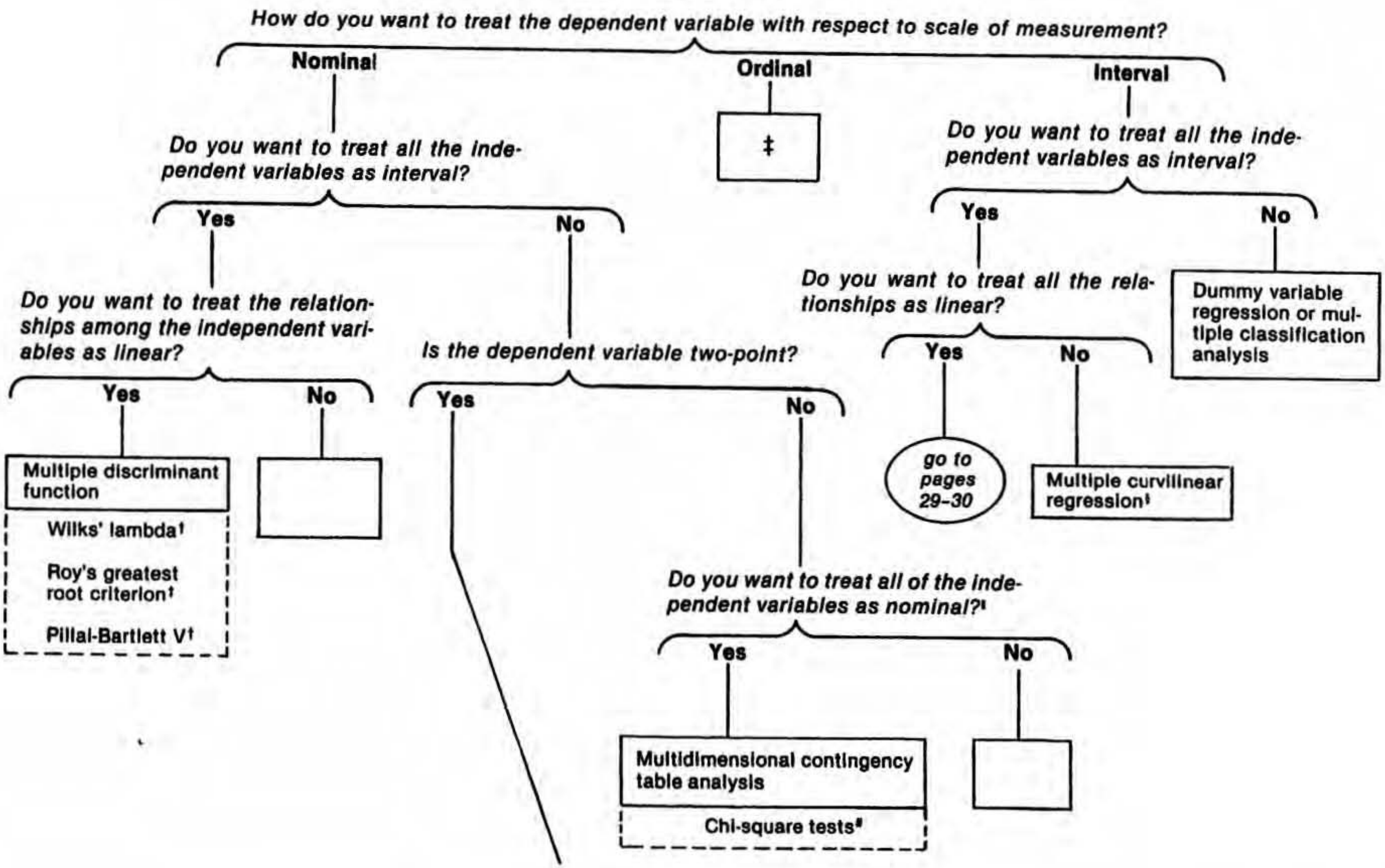
[‡] See note 3 in Appendix C.

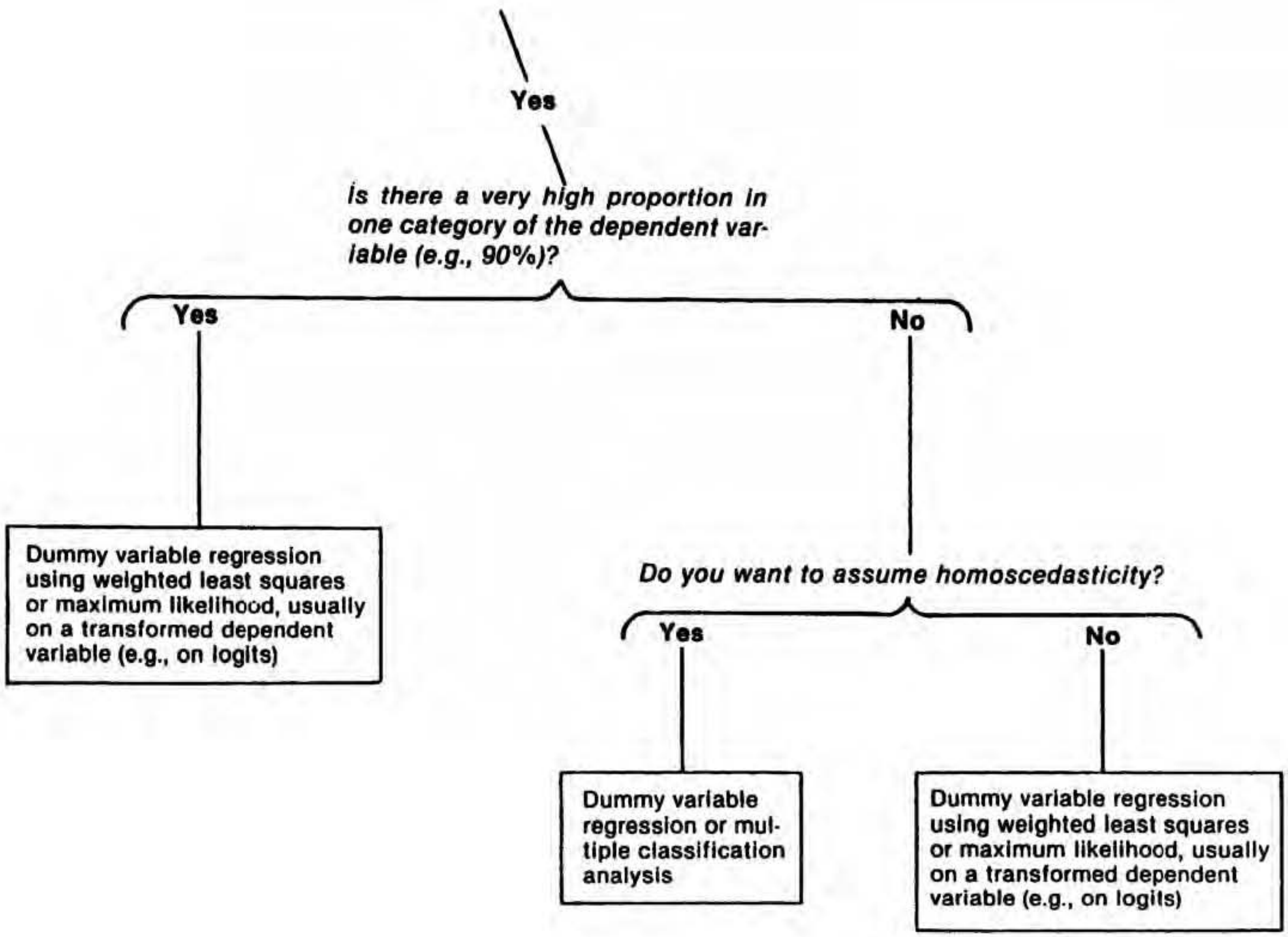
[#] There are various chi-square test statistics including Pearson, maximum likelihood, and Neyman.

†† 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, β)‡

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

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 correlation[2] $(r^2_{12\cdot3,\ldots,k})$*

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

Page 7

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

Page 8

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

Page 9

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

Page 10

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

Page 11

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

Page 12

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

Kelley's epsilon^2	Kelley, 1935; Glass and Hakstian, 1969
F test for eta^2, omega^2, Kelley's epsilon^2, 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

Page 15

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

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

Page 16

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

Page 17

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; 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); Landis et al., 1976 (GENCAT); Fienberg, 1977 (General)
Chi-square tests	Fienberg, 1977, p. 36 (Pearson and maximum likelihood)

Page 18

Canonical correlation	Cooley and Lohnes, 1971, p. 168; 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

Page 21

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)

Page 22

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

Page 23

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; 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

Page 24

Multivariate analysis of variance	Cooley and Lohnes, 1971, p. 223; Harris, 1975, p. 118; 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
Multivariate binary segmentation techniques	Gillo, 1972 (MAID); Gillo and Shelley, 1974

Page 25

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); Bock and Yates, 1973 (MULTIQUAL)
Chi-square tests	Bock, 1975, p. 518 (Pearson and maximum likelihood)

Page 26

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); 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; Rao, 1965, p. 178

Pages 27–28

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; 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); DuMouchel, 1974, 1976 (Maximum likelihood – DREG); Landis et al., 1967 (GENCAT)
Dummy variable regression or multiple classification analysis	Draper and Smith, 1966, p. 134; Andrews et al., 1973; Kerlinger and Pedhazur, 1973, p. 101
Multidimensional contingency table analysis	Andrews and Messenger, 1973 (MNA); 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)
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; 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 REG	P1R P4F	–
F test for regression coefficient	REGRESSN	REGRESSION	REGRESSION†	GLM REG	P1R	–
Coefficient from curvilinear regression	–	POLY	REGRESSION*,† ONEWAY	GLM	P5R	–
F test for coefficient from curvilinear regression	–	POLY	REGRESSION*,† 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 ŀ	–	–	–	–	–	–
Page 7						
Pearson's product moment r	MDC	CORRELATE MCORR	PEARSON CORR CROSSTABS	CORR	P8D P4F	–
Fisher's r to Z transformation and the critical ratio of Z	MDC	CORRELATE MCORR	PEARSON CORR 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 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	–	–

Omega²	–	–	–	GLM ANOVA	–	–
Intraclass correlation coefficient	–	ANOVA*	–	GLM ANOVA	–	–
Kelley's epsilon²	ANOVA** MCA**	–	–	–	–	–
F test for eta², omega², Kelley's epsilon², and intraclass correlation coefficient	ANOVA	ANOVA	BREAKDOWN ANOVA	GLM ANOVA	P7D*	–
Pages 13–14						
Analysis of variance	ANOVA	ANOVA	ANOVA ONEWAY BREAKDOWN MANOVA	GLM ANOVA	P1V P7D	–
F test for analysis of variance	ANOVA	ANOVA	ANOVA ONEWAY BREAKDOWN MANOVA	GLM ANOVA	P1V P7D	–
Welch statistic	–	–	–	–	P7D	–
Brown-Forsythe statistic	–	–	–	–	P7D	–
t test	–	–	T-TEST	T-TEST	P7D	–
Bartlett's test	–	ANOVA	ONEWAY 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 epsilon² is labelled adjusted eta².

	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 MANOVA	GLM	P1V P2V P4V	–
F test for covariance analysis	MANOVA	COVAR	ANOVA MANOVA	GLM	P1V P2V 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 RELIABILITY	–	–	–
Analysis of variance with repeated measures	–	–	RELIABILITY MANOVA	GLM ANOVA	P2V 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 MDSCAL TORSCA KYST ALSCAL
Multidimensional contingency table analysis	–	–	–	FUNCAT	P4F	ECTA GENCAT
Chi-square tests	–	–	–	FUNCAT	P4F	ECTA GENCAT
Clustering techniques such as single linkage, complete linkage, average linkage, K-means	CLUSTER	CLUSTER	–	VARCLUS	P1M	–
Page 21 [illegible]	–	–	–	–	–	–
Three-way non-metric multidimensional scaling techniques	–	–	–	ALSCAL	–	INDSCAL PARAFAC PINDIS CANDELINC MULTISCAL ALSCAL 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						

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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