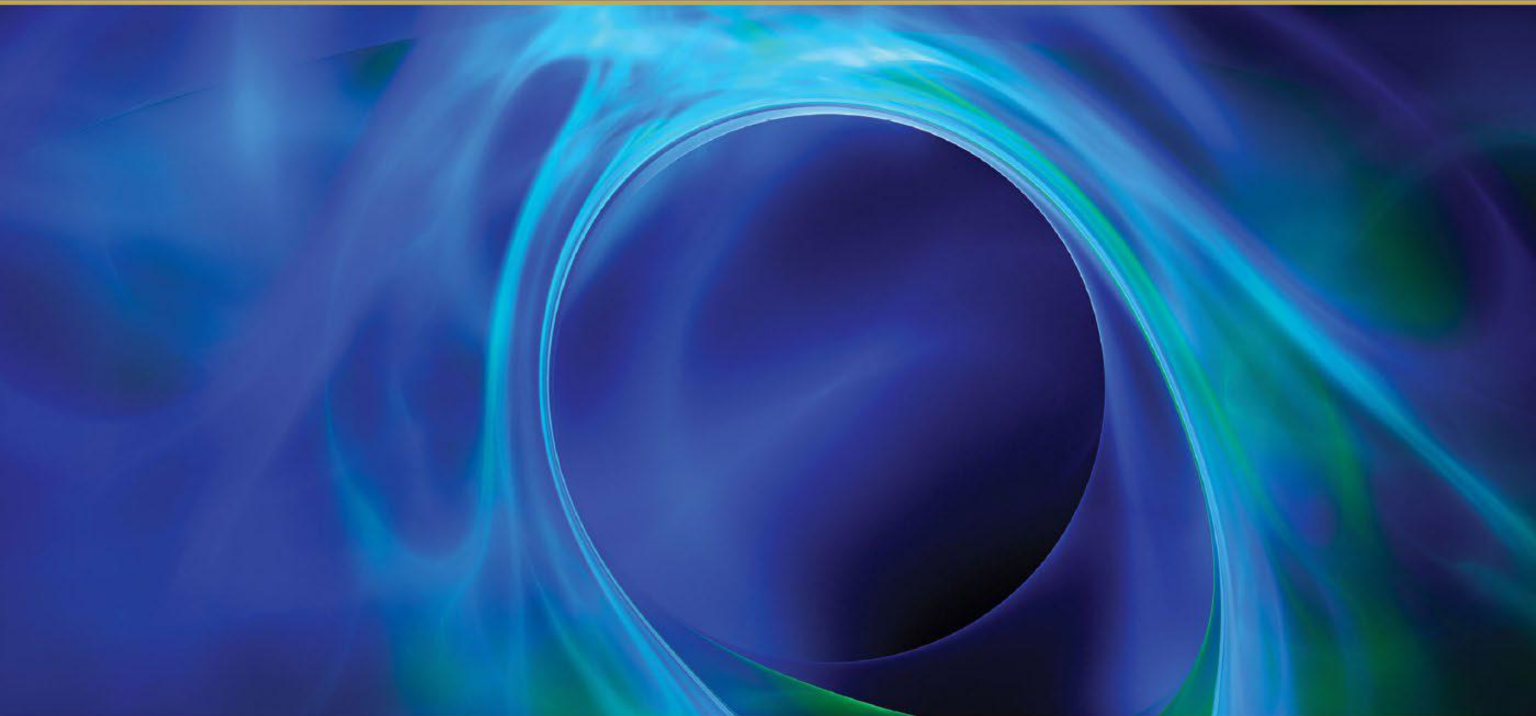
Applied Multivariate Research

3 Edition

Design and Interpretation



Lawrence S. Meyers
Glenn Gamst
A. J. Guarino

THIRD EDITION

Applied Multivariate Research

SAGE was founded in 1965 by Sara Miller McCune to support the dissemination of usable knowledge by publishing innovative and high-quality research and teaching content. Today, we publish over 900 journals, including those of more than 400 learned societies, more than 800 new books per year, and a growing range of library products including archives, data, case studies, reports, and video. SAGE remains majority-owned by our founder, and after Sara's lifetime will become owned by a charitable trust that secures our continued independence.

Los Angeles | London | New Delhi | Singapore | Washington DC | Melbourne

THIRD EDITION

Applied Multivariate Research

Design and Interpretation

Lawrence S. Meyers
California State University, Sacramento

Glenn Gamst
University of La Verne

A. J. Guarino
MGH Institute of Health Professions

SAGE

Los Angeles | London | New Delhi
Singapore | Washington DC | Melbourne

SAGE

FOR INFORMATION:

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

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

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

SAGE Publications Asia-Pacific Pte. Ltd.
3 Church Street
#10-04 Samsung Hub
Singapore 049483

Acquisitions Editor: Leah Fargotstein
Editorial Assistant: Yvonne McDuffee
Production Editor: Olivia Weber-Stenis
Copy Editor: Christina West
Typesetter: C&M Digitals (P) Ltd.
Proofreader: Jennifer Grubba
Indexer: Sheila Bodell
Cover Designer: Anupama Krishnan
Marketing Manager: Nicole Elliott

Printed in the United States of America

Library of Congress Cataloging-in-Publication Data

Names: Meyers, Lawrence S., author. | Gamst, Glenn, author. | Guarino, A. J., author.

Title: Applied multivariate research : design and interpretation / Lawrence S. Meyers, California State University, Sacramento, Glenn Gamst, University of La Verne, A. J. Guarino, MGH Institute of Health Professions.

Description: Third Edition. | Thousand Oaks : SAGE Publications, Inc., 2016. | Revised edition of the authors' Applied multivariate research, 2013. | Includes bibliographical references and index.

Identifiers: LCCN 2016030496 | ISBN 9781506329765 (hardcover : alk. paper)

Subjects: LCSH: Multivariate analysis. | Social sciences—Statistical methods.

Classification: LCC HA31.3 .M487 2016 | DDC 300.1/519535—dc23
LC record available at https://lccn.loc.gov/2016030496

This book is printed on acid-free paper.

16 17 18 19 20 10 9 8 7 6 5 4 3 2 1

Brief Contents

Preface xxxv

About the Authors xxxvii

PART I: FUNDAMENTALS OF MULTIVARIATE DESIGN 1

Chapter 1: An Introduction to Multivariate Design 2

Chapter 2: Some Fundamental Research Design Concepts 9

Chapter 3A: Data Screening 31

Chapter 3B: Data Screening Using IBM SPSS 62

PART II: BASIC AND ADVANCED REGRESSION ANALYSIS 123

Chapter 4A: Bivariate Correlation and Simple Linear Regression 124

Chapter 4B: Bivariate Correlation and Simple Linear Regression Using IBM SPSS 149

Chapter 5A: Multiple Regression Analysis 157

Chapter 5B: Multiple Regression Analysis Using IBM SPSS 192

Chapter 6A: Beyond Statistical Regression 205

Chapter 6B: Beyond Statistical Regression Using IBM SPSS 231

Chapter 7A: Canonical Correlation Analysis 278

Chapter 7B: Canonical Correlation Analysis Using IBM SPSS 287

Chapter 8A: Multilevel Modeling 297

Chapter 8B: Multilevel Modeling Using IBM SPSS 312

Chapter 9A: Binary and Multinomial Logistic Regression and ROC Analysis 346

Chapter 9B: Binary and Multinomial Logistic Regression and ROC Analysis Using IBM SPSS 378

PART III: STRUCTURAL RELATIONSHIPS OF MEASURED AND LATENT VARIABLES 403

Chapter 10A: Principal Components Analysis and Exploratory Factor Analysis 404

Chapter 10B: Principal Components Analysis and Exploratory Factor Analysis Using IBM SPSS 445

Chapter 11A: Confirmatory Factor Analysis 493

Chapter 11B: Confirmatory Factor Analysis Using IBM SPSS Amos 524

Chapter 12A: Path Analysis: Multiple Regression Analysis 551

Chapter 12B: Path Analysis: Multiple Regression Analysis Using IBM SPSS 559

Chapter 13A: Path Analysis: Structural Equation Modeling 568

Chapter 13B: Path Analysis: Structural Equation Modeling Using IBM SPSS Amos 574

Chapter 14A: Structural Equation Modeling 583

Chapter 14B: Structural Equation Modeling Using IBM SPSS Amos 596

Chapter 15A: Measurement and Structural Equation Modeling Invariance: Applying a Model to a Different Group 628

Chapter 15B: Assessing Measurement and Structural Invariance for Confirmatory Factor Analysis and Structural Equation Models Using IBM SPSS Amos 634

PART IV: CONSOLIDATING STIMULI AND CASES 689

Chapter 16A: Multidimensional Scaling 690

Chapter 16B: Multidimensional Scaling Using IBM SPSS 707

Chapter 17A: Cluster Analysis 734

Chapter 17B: Cluster Analysis Using IBM SPSS 747

PART V: COMPARING SCORES 763

Chapter 18A: Between Subjects Comparisons of Means 764

Chapter 18B: Between Subjects ANCOVA, MANOVA, and MANCOVA Using IBM SPSS 790

Chapter 19A: Discriminant Function Analysis 867

Chapter 19B: Three-Group Discriminant Function Analysis Using IBM SPSS 886

Chapter 20A: Survival Analysis 902

Chapter 20B: Survival Analysis Using IBM SPSS 908

References 935

Appendix A: Statistics Tables 959

Author Index 961

Subject Index 969

Detailed Contents

Preface xxxv

About the Authors xxxvii

PART I: FUNDAMENTALS OF MULTIVARIATE DESIGN 1

Chapter 1: An Introduction to Multivariate Design 2
- 1.1 The Use of Multivariate Designs 2
- 1.2 The Definition of the Multivariate Domain 2
- 1.3 The Importance of Multivariate Designs 3
- 1.4 The General Form of a Variate 4
- 1.5 The Type of Variables Combined to Form a Variate 4
- 1.6 The General Organization of the Book 5
  - *1.6.1 The Chapters Are in Pairs* 5
  - *1.6.2 Part I: Fundamentals of Multivariate Design* 6
  - *1.6.3 Part II: Basic and Advanced Regression Analysis* 6
  - *1.6.4 Part III: Structural Relationships of Measured and Latent Variables* 7
  - *1.6.5 Part IV: Synthesizing/Categorizing Data* 7
  - *1.6.6 Part V: Comparing Means* 8

Chapter 2: Some Fundamental Research Design Concepts 9
- 2.1 Populations and Samples 9
- 2.2 Variables and Scales of Measurement 10
  - *2.2.1 Variables* 10
  - *2.2.2 Five Scales of Measurement* 11
    - 2.2.2.1 Nominal Scales 11
    - 2.2.2.2 Ordinal Scales 11
    - 2.2.2.3 Summative Response Scales 12
    - 2.2.2.4 Interval Scales 12
    - 2.2.2.5 Ratio Scales 13
  - *2.2.3 Algebraic Properties of the Scales* 13
  - *2.2.4 Qualitative Versus Quantitative Measurement* 14
  - *2.2.5 Criticisms of Stevens's Schema* 15
- 2.3 Independent Variables, Dependent Variables, and Covariates 15
  - *2.3.1 Independent Variables* 16
  - *2.3.2 Dependent Variables* 16
  - *2.3.3 Covariates* 16
- 2.4 Between Subjects and Within Subjects Independent Variables 17
  - *2.4.1 Between Subjects Variables* 17
  - *2.4.2 Within Subjects Variables* 17
- 2.5 Latent Variables and Measured Variables 18
  - *2.5.1 Latent Variables* 18
  - *2.5.2 Measured Variables* 18
  - *2.5.3 Linking Latent Variables to Measured Variables* 18
  - *2.5.4 Variates as Latent Variables* 19
- 2.6 Endogenous and Exogenous Variables 20
- 2.7 Statistical Significance 20

2.7.1 Degrees of Freedom 20
2.7.2 Sampling Distributions 21
2.7.3 The Role of Sample Size 22
2.7.4 Determination of Significance 22
2.7.5 Levels of Significance 23
2.7.6 Statistical Significance Versus Confidence Interval Estimation 24
2.7.7 Null Hypothesis 25
2.7.8 Type I and Type II Errors 25
2.7.9 The Current Status of Statistical Significance Testing 26
2.8 Statistical Power 26
2.8.1 Definition of Power 27
2.8.2 Alpha Level 27
2.8.3 Effect Size 28
2.8.4 Sample Size 29
2.9 Recommended Readings 30

Chapter 3A: Data Screening 31
3A.1 Overview 31
3A.2 Value Cleaning 31
3A.2.1 Overview 31
3A.2.2 Qualitative Numerical Codes 32
3A.2.3 Quantitative Numerical Scores 32
3A.2.4 Multiple Response Coding 33
3A.2.5 The Process of Value Cleaning 34
3A.2.6 Using Frequency Tables for Data Cleaning 35
3A.3 Patterns of Missing Values 35
3A.3.1 Patterns and Mechanisms of Missing Data 37
3A.3.2 Statistical Tests of MCAR 38
3A.3.3 Looking for Patterns 39
3A.4 Overview of Methods of Handling Missing Data 40
3A.5 Deletion Methods of Handling Missing Data 41
3A.5.1 Deletion Methods: Listwise 41
3A.5.2 Deletion Methods: Pairwise 42
3A.6 Single Imputation Methods of Handling Missing Data 42
3A.6.1 Single Imputation: Mean Substitution 43
3A.6.2 Single Imputation: Multiple Regression 44
3A.7 Modern Imputation Methods of Handling Missing Data 45
3A.7.1 Single Imputation: EM Imputation 45
3A.7.2 FIML Imputation 46
3A.7.3 MI Analysis 46
3A.8 Recommendations for Handling Missing Data 47
3A.9 Outliers 48
3A.9.1 Causes of Outliers 48
3A.9.2 Statistical Detection of Univariate Outliers: z Scores 49
3A.9.3 Graphical Detection of Univariate Outliers: Box Plots 49
3A.9.3.1 The General Form of the Box Plot 49
3A.9.3.2 An Example of a Box Plot 51
3A.9.4 Detection of Multivariate Outliers 51
3A.9.4.1 Detection of Multivariate Outliers: Scatterplot Matrices 51
3A.9.4.2 Detection of Multivariate Outliers: Mahalanobis Distance 52
3A.10 Using Descriptive Statistics in Data Screening 53
3A.11 Using Pictorial Representations in Data Screening 54
3A.11.1 Histograms and Bar Graphs 54
3A.11.2 Stem-and-Leaf Plots 54
3A.12 Multivariate Statistical Assumptions Underlying the General Linear Model 56
3A.12.1 Normality 56
3A.12.1.1 Statistical Approaches to Assessing Normality 57

3A.12.1.2 Graphical Approaches to Assessing Normality 57
3A.12.1.3 Multivariate Approaches to Assessing Normality 57
3A.12.2 Linearity 58
3A.12.3 Homoscedasticity 58
3A.12.4 Independence of Errors 59
3A.13 Data Transformations 60
3A.14 Recommended Readings 61

Chapter 3B: Data Screening Using IBM SPSS 62
3B.1 The Look of IBM SPSS 62
3B.2 Data Cleaning: All Variables 63
3B.3 Screening Quantitative Variables 64
3B.4 Missing Values: Overview 67
3B.5 Missing Value Analysis 67
3B.5.1 Missing Value Analysis: Main Dialog Screen 67
3B.5.2 Missing Value Analysis: Descriptives 68
3B.5.3 Missing Value Analysis: Patterns 71
3B.5.4 Missing Value Analysis: A Test of MCAR 74
3B.6 Multiple Imputation 75
3B.6.1 Multiple Imputation: Pattern Analysis 75
3B.6.2 Multiple Imputation: Automatic Multiple Imputation 78
3B.6.2.1 The Recommended Preliminary: Setting a Random Seed 78
3B.6.2.2 Performing the Multiple Imputation Procedure 78
3B.6.3 Structure of the Multiple Imputed Data Set 84
3B.6.4 Splitting the Multiple Imputed Data Set 84
3B.6.5 Conducting a Statistical Analysis With Multiple Imputed Data 85
3B.7 Mean Substitution as a Single Imputation Approach 86
3B.8 Univariate Outliers 87
3B.9 Normality 98
3B.9.1 Assessing Normality 98
3B.9.2 Transforming Variables to Achieve Normality 102
3B.10 Linearity 104
3B.11 Multivariate Outliers 105
3B.12 Screening Within Levels of Categorical Variables 112
3B.12.1 The Distribution of Gender 113
3B.12.2 Univariate Outliers 113
3B.12.3 Normality 114
3B.12.4 Homoscedasticity 116
3B.12.5 Homogeneity of Variance–Covariance Matrices 116
3B.13 Reporting the Data Screening Results 121

PART II: BASIC AND ADVANCED REGRESSION ANALYSIS 123

Chapter 4A: Bivariate Correlation and Simple Linear Regression 124
4A.1 The Concept of Correlation 124
4A.2 Different Types of Relationships 125
4A.2.1 Perfect Positive Relationships 125
4A.2.2 Perfect Negative Relationships 127
4A.2.3 Less-Than-Perfect Positive Relationships 127
4A.2.4 Absence of Relationship With Variance on Both Variables 128
4A.2.5 Absence of Relationship With No Variance on One Variable 129
4A.2.6 Covariation Is Not the Same Thing as Mean Difference 130
4A.3 Statistical Significance of the Correlation Coefficient 131
4A.3.1 Interpretation of Statistical Significance 131
4A.3.2 Statistical Significance and Sample Size 132

4A.4 Strength of Relationship 133
4A.4.1 Guidelines for Assessing Relationship Strength 133
4A.4.2 Relationship Strength Is Shared Variance 133
4A.4.3 Indexing Relationship Strength by r^2 134
4A.4.4 Alternative Measures of Strength of Relationship 135
4A.4.5 Relation of r and r^2 135
4A.4.6 Calculating the Mean Correlation 135
4A.5 Pearson Correlation Using a Quantitative Variable and a Dichotomous Nominal Variable 136
4A.5.1 Why We Can Legitimately Compute a Pearson r With One Dichotomous (Two-Category) Predictor Variable 136
4A.5.2 Why We Cannot Legitimately Compute a Pearson r Using One Variable With Three or More Categories 137
4A.6 Simple Linear Regression 139
4A.6.1 An Overview of the Regression Process 139
4A.6.2 The Least Squares Solution 139
4A.6.3 Raw Scores and Standard Scores 140
4A.6.4 The Regression Equations 141
4A.6.4.1 The Raw Score Model 142
4A.6.4.2 The Standardized Model 142
4A.6.5 Interpreting a Regression Model 143
4A.7 Statistical Error in Prediction: Why Bother With Regression? 144
4A.8 How Simple Linear Regression Is Used 146
4A.9 Factors Affecting the Computed Pearson *r* and Regression Coefficients 146
4A.9.1 Outliers 146
4A.9.2 Range (Variance) Restriction 147
4A.9.3 Nonlinearity 148
4A.10 Recommended Readings 148

Chapter 4B: Bivariate Correlation and Simple Linear Regression Using IBM SPSS 149
4B.1 Bivariate Correlation: Analysis Setup 149
4B.1.1 Main Dialog Window 149
4B.1.2 Options Window 149
4B.1.3 Output From the Correlation Analysis 151
4B.2 Simple Linear Regression 152
4B.2.1 Main Regression Dialog Window 152
4B.2.2 Statistics Tab 152
4B.2.3 Simple Linear Regression Output 153
4B.3 Reporting Simple Linear Regression Results 156

Chapter 5A: Multiple Regression Analysis 157
5A.1 General Considerations 157
5A.2 Statistical Regression Methods 158
5A.3 The Two Classes of Variables in a Multiple Regression Analysis 158
5A.3.1 The Variable Being Predicted 158
5A.3.2 The Variables Used as Predictors 158
5A.4 Multiple Regression Research 160
5A.4.1 Research Problems Suggesting a Regression Approach 160
5A.4.2 The Statistical Goal in a Regression Analysis 160
5A.4.3 The Regression Weights For the Predictors 160
5A.4.4 Fully Specifying the Regression Model 161
5A.5 The Regression Equations 161
5A.5.1 The Raw Score Model 161
5A.5.2 The Standardized Model 163
5A.6 The Variate in Multiple Regression 164
5A.7 The Standard (Simultaneous) Regression Method 165
5A.7.1 The Example to Be Used 165

5A.7.2 Correlations of the Variables 165
5A.7.3 Building the Regression Equation 166
5A.8 Partial Correlation 168
5A.9 The Squared Multiple Correlation 168
5A.10 The Squared Semipartial Correlation 170
5A.10.1 The Squared Semipartial Correlation Itself 170
5A.10.2 The Difference Between the Squared Semipartial Correlation and the Squared Partial Correlation 170
5A.10.3 The Squared Semipartial Correlation and the Squared Multiple Correlation 172
5A.11 Structure Coefficients 173
5A.12 Statistical Summary of the Regression Solution 174
5A.13 Evaluating the Overall Model 174
5A.13.1 Is the Model Statistically Significant? 174
5A.13.2 The Amount of Variance Explained by the Model: R^2 and Adjusted R^2 175
5A.13.2.1 Variance Explained: The Straightforward Portion of the Answer 175
5A.13.2.2 Variance Explained: R^2 Is Somewhat Inflated 175
5A.13.2.3 Variance Explained: Empirical Strategies for Estimating the Amount of R^2 Shrinkage 176
5A.13.2.4 Variance Explained: Analytic Strategies for Estimating the Amount of R^2 Shrinkage 177
5A.14 Evaluating the Individual Predictor Results 179
5A.14.1 Variables in the Model 179
5A.14.2 The Regression Equations 179
5A.14.3 t Tests 179
5A.14.4 b Coefficients 180
5A.14.5 Beta Coefficients 180
5A.14.5.1 General Interpretation 180
5A.14.5.2 The Case for Using Beta Coefficients to Evaluate Predictors 180
5A.14.5.3 Concerns With Using the Beta Coefficients to Evaluate Predictors 181
5A.14.5.4 Recommendations for Using Betas 182
5A.14.6 Pearson Correlations of the Predictors With the Criterion Variable 182
5A.14.7 Squared Semipartial Correlations 182
5A.14.8 The Structure Coefficients 183
5A.15 Step Methods of Building the Model 184
5A.16 The Forward Method 184
5A.17 The Backward Method 185
5A.18 Backward Versus Forward Solutions 185
5A.19 The Stepwise Method 186
5A.20 Evaluation of the Statistical Methods 187
5A.20.1 Benefits of the Standard Method 187
5A.20.2 Benefits of the Step Methods 187
5A.20.3 Criticisms of the Statistical Methods as a Set 187
5A.20.4 Balancing the Value of All the Statistical Methods of Building the Model 188
5A.21 Collinearity and Multicollinearity 189
5A.22 Recommended Readings 190

Chapter 5B: Multiple Regression Analysis Using IBM SPSS 192
5B.1 Standard Multiple Regression 192
5B.1.1 Analysis Setup: Main Regression Dialog Window 192

5B.1.2 Analysis Setup: Statistics Window 192
5B.1.3 Analysis Setup: Options Window 194
5B.1.4 Analysis Output: Descriptives and Correlations 194
5B.1.5 Analysis Output: Omnibus Analysis 194
5B.1.6 Analysis Output: Individual Predictor Results 195
5B.1.7 Reporting Standard Multiple Regression Results 197
5B.2 Stepwise Multiple Regression 199
5B.2.1 Analysis Setup: Main Regression Dialog Window 199
5B.2.2 Analysis Setup: Statistics Window 199
5B.2.3 Analysis Setup: Options Window 200
5B.2.4 Analysis Output: Descriptives and Correlations 200
5B.2.5 Analysis Output: Omnibus Analysis 200
5B.2.6 Analysis Output: Individual Predictor Results 202
5B.2.7 Reporting the Stepwise Multiple Regression Results 204

Chapter 6A: Beyond Statistical Regression 205
6A.1 A Larger World of Regression 205
6A.2 Hierarchical Linear Regression 205
6A.2.1 Overview 205
6A.2.2 An Example 206
6A.2.3 Other Issues in the Context of Hierarchical Regression 208
6A.3 Suppressor Variables 208
6A.3.1 Overview 208
6A.3.2 An Example 209
6A.4 Linear and Nonlinear Regression 210
6A.4.1 Completely Linear Models 210
6A.4.2 Intrinsically Linear Models 211
6A.4.2.1 Overview 211
6A.4.2.2 Log Transformation 211
6A.4.2.3 Logit Transformation 211
6A.4.2.4 Polynomial Transformations 212
6A.4.3 Intrinsically Nonlinear Models 213
6A.5 Dummy and Effect Coding 213
6A.5.1 The Elements of Dummy and Effect Coding 213
6A.5.1.1 The Number of Code Sets Required 214
6A.5.1.2 The Categories to Be Coded 214
6A.5.1.3 The Values Used as Codes 215
6A.5.1.4 Representing the Categorical Variable in the Regression Analysis 215
6A.5.2 Dummy Coding 215
6A.5.3 Effect Coding 216
6A.6 Moderator Variables and Interactions 217
6A.7 Simple Mediation: A Minimal Path Analysis 220
6A.7.1 The Concept of Mediation 221
6A.7.2 The Conditions for Using Mediation 222
6A.7.3 Conceptualizing Mediation 222
6A.7.4 An Example of a Mediation Analysis 223
6A.7.5 The Individual Constituents of a Mediation Analysis 223
6A.7.6 Testing the Statistical Significance of the Mediated Effect 225
6A.7.6.1 Overview 225
6A.7.6.2 Testing the Indirect Effect: The Sobel Family of Equations 225
6A.7.6.3 Comparing the Two Direct Paths: The Freedman–Schatzkin Procedure 227

6A.7.7 The Strength of the Mediated Effect 229
6A.8 Recommended Readings 230

Chapter 6B: Beyond Statistical Regression Using IBM SPSS 231
6B.1 Hierarchical Linear Regression 231
6B.1.1 Hierarchical Regression Analysis Setup 231
6B.1.2 Hierarchical Regression Analysis Output 233
6B.1.3 Reporting the Hierarchical Multiple Regression Results 236
6B.2 Polynomial Regression 238
6B.2.1 The Example for Polynomial Regression 238
6B.2.2 Polynomial Regression Setup 239
6B.2.3 Polynomial Regression Output 241
6B.2.4 Reporting the Polynomial Regression Results 245
6B.3 Dummy and Effect Coding 245
6B.3.1 The Example for Dummy and Effect Coding 245
6B.3.2 The Analysis Strategy to Illustrate the Coding 247
6B.3.3 Analysis of Variance 247
6B.3.3.1 ANOVA Setup 247
6B.3.3.2 ANOVA Output 248
6B.3.4 Dummy Coded Regression 249
6B.3.4.1 Dummy Coded Regression Setup 249
6B.3.4.2 Dummy Coded Regression Output 251
6B.3.5 Effects Coded Regression 252
6B.3.5.1 Effects Coded Regression Setup 252
6B.3.5.2 Effects Coded Regression Output 252
6B.3.6 Interface of the Three Analyses 254
6B.3.6.1 Summary and Model Summary Tables 254
6B.3.6.2 Group Means and Regression Coefficients 254
6B.4 Interaction Effects of Quantitative Variables in Regression 255
6B.4.1 The Variables and Their Roles 255
6B.4.2 Centering the Predictor and Moderator Variables 256
6B.4.3 Constructing the Variables 256
6B.4.4 Performing the Centered Regression Analysis 261
6B.4.5 Additional Analyses at ±1 SD for the Moderator Variable 261
6B.4.5.1 An Additional Analysis at +1 SD for the Moderator Variable 263
6B.4.5.2 An Additional Analysis at −1 SD for the Moderator Variable 266
6B.4.6 Plotting the Simple Slopes 268
6B.4.6.1 Plotting the Simple Slopes in IBM SPSS 268
6B.4.6.2 Plotting the Simple Slopes by Hand 268
6B.4.7 Reporting the Multiple Regression Interaction Results 270
6B.5 Mediation 271
6B.5.1 The Mediation Model Example 271
6B.5.2 Evaluating the Direct (Unmediated) Effect of Positive Affect on the Dependent Variable of Self-Control 272
6B.5.3 Evaluating the Effect of Positive Affect on the Mediator Variable of Self-Esteem 273
6B.5.4 Evaluating the Mediated Effect of Positive Affect via Self-Esteem on the Dependent Variable of Self-Control 273
6B.5.5 Reporting the Results of the Mediation Analysis 276

Chapter 7A: Canonical Correlation Analysis 278
7A.1 Overview 278
7A.2 Canonical Functions or Roots 279

7A.2.1 The Definition of a Canonical Function or Root 279
7A.2.2 The Maximum Number of Canonical Functions or Roots That Can Be Extracted 279
7A.3 The Index of Shared Variance 280
7A.4 The Dynamics of Extracting Canonical Functions 280
7A.5 Accounting for Variance: Eigenvalues and Theta Values 281
7A.5.1 Overview 281
7A.5.2 Eigenvalues 281
7A.5.3 Theta Values (Squared Canonical Correlations) 282
7A.6 The Multivariate Tests of Statistical Significance 282
7A.6.1 The Omnibus Tests 282
7A.6.2 The Dimension Reduction Analysis 283
7A.7 Specifying the Amount of Variance Explained in Canonical Correlation Analysis 284
7A.8 Coefficients Associated With the Canonical Functions 284
7A.8.1 Weighting Coefficients 284
7A.8.2 Structure Coefficients 285
7A.9 Interpreting the Canonical Functions 285
7A.9.1 General Strategy 285
7A.9.2 Rotation of the Canonical Functions 285
7A.10 Recommended Readings 285

Chapter 7B: Canonical Correlation Analysis Using IBM SPSS 287
7B.1 Canonical Correlation: Analysis Setup 287
7B.2 Canonical Correlation: Overview of Output 288
7B.3 Canonical Correlation: Multivariate Tests of Significance 288
7B.4 Canonical Correlation: Eigenvalues and Canonical Correlations 289
7B.5 Canonical Correlation: Dimension Reduction Analysis 290
7B.6 Canonical Correlation: How Many Functions Should Be Interpreted? 291
7B.7 Canonical Correlation: The Coefficients in the Output 292
7B.8 Canonical Correlation: Interpreting the Dependent Variates 292
7B.9 Canonical Correlation: Interpreting the Predictor Variates 293
7B.10 Canonical Correlation: Interpreting the Canonical Functions 294
7B.11 Reporting of the Canonical Correlation Analysis Results 295

Chapter 8A: Multilevel Modeling 297
8A.1 The Name of the Procedure 297
8A.2 The Rise of Multilevel Modeling 297
8A.3 The Defining Feature of Multilevel Modeling: Hierarchically Structured Data 298
8A.4 Nesting and the Independence Assumption 298
8A.5 The Intraclass Correlation as an Index of Clustering 299
8A.6 Consequences of Violating the Independence Assumption 300
8A.6.1 Sample Size Distortion 300
8A.6.2 Underestimating Standard Errors 301
8A.6.3 Alpha-Level Inflation 301
8A.7 Some Ways in Which Level 2 Groups Can Differ 302
8A.8 The Random Coefficient Regression Model 304
8A.8.1 Generality of Approach 304
8A.8.2 Fixed and Random Coefficients 304
8A.8.3 Guidelines for Sample Sizes 305
8A.9 Centering the Variables 305
8A.9.1 The Centering Options 306
8A.9.1.1 Grand Mean Centering 306
8A.9.1.2 Group Mean Centering 306
8A.9.2 Centering the Level 2 Predictor 306
8A.9.3 Centering the Level 1 Predictor 307

8A.9.3.1 The Research Is Focused on the Level 1 Predictor 307
8A.9.3.2 The Research Is Focused on the Level 2 Predictor 307
8A.9.3.3 The Research Is Focused on Both Levels 308
8A.9.3.4 The Research Is Focused on Cross-Level or Level 1 Interactions 308
8A.9.3.5 The Research Is Focused on Level 2 Interactions 308
8A.10 The Process of Building the Multilevel Model 308
8A.10.1 Assembling the Measured Variables 308
8A.10.2 Assessing the Unconditional Model to Compute the ICC 309
8A.10.3 Computing Centered Variables for the Analysis 309
8A.10.4 Classifying the Predictors as Factors or Covariates 309
8A.10.5 Determining the Fixed and Random Effects 309
8A.10.6 Building the Multilevel Models 310
8A.10.7 The Analysis Procedure for Multilevel Models 310
8A.11 Recommended Readings 311

Chapter 8B: Multilevel Modeling Using IBM SPSS 312
8B.1 Numerical Example 312
8B.2 Assessing the Unconditional Model 312
8B.3 Centering the Covariates 317
8B.3.1 Level 1 Centering of the Individual Experience Scores 318
8B.3.2 Level 2 Centering of the Dealership Experience Scores 321
8B.4 Building the Multilevel Models: Overview 322
8B.5 Building the First Model 323
8B.5.1 The First Model: Setup 323
8B.5.2 The First Model: Output 325
8B.6 Building the Second Model 331
8B.6.1 The Second Model: Setup 331
8B.6.2 The Second Model: Output 332
8B.7 Building the Third Model 335
8B.7.1 The Third Model: Setup 335
8B.7.2 The Third Model: Output 338
8B.8 Building the Fourth Model 340
8B.8.1 The Fourth Model: Setup 340
8B.8.2 The Fourth Model: Output 342
8B.9 Reporting the Multilevel Modeling Results 344

Chapter 9A: Binary and Multinomial Logistic Regression and ROC Analysis 346
9A.1 Overview 346
9A.1.1 Regression as Discussed in Prior Chapters 346
9A.1.2 Types of Logistic Regression 346
9A.1.3 The Prevalence of Logistic Regression 347
9A.2 The Variables in Logistic Regression Analysis 347
9A.3 Assumptions of Logistic Regression 347
9A.4 Coding of the Binary Variables in Logistic Regression 348
9A.4.1 Coding of the Binary Predictor Variables 348
9A.4.1.1 Coding of the Binary Predictor Variables in Binary Logistic Regression 348
9A.4.1.2 Coding of the Binary Predictor Variables in Multinomial Logistic Regression 349
9A.4.1.3 Making Sure We Correctly Interpret the Odds Ratio 349
9A.4.2 Coding of the Categorical Outcome Variable 350
9A.5 The Shape of the Logistic Regression Function 351

9A.5.1 Least Squares Is Not Appropriate in Logistic Regression 351
9A.5.2 The Logistic Function 351
9A.6 Probability, Odds, and Odds Ratios 353
9A.6.1 Probability 353
9A.6.2 Odds 354
9A.6.3 Odds Ratio 354
9A.6.4 Adjusted Odds Ratio 355
9A.7 The Logistic Regression Model 355
9A.7.1 The Logistic Regression Model: The Predictor Side 355
9A.7.2 The Logistic Regression Model: The Interim (Linear) Log Odds Outcome Variable 355
9A.7.3 The Logistic Regression Model: The Full Equation 356
9A.8 Interpreting Logistic Regression Results in Simpler Language 357
9A.8.1 Generating the Predicted Probability of Target Group Membership 357
9A.8.2 Making the Outcome Prediction 358
9A.8.3 The Odds Ratio 358
9A.9 Binary Logistic Regression With a Single Binary Predictor 358
9A.9.1 Obtaining the Predicted Probability 358
9A.9.2 Making the Decision 359
9A.9.3 Obtaining the Odds Ratio 360
9A.10 Binary Logistic Regression With a Single Quantitative Predictor 360
9A.10.1 Obtaining the Predicted Probability 360
9A.10.2 Making the Decision 362
9A.10.3 Obtaining the Odds Ratio 362
9A.11 Binary Logistic Regression With a Categorical and a Quantitative Predictor 362
9A.12 Evaluating the Logistic Model 363
9A.12.1 The −2 Log Likelihood Ratio 363
9A.12.2 Omnibus Chi Square Test 364
9A.12.3 Pseudo R^2 364
9A.12.4 Hosmer and Lemeshow Test 364
9A.12.5 Wald Test of Significant Coefficients 365
9A.12.6 Classification Results 365
9A.13 Strategies for Building the Logistic Regression Model 365
9A.13.1 Strategies Available in a Binary Logistic Regression Model 366
9A.13.2 Strategies Available in Multinomial Logistic Regression Model 366
9A.14 ROC Analysis 367
9A.14.1 ROC Analysis: Overview 367
9A.14.2 ROC Analysis: The Classification Table 367
9A.14.3 ROC Analysis: The ROC Curve 368
9A.14.4 ROC Analysis: The Area Under the ROC Curve 370
9A.14.5 ROC Analysis: The Decision Threshold 370
9A.14.6 ROC Analysis: Coordinates of the ROC Curve 373
9A.14.6.1 Coordinates of the ROC Curve: The Plotted Values 373
9A.14.6.2 Coordinates of the ROC Curve: The Positive Likelihood Ratio 374
9A.14.6.3 Coordinates of the ROC Curve: The Positive Predictive Value 374
9A.14.6.4 Coordinates of the ROC Curve: Using All of the Information 375
9A.14.7 ROC Analysis: Decision Making Using the Coordinates of the ROC Curve 375
9A.14.8 ROC Analysis: The Decision Threshold in Binary Logistic Regression 376
9A.15 Recommended Readings 376

Chapter 9B: Binary and Multinomial Logistic Regression and ROC Analysis Using IBM SPSS 378
9B.1 Binary Logistic Regression 378
9B.1.1 Numerical Example 378
9B.1.2 Binary Logistic Regression Analysis Setup 378
9B.1.3 Binary Logistic Regression Analysis Output 379
9B.1.3.1 Administrative Output 379
9B.1.3.2 Block 0 Output 379
9B.1.3.3 Model Evaluation Output 381
9B.1.3.4 Classification Table and Odds Ratio 383
9B.1.4 Reporting the Results of Binary Logistic Regression 385
9B.2 ROC Analysis 386
9B.2.1 Save Predicted Probabilities From the Logistic Regression 386
9B.2.2 An ROC Analysis Is Worth Considering 386
9B.2.3 Performing the ROC Analysis 387
9B.2.4 The Output From the ROC Analysis 388
9B.2.5 Performing a Logistic Regression Analysis With Revised Cut Value 392
9B.2.6 Output of Logistic Regression Analysis With Revised Cut Value 393
9B.2.7 Reporting the Results of ROC-Modified Binary Logistic Regression 394
9B.3 Multinomial Logistic Regression 395
9B.3.1 Numerical Example 395
9B.3.2 Multinomial Logistic Regression Analysis Setup 396
9B.3.3 Multinomial Logistic Regression Analysis Output 397
9B.3.3.1 Model Fit Output 397
9B.3.3.2 Likelihood Ratio Tests 397
9B.3.3.3 Classification Table and Parameter Estimates 397
9B.3.4 Reporting the Results of Multinomial Logistic Regression 400

PART III: STRUCTURAL RELATIONSHIPS OF MEASURED AND LATENT VARIABLES 403

Chapter 10A: Principal Components Analysis and Exploratory Factor Analysis 404
10A.1 Orientation and Terminology 404
10A.2 Origins of Factor Analysis 405
10A.3 How Factor Analysis Is Used in Psychological Research 405
10A.4 The General Organization of This Chapter 405
10A.5 Where the Analysis Begins: The Correlation Matrix 406
10A.5.1 A Three-Variable Example 406
10A.5.2 A Four-Variable Example 406
10A.5.3 A Six-Variable Example 408
10A.5.4 Introducing a Little Fuzziness Into the Example: Modest Relationship Strengths 409
10A.6 Acquiring Perspective on Factor Analysis 410
10A.6.1 The Importance of Individual Variables 411
10A.6.2 How Much Information Is Lost in the Crunch 412
10A.6.3 When Visual Inspection No Longer Works 412
10A.7 Important Distinctions Within Our Generic Label of Factor Analysis 412
10A.7.1 Principal Components Analysis and Factor Analysis 412
10A.7.2 An Extraction Phase and a Rotation Phase 413
10A.7.3 Our Approach 413
10A.8 The First Phase: Component Extraction 413
10A.8.1 The Concept of Extraction 413

10A.8.2 What Is a Component? 414
10A.8.3 The Component Refers to the Whole Sample, Not a Subset 414
10A.8.4 The Total Variance Is Equal to the Number of Variables 414
10A.8.5 The Extraction Process 414
10A.8.6 A Pictorial Illustration 414
10A.8.7 The Rules of Component Extraction 415
10A.8.8 Extracting Components 416
10A.8.9 Point of Diminishing Returns 418
10A.9 Distances of Variables From a Component 418
10A.9.1 Correlation as a Distance Measure 418
10A.9.2 Distance Between a Component and the Variables 419
10A.9.3 Eigenvalues 420
10A.10 Principal Components Analysis Versus Factor Analysis 421
10A.10.1 Causal Flow 421
10A.10.2 Variance Explained 422
10A.11 Different Extraction Methods 423
10A.11.1 Principal Components Analysis 423
10A.11.2 Principal Axis Factoring 423
10A.11.3 Unweighted and Generalized Least Squares Factoring 424
10A.11.4 Maximum Likelihood Factoring 424
10A.11.5 Alpha Factoring 424
10A.11.6 Image Factoring 424
10A.12 Recommendations Concerning Extraction 425
10A.13 The Rotation Process 425
10A.13.1 Introduction 425
10A.13.2 The Goal of Simple Structure: The Least Squares Rule in Operation 426
10A.13.3 Achieving Simple Structure 426
10A.14 Orthogonal Factor Rotation Methods 429
10A.14.1 Varimax Rotation 429
10A.14.2 Quartimax Rotation 430
10A.14.3 Equimax Rotation 430
10A.15 Oblique Factor Rotation 430
10A.16 Choosing Between Orthogonal and Oblique Rotation Strategies 431
10A.17 The Factor Analysis Output 432
10A.17.1 Variance Accounted for in the Initial Solution 432
10A.17.2 Eigenvalue Plot (Scree Plot) 434
10A.17.3 The Rotated Factor Matrix 435
10A.17.3.1 Varimax Rotated Factor Matrix 435
10A.17.3.2 Obliquely Rotated Factor Matrix: Overview 435
10A.17.3.3 Obliquely Rotated Factor Matrix: Pattern Matrix 435
10A.17.3.4 Obliquely Rotated Factor Matrix: Structure Matrix 435
10A.17.3.5 The Magnitude of the Variable Weights 436
10A.17.3.6 Recommendations 436
10A.18 Interpreting Factors Based on the Rotated Matrices 436
10A.18.1 Discerning the Common Quality 436
10A.18.2 Negative Factor Coefficients 437
10A.18.3 Recommendations: Interpreting the Structure or Pattern Matrices 437
10A.19 Selecting the Factor Solution 439
10A.19.1 There Is No Easy Answer 439
10A.19.2 Suggested Statistical Solutions to the Number of Factors Question 439
10A.19.4 Features/Issues to Take Into Account in Interpreting the Results 440
10A.19.4.1 Theoretical/Empirical Milieu 440
10A.19.4.2 Scree Plot 441

10A.19.4.3 Amount of Variance Explained 441
10A.19.4.4 Number of Variables Used to Represent Factors 441
10A.19.4.5 Magnitudes of the Pattern/Structure Coefficients 441
10A.19.4.6 Reasonableness of the Interpretation 441
10A.19.5 Our Recommendations 441
10A.20 Sample Size Issues 442
10A.21 Building Reliable Subscales 442
10A.22 Recommended Readings 443

Chapter 10B: Principal Components Analysis and Exploratory Factor Analysis Using IBM SPSS 445
10B.1 Numerical Example 445
10B.2 Preliminary Principal Components Analysis 446
10B.2.1 Preliminary Principal Components Analysis Setup 446
10B.2.1.1 Descriptive Statistics 446
10B.2.1.2 Component Extraction 448
10B.2.1.3 Component Rotation 449
10B.2.1.4 Options 449
10B.2.2 Preliminary Principal Components Analysis Output 449
10B.2.2.1 Descriptive Statistics 449
10B.2.2.2 Explained Variance 452
10B.2.2.3 The Scree Plot 452
10B.2.2.4 The Component Matrix 452
10B.2.2.5 Communalities 453
10B.3 Principal Components Analysis With a Promax Rotation: Two-Component Solution 455
10B.3.1 Principal Components Analysis With a Promax Rotation: Two-Component Solution Setup 456
10B.3.2 Principal Components Analysis With a Promax Rotation: Two-Component Solution Selected Output 457
10B.4 ULS Analysis With a Promax Rotation: Two-Factor Solution 459
10B.5 Wrap-Up of the Two-Factor Solution 461
10B.6 Looking for Six Dimensions 461
10B.7 Principal Components Analysis With a Promax Rotation: Six-Component Solution 463
10B.7.1 First Principal Components/Promax Rotated Component 466
10B.7.2 Second Principal Components/Promax Rotated Component 466
10B.7.3 Third Principal Components/Promax Rotated Component 466
10B.7.4 Fourth Principal Components/Promax Rotated Component 466
10B.7.5 Fifth Principal Components/Promax Rotated Component 467
10B.7.6 Sixth Principal Components/Promax Rotated Component 467
10B.8 ULS Analysis With a Promax Rotation: Six-Component Solution 467
10B.8.1 First ULS/Promax Rotated Factor 469
10B.8.2 Second ULS/Promax Rotated Factor 470
10B.8.3 Third ULS/Promax Rotated Factor 470
10B.8.4 Fourth ULS/Promax Rotated Factor 470
10B.8.5 Fifth ULS/Promax Rotated Factor 470
10B.8.6 Sixth ULS/Promax Rotated Factor 470
10B.9 Principal Axis Factor Analysis With a Promax Rotation: Six-Component Solution 470
10B.9.1 First Principal Axis/Promax Rotated Factor 473
10B.9.2 Second Principal Axis/Promax Rotated Factor 473

10B.9.3 Third Principal Axis/Promax Rotated Factor 473
10B.9.4 Fourth Principal Axis/Promax Rotated Factor 473
10B.9.5 Fifth Principal Axis/Promax Rotated Factor 473
10B.9.6 Sixth Principal Axis/Promax Rotated Factor 473
10B.10 Wrap-Up of the Six-Factor Solution 474
10B.11 Assessing Reliability: Our General Strategy 474
10B.11.1 Which Scales to Build 474
10B.11.2 Recoding Variables as Needed 475
10B.12 Assessing Reliability: The Global Domains 476
10B.12.1 Assessing Reliability: The Intrinsic Global Domain Analysis Setup 477
10B.12.2 Assessing Reliability: Intrinsic Global Domain Selected Output 477
10B.12.3 Assessing Reliability: The Extrinsic Global Domain 478
10B.12.4 Assessing Reliability: Interpreting the Reliability of the Two Global Domains 478
10B.13 Assessing Reliability: The Six Item Sets Based on the ULS/Promax Structure 478
10B.14 Computing Scales Based on the ULS Promax Structure 480
10B.14.1 Strategies for Computing Scales 480
10B.14.2 Computing the New Variables 481
10B.15 Using the Computed Variables in Further Analyses 487
10B.16 Reporting the Exploratory Factor Analysis Results 489

Chapter 11A: Confirmatory Factor Analysis 493
11A.1 Overview 493
11A.1.1 Working With Latent Variables 493
11A.1.2 General Differences Between Exploratory and Confirmatory Factor Analysis 494
11A.1.3 Placing Confirmatory Factor Analysis in a Larger Context 494
11A.2 The General Form of a Confirmatory Model 495
11A.2.1 Measured Variables 495
11A.2.2 Latent Variables or Factors 496
11A.2.3 Error/Residual/Disturbance/Unique Variables 497
11A.2.4 Paths 497
11A.2.5 Parameter Constraints 498
11A.3 The Difference Between Latent and Measured Variables 498
11A.3.1 The Clear Differences Between Latent and Measured Variables 499
11A.3.2 The Fuzzy Differences Between Latent and Measured Variables 499
11A.3.3 Resolving the Differences Between Latent and Measured Variables 499
11A.4 Contrasting Principal Components Analysis and Exploratory Factor Analysis With Confirmatory Factor Analysis 500
11A.4.1 The Structure of Principal Components Analysis 500
11A.4.2 The Structure of Principal Axis Factor Analysis 502
11A.4.3 The Structure of Confirmatory Factor Analysis 504
11A.5 Confirmatory Factor Analysis Is Theory Based 506
11A.6 The Logic of Performing a Confirmatory Factor Analysis 507
11A.7 Model Specification 507
11A.8 Model Identification 509
11A.8.1 Overview of Model Identification 509
11A.8.2 Determining the Number of Known Elements 509
11A.8.3 Scaling the Latent Variable 510

11A.8.3.1 Placing a Constraint on a Path to Scale the Latent Variable 510
11A.8.3.2 Selecting the Measured Indicator as the Reference Variable 511
11A.8.4 Determining the Number of Unknown Elements 514
11A.8.5 Resolving the Number of Known and Unknown Elements 514
11A.9 Model Estimation 515
11A.10 Model Evaluation Overview 515
11A.11 Assessing Fit of Hypothesized Models 515
11A.11.1 The Multitude of Fit Indexes 515
11A.11.2 Categorizing the Fit Indexes 516
11A.11.3 Absolute Fit Measures 517
11A.11.4 Relative Fit Measures 518
11A.11.5 Parsimonious Fit Measures 519
11A.11.6 Model Comparison Measures 519
11A.11.7 Which Fit Measures to Report? 519
11A.12 Model Estimation: Assessing Pattern Coefficients 520
11A.13 Model Respecification 521
11A.14 General Considerations 522
11A.15 Recommended Readings 522

Chapter 11B: Confirmatory Factor Analysis Using IBM SPSS Amos 524
11B.1 Using IBM SPSS Amos 524
11B.1.1 Opening IBM SPSS Amos 524
11B.1.2 Screen Setup 525
11B.1.3 Drawing Functions 526
11B.1.4 Editing Functions 528
11B.2 Numerical Example 530
11B.3 Analysis Setup to Specify the Model 531
11B.3.1 Drawing the Model 531
11B.3.2 Naming the Variables in the Model 532
11B.3.2.1 Naming the Measured Indicator Variables 532
11B.3.2.2 Naming the Latent Variables 532
11B.3.2.3 Naming the Error Variables 534
11B.3.3 Drawing the Correlation Paths in the Model 534
11B.4 Model Identification 536
11B.5 Structuring and Performing the Analysis 537
11B.5.1 The Analysis Properties Window 537
11B.5.2 Changes to the Data 539
11B.5.3 Saving the File 539
11B.5.4 Performing the Analysis 539
11B.6 Working With the Analysis Output 539
11B.6.1 The Pictorial Representation of the Model 540
11B.6.2 Text Output: Notes For Model 540
11B.6.3 Text Output: Model Fit 541
11B.6.4 Text Output: Modification Indices 543
11B.7 Respecifying the Model 544
11B.8 Output From the Respecified Model 544
11B.8.1 The Pictorial Representation of the Respecified Model 545
11B.8.2 Text Output: Model Fit 545
11B.8.3 Text Output: Modification Indices 545
11B.8.4 Text Output: Coefficients 546
11B.9 Reporting Confirmatory Factor Analysis Results 549

Chapter 12A: Path Analysis: Multiple Regression Analysis 551
12A.1 Overview 551
12A.2 The Concept of a Path Model 551
12A.3 The Appeal of Path Over Multiple Regression Analysis 553
12A.4 Causality and Path Analysis 553
12A.4.1 Causality Is an Inference 553
12A.4.2 Causality and Research Methods 554

12A.5 The Roles Played by Variables in a Path Structure 554
12A.5.1 Endogenous and Exogenous Variables 555
12A.5.2 Dependent and Independent Variables 555
12A.5.3 Relating the Two Classification Schemas 556
12A.6 The Assumptions of Path Analysis 556
12A.7 Missing Values in Path Analysis 557
12A.8 The Multiple Regression Approach to Path Analysis 557
12A.9 Indirect and Total Effects 558
12A.10 Recommended Readings 558

Chapter 12B: Path Analysis: Multiple Regression Analysis Using IBM SPSS 559
12B.1 The Data Set and Model Used in Our Example 559
12B.2 Identifying the Variables in Each Analysis 559
12B.3 Predicting Months_Teaching 560
12B.3.1 Predicting Months_Teaching: Analysis Setup 560
12B.3.2 Predicting Months_Teaching: Output 560
12B.4 Predicting Good_Teaching 561
12B.4.1 Predicting Good_Teaching: Analysis Setup 561
12B.4.2 Predicting Good_Teaching: Output 561
12B.5 Reporting the Path Analysis Results 565

Chapter 13A: Path Analysis: Structural Equation Modeling 568
13A.1 Comparing Multiple Regression and Structural Equation Model Approaches 568
13A.1.1 Evaluating Overall Fit 568
13A.1.2 The Information Used in Estimating the Path Coefficients 569
13A.1.3 The Iteration Process 569
13A.2 Differences Between the Equations Underlying Multiple Regression and Structural Equation Model Procedures 569
13A.3 Configuring the Structural Model 570
13A.4 Identifying the Structural Equation Model 571
13A.4.1 Number of Known Elements 571
13A.4.2 Number of Unknown Elements 572
13A.4.3 Achieving Model Identification 572
13A.5 Recommended Readings 572

Chapter 13B: Path Analysis: Structural Equation Modeling Using IBM SPSS Amos 574
13B.1 Overview 574
13B.2 The Data Set and Model Used in Our Example 574
13B.3 Analysis Setup 574
13B.3.1 Drawing the Model 574
13B.3.2 Naming the Variables in the Model 575
13B.3.3 Structuring the Analysis 576
13B.3.4 Saving the IBM SPSS Amos File 577
13B.3.5 Performing the Analysis 577
13B.4 The Analysis Output 578
13B.4.1 Viewing the Results Graphically 578
13B.4.2 Text Output: Model Fit 578
13B.4.3 Text Output: Coefficients 578
13B.4.4 Text Output: Squared Multiple Correlations 579
13B.4.5 Text Output: Direct and Indirect Effects 581
13B.5 Reporting the Path Analysis Results 582

Chapter 14A: Structural Equation Modeling 583
14A.1 Overview of Structural Equation Modeling 583

14A.1.1 Structural Modeling Resembles Path Analysis but With Latent Variables 583
14A.1.2 Structural Modeling Includes Both a Measurement and a Structural Model 583
14A.1.3 An Example of a Simple Structural Equation Model 584
14A.1.4 Mixing Measured and Latent Variables in a Structural Model 585
14A.2 Model Quality and the Structural Aspects of the Model 586
14A.2.1 The Quality of Model Fit 586
14A.2.2 The Structural Aspects of the Model 587
14A.2.3 Step Strategies to Bolster the Measurement Model 588
14A.3 Latent Variables and Their Indicators 589
14A.3.1 Latent Variables Are Known Indirectly 589
14A.3.2 One Indicator Is Not Enough 590
14A.3.3 The Aspects of the Construct Need to Be Represented 590
14A.3.4 More Indicators (Generally) Are Better at Capturing the Nature of the Construct 591
14A.3.5 More Indicators Facilitate Model Identification 591
14A.3.6 The Use of Item Parcels as Indicators 591
14A.4 Identifying Structural Equation Models 594
14A.5 Recommended Readings 594

Chapter 14B: Structural Equation Modeling Using IBM SPSS Amos 596
14B.1 Overview 596
14B.2 The Data Set and Model Used in Our Example 596
14B.3 Model Configuration and Analysis Setup 597
14B.3.1 Drawing the Model 597
14B.3.2 Naming the Measured and Latent Variables in the Model 597
14B.4 Model Identification 599
14B.4.1 Number of Known Elements 599
14B.4.2 Number of Unknown Elements 601
14B.4.3 Achieving Model Identification 601
14B.5 Generating the Output 601
14B.5.1 Structuring the Analysis 601
14B.5.2 Saving the IBM SPSS Amos File 602
14B.5.3 Performing the Analysis 602
14B.6 Analysis Output for the Model 603
14B.6.1 Viewing the Results Graphically 603
14B.6.2 Text Output: Model Fit 603
14B.6.3 Text Output: Modification Indexes 604
14B.7 Configuring and Evaluating the Respecified Model 604
14B.7.1 Respecifying the Model 604
14B.7.2 Viewing the Respecified Model Results Graphically 605
14B.7.3 Text Output: Respecified Model Fit 605
14B.7.4 Text Output: Coefficients 607
14B.7.5 Text Output: Squared Multiple Correlations 607
14B.7.6 Text Output: Direct and Indirect Effects 608
14B.8 Summary of the Results of the Model and Noting the Follow-up Analyses 608
14B.8.1 Summary Thus Far 608
14B.8.2 To Be Performed Follow-up Analyses: Assessing the Indirect Effects 609
14B.8.3 To Be Performed Follow-up Analyses: Assessing the Possibility of Obtaining Complete Mediation in the Full Model by Evaluating the Unmediated Model 609

14B.8.4 To Be Performed Follow-up Analyses: Assessing the Two Simple Mediation Structures 611
14B.9 Assessing the Indirect Effects in the Full Model 613
14B.9.1 The Indirect Effect Through Self_Regulation 613
14B.9.2 The Indirect Effect Through Work_Ethic 613
14B.10 Assessing the Possibility of Having Obtained Complete Mediation in the Full Model 613
14B.10.1 The Context for Our Assessment 613
14B.10.2 Drawing the Model and Performing the Analysis 613
14B.10.3 Viewing the Unmediated Model Results Graphically 614
14B.10.4 Text Output: Coefficients 614
14B.11 Assessing Mediation Through Self_Regulation 615
14B.11.1 Drawing the Self_Regulation Mediated Model and Performing the Analysis 615
14B.11.2 Viewing the Self_Regulation Mediated Model Results Graphically 616
14B.11.3 Text Output: Self_Regulation Mediated Model Fit 616
14B.11.4 Text Output: Self_Regulation Mediated Model Coefficients 616
14B.11.5 Evaluation of Partial Mediation in the Self_Regulation Mediated Model 618
14B.12 Assessing Mediation Through Extrinsic_Goals 620
14B.12.1 Drawing the Extrinsic_Goals Mediated Model and Performing the Analysis 620
14B.12.2 Viewing the Extrinsic_Goals Mediated Model Results Graphically 620
14B.12.3 Text Output: Extrinsic_Goals Mediated Model Fit 621
14B.12.4 Text Output: Extrinsic_Goals Mediated Model Coefficients 621
14B.12.5 Evaluation of Partial Mediation in the Extrinsic_Goals Mediated Model 623
14B.13 Synthesis of the Results 625
14B.14 Reporting the SEM Results 625

Chapter 15A: Measurement and Structural Equation Modeling Invariance: Applying a Model to a Different Group 628
15A.1 Overview 628
15A.2 The General Strategy Used to Compare Groups 629
15A.3 The Omnibus Model Comparison Phase 629
15A.3.1 The Two Models Being Compared 629
15A.3.2 The Unconstrained Model 630
15A.3.3 The Constrained Models 630
15A.3.4 Chi Square Difference Test 630
15A.4 The Coefficient Comparison Phase 631
15A.4.1 The Comparison Strategy 631
15A.4.2 The Parameters That Are Compared 631
15A.5 Recommended Readings 632

Chapter 15B: Assessing Measurement and Structural Invariance for Confirmatory Factor Analysis and Structural Equation Models Using IBM SPSS Amos 634
15B.1 Overview and General Analysis Strategy 634
15B.1.1 Overview 634
15B.1.2 General Analysis Strategy 635
15B.2 The Data Set Used for Examining Invariance in Both the Confirmatory Factor Analysis and Structural Equation Model Examples 635
15B.3 Confirmatory Factor Analysis Invariance: Global Preliminary Analysis 636

15B.3.1 Drawing the Model: Global Confirmatory Factor Analysis 636
15B.3.2 Model Identification: Global Confirmatory Factor Analysis 637
15B.3.3 Analysis Setup: Global Confirmatory Factor Analysis 637
15B.3.4 Analysis Output: Global Confirmatory Factor Analysis 637
15B.4 Confirmatory Factor Analysis Invariance: Group 1 (Rural) Analysis 639
15B.5 Confirmatory Factor Analysis Invariance: Group 2 Analysis 641
15B.6 Confirmatory Factor Analysis Invariance: Model Evaluation Setup 643
15B.6.1 Model Evaluation Setup for the Confirmatory Factor Analysis: General Strategy 643
15B.6.2 Model Evaluation Setup for the Confirmatory Factor Analysis: Naming the Groups 645
15B.6.3 Model Evaluation Setup for the Confirmatory Factor Analysis: Linking the Groups to the Data File 645
15B.6.4 Model Evaluation Setup for the Confirmatory Factor Analysis: Specifying the Analysis Properties 648
15B.6.5 Model Evaluation Setup for the Confirmatory Factor Analysis: Specifying the Constraints on the Models to Be Evaluated 648
15B.6.6 Model Evaluation Setup for the Confirmatory Factor Analysis: The Parameter Labels 651
15B.6.7 Model Evaluation Setup for the Confirmatory Factor Analysis: Performing the Analysis 653
15B.7 Confirmatory Factor Analysis Invariance: Model Evaluation Output 654
15B.7.1 Model Evaluation for the Confirmatory Factor Invariance Analysis Output: Initial Graphic Output 654
15B.7.2 Model Evaluation for the Confirmatory Factor Invariance Analysis Output: Model Fit Output 655
15B.7.3 Model Evaluation for the Confirmatory Factor Invariance Analysis Output: Model Comparison Output 655
15B.7.3.1 Assuming the Unconstrained Model to Be Correct 655
15B.7.3.2 Assuming the Unconstrained and Measurement Weights Models to Be Correct 658
15B.7.4 Model Evaluation for the Confirmatory Factor Invariance Analysis Output: Unstandardized and Standardized Coefficients Based on the Unconstrained Model 658
15B.7.5 Model Evaluation for the Confirmatory Factor Invariance Analysis Output: Pairwise Unconstrained Model Parameter Comparisons 661
15B.8 Reporting the Confirmatory Factor Analysis Invariance Results 664
15B.9 Structural Equation Model Invariance: Global Preliminary Analysis 666
15B.9.1 Drawing the Model: Global Structural Equation Model Analysis 666
15B.9.2 Model Identification: Global Structural Equation Model Analysis 666
15B.9.3 Analysis Setup: Global Structural Equation Model Analysis 667

15B.9.4 Analysis Output: Global Structural Equation Model Analysis 667
15B.10 Structural Equation Model Invariance: Group 1 (Rural) Analysis 669
15B.11 Structural Equation Model Invariance: Group 2 Analysis 671
15B.12 Structural Equation Model Invariance: Model Evaluation Setup 672
15B.13 Structural Equation Model Invariance: Model Evaluation Output 676
15B.13.1 Model Evaluation for the Structural Equation Model Invariance Output: Initial Graphic Output 676
15B.13.2 Model Evaluation for the Structural Equation Model Invariance Analysis Output: Model Fit Output 677
15B.13.3 Model Evaluation for the Structural Equation Model Invariance Analysis Output: Model Comparison Output 679
15B.13.3.1 Assuming the Unconstrained Model to Be Correct 680
15B.13.3.2 Assuming the Unconstrained and Measurement Weights Models to Be Correct 680
15B.13.4 Model Evaluation for the Structural Equation Model Invariance Analysis Output: Unstandardized and Standardized Coefficients Based on the Unconstrained Model 681
15B.13.5 Model Evaluation for the Structural Equation Model Invariance Analysis Output: Squared Multiple Correlations Based on the Unconstrained Model 683
15B.13.6 Model Evaluation for the Structural Equation Model Invariance Output: Pairwise Unconstrained Model Parameter Comparisons 684
15B.14 Reporting the Structural Equation Model Invariance Results 686

PART IV: CONSOLIDATING STIMULI AND CASES 689

Chapter 16A: Multidimensional Scaling 690
16A.1 Overview 690
16A.1.1 Dimensions in Multidimensional Scaling 690
16A.1.2 Some Conditions Underlying the Interpretation of the Dimensions 690
16A.1.3 Fitting Dimensions to the Data 691
16A.2 The Paired Comparison Method 691
16A.3 Dissimilarity Data in MDS 692
16A.4 Similarity/Dissimilarity Conceived as an Index of Distance 692
16A.5 Dimensionality in MDS 693
16A.6 Data Collection Methods 694
16A.6.1 Direct Judgment Methods 695
16A.6.1.1 Direct Judgment: Rating Methods 695
16A.6.1.2 Direct Judgment: Multiple Ratio Methods 695
16A.6.1.3 Direct Judgment: Rank-Order Methods 695
16A.6.1.4 Direct Judgment: Sorting Methods 695
16A.6.2 Indirect Methods 695
16A.6.2.1 Indirect Methods: Confusion Data Methods 695
16A.6.2.2 Indirect Methods: Frequency of Co-Occurrence Methods 696
16A.6.2.3 Indirect Methods: Reaction Time 696

16A.7 Similarity Versus Dissimilarity 696
16A.8 Distance Models 696
16A.8.1 Euclidian Distance Between Objects 696
16A.8.2 Alternating Least Squares Scaling 698
16A.9 A Classification Schema for MDS Techniques 698
16A.9.1 Measurement Level of Data 699
16A.9.2 Data Shape 699
16A.9.3 Data Matrix Conditionality 699
16A.10 Types of MDS Models 700
16A.10.1 Classical MDS 700
16A.10.2 Replicated MDS 700
16A.10.3 Weighted MDS 701
16A.10.4 A Decision Tree for Determining the Appropriate MDS Model 702
16A.11 Assessing Model Fit 702
16A.11.1 Stress as a Fit Index 703
16A.11.2 S-Stress as a Fit Index 703
16A.11.3 R^2 as a Fit Index 703
16A.11.4 The Weirdness Index as a Fit Index 704
16A.11.5 Goodness-of-Fit Graphs as a Fit Index 704
16A.11.5.1 Linear Fit Scatterplots 704
16A.11.5.2 Transformation Scatterplots 704
16A.11.5.3 Scree Plots 704
16A.12 Recommended Readings 705

Chapter 16B: Multidimensional Scaling Using IBM SPSS 707
16B.1 The Structure of This Chapter 707
16B.2 Metric CMDS 707
16B.2.1 Metric CMDS: Our Numerical Example 707
16B.2.2 Metric CMDS: The Data Structure 707
16B.2.3 Metric CMDS: Analysis Setup 709
16B.2.4 Metric CMDS: Selected Output 711
16B.2.4.1 Iteration History 711
16B.2.4.2 Fit Information 711
16B.2.4.3 Scatterplot of Linear Fit Euclidean Distance 712
16B.2.4.4 Scaled Disparities 712
16B.2.4.5 Stimulus Coordinates for the Solution 713
16B.2.4.6 The Perceptual Map 715
16B.2.5 Reporting the Metric CMDS Results 715
16B.3 Nonmetric CMDS 716
16B.3.1 Nonmetric CMDS: Our Numeric Example 716
16B.3.2 Nonmetric CMDS: Analysis Setup 717
16B.3.3 Nonmetric CMDS: Selected Output 719
16B.3.3.1 Iteration History 719
16B.3.3.2 Fit Information 721
16B.3.3.3 Scatterplots 721
16B.3.3.4 Stimulus Coordinates for the Solution 721
16B.3.3.5 The Perceptual Map 722
16B.3.4 Reporting the Nonmetric CMDS Results 723
16B.4 Metric WMDS 723
16B.4.1 Metric WMDS: Our Numeric Example 723
16B.4.2 Metric WMDS: Analysis Setup 725
16B.4.3 Metric WMDS: Selected Output 726
16B.4.3.1 Iteration History and Fit Indexes 726
16B.4.3.2 Subject Weights and Degrees of Weirdness 727
16B.4.3.3 Scaled Disparities 727
16B.4.3.4 Derived Subject Weights 727
16B.4.3.5 Scatterplot of Linear Fit 728

16B.4.3.6 Flattened Subject Weights 728
16B.4.3.7 Stimulus Coordinates and Perceptual Map 732
16B.4.4 Reporting the Metric WMDS Results 733

Chapter 17A: Cluster Analysis 734
17A.1 Introduction 734
17A.2 Two Types of Clustering 734
17A.3 Hierarchical Clustering 735
17A.3.1 Overview 735
17A.3.2 The Clustering Process 735
17A.3.3 Separating Two Issues: Distance and Linkage 736
17A.3.4 Standardizing the Variables 736
17A.3.5 Distance Measures 737
17A.3.5.1 Squared Euclidian Distance 737
17A.3.5.2 Euclidian Distance 737
17A.3.5.3 City Block Distance 738
17A.3.5.4 Chebychev Distance 738
17A.3.5.5 Minkowski Distance 738
17A.3.5.6 Power Metric Distance 738
17A.3.6 Linkage Methods 739
17A.3.6.1 Unweighted Pair-Group Method With Arithmetic Averages Method 739
17A.3.6.2 Average Linkage Within Groups Method 739
17A.3.6.3 Nearest Neighbor Method 740
17A.3.6.4 Furthest Neighbor Method 740
17A.3.6.5 Ward's Method 740
17A.3.6.6 The Centroid and Median Methods 741
17A.3.7 Distance and Linkage Recommendations 741
17A.3.8 The Output of Interest 741
17A.3.9 The Interpretation of the Output 743
17A.4 *k*-Means Clustering 743
17A.4.1 Overview 743
17A.4.2 Phases of the Analysis 744
17A.4.3 Results of the Analysis 744
17A.4.3.1 Final Cluster Centers 744
17A.4.3.2 Cluster Membership 745
17A.5 Recommended Readings 746

Chapter 17B: Cluster Analysis Using IBM SPSS 747
17B.1 Hierarchical Cluster Analysis 747
17B.1.1 Hierarchical Cluster Analysis Setup 747
17B.1.2 Hierarchical Cluster Analysis Output 749
17B.1.2.1 The Proximity Matrix 749
17B.1.2.2 The Icicle Plot, the Agglomeration Schedule, and the Cluster Membership Table 752
17B.1.3 Reporting the Hierarchical Cluster Analysis Results 753
17B.2 *k*-Means Cluster Analysis 754
17B.2.1 z Score Transformation 754
17B.2.2 k-Means Cluster Analysis Setup 756
17B.2.3 k-Means Cluster Analysis Output 757
17B.2.4 Reporting k-Means Cluster Analysis Results 760

PART V: COMPARING SCORES 763

Chapter 18A: Between Subjects Comparisons of Means 764
18A.1 Overview 764
18A.2 Historical Context 764
18A.3 A Brief Review of Some Basic Concepts 765

18A.3.1 The General Linear Model 765
18A.3.2 Between Subjects Independent Variables 766
18A.3.3 Means and Variabilities of Dependent Variables 767
18A.4 Using Multiple Dependent Variables 767
18A.4.1 The Difference Between Univariate (ANOVA) and Multivariate (MANOVA) Designs 767
18A.4.2 Some Reasons for Using Multiple Dependent Variables 768
18A.4.3 The Dynamic Underlying a MANOVA 768
18A.4.4 Benefits of Using MANOVA 769
18A.4.5 Correlations of the Dependent Variables in a MANOVA 769
18A.4.6 The Equal Variance Assumption Regarding the Dependent Variables in a MANOVA 771
18A.5 Evaluating Statistical Significance 771
18A.5.1 Multivariate Effects 771
18A.5.2 Univariate Effects 772
18A.6 Strength of Effect 772
18A.6.1 Multivariate Effects: 1 – Wilks' Lambda and Pillai's Trace 772
18A.6.2 Univariate Effects: Eta Squared and Partial Eta Squared 773
18A.7 Designs, Effects, and Partitioning of the Variance 774
18A.7.1 Partitioning the Variance of the Dependent Variable(s): One-Way Designs 774
18A.7.2 Partitioning the Variance of the Dependent Variable(s): Two-Way Designs 775
18A.8 Post-ANOVA Comparisons of Means 777
18A.8.1 Post-ANOVA Comparisons: Multiple Comparisons Tests for Main Effects 778
18A.8.2 Post-ANOVA Comparisons: Simple Effects Tests for Interaction Effects 779
18A.9 Hierarchical Analysis of Effects 780
18A.9.1 Interactions Supersede Main Effects 780
18A.9.2 Multivariate Effects Control Univariate Effects 781
18A.10 Covariance Analysis 782
18A.10.1 Using the Covariate as a Basis of Adjusting Scores 782
18A.10.2 The Dynamics of Covariance Analysis 782
18A.10.3 Additional Assumptions Underlying Covariance Analysis 783
18A.10.4 Some Considerations Regarding Covariance Analysis 785
18A.10.4.1 Reliability of the Covariates 785
18A.10.4.2 Using Pre-Existing Groups 786
18A.10.5 Adjusted Versus Observed Means 786
18A.10.6 Performing Multiple Comparisons on the Adjusted Means 788
18A.11 Recommended Readings 789

Chapter 18B: Between Subjects ANCOVA, MANOVA, and MANCOVA Using IBM SPSS 790
18B.1 One-Way ANOVA Without the Covariate 790
18B.1.1 Numerical Example 790
18B.1.2 Omnibus One-Way Between Subjects Analysis Setup 791
18B.1.3 Omnibus One-Way Between Subjects Output 792
18B.2 One-Way ANCOVA 793
18B.2.1 Numerical Example 794

18B.2.2 Evaluating the Additional ANCOVA Assumption: Linearity of Regression 795
18B.2.3 Evaluating the Additional ANCOVA Assumption: Homogeneity of Regression 795
18B.2.4 ANCOVA Analysis Setup 800
18B.2.5 ANCOVA Analysis Output 803
18B.2.6 Reporting the ANOVA/ ANCOVA Results 806
18B.3 Three-Group MANOVA 806
18B.3.1 Numerical Example 806
18B.3.2 Three-Group MANOVA: Correlations of the Dependent Variables 807
18B.3.3 Three-Group MANOVA Setup 808
18B.3.4 Three-Group MANOVA Output 811
18B.3.4.1 Descriptive Output 811
18B.3.4.2 The Box and Bartlett Tests 812
18B.3.4.3 The Multivariate Tests 812
18B.3.4.4 The Levene Test 812
18B.3.4.5 Tests of the Univariate Effects 814
18B.3.4.6 Strength of Effect of the Univariate Effects 814
18B.3.4.7 Post Hoc Paired Comparisons 814
18B.3.5 Reporting the Three-Group MANOVA Results 818
18B.4 Two-Group MANCOVA 819
18B.4.1 Numerical Example 819
18B.4.2 Two-Group MANOVA Analysis Strategy 820
18B.4.3 Correlation of the Dependent Variables 820
18B.4.4 Two-Group MANOVA Setup 820
18B.4.5 Two-Group MANOVA Output 823
18B.4.5.1 Descriptive Output 823
18B.4.5.2 The Box and Bartlett Tests 823
18B.4.5.3 The Multivariate Tests 824
18B.4.5.4 The Levene Test 824
18B.4.5.5 Tests of the Univariate Effects 824
18B.4.6 Two-Group MANCOVA: Evaluating the Linearity of Regression Assumption 825
18B.4.7 Two-Group MANCOVA: Evaluating the Homogeneity of Regression Assumption 828
18B.4.8 Two-Group MANCOVA Setup 832
18B.4.9 Two-Group MANCOVA Output 832
18B.4.9.1 The Box and Bartlett Tests 832
18B.4.9.2 The Multivariate Tests 835
18B.4.9.3 The Levene Test 836
18B.4.9.4 Tests of the Univariate Effects 836
18B.4.9.5 Estimated Marginal Means 837
18B.4.10 Reporting the Two-Group MANCOVA Results 838
18B.5 Two-Way MANOVA Without the Covariate 840
18B.5.1 Numerical Example 840
18B.5.2 Correlations of the Dependent Variables 840
18B.5.3 Two-Way MANOVA Setup 840
18B.5.4 Two-Way MANOVA Output 843
18B.5.4.1 Descriptive Output 843
18B.5.4.2 The Box and Bartlett Tests 843
18B.5.4.3 The Multivariate Tests 843
18B.5.4.4 The Levene Test 845

18B.5.4.5 Tests of the Univariate Effects 845
18B.5.5 Setup and Output for the Post Hoc Tests on the Family Variable for the Two-Way MANOVA 848
18B.6 Two-Way MANOVA Incorporating the Covariate (MANCOVA) 849
18B.6.1 Two-Way MANCOVA: Evaluating the Linearity of Regression Assumption for Each Dependent Variable 850
18B.6.2 Two-Way MANCOVA: Evaluating the Homogeneity of Regression Assumption 851
18B.6.3 Two-Way MANCOVA Setup 857
18B.6.4 Two-Way MANCOVA Output 859
18B.6.5 Two-Way MANCOVA Multiple Comparisons Setup 863
18B.6.6 Two-Way MANCOVA Multiple Comparisons Output 863
18B.6.7 Reporting the Two-Way MANCOVA Results 865

Chapter 19A: Discriminant Function Analysis 867
19A.1 Overview 867
19A.2 The Formal Roles of the Variables in Discriminant Function Analysis and MANOVA 868
19A.3 Discriminant Function Analysis and Logistic Analysis Compared 869
19A.4 Sample Size for Discriminant Analysis 869
19A.5 The Discriminant Model 870
19A.5.1 The General Form of a Discriminative Function 870
19A.5.2 Maximum Likelihood Is Used to Generate the Discriminant Function 871
19A.6 Extracting Multiple Discriminant Functions 871
19A.6.1 The Number of Discriminant Functions That Can Be Extracted 871
19A.6.2 The General Interpretation of Each Discriminant Function 871
19A.7 Dynamics of Extracting Discriminant Functions 872
19A.7.1 Extracting Discriminant Functions 872
19A.7.2 Rotating Discriminant Functions 872
19A.8 Interpreting the Discriminant Function 873
19A.8.1 Unstandardized Discriminant Coefficients 873
19A.8.2 Standardized Discriminant Coefficients 873
19A.8.3 Structure Coefficients 873
19A.9 Assessing Statistical Significance and the Relative Strength of the Discriminative Functions 875
19A.9.1 Wilks' Lambda 875
19A.9.2 Precedence of Testing Statistical Significance: Dimension Reduction Analysis 875
19A.9.3 Eigenvalues 876
19A.9.4 Canonical Correlations 877
19A.10 Using Discriminant Function Analysis for Classification 877
19A.10.1 The Classification Table 877
19A.10.2 Taking Group Sample Sizes Into Account When Classifying Cases 878
19A.10.3 Assessing Classification Being Better Than Chance: Press' Q 879
19A.10.4 Two Strategies for Performing the Classification Analysis 881
19A.10.5 Classification Function Coefficients 881
19A.11 Different Discriminant Function Methods 883
19A.11.1 The Standard Method 883
19A.11.2 The Stepwise Methods 883
19A.11.2.1 Wilks' Lambda 884
19A.11.2.2 Unexplained Variance 884

19A.11.2.3 Mahalanobis Distance 884
19A.11.2.4 Smallest F Ratio 884
19A.11.2.5 Rao's V 884
19A.11.3 The Criteria for Entry and Removal 885
19A.12 Recommended Readings 885

Chapter 19B: Three-Group Discriminant Function Analysis Using IBM SPSS 886
19B.1 Numerical Example 886
19B.2 Analysis Setup 886
19B.2.1 The Initial Dialog Window 886
19B.2.2 The Statistics Window 887
19B.2.3 The Classify Window 888
19B.3 Analysis Output 889
19B.3.1 Descriptive Statistics 889
19B.3.2 Homogeneity of Covariance 890
19B.3.3 Univariate ANOVAs 890
19B.3.4 Wilks' Lambda 893
19B.3.5 Eigenvalues and Canonical Correlations 893
19B.3.6 Discriminant Function Coefficients 894
19B.3.7 Structure Coefficients 895
19B.3.8 Values of the Group Centroids 896
19B.3.9 Graphically Representing the Groups 897
19B.3.10 Classification Output 898
19B.4 Reporting the Results of a Three-Group Discriminant Function Analysis 900

Chapter 20A: Survival Analysis 902
20A.1 Overview 902
20A.2 The Dependent Variable in Survival Analysis 902
20A.3 Ordinary Least Squares Regression Versus Survival Analysis 903
20A.4 Censored Observations 904
20A.4.1 Left Censored Observations 904
20A.4.2 Interval Censored Observations 904
20A.4.3 Right Censored Observations 904
20A.5 Overview of Analysis Techniques for Survival Analysis in IBM SPSS 905
20A.6 Life Table Analysis 905
20A.7 Kaplan–Meier (Product-Limit) Survival Function Analysis 906
20A.8 Cox Proportional Hazard Regression Model 906
20A.9 Recommended Readings 907

Chapter 20B: Survival Analysis Using IBM SPSS 908
20B.1 Numerical Example 908
20B.2.1 Life Tables Analysis: Analysis Setup 909
20B.2.2 Output From the Life Table Analysis 910
20B.2.3 Reporting the Life Table Analysis Results 914
20B.3 Kaplan–Meier (Product-Limit) Survival Function Analysis 914
20B.3.1 Numerical Example and Analysis Strategy 914
20B.3.2 Analysis Setup: Comparing Males and Females 915
20B.3.3 Analysis Output: Comparing Males and Females 916
20B.3.4 Analysis Setup: Comparing Males and Females With Make of Car as a Stratification Variable 919
20B.3.5 Analysis Output: Comparing Males and Females With Stratification (Pooled Over Strata) 920
20B.3.6 Analysis Setup and Output: Comparing Males and Females With Stratification (Pairwise Over Strata) 922
20B.3.7 Analysis Setup and Output: Comparing Males and Females With Stratification (for Each Stratum) 922

20B.3.8 Analysis Setup and Output: Comparing Males and Females With Stratification (Pairwise for Each Stratum) 923
20B.3.9 Reporting the Kaplan–Meier (Product-Limit) Survival Function Results 924
20B.4 Cox Proportional Hazard Regression Model 926
20B.4.1 Numerical Example and Analysis Strategy 926
20B.4.2 Analysis Setup: Cox Regression 926
20B.4.3 Analysis Output: Cox Regression 929
20B.4.4 Reporting the Cox Regression Results 934

References 935

Appendix A: Statistics Tables 959

Author Index 961

Subject Index 969

Preface

We are extremely pleased and grateful that SAGE asked us to put together a third edition of *Applied Multivariate Research: Design and Interpretation*. This edition reflects and attempts to not only incorporate feedback we have received from several anonymous reviewers at the start of our revision process, but it also integrates the suggestions, questions, and feedback provided to us by both readers of the second edition and the students in our courses. Because we use the book in our introductory graduate-level statistics/research design courses, we have also seen where we might make changes to help our students better understand, work with, and follow the material.

In preparing the third edition, we have once again reaffirmed the goals we expressed in originally writing this book:

- We hope to communicate in a relatively readable, understandable, and (mostly) nonmathematical manner the conceptual bases of a range of multivariate research designs and analyses. At the same time, we have attempted to not unduly dilute or oversimplify the material.
- We want to demonstrate how to perform, interpret, and report the results of multivariate analyses in a direct and understandable manner.
- We have continued our practice of preparing two companion (paired) chapters for each topic, an "A" chapter presenting the conceptual treatment of the topic and a "B" chapter presenting the step-by-step data analysis, data interpretation, and reporting of the results so that the above two goals can be met.

We have used Version 23 of IBM SPSS and IBM SPSS Amos for this third edition, recognizing that later versions will be available by the time this book is published. All of the data sets used as examples are available on the SAGE website (www.sagepub.com/meyers) so that interested users can replicate our analyses on the example data sets.

In addition to updating and carefully editing the material, we restructured the order in which we cover the topics in the third edition:

- Because it was so fundamental in presenting the general linear model and serving as a foundation for the rest of the material covered in this book, we moved our treatment of correlation and regression to the front of the book immediately following our data screening chapters.
- We placed canonical correlation analysis directly after the chapters covering advanced regression analyses.
- The confirmatory factor analysis chapters were moved to an earlier location and now directly follow the exploratory factor analysis/principal components analysis chapters.
- We moved the analysis of variance (ANOVA)/multivariate analysis of variance (MANOVA) chapters to a location late in the book, and we placed the chapter on discriminant function analysis directly following the MANOVA chapters.

- We added a pair of chapters covering survival analysis at the end of the book.
- Users of the second edition will also notice that the "A" chapters covering confirmatory factor analysis, structural equation modeling, and assessing model invariance were largely rewritten; further, their companion "B" chapters were completely rewritten with the example analyses being made much more extensive and complete. The treatment of ANOVA/MANOVA was also extensively modified from the previous edition, with the focus in this third edition being on covariance and multivariate (between subjects) analyses and their combination (MANCOVA).

We have used data sets from the research of some of our students, including Jacquelyn Johnson, Rosalyn Sandoval, and Leanne Stanley. We appreciate their willingness to share their data sets with us, and we value the time we have spent teaching and supervising them. We were sad to see the editor of our previous two editions, Vicki Knight, retire but we look forward to working with our new SAGE editor Leah Fargotstein and her staff as we move forward.

Our overriding goal in writing this book was to make the world of multivariate research design and analysis understandable to a wide audience, and we sincerely hope that this book is helpful in that regard to its readers and users.

Acknowledgments

With the retirement of Vicki Knight, Leah Fargotstein has stepped up as our new editor. She has taken over the reigns and has done a terrific job in preparing us to put this book into production. Our copy editor, Christina West, has done a wonderful job as well. Christina's skill and keen eye are matched by her incredible speed and cheerful demeanor. Finally, based on some of the questions raised by our graduate students and some of the nuances they explored in their data analysis, we were able to address issues in some of these chapters that we might not otherwise have covered, and we are grateful for their interest and attentiveness in improving the coverage of the topics in this book.

About the Authors

Lawrence S. Meyers earned his doctorate in experimental psychology and has been a Professor in the Psychology Department at California State University, Sacramento, for a number of years. He supervises research students and teaches research design courses as well as history of psychology at both the undergraduate and graduate levels. His areas of expertise include test development and validation.

Glenn Gamst is Professor and Chair of the Psychology Department at the University of La Verne, where he teaches the doctoral advanced statistics sequence. His research interests include the effects of multicultural variables on clinical outcome. Additional research interests focus on conversation memory and discourse processing. He received his PhD in experimental psychology from the University of Arkansas.

A. J. Guarino is a professor of biostatistics at Massachusetts General Hospital, Institute of Health Professions. He is the statistician on numerous National Institutes of Health grants and a reviewer on several research journals. He received his BA from the University of California, Berkeley, and a PhD in statistics and research methodologies from the Department of Educational Psychology at the University of Southern California.

PART I

FUNDAMENTALS OF MULTIVARIATE DESIGN

CHAPTER 1

An Introduction to Multivariate Design

1.1 The Use of Multivariate Designs

The use of multivariate research designs has grown very rapidly in the behavioral and social sciences throughout the past quarter century. This has been made possible in no small part by increased availability of sophisticated statistical software packages, such as IBM SPSS, SAS, and Stata. But even with the increased availability of such software, behavioral and social science researchers have been using some multivariate techniques (e.g., factor analysis, multiple regression) for a very long time.

Multivariate designs can be distinguished from the univariate and bivariate designs with which readers are likely already familiar. Experimental designs that are analyzed with t tests or analysis of variance (ANOVA) are univariate designs, so named because there is only a single dependent variable in the design and analysis of the data (Gamst, Meyers, & Guarino, 2008). A t ratio or an F ratio is generated to test whether the group means are significantly different.

A bivariate design derives its name from the fact that there are only two variables that are analyzed together; it is exemplified by a simple correlation design. The variables in such a design are often signified as X and Y and, unless we are predicting one (the Y variable) from the other (the X variable), which variable is assigned which letter is arbitrary. The degree to which the measures are correlated is assessed with a correlation coefficient such as the Pearson correlation coefficient (Pearson r).

1.2 The Definition of the Multivariate Domain

To be considered a multivariate research design, the study must have more variables than are contained in either a univariate or bivariate design. Furthermore, some subset of these variables must be analyzed together, that is, they must be combined in some manner to form a composite variable or *variate*. The most common way to combine variables is by forming a *weighted linear composite* where each variable is weighted in a manner determined by the analysis. This resulting weighted linear composite is known as a variate. There are several contexts where we form such variates, three examples of which are as follows:

- In an experimental design in which we wished to compare the performance of three types of memory training, we could measure two or more variables as indicators of performance. These variables could then be combined into a single weighted composite measure when we would perform a multivariate analysis of variance (MANOVA). For example, we could assess both number of correct responses and speed of responding in a memory task that taken together might be interpreted as reflecting performance efficiency.
- In a prediction (regression) design, we might use self-esteem, extraversion, and product knowledge to predict dollars of sales for a set of salespeople in a multiple regression analysis. The variate in this instance might be thought of as sales effectiveness.
- To determine which items on a personality inventory might comprise separate subscales that measure aspects of a more global construct, we might perform a factor analysis on the responses to those items. Each factor would be a weighted linear combination of the inventory items.

1.3 The Importance of Multivariate Designs

The importance of multivariate designs is becoming increasingly well recognized. It also appears that the judged utility of these designs seems to be growing as well. Here are two of the advantages of multivariate research designs over univariate research designs based on those offered by Pituch and Stevens (2016):

- Many experimental treatments are likely to affect the study participants in more than one way.
- Using multiple criterion measures can paint a more complete and detailed description of the phenomenon under investigation.

A similar argument is made by Harris (2013):

> However, for very excellent reasons, researchers in all of the sciences—behavioral, biological, or physical—have long since abandoned sole reliance on the classic univariate design. It has become abundantly clear that a given experimental manipulation . . . will affect many somewhat different but partially correlated aspects of the organism's behavior. Similarly, many different pieces of information about an applicant . . . may be of value in predicting his or her . . . [behavior], and it is necessary to consider how to combine all of these pieces of information into a single "best" prediction. (p. 11)

In summary, there is general consensus about the value of multivariate designs for two very general reasons. First, we all seem to agree that individuals generate many behaviors and respond in many different although related ways to the situations they encounter in their lives. Univariate analyses are able to address this level of complexity in only a piecemeal fashion because they can examine only one aspect at a time. Multivariate analysis affords us the opportunity to examine the phenomenon under study by determining how the multiple variables interface.

The second reason why the field appears to have reached consensus on the importance of multivariate design is that we hold the causes of behavior to be complex and multivariate. Thus, predicting behavior is best done with more rather than less information. Most of us believe that several reasons explain why we feel or act as we do. For example, the degree to which we strive to achieve a particular goal, the amount of empathy we exhibit in our relationships, and the likelihood of following a medical regime may depend on a host of factors rather than just a single predictor variable. Only when we take into account a set of relevant variables—that is, when we take a multivariate approach—have we any realistic hope of reasonably accurately predicting the level—or understanding the nature—of a given construct. This, again, is the realm of multivariate design.

1.4 The General Form of a Variate

The general form of a variate—a weighted composite—is an equation or function. In the weighted linear composite shown below, the letter X with subscripts symbolizes each variable in the variate. A weight is assigned to each variable by multiplying the variable by this value; this weight is referred to as a *coefficient* in many multivariate applications. Thus, in the expression w_2X_2, the term w_2 is the weight that X_2 is assigned (multiplied by) in the weighted composite, that is, w_2 is the coefficient associated with X_2. A weighted composite of three variables would take this general form:

$$\text{Weighted composite} = w_1X_1 + w_2X_2 + w_3X_3$$

These weighted composites are given a variety of names, including *variates*, *composite variables*, and *synthetic variables* (Grimm & Yarnold, 2000). Variates are therefore not directly measured by the researchers in the process of data collection but are created or computed as part of or as the result of the multivariate data analysis. Because they are not directly measured, what they assess is often referred to as a *latent construct*, and the variate is often referred to as a *latent variable*. We will have quite a bit to say about variates (weighted linear composites or latent variables) throughout this book.

1.5 The Type of Variables Combined to Form a Variate

Variates may be weighted composites of either independent variables (i.e., manipulated or predictor variables) or dependent variables (variables representing the outcome of the research), or they may be weighted composites of variables playing neither role in the analysis. Examples where the analysis creates a variate composed of independent variables are multiple regression and logistic regression designs. In these designs, two or more independent variables are combined together to predict the value of a dependent variable. For example, the number of delinquent acts performed by teenagers might be found to be predictable from the number of hours per week they play violent video games, the number of hours per week they spend doing homework (this would be negatively weighted because more homework time would presumably predict fewer delinquent acts), and the number of hours per week they spend with other teens who have committed at least one delinquent act in the past year.

Multivariate analyses can also create composites of dependent variables. The classic example of this is a MANOVA design. This general type of design can contain one or more independent variables, but there must be at least two dependent variables in the analysis. These dependent variables are combined together into a composite, and an ANOVA is performed on this computed variate. The statistical significance of group differences on this variate is then tested by a multivariate F statistic (in contrast to the univariate F ratio that readers have presumably studied in prior coursework).

Sometimes variables do not need to play the explicit role of either independent or dependent variable and yet will be absorbed into a weighted linear composite in the statistical analysis. This occurs in principal components and exploratory factor analysis, where we attempt to identify which variables (e.g., items on an inventory) are associated with a particular underlying dimension, component, or factor. These components or factors are weighted linear composites of the variables in the analysis.

It is possible that the prior experience of readers is such that great emphasis has been placed on the differences between dependent and independent variables. If so, it might be somewhat disconcerting to learn that variates can be composed of either class of variables. But it turns out that, in the analysis of data, dependent and independent are roles that are assigned to variables by the researchers rather than absolute attributes of the variables themselves. And just as actresses in the theater can play different roles in different productions, so too can variables play different roles in different analyses. This can be seen very forcefully in the context of path analysis (Chapters 12A and 13A) and structural equation modeling (Chapter 14A), and the interfacing of MANOVA (Chapter 18A) with discriminant function analysis (Chapter 19A).

1.6 The General Organization of the Book

The domain of multivariate research design is quite large, and selecting which topics to include and which to omit is a difficult task for authors. Most of the multivariate procedures we cover in this book are very much related to each other in that they are different surface ways of expressing the same underlying model: the general linear model. The general linear model can be generally represented by the weighted linear composite discussed in Section 1.4. For example, multiple regression analysis involves generating a weighted linear composite of quantitatively measured variables to predict the value of a single outcome variable and canonical correlation analysis involves generating a weighted linear composite of quantitatively measured variables to predict the value of a weighted linear composite of other quantitatively measured variables.

Separating the chapters into groupings (Parts) is therefore done as a convenience for the readers. The groupings that we use, and even the ordering of the chapters within the groupings, is more of a matter of personal expression than a true classification system. The organizational structure of the multivariate domain is sufficiently fluid that we have opted for a somewhat different grouping of our chapters and chapter order in this third edition compared to our previous edition.

1.6.1 The Chapters Are in Pairs

Beginning with the third chapter, each topic is presented in the form of a pair of chapters labeled "A" and "B." The "A" chapter of the pair treats the topic at a relatively broad, conceptual level, focusing on the uses to which the design is often put, the rationale underlying the procedure, a description of how the procedure works, some of the decisions that are likely to be encountered in performing the analysis, and some issues of controversy when they are germane to the discussion. The "B" chapter of the pair describes a step-by-step procedure or set of procedures to perform the analysis in IBM SPSS (or, in most of the Part III chapters, IBM SPSS Amos), and how to interpret the output of the analysis. Some of the data sets that we use for our examples are modified versions (sometimes very substantially) of ones our students have collected in their research, and we use them with the permission of those students.

For each procedure that we perform in our "B" chapters, we present an example of how the results might be reported. It should be emphasized that there is no one best way to report results—we just wanted to illustrate one (hopefully) acceptable way to accomplish this. Readers are encouraged to consult Cooper (2010) for his suggestions on preparing results sections for dissemination. SAGE has established a place for the data files for the analyses demonstrated in each of the "B" chapters on their website (www.sagepub.com/meyers).

1.6.2 Part I: Fundamentals of Multivariate Design

The chapters in this part of the book introduce readers to the foundations or cornerstones of designing research and analyzing data. Our first chapter—the one that you are reading—discusses the idea of multivariate design and addresses the structure of this book. The second chapter on fundamental research concepts covers both some basics that readers have learned about in prior courses and possibly some new concepts and terms that will be explicated in much greater detail throughout this book. Data screening is covered in Chapters 3A and 3B. These issues are applicable to all the procedures we cover later, and so we cover them once in this pair of early chapters. We discuss ways to correct data entry mistakes, how to evaluate statistical assumptions underlying the data analysis, and how to handle missing data and outliers.

1.6.3 Part II: Basic and Advanced Regression Analysis

Regression procedures are used to predict the value of a single variable. Pearson correlation (used to describe the degree of linear relationship that is observed between two measures) and ordinary least squares simple linear regression (where we use one quantitative variable to predict a single outcome variable) are covered in Chapters 4A and 4B. Multiple regression analysis is an extension of simple linear regression when we use multiple measures to predict the outcome variable. The basics of this procedure are covered in Chapters 5A and 5B, and some (more advanced) variations of it are discussed in Chapters 6A and 6B.

Canonical correlation analysis, presented in Chapters 7A and 7B, is an extension of multiple regression analysis in which a set of quantitative independent variables is used to predict the values of a set of quantitative dependent variables. In many ways the process of interpreting the results strongly resembles and thus anticipates what we do in principal components and factor analysis.

When the limitations of ordinary least squares regression are exceeded, alternative regression techniques need to be initiated. Two such alternatives are presented in the next two pairs of chapters. Ordinary least squares regression assumes that the cases in the analysis are independent of each other, an assumption that is violated where cases are nested, that is, hierarchically organized. Examples of such organization are students within separate classrooms and clients of particular mental health clinics in a larger health system. In predicting an outcome variable, such as standardized test scores of the students, the children within a given classroom may be more related to each other on the outcome variable than they are to other students selected at random from the entire school or school district. To the extent that the children within a classroom are more alike than students selected at random, that is, to the extent that nesting is important, the assumption of independence is violated and we must use multilevel modeling in predicting the outcome variable. This topic is presented in Chapters 8A and 8B.

Ordinary least squares regression also assumes that the variable being predicted is measured on a quantitative scale of measurement. Yet it is often the case that we wish to predict to which group cases in the data file belong; here, group assignment is represented as a categorical variable. For example, we might want to predict whether an individual is likely to succeed or not succeed in a given program based on a set of variables. This type of prediction can be performed using binary or multinomial logistic regression, topics discussed in Chapters 9A and 9B. Prediction of a binary variable entails setting a decision point so that cases are classified or predicted as belonging to either one group or the other based on their score on a continuum. One powerful and commonly used procedure used to facilitate the trade-offs in selecting that decision point is receiver operating characteristic (ROC) curve analysis, and this topic is included within the logistic regression chapters.

1.6.4 Part III: Structural Relationships of Measured and Latent Variables

We very generally mean by structure some underlying relationships among the variables that can be brought to the surface by the statistical analysis or incorporated within a model specified by the researchers that can then be evaluated against the data. Often, but not always, these underlying relationships are organized into themes or dimensions. This is the realm of latent variables.

Principal components analysis and exploratory factor analysis, discussed in Chapters 10A and 10B, both describe the dimensions (latent variables) underlying a set of variables. For example, although a paper-and-pencil inventory may contain more than two dozen items, these items may tap into only three or four latent main themes or dimensions. Principal components analysis and exploratory factor analysis can be used to identify which items relate to each dimension.

Principal components analysis and exploratory factor analysis (both are discussed in Chapters 10A and 10B) are analogous to an inductive approach in that researchers employ a bottom-up strategy by developing a conclusion from specific observations. That is, the researchers determine the interpretation of the factor by examining the variate that emerged from the analysis. Confirmatory factor analysis (presented in Chapters 11A and 11B) seeks to determine if the number of factors and their respective measured variables as specified in a model hypothesized by the researchers is supported by the data set—that is, they determine the extent to which the proposed model fits the data.

Path (sometimes called causal) structures are presented in the next two sets of chapters. Such structures extend the thinking behind a multiple regression design to consider relationships and lines of influence among the predictors rather than just between a set of predictors and the outcome variable. When the variables in the hypothesized structure are all measured variables, we speak of path analysis, which can be analyzed through ordinary least squares regression (treated in Chapters 12A and 12B) or through structural equation modeling using IBM SPSS Amos (treated in Chapters 13A and 13B). When we have included latent variables in the path structure, the analysis becomes one of structural equation modeling and must be done in IBM SPSS Amos (or comparable specialized software); this topic is treated in Chapters 14A and 14B.

It is also possible to ask if a confirmatory factor structure and/or a structural equation model are equally applicable to two or more groups (e.g., males and females; Asian American, White American, and Latino/a American students). To address such a research question, we perform an invariance analysis on the structural configuration, and this topic is addressed in Chapters 15A and 15B.

1.6.5 Part IV: Synthesizing/Categorizing Data

Chapters 16A and 16B are devoted to multidimensional scaling. Objects or stimuli (e.g., brands of cars, retail stores) are assessed using a paired comparison procedure to determine the degree to which they are dissimilar. These dissimilarity data are analyzed in terms of the distance between the objects.

In turn, the distances between the objects are arrayed or represented in a space defined by the number of dimensions specified by the researchers who then attempt to interpret these dimensions along which the objects appear to differ.

Cluster analysis is presented in Chapters 17A and 17B. Rather than using common demographic variables to define groups (e.g., females and males), we group the cases (e.g., participants in a research study, presidents of the United States, brands of beer) on the basis of how they relate based on a set of quantitative variables. These groupings are called clusters. Two different approaches, hierarchical cluster analysis and *k*-means clustering, are described in the chapters.

1.6.6 Part V: Comparing Means

Part V addresses comparison of means. Chapters 18A and 18B cover analysis of covariance (ANCOVA), multivariate analysis of variance (MANOVA), and multivariate analysis of covariance (MANCOVA) using one-way and two-way between subjects designs. Discriminant function analysis is the flip side of MANOVA in which variates are generated to distinguish and characterize the groups in the analysis, and it is covered in Chapters 19A and 19B. Chapters 20A and 20B examine several techniques variously labeled as survival analysis. Survival analysis examines in a general sense the time interval between two events, often in the form of how long cases remain in one state (e.g., obtain their first full-time job) before changing to another state (e.g., change jobs). Three approaches are covered in these chapters: life tables, the Kaplan–Meier method, and Cox regression.

CHAPTER 2

Some Fundamental Research Design Concepts

We start our treatment of multivariate research design with a discussion, and for many readers a review, of some fundamental concepts that will serve as building blocks for the general arena of research design as well as some advanced concepts that are relevant to some of the material we cover in this book. These advanced concepts will be revisited in greater depth in later chapters.

2.1 Populations and Samples

A *population* is composed of all entities fitting the boundary conditions of whom or what we are intending to subsume (generalize to) in our research. Populations are typically made up of people or other entities meeting certain criteria. In basic behavioral science research, the population of interest is often "all humans." Some applied research may target smaller and more specific populations, such as "all breast cancer survivors" or "all senior citizens in community outreach programs." Some disciplines may focus on different types of entities such as schools in a given school district, hospitals meeting certain criteria, stores or offices of a given corporation, and so on.

In most situations, it is not possible to include all the population members in a research study. Instead, we select a workable number of individuals or entities (*cases* is the most general label) to represent the population. That set of cases in the study is the *sample*. Very often, the intention of the researchers is to study some process or phenomenon in the sample in order to generalize their conclusions to the population from which the sample was drawn.

Generalizing from the sample to the population is a delicate matter resting so strongly on a set of technical issues (e.g., sampling can be completely random or random based on some stratification of the population) that most research methods textbooks cover this topic in detail; indeed, there is enough complexity in procedures used for sampling that entire books have been written on it (e.g., Fuller, 2009; Levy & Lemeshow, 2008; Lohr, 2010; S. K. Thompson, 2002).

One issue affecting generalization concerns the extrapolation of the statistical results to the population and is strongly related to tests of statistical significance. Most tests of statistical significance are based on the data obtained from the sample, but they are really testing the null hypothesis stating (a) that there is no relationship in the population between or among the variables that we are studying or (b) that the sample means we are comparing were drawn from the same population. The null hypothesis is almost always different from the research hypothesis, which typically asserts that there will be significant correlations between the variables or there will be a significant difference between the treatment conditions. Statistical significance is part of a larger and more complex picture that is described in Sections 2.7 and 2.8.

Extrapolation of the statistical findings from the sample to the population presumes that the sample is representative of the population. The representativeness of a sample is itself a complex issue. In most situations, we prefer to randomly sample cases from the population, trusting that such randomness will result in the sample strongly resembling its parent population; however, randomness works in the very long run and concerns about such representativeness tend to be of greater concern with increasingly smaller sample sizes.

Another issue that affects generalization from the sample results to the population is attrition within the sample. Attrition is usually thought of as a loss of cases over time in a longitudinal design, but multivariate analyses are subject to this concern as well. Most of the multivariate statistical procedures require the cases to have valid values on all the measures (variables in the data analysis). With multiple measures taken on each case, it is possible that some of the cases will have missing data on at least one of the variables. When a particular case has a missing value on even one measure, that case will in many instances be removed from the entire multivariate analysis. If many participants are excluded in this manner, the possibility exists that those cases remaining in the analysis will comprise a subsample somewhat or even quite different from the sample as a whole (e.g., participants of one of the two sexes may be disproportionally dropped). Under such a circumstance, conclusions based on the results of analyses on the cases remaining may not be properly generalized back to the main sample and, by extension, to the original population. Much of Chapters 3A and 3B are devoted to dealing with the issue of missing values.

2.2 Variables and Scales of Measurement

2.2.1 Variables

It is difficult to read a textbook on research design or statistics without immediately encountering the notion of a variable. It is truly one of our fundamental concepts, and it tends to take on increasingly enriched meaning to students as they progress into more advanced coursework.

As a general characterization, *a variable is a construct that can take on different values*. When we assign values to variables, we speak of *measurement*. These values can be, and very often are, numbers that have *quantitative* meaning. Examples of quantitatively based variables include grade point average, which can take on numerical values between 0 and 4; the number of dollars in weekly vehicle sales, which can take on values in hundreds of thousands of dollars; and a score on a standardized test such as the Graduate Record Examination (GRE) revised General Test, which can range from 130 to 170. In data files, these values will be reproduced in the same form (e.g., a case would have 3.68 recorded for grade point average, 527,000 dollars recorded for weekly vehicle sales, and 161 recorded for test score).

Alternatively, the different values that variables can take may simply be names or identifiers for classes (categories) of individuals or entities. For example, breeds (e.g., collie, golden retriever) represent different types of dogs and sex labels (e.g., female, male) represent biologically different individuals. Categories can also be assigned arbitrary numerical codes, a strategy commonly used in representing these categories in data files. For example, we might code females as 1 and males as 2 under the variable of sex of participant.

Whether quantitatively based or categorically based, all the values for variables have been assigned through a set of rules defining a measurement operation. These measurement operations represent different scales of measurement.

2.2.2 Five Scales of Measurement

Although the essentials of measurement scales were known for some time before he formalized our treatment of them, it was S. S. Stevens who impressed this topic on the consciousness of behavioral scientists. As Stevens (1951) tells us, he initially broached this issue in a 1941 presentation to the International Congress for the Unity of Science. Stevens published a brief article addressing scales of measurement a few years later in *Science* (Stevens, 1946), but it was the prominent treatment of this topic in his lead chapter in the *Handbook of Experimental Psychology*, which he edited (Stevens, 1951), that most writers cite as the primary historical source.

Measurement (of variables) comprises sets of rules governing the way that values are assigned to entities. Each set of rules defines a scale of measurement, affecting both the kinds of manipulations we can appropriately perform on the values as well as the meaning we can derive from those values. Stevens (1951) identified four ordered scales: nominal, ordinal, interval, and ratio in that fixed order. Each scale includes an extra feature or rule over the one in the scale before it. We add a fifth scale to Stevens's treatment—the summative response scale—placing it between the ordinal and the interval scale. We summarize below the essence of each scale.

2.2.2.1 Nominal Scales

A *nominal* scale of measurement, sometimes called a *categorical* scale, a *qualitative* scale, or a *classification system*, has only one rule underlying its use: Cases will be identified as being different on the variable that is measured by assigning them to different predefined categories of the variable. There is no quantitative dimension implied here at all, no implication that one entity is in any way "more" or "less" than another. Examples of nominal scales include sex and race/ethnicity categories, types of businesses where people work, and medical conditions people have.

Differences between the cases are defined by the nominal or classification system. For example, individuals may be classified as female or male based on biological features. Within this classification system, the set of individuals identified as one of the two sexes may still represent a very diverse group who may differ substantially on a host of other characteristics. Although they are all classified as the same sex, it does not mean that they are identical in any other respect.

Numerical coding of categorical variables is regularly done when we are entering data into an IBM SPSS data file. Thus, in a study comparing students who enjoy reading different kinds of books for leisure, we might use 1 to denote a preference for science fiction, 2 to indicate a preference for mystery novels, and 3 to signify a preference for humor. In this situation, the numeric codes do not imply anything quantitative; they are used exclusively to represent different categories of preference.

2.2.2.2 Ordinal Scales

An *ordinal* scale of measurement uses numbers exclusively to represent the quantitative standing of cases on a variable. As was true for nominal scales, different numbers represent different information. But ordinal scales add this additional rule: The numbers convey "less than" and "more than" information, and so apply to variables that have features that can be quantitatively indexed (e.g., extension, intensity). Ordinal information translates most easily to a rank ordering of cases where 1 represents "the most" of whatever quantity is being measured, 2 represents "less than 1 but more than 3," 3 represents "less than 2 but more than 4," and so on.

Cases may be ranked in the order in which they align themselves on some quantitative dimension, but it is not possible from the ranking information to determine how far apart they are on the underlying dimension. For example, if we were ranking the height of three people, the one 7 feet tall would be ranked 1, the one 5 feet and 2 inches tall would be ranked 2, and the one 5 feet and 1 inch tall would be ranked 3. From the ranked data, we could not determine that two of the individuals were quite close in height.

2.2.2.3 Summative Response Scales

A *summative response* scale requires respondents to assign values to entities based on an underlying continuum defined by the anchors on the scale. The numbers are ordered, typically in an ascending way, to reflect more of the property being rated. Most common are 5-point and 7-point scales (Gamst, Meyers, Burke, & Guarino, 2015). These scales originated in the classic work of Louis Thurstone in the late 1920s (1927a, 1927b, 1928, 1929; Thurstone & Chave, 1929) in his pioneering work to develop interval-level measurement scales to assess attitudes. Based on Thurstone's time-consuming and resource-intensive scale development techniques, summative response scales were developed by Rensis Likert (pronounced "lick-ert" by the man himself) in the early 1930s to make the process more efficient (Likert, 1932), and he and his colleagues widely disseminated this scaling process later that decade (Likert, Roslow, & Murphy, 1934; Murphy & Likert, 1937). Derivatives of Likert's scale have become increasingly popular ever since.

It is called a summative scale because it is possible to add (sum) the ratings of a set of items together and to divide that sum by a constant (usually in the process of taking a mean) to obtain an individual's score on the set of items (an inventory). We will address this in a little more detail after introducing all the scales, but we wish to briefly illustrate here that the average (mean) derived from a summative response scale is meaningful, thus rendering this type of scale closer to interval-level than to ordinal-level measurement. The values may not represent equal distance between adjacent numbers (as required by interval scales), but the spacing is close enough to equal to meaningfully interpret averages of the values.

To illustrate that interpreting a mean of the scale values is meaningful, let's say that we administered a short self-esteem inventory to a class of medical students. Let's further say that one item on the inventory read, "I feel that I am a worthwhile person." Assume that items were rated on a 5-point scale with higher values indicating more endorsement of the statement. Let's further say that the mean for this item based on all the students in the class was 4.75. Is that value interpretable? Yes, it indicates that the individuals in the sample on average believed pretty strongly that the content of the item was quite true for them—namely, that they were worthwhile people.

2.2.2.4 Interval Scales

An *interval* scale of measurement has all the properties of nominal, ordinal, and summative response scales but includes one more important feature. Fixed intervals between the numbers represent equal intervals on the variable. It is also worthwhile noting that interval scales may have zero points, but the zero value is an arbitrary point on the scale (this contrasts with ratio scales as noted in Section 2.2.2.5).

The most common illustration of an equal interval scale is the Fahrenheit or Celsius temperature scale. These are interval scales in the sense that a 20° difference in one region of the scale represents the same amount of difference represented by a 20° difference in another region of the scale. According to Stevens (1951), "Equal intervals of temperature are scaled off by noting equal volumes of expansion" (p. 27). As an example of the arbitrariness of a zero value on an interval scale of measurement, consider that 0° does not mean the absence of temperature but is the temperature on the Celsius scale at which water freezes.

As was true for summative response scales, it is meaningful to average the data collected on an interval scale of measurement. We may therefore say that the average high temperature in our hometown this past week was 51.4 °F.

2.2.2.5 Ratio Scales

A *ratio* scale of measurement has all the properties of nominal, ordinal, summative response, and interval scales but includes one more important feature. Ratio scales have an absolute zero point on the variable, where zero means absence of the property that is measured. Common examples of ratio scales are time (e.g., minutes, years) and distance (e.g., centimeters, miles). Further, because the zero value is absolute, it is possible to interpret ratios of the numbers in a meaningful way. We can thus say that 4 hours is twice as long as 2 hours or that 3 miles is half the distance of 6 miles.

2.2.3 Algebraic Properties of the Scales

As we suggested above, the sorts of algebraic operations or manipulations that we can legitimately perform on data obtained from each of the scales of measurement is different and will thus limit the kind of data analysis we are able to appropriately use. We will discuss Stevens's classic set of four scales first and then fit summative response scales into what we have said.

Nominal measurement is not quantitatively based. Because of that, the only operations that can legitimately be performed on the data would be that of determining equality or inequality. For example, if we were going to classify entities in our world as either "animals" or "trees," then skunks and chipmunks would be classified as animals (and thus defined as being equal or comparable in this measurement or classification system), whereas redwood trees and birch trees would be classified as trees (and thus also defined as being equal). However, diamonds and phosphorus would not be classified in this system. Based on our classifying operation, it is legitimate to count the number of occurrences we observed in each category and to compare the counts to determine which is greater. We could thus say that in a given area, there were 25 animals and 41 trees. We can also assess the observed frequencies against some predetermined expectations (as is done in a chi square analysis).

Ordinal measurement allows us to compare cases in a quantitative manner but only to the extent of making greater-than or less-than determinations. If students are ranked in terms of their height, we may say that one student is taller than another. But it would not make much sense to identify two students whose ranks were 1 and 7 and to add those ranks together (to say that their total rank was 8 makes no sense) or take an average of the two ranks (to say that their average rank was 4 likewise makes no sense).

Interval measurement, where the quantitative scale is marked in terms of equal intervals, allows us to perform adding (subtracting) and averaging to the operations of equality/inequality and greater-than/less-than judgments. Thus, we can legitimately add the daily temperatures for the past 7 days and divide by 7 to arrive at a meaningful value: the average temperature for the week. It is also meaningful to compute a measure of dispersion of the scores, so that we could legitimately calculate a standard deviation.

Ratio measurement, with its absolute zero point, allows us to divide and multiply values to arrive at meaningful results in addition to doing all the above-mentioned operations. We cannot meaningfully interpret ratios on any of the other scales. To use Fahrenheit temperature (interval measurement) as an example, we would be incorrect in asserting that 40° is twice as warm as 20° because there is no absolute zero point to ground us. If you are not sure about this, just remember that a Celsius temperature scale is a transformation of the Fahrenheit scale. These Fahrenheit temperatures would have different values on the Celsius scale but would represent the same temperatures. And the Celsius ratio would yield a different value. This can be contrasted to the Kelvin scale of temperature where zero really does mean the absence of any heat. Using this latter scale with its absolute or true zero point, one can make ratio assertions about temperatures.

Now consider the scale we added to Stevens's list—summative response scales. It allows more operations than an ordinal scale because we can add (and subtract) its values and obtain a meaningful average. Despite this feature, however, some authors (e.g., Allen & Yen, 1979) have unequivocally placed these ratings scales within the province of ordinal measures. Historically, however, the scales have been treated more liberally. Likert (1932) himself argued that his scaling technique correlated close to 1 with the results of Thurstone's (1928; Thurstone & Chave, 1929) much more elaborate method that appeared to generate an equal interval scale assessing attitudes toward a particular issue. Guilford (1954), in his book *Psychometric Methods*, allowed summative response scales to at least have more interval-like properties than rank order scales, and Edwards (1957) goes a bit further, stating, "if our interest is in comparing the mean attitude scores of two or more groups, this can be done with summated-rating scales as well as with equal-appearing interval scales" (p. 157). Summarizing a study by Spector (1976), Ghiselli, Campbell, and Zedeck (1981) tell us, "Of particular interest with regard to Spector's research results is the finding that a majority of existing attitude scales *do* use categories of approximately equal intervals" (p. 414). Given the summary by Ghiselli et al., it is thus possible that people might treat summative response scales psychologically (cognitively) as approximating interval measurement.

Although it may be the case that some researchers will question the degree to which the points on a summative response scale are precisely evenly spaced (Velleman & Wilkinson, 1993), the vast majority of research published in the behavioral and social sciences over the past half century or more has used summative response scales as though they met interval properties. Researchers have added the scale points, have taken means and standard deviations, and have used these measurements in statistical analyses that ordinarily require interval or ratio measurement to properly interpret the results. In our view, this treatment of summative response scales is acceptable, appropriate, and quite useful. We therefore recommend that data analysis procedures that are ordinarily applied to interval and ratio measured variables also be applied to variables measured on a summative response scale.

2.2.4 Qualitative Versus Quantitative Measurement

It is possible to identify two categories into which we can classify subsets of these measurement scales: qualitative (categorical) and quantitative measurements. Qualitative measurement characterizes what we obtain from the nominal scale of measurement. There is no implied underlying quantitative dimension here even if the nominal values are numerical codes. Researchers sometimes call qualitative variables by other names, such as the following:

- Categorical variables
- Nonmetric variables
- Dichotomous variables (when there are only two values or categories)
- Grouped variables
- Classification variables

It is useful for our purposes to think of quantitative measurement in a somewhat restrictive manner. Although the ordinal scale certainly presumes an underlying quantitative dimension, we would generally propose thinking in terms of those scales for which it is meaningful and informative to compute a mean and standard deviation. With the ability to compute a mean and standard deviation and all that this ability implies, the gateway is open to performing a whole range of parametric statistical procedures, such as Pearson correlation and analysis of variance (ANOVA), as well as the host of multivariate procedures we discuss in this book. As we have seen, summative response, interval, and ratio scales meet this standard. Researchers sometimes call quantitative variables by other names, such as the following:

- Continuous variables (although technically, many quantitative variables can be assessed only in discrete steps even if the steps are very close together)
- Metric variables
- Ungrouped variables

2.2.5 Criticisms of Stevens's Schema

Most textbooks and common practice use the scale types Stevens proposed as part of the shared language of behavioral sciences. However, there may be pitfalls in accepting some of the details of the schema, and other classification systems (e.g., Mosteller & Tukey, 1977) of scale types have been proposed. Velleman and Wilkinson (1993) have provided an interesting history of many of the critiques of Stevens's notions of scale types. For example, some (e.g., Guttman, 1977; Lord, 1953a) have forcefully argued that the kinds of mathematical operations we perform on our data depend more on the sorts of questions that we are asking than on the particular level of the scale that best describes the data (but see Scholten & Borsboom, 2009). The approach to Stevens's scales that we have outlined should therefore be treated as a good starting point for understanding some basics of the scale types and implications for the sorts of data analysis that are appropriate to each.

2.3 Independent Variables, Dependent Variables, and Covariates

The concept of a variable is so central to research design, measurement, and statistical analysis that we find it applied in several different contexts. Especially in multivariate analyses, variables can play different roles in different analyses. Sometimes, variables can even assume multiple roles within a single analysis (e.g., as described in Chapters 6A, 12A, and 13A, a mediator variable in a path analysis is simultaneously a predicted/dependent variable in one portion of the analysis and a predictor/independent variable in another portion of the analysis). We therefore encourage readers to think of the variables in an analysis in this way—as entities specified by researchers to play their roles in a particular analysis, one role in this analysis, perhaps a second role in another analysis, perhaps multiple roles in some other analysis. The following sections present some of these different roles.

2.3.1 Independent Variables

In the prototypical experimental study, the independent variable represents the manipulation of the researchers. In a simple sense, it represents the treatment effect (what the researchers manipulate, vary, administer, etc.) contrasted with a control condition. Some of its features are as follows:

- It could have only two levels (e.g., control and experimental), but it could easily have three (e.g., control, placebo, and experimental) or more.
- It is only a single entity or continuum no matter how many levels represent it.
- In an experimental context, it is often, but not always, based on qualitative measurement; in a prediction (regression) context, it is almost always based on quantitative measurement.

Variables are also specifically identified as independent variables in the analysis of data. In a regression analysis, for example, the variables used as the predictors are the independent variables.

2.3.2 Dependent Variables

In the prototypical experiment, the dependent variable represents the outcome measure (response or performance) of the participants that is measured by the researchers. In a correlation/prediction design, all the measures can be thought of as dependent variables because researchers do not actively intervene by manipulating any variables (although we can also just think of them as measured variables). In general, dependent variables may be assessed on any scale of measurement. For the types of designs that we cover in this book, the dependent variables are almost always measured on one of the quantitative measurement scales.

Variables are also specifically identified as dependent variables in the analysis of data. In an ANOVA, for example, it is the variance of the dependent variable that is to be explained by the independent variables in the study. It is the variable representing the behavior of the participants. That is, when we say, "The mean for females was 3.52," what we are really saying is, "The mean value on the dependent variable for females was 3.52." As another example, in multiple regression analysis, the criterion variable—the variable being predicted by the independent variables—is known as the dependent variable.

2.3.3 Covariates

A covariate is a variable that either actually or potentially correlates (covaries) with a dependent variable. It is important to recognize the possible influence of a covariate because, without taking it into account, the relationship we observe between two dependent variables or between a dependent variable and an independent variable may lead us to an incorrect conclusion. That is, we would ordinarily infer from the existence of a relationship between two variables that they are directly associated. But that association may be mediated or caused by a third variable—the covariate.

A classic but simplified example is the relatively strong correlation between ice cream sales and crime rate. Higher crime rates are associated with greater quantities of ice cream being sold. Yes, the two variables are correlated; conceptually, however, they are not directly but only coincidentally associated. What mediates this relationship is the weather or the season of the year. For a variety of reasons, certain types of crimes are more likely to occur—or are facilitated by—the warmer weather during the summer months. Presumably, these crimes would take place whether or not ice cream was