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CHAPTER 6

MULTIVARIATE ANALYSIS OF VARIANCE AND COVARIANCE

All of the statistical analysis techniques discussed to this point have involved only one dependent variable. In this chapter, for the first time, we consider *multivariate statistics*—statistical procedures that involve more than one dependent variable. The focus of this chapter is on two of the most widely used multivariate procedures: the multivariate variations of analysis of variance and analysis of covariance. These versions of analysis of variance and covariance are designed to handle two or more dependent variables within the standard ANOVA/ANCOVA designs. We begin by discussing multivariate analysis of variance in detail, followed by a discussion of the application of covariance analysis in the multivariate setting.

I. MANOVA

Like ANOVA, multivariate analysis of variance (MANOVA) is designed to test the significance of group differences. The only substantial difference between the two procedures is that MANOVA can include several dependent variables, whereas ANOVA can handle only one DV. Oftentimes, these multiple dependent variables consist of different measures of essentially the same thing (Aron & Aron, 1999), but this need not always be the case. At a minimum, the DVs should have some degree of linearity and share a common conceptual meaning (Stevens, 1992). They should "make sense" as a group of variables. As you will soon see, the basic logic behind a MANOVA is essentially the same as in a univariate analysis of variance.

SECTION 6.1 PRACTICAL VIEW

Purpose

The clear advantage of a multivariate analysis of variance over a univariate analysis of variance is the inclusion of multiple dependent variables. Stevens (1992) provides two reasons why a researcher should be interested in using more than one DV when comparing treatments or groups based on differing characteristics:

(1) Any worthwhile treatment or substantial characteristic will likely affect subjects in more than one way; hence, the need for additional criterion (dependent) measures.
(2) The use of several criterion measures permits the researcher to obtain a more "holistic" picture, and therefore a more detailed description, of the phenomenon under investigation (pp. 151-152). This stems from the idea that it is extremely difficult to obtain a "good" measure of a trait (e.g.,

math achievement, self-esteem, etc.) from one variable; multiple measures on variables representing a common characteristic are bound to be more representative of that characteristic.

ANOVA tests whether mean differences among *k* groups on a single DV are significant, or likely to have occurred by chance. However, when we move to the multivariate situation, the multiple DVs are treated in combination. In other words, MANOVA tests whether mean differences among *k* groups on a *combination of DVs* are likely to have occurred by chance. As part of the actual analysis, a "new" DV is created. This new DV is, in fact, a linear combination of the original measured DVs, combined in such a way as to maximize the group differences (i.e., separate the *k* groups as much as possible). The new DV is created by developing a linear equation where each measured DV has an associated weight and, when combined and summed, creates maximum separation of group means with respect to the new DV:

$$Y_{new} = a_1Y_1 + a_2Y_2 + a_3Y_3 + \ldots + a_nY_n, \qquad \text{(Equation 6.1)}$$

where Y_n is an original DV, a_n is its associated weight, and n is the total number of original measured DVs. An ANOVA is then conducted on this newly created variable.

Let us consider the following example: Assume we wanted to investigate the differences in worker productivity, as measured by income level (DV_1) and hours worked (DV_2), for individuals of different age categories (IV). Our analysis would involve the creation of a new DV, which would be a linear combination (DV_{new}) of our subjects' income levels and numbers of hours worked that maximizes the separation of our age category groups. Our new DV would then be subjected to a univariate ANOVA by comparing variances on DV_{new} for the various groups as defined by age category.

One could also have a *factorial MANOVA*—a design that would involve multiple IVs as well as multiple DVs. In this situation, a different linear combination of DVs is formed for each main effect and each interaction (Tabachnick & Fidell, 1996). For example, we might consider investigating the effects of gender (IV_1) and job satisfaction (IV_2) on employee income (DV_1) and years of education (DV_2). Our analysis would actually provide three new DVs—the first linear combination would maximize the separation between males and females (IV_1), the second linear combination would maximize the separation among job satisfaction categories (IV_2), and the third would maximize the separation among the various cells of the interaction between gender and job satisfaction.

At this point, one might be inclined to question why a researcher would want to engage in a multivariate analysis of variance, as opposed to simply doing a couple of comparatively simple analyses of variance. MANOVA has several advantages over its simpler univariate counterpart (Tabachnick & Fidell, 1996). First, as previously mentioned, by measuring several DVs instead of only one, the chances of discovering what actually changes as a result of the differing treatments or characteristics (and any interactions) improves immensely. If we wanted to know what measures of work productivity are affected by gender and age, we improve our chances of uncovering these effects by including hours worked as well as income level.

There are also several statistical reasons for preferring a multivariate analysis over a univariate one (Stevens, 1992). A second advantage is that, under certain conditions, MANOVA may reveal differences not shown in separate ANOVAs (Tabachnick & Fidell, 1996; Stevens, 1992). Assume we have a one-way design, with two levels on the IV and two DVs. If separate ANOVAs are conducted on two DVs, the distributions for each of the two groups (and for each DV) might overlap sufficiently, such that a mean difference probably would not be found. However, when the two DVs are considered in combination with each other, the two groups may differ substantially and could result in a statistically significant difference between groups. Therefore, a MANOVA may sometimes be more powerful than separate ANOVAs.

Third, the use of several univariate analyses leads to a greatly inflated overall Type I error rate. Consider a simple design with one IV (with two levels) and five DVs. If we assume that we wanted to test for group differences on each of the DVs (at $\alpha = .05$ level of significance), we would have to conduct five univariate tests. Recall that at an α-level of .05, we are assuming a 95% chance of no Type I errors. Because of the assumption of independence, we can multiply the probabilities. The effect of these error rates is compounded over all of the tests such that the overall probability of *not* making a Type I error becomes:

$$(.95)(.95)(.95)(.95)(.95) = .77$$

In other words, the probability of at least one false rejection (i.e., Type I error) becomes

$$1 - .77 = .23$$

which, as we all know, is an unacceptably high rate of possible statistical decision error (Stevens, 1992). Therefore, using this approach of fragmented univariate tests results in an overall error rate which is entirely too risky. The use of MANOVA includes a condition that maintains the overall error rate at the .05 level, or whatever α-level is pre-selected (Harris, 1998).

Finally, the use of several univariate tests ignores some very important information. Recall that if several DVs are included in an analysis, they should be correlated to some degree. A multivariate analysis incorporates the intercorrelations among DVs into the analysis (this is essentially the basis for the linear combination of DVs).

The reader should keep in mind, however, that there are disadvantages in the use of MANOVA. The main disadvantage is the fact that MANOVA is substantially more complicated than ANOVA (Tabachnick & Fidell, 1996). In the use of MANOVA, there are several important assumptions that need to be met. Furthermore, the results are sometimes ambiguous with respect to the effects of IVs on individual DVs. Finally, situations in which MANOVA is more powerful than ANOVA, as discussed a few paragraphs ago, are quite limited; often the multivariate procedure is much *less* powerful than ANOVA (Tabachnick & Fidell, 1996). It has been recommended that one carefully consider the need for additional DVs in an analysis in light of the added complexity (Tabachnick & Fidell, 1996).

In the univariate case, the null hypothesis stated that the population means are equal:

$$H_0: \mu_1 = \mu_2 = \mu_3 = \ldots = \mu_k$$

The calculations for MANOVA, however, are based on matrix algebra (as opposed to scalar algebra). The null hypothesis in MANOVA states that the population *mean vectors* are equal:

$$H_0: \boldsymbol{\mu}_1 = \boldsymbol{\mu}_2 = \boldsymbol{\mu}_3 = \ldots = \boldsymbol{\mu}_k$$

For the univariate analysis of variance, recall that the *F*-statistic is used to test the tenability of the null hypothesis. This test statistic is calculated by dividing the variance between the groups by the variance within the groups. There are several available test statistics for multivariate analysis of variance, but the most commonly used criterion is Wilks' Lambda (Λ). (Other test statistics for MANOVA include Pillai's Trace, Hotelling's Trace, and Roy's Largest Root.) Without going into great detail, Wilks' Lambda is obtained by calculating $|\mathbf{W}|$ (a measure of the within-groups sum-of-squares and cross-products matrix—a multivariate generalization of the univariate sum-of-squares within [SS_W]) and dividing it by |**T**| (a measure of the total sum-of-squares and cross-products matrix—also a multivariate generalization, this time of the total sum-of-squares [SS_T]). The obtained value of Wilks' Λ ranges from zero to one. It is important to note that Wilks' Λ is an *inverse criterion*; i.e., the smaller the value of Λ, the more evidence for treatment effects or group differences (Stevens, 1992). The reader should realize that this is the opposite relationship that F has to the amount of treatment effect.

In conducting a MANOVA, one first tests the overall multivariate hypothesis (i.e., that all groups are equal on the combination of DVs). This is accomplished by evaluating the significance of the test associated with Λ. If the null hypothesis is retained, it is common practice to stop the interpretation of the analysis at this point and conclude that the treatments or conditions have no effect on the DVs. However, if the overall multivariate test is significant, the researcher then would likely wish to discover which of the DVs is being affected by the IV(s). To accomplish this, one conducts a series of univariate analyses of variance on the individual DVs. This will undoubtedly result in multiple tests of significance, which will result in an inflated Type I error rate.

To counteract the potential of an inflated error rate due to multiple ANOVAs, an adjustment must be made to the alpha level used for the tests. This *Bonferroni-type* adjustment involves setting a more stringent alpha level for the test of each DV so that the alpha for the *set* of DVs does not exceed some critical value (Tabachnick & Fidell, 1996). That critical value for testing each DV is usually the overall α-level for the analysis (e.g., $\alpha = .05$) divided by the number of DVs. For example, if one had three DVs and wanted an overall α equal to .05, each univariate test could be conducted at $\alpha = .016$, since .05/3=.0167. One should note that rounding down is necessary to create an overall alpha less than .05. The following equation may be used to check adjustment decisions:

$$\alpha = 1 - [(1 - \alpha_1)(1 - \alpha_2)\ldots(1 - \alpha_p)]$$

where the overall error rate (α) is based on the error rate for testing the first DV (α_1), the second DV (α_2), and all others to the p^{th} DV (α_p). All alphas can be set at the same level, or more important DVs can be given more liberal alphas (Tabachnick & Fidell, 1996).

Finally, for any univariate test of a DV that results in significance, one then conducts univariate post hoc tests (as discussed in Chapter 4) in order to identify where specific differences lie (i.e., which levels of the IV are different from which other levels). To summarize the analysis procedure for MANOVA, a researcher would follow these steps:

(1) Examine the overall multivariate test of significance—if the results are significant, proceed to the next step; if not, stop.
(2) Examine the univariate tests of individual DVs—if any are significant, proceed to the next step; if not, stop.
(3) Examine the post hoc tests for individual DVs.

Sample Research Questions

In our first sample study in this chapter, we are concerned with investigating differences in worker productivity, as measured by income level (DV_1) and hours worked (DV_2), for individuals of different age categories (IV)—a one-way MANOVA design. Therefore, this study would address the following research questions:

(1) Are there significant mean differences in worker productivity (as measured by the combination of income and hours worked) for individuals of different ages?
(2) Are there significant mean differences in income levels for individuals of different ages?

(2a) If so, which age categories differ?

(3) Are there significant mean differences in hours worked for individuals of different ages?

(3a) If so, which age categories differ?

Our second sample study will demonstrate a two-way MANOVA where we investigate the gender (IV_1) and job satisfaction (IV_2) differences in income level (DV_1) and years of education (DV_2). One should note the following questions address the MANOVA analysis, univariate ANOVA analyses, and post hoc analyses:

(1) a. Are there significant mean differences in the combined DV of income and years of education for males and females?

b. Are there significant mean differences in the combined DV of income and years of education for different levels of job satisfaction? If so, which job satisfaction categories differ?

c. Is there a significant interaction between gender and job satisfaction on the combined DV of income and years of education?

(2) a. Are there significant mean differences on income between males and females?

b. Are there significant mean differences on income between different levels of job satisfaction? If so, which job satisfaction categories differ?

c. Is there a significant interaction between gender and job satisfaction on income?

(3) a. Are there significant mean differences in years of education between males and females?

b. Are there significant mean differences in years of education among different levels of job satisfaction? If so, which job satisfaction categories differ?

c. Is there a significant interaction between gender and job satisfaction on years of education?

SECTION 6.2 ASSUMPTIONS AND LIMITATIONS

Since we are introducing our first truly multivariate technique in this chapter, we have a "new" set of statistical assumptions to discuss. They are new in that they apply to the multivariate situation; however, they are quite analogous to the assumptions for univariate analysis of variance, which we have already examined (see Chapter 4). For multivariate analysis of variance, these assumptions are:

(1) The observations within each sample must be randomly sampled and must be independent of each other.

(2) The observations on all dependent variables must follow a multivariate normal distribution in each group.

(3) The population covariance matrices for the dependent variables in each group must be equal (this assumption is often referred to as the *homogeneity of covariance matrices* assumption or the assumption of homoscedasticity).

(4) The relationships among all pairs of DVs for each cell in the data matrix must be linear.

As a reminder to the reader, the assumption of independence is primarily a design issue, not a statistical one. Provided the researcher has randomly sampled and assigned subjects to treatments, it is usually safe to believe that this assumption has not been violated. We will focus our attention on the assumptions of multivariate normality, homogeneity of covariance matrices, and linearity.

Methods of Testing Assumptions

As discussed in Chapter 3, multivariate normality implies that the sampling distribution of the means of each DV in each cell and all linear combinations of DVs are normally distributed (Tabachnick & Fidell, 1996). Multivariate normality is a difficult entity to describe and even more difficult to assess. Initial screening for multivariate normality consists of assessments for univariate normality (see Chapter 3) for all variables, as well as examinations of all bivariate scatterplots (see Chapter 3) to check that they are approximately elliptical (Stevens, 1992). Specific graphical tests for multivariate normality do exist, but are not available in standard statistical software packages (Stevens, 1996) and will not be discussed here.

It is probably most important to remember that both ANOVA and MANOVA are robust to moderate violations of normality, provided the violation is created by skewness and not by outliers (Tabachnick & Fidell, 1996). With equal or unequal sample sizes and only a few DVs, a sample size of about 20 in the smallest cell should be sufficient to ensure robustness to violations of univariate and multivariate normality. If it is determined that the data have substantially deviated from normal, transformations of the original data should be considered.

Recall that the assumption of equal covariance matrices (i.e., homoscedasticity) is a necessary condition for multivariate normality (Tabachnick & Fidell, 1996). The failure of the relationship between two variables to be homoscedastic is caused either by the nonnormality of one of the variables or by the fact that one of the variables may have some sort of relationship to the transformation of the other variable. Therefore, checking for univariate and multivariate normality is a good starting point for assessing possible violations of homoscedasticity. Specifically, possible violations of this assumption may be assessed by interpreting the results of Box's Test. The reader should note that a violation of the assumption of homoscedasticity, similar to a violation of homogeneity, will not prove fatal to an analysis (Tabachnick & Fidell, 1996; Kennedy & Bush, 1985). However, the results will be greatly improved if the heteroscedasticity is identified and corrected (Tabachnick & Fidell, 1996) by means of data transformations. On the other hand, if homogeneity of variance-covariance is violated, a more robust multivariate test statistic, Pillai's Trace, can be selected when interpreting the multivariate results.

Linearity is best assessed through inspection of bivariate scatterplots. If both variables in the pair are normally distributed and linearly related, the shape of the scatterplot should be elliptical. If one of the variables is not normally distributed, the relationship will not be linear and the scatterplot between the two variables will not appear oval shaped. As mentioned in Chapter 3, assessing linearity by means of bivariate scatterplots is an extremely subjective procedure. In situations where nonlinearity between variables is apparent, the data can once again be transformed in order to enhance the linear relationship.

SECTION 6.3 PROCESS AND LOGIC

The Logic Behind MANOVA

As previously mentioned, the calculations for MANOVA somewhat parallel those for a univariate ANOVA, although they exist in multivariate form (i.e., they rely on matrix algebra). Since several variables are involved in this analysis, calculations are based on a *matrix* of values, as opposed to the mathematical manipulations of a single value. Specifically, the matrix used in the calculations is the sum-of-squares and cross-products (SSCP) matrix, which you will recall is the precursor to the variance-covariance matrix (see Chapter 1).

In univariate ANOVA, recollect that the calculations are based on a partitioning of the total sum-of-squares into the sum-of-squares between the groups and the sum-of-squares within the groups:

$$SS_{\text{Total}} = SS_{\text{Between}} + SS_{\text{Within}}$$

In MANOVA, the calculations are based on the corresponding matrix analogue (Stevens, 1992), in which the total sum-of-squares and cross-products matrix (**T**) is partitioned into a between sum-of-squares and cross-products matrix (**B**) and a within sum-of-squares and cross-products matrix (**W**):

$$SSCP_{\text{Total}} = SSCP_{\text{Between}} + SSCP_{\text{Within}}$$

or

$$\mathbf{T} = \mathbf{B} + \mathbf{W} \qquad \text{(Equation 6.2)}$$

Wilks' Lambda (Λ) is then calculated by using the *determinants*—a sort of *generalized* variance for an entire set of variables—of the SSCP matrices (Stevens, 1992). The resulting formula for Λ becomes:

$$\Lambda = \frac{|\mathbf{W}|}{|\mathbf{T}|} = \frac{|\mathbf{W}|}{|\mathbf{B} + \mathbf{W}|} \qquad \text{(Equation 6.3)}$$

If there is no treatment effect or group differences, then $\mathbf{B} = 0$ and $\Lambda = 1$ indicating no differences between groups on the linear combination of DVs; whereas, if **B** were very large (i.e., substantially greater than 0), then Λ would approach 0, indicating significant group differences on the combination of DVs.

As in all of our previously discussed ANOVA designs, we can again obtain a measure of strength of association, or effect size. Recall that eta squared (η^2) is a measure of the magnitude of the relationship between the independent and dependent variables and is interpreted as the proportion of variance in the dependent variable explained by the independent variable(s) in the sample. For MANOVA, eta squared is obtained in the following manner:

$$\eta^2 = 1 - \Lambda$$

In the multivariate situation, η^2 is interpreted as the variance accounted for in the best linear combination of DVs by the IV(s) and/or interactions of IVs.

Interpretation of Results

The MANOVA procedure generates several test statistics to evaluate group differences on the combined DV: Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root. When the IV has only two categories, the *F* test for Pillai's Trace, Wilks' Lambda, and Hotelling's Trace will be identical. When the IV has three or more categories, the *F* test for these three statistics will differ slightly but will maintain consistent significance or non-significance. Although these test statistics may vary only slightly, Wilks' Lambda is the most commonly reported MANOVA statistic. Pillai's Trace is used when homogeneity of variance-covariance is in question. If two or more IVs are included in the analysis, factor interaction must be evaluated before main effects.

In addition to the multivariate tests, the output for MANOVA typically includes the test for homogeneity of variance-covariance (Box's Test), univariate ANOVAs, and univariate post hoc tests. Since homogeneity of variance-covariance is a test assumption for MANOVA and has implications in how to interpret the multivariate tests, the results of Box's Test should be evaluated first. Highly sensitive to the violation of normality, Box's Test should be interpreted with caution. Typically, if Box's Test is significant at $p<.001$ and group sample sizes are extremely unequal, then robustness cannot be assumed due to unequal variances among groups (Tabachnick & Fidell, 1996). In such a situation, a more robust MANOVA test statistic, Pillai's Trace, is utilized when interpreting the MANOVA results. If equal variances are assumed, Wilks' Lambda is commonly used as the MANOVA test statistic. Once the test statistic has been determined, factor interaction (*F* ratio and *p* value) should be assessed if two or more IVs are included in the analysis. Like two-way ANOVA, if interaction is significant, then inferences drawn from the main effects are limited. If factor interaction is *not* significant, then one should proceed to examine the *F* ratios and *p* values for each main effect. When multivariate significance is found, the univariate ANOVA results can indicate the degree to which groups differ for each DV. A more conservative alpha level should be applied using the Bonferroni adjustment. Post hoc results can then indicate which groups are significantly different for the DV if univariate significance is found for that particular DV.

In summary, the first step in interpreting the MANOVA results is to evaluate the Box's Test. If homogeneity of variance-covariance is assumed, utilize the Wilks' Lambda statistic when interpreting the multivariate tests. If the assumption of equal variances is violated, use Pillai's Trace. Once the multivariate test statistic has been identified, examine the significance (*F* ratios and *p* values) of factor interaction. This is necessary only if two or more IVs are included. Next evaluate the *F* ratios and *p* values for each factor's main effect. If multivariate significance is found, interpret the univariate ANOVA results to determine significant group differences for each DV. If univariate significance is revealed, examine the post hoc results to identify which groups are significantly different for each DV.

For our example that investigates age category (*agecat4*) differences in respondent's income (*rincom91*) and hours worked per week (*hrs1*), data were screened for missing data and outliers and then examined for fulfillment of test assumptions. Data screening led to the transformation of *rincom91* to *rincom2* in order to eliminate all cases with income equal to zero and cases equal to or exceeding 22. *Hrs1* was also transformed to *hrs2* as a means of reducing the number of outliers; those less than or equal to 16 were recoded 17, and those greater than or equal to 80 were recoded 79. Although normality of these transformed variables is still questionable, group sample sizes are quite large and fairly equivalent. Therefore, normality will be assumed. Linearity of the two DVs was then tested by creating a scatterplot and calculating the Pearson correlation coefficient. Results indicate a linear relationship. Although the correlation coefficient is statistically significant, it is still quite low (r=.253, p<.001). The last assumption, homogeneity of variance-covariance, will be tested within MANOVA. Thus, MANOVA was conducted utilizing the **Multivariate** procedure. The Box's Test (see Figure 6.1) reveals that equal variances can be assumed, $F(9, 2886561)$=.766, p=.648; therefore, Wilks' Lambda will be used as the test statistic. Figure 6.2 presents the MANOVA results. The Wilks' Lambda criteria indicates significant group differences in age category with respect to income and hours worked per week, Wilks' Λ=.909, $F(6,1360)$=11.04, p<.001, multivariate η^2=.046. Univariate ANOVA results (see Figure 6.3) were interpreted using a more conservative alpha level (α=.025). Results reveal that age category significantly differs for only income ($F(3, 681)$=21.00, p<.001, partial η^2=.085) and not hours worked per week ($F(3, 681)$=.167, p=.919, partial η^2=.001). Examination of post hoc results reveal that income of those 18-29 years of age significantly differs from all other age categories (see Figure 6.4). In addition, income for individuals 30-39 years differ from those 40-49 years.

Figure 6.1 Box's Test for Homogeneity of Variance-Covariance.

Box's Test of Equality of Covariance Matrices [a]

Box's M	6.936
F	.766
df1	9
df2	2886561
Sig.	.648

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept+AGECAT4

Box's test is not significant. Use Wilks' Lambda criteria.

Figure 6.2 Multivariate Tests for Income and Hours Worked by Age Category.

Multivariate Tests [c]

Effect		Value	F	Hypothesis df	Error df	Sig.	Eta Squared
Intercept	Pillai's Trace	.957	7507.272[a]	2.000	680.000	.000	.957
	Wilks' Lambda	.043	7507.272[a]	2.000	680.000	.000	.957
	Hotelling's Trace	22.080	7507.272[a]	2.000	680.000	.000	.957
	Roy's Largest Root	22.080	7507.272[a]	2.000	680.000	.000	.957
AGECAT4	Pillai's Trace	.091	10.791	6.000	1362.000	.000	.045
	Wilks' Lambda	.909	11.035[a]	6.000	1360.000	.000	.046
	Hotelling's Trace	.100	11.279	6.000	1358.000	.000	.047
	Roy's Largest Root	.099	22.457[b]	3.000	681.000	.000	.090

a. Exact statistic

b. The statistic is an upper bound on F that yields a lower bound on the significance level.

c. Design: Intercept+AGECAT4

Indicates that age category significantly differs for the combined DV.

Figure 6.3 Univariate ANOVA Summary Table.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Eta Squared
Corrected Model	RINCOM2	1029.016[a]	3	343.005	20.995	.000	.085
	HRS2	64.281[b]	3	21.427	.167	.919	.001
Intercept	RINCOM2	128493.5	1	128493.5	7864.965	.000	.920
	HRS2	1410954	1	1410954	10972.708	.000	.942
AGECAT4	RINCOM2	1029.016	3	343.005	20.995	.000	.085
	HRS2	64.281	3	21.427	.167	.919	.001
Error	RINCOM2	11125.807	681	16.337			
	HRS2	87568.119	681	128.588			
Total	RINCOM2	149966.0	685				
	HRS2	1575151	685				
Corrected Total	RINCOM2	12154.823	684				
	HRS2	87632.400	684				

a. R Squared = .085 (Adjusted R Squared = .081)

b. R Squared = .001 (Adjusted R Squared = -.004)

Indicates that age category significantly effects income but NOT hours worked.

Writing Up Results

Once again, any data transformations utilized to increase the likelihood of fulfilling test assumptions should be reported in the summary of results. The summary should then report the results from the multivariate tests by first indicating the test statistic utilized and its respective value and then reporting the *F* ratio, degrees of freedom, *p* value, and effect size for each IV main effect. If follow-up analysis was conducted using Univariate ANOVA, these results should be summarized next. Report the *F* ratio, degrees of freedom, *p* value, and effect size for the main effect on each DV. Utilize the post hoc results to indicate which groups were significantly different within each DV. Finally, you may want to create a table of means and standard deviations for each DV by the IV categories. In summary, the MANOVA results narrative should address the following:

(1) Subject elimination and/or variable transformation;
(2) MANOVA results (test statistic, *F*-ratio, degrees of freedom, *p*-value, and effect size);
    (a) Main effects for each IV on the combined DV;
    (b) Main effect for the interaction between IVs;
(3) Univariate ANOVA results (*F*-ratio, degrees of freedom, *p*-value, and effect size);
    (a) Main effect for each IV and DV;
    (b) Comparison of means to indicate which groups differ on each DV;
(4) Post hoc results (mean differences and levels of significance).

Utilizing our previous example, the following statement applies the results from Figures 6.1–6.4. A one-way multivariate analysis of variance (MANOVA) was conducted to determine age category differences in income and hours worked per week. Prior to the test, variables were transformed to eliminate outliers. Cases with income equal to zero or equal to or exceeding 22 were eliminated. Hours worked per week was also transformed; those less than or equal to 16 were recoded 17 and those greater than or equal to 80 were recoded 79. MANOVA results revealed significant differences among the age categories on the dependent variables, Wilks' Λ=.909, $F(6,1360)$=11.04, p<.001, multivariate η^2=.046. Analysis of variance (ANOVA) was conducted on each dependent variable as a follow-up test to MANOVA. Age category differences were significant for income, $F(3, 681)$=21.00, p<.001, partial η^2=.085. Differences in hours worked per week were not significant, $F(3, 681)$=.167, p=.919, partial η^2=.001. The Bonferroni post hoc analysis revealed that income of those 18-29 years significantly differs from all other age categories. In addition, income for individuals 30-39 years differs from those 40-49. Table 1 presents means and standard deviations for income and hours worked per week by age category.

Table 1 Means and Standard Deviations for Income and Hours Worked per Week by Age Category

	Income		**Hours Worked per Week**	
Age	*M*	*SD*	*M*	*SD*
18-29 years	11.87	4.14	46.32	10.32
30-39 years	14.03	3.88	47.03	11.42
40-49 years	15.32	3.87	46.49	11.75
50+ years	14.96	4.42	46.33	11.51

Figure 6.4 Post Hoc Results for Income and Hours Worked by Age Category.

Multiple Comparisons

Bonferroni

Dependent Variable	(I) 4 categories of age	(J) 4 categories of age	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
RINCOM2	1 18-29	2 30-39	-2.1643*	.4486	.000	-3.3513	-.9774
		3 40-49	-3.4576*	.4603	.000	-4.6754	-2.2397
		4 50+	-3.0903*	.4935	.000	-4.3960	-1.7846
	2 30-39	1 18-29	2.1643*	.4486	.000	.9774	3.3513
		3 40-49	-1.2932*	.3972	.007	-2.3443	-.2421
		4 50+	-.9259	.4353	.203	-2.0776	.2258
	3 40-49	1 18-29	3.4576*	.4603	.000	2.2397	4.6754
		2 30-39	1.2932*	.3972	.007	.2421	2.3443
		4 50+	.3673	.4473	1.000	-.8163	1.5509
	4 50+	1 18-29	3.0903*	.4935	.000	1.7846	4.3960
		2 30-39	.9259	.4353	.203	-.2258	2.0776
		3 40-49	-.3673	.4473	1.000	-1.5509	.8163
HRS2	1 18-29	2 30-39	-.7112	1.2585	1.000	-4.0412	2.6187
		3 40-49	-.1694	1.2913	1.000	-3.5861	3.2473
		4 50+	-5.929E-03	1.3844	1.000	-3.6690	3.6572
	2 30-39	1 18-29	.7112	1.2585	1.000	-2.6187	4.0412
		3 40-49	.5418	1.1145	1.000	-2.4070	3.4907
		4 50+	.7053	1.2211	1.000	-2.5258	3.9364
	3 40-49	1 18-29	.1694	1.2913	1.000	-3.2473	3.5861
		2 30-39	-.5418	1.1145	1.000	-3.4907	2.4070
		4 50+	.1634	1.2549	1.000	-3.1570	3.4839
	4 50+	1 18-29	5.929E-03	1.3844	1.000	-3.6572	3.6690
		2 30-39	-.7053	1.2211	1.000	-3.9364	2.5258
		3 40-49	-.1634	1.2549	1.000	-3.4839	3.1570

Based on observed means.

*. The mean difference is significant at the .05 level.

SECTION 6.4 MANOVA SAMPLE STUDY AND ANALYSIS

This section provides a complete example that applies the entire process of conducting MANOVA: development of research questions and hypotheses, data screening methods, test methods, interpretation of output, and presentation of results. The SPSS data set *gssft.sav* is utilized. Our previous example demonstrates a one-way MANOVA, while this example will present a two-way MANOVA.

Problem

This time, we are interested in determining the degree to which gender and job satisfaction affects income and years of education among employees. Since two IVs are tested in this analysis, questions must also take into account the possible interaction between factors. The following research questions and respective null hypotheses address the multivariate main effects for each IV and the possible interaction between factors.

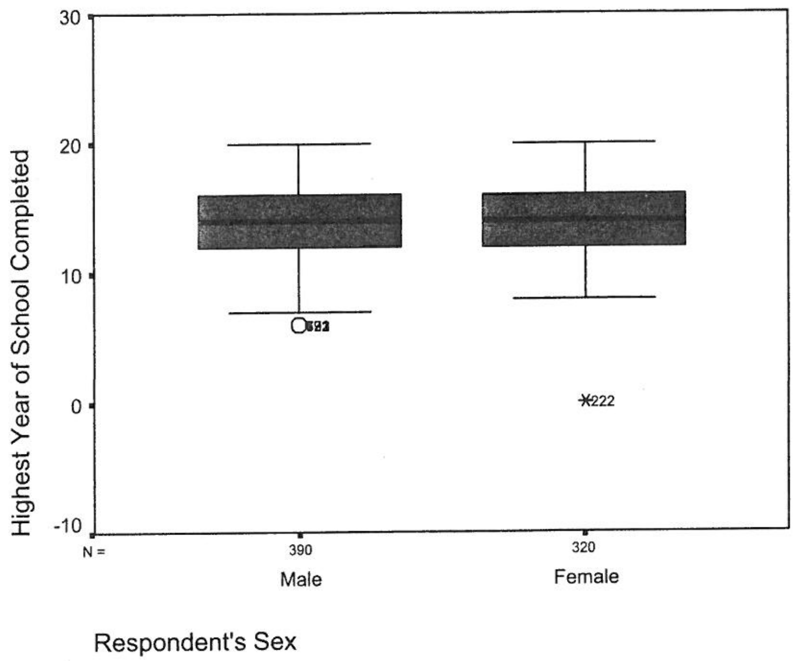
Research Questions		***Null Hypotheses***
RQ1: Do income and years of education differ by gender among employees?	→	H_01: Income and years of education will not differ by gender among employees.
RQ2: Do income and years of education differ by job satisfaction among employees?	→	H_02: Income and years of education will not differ by job satisfaction among employees.
RQ3: Do gender and job satisfaction interact in the effect on income and years of education?	→	H_03: Gender and job satisfaction will not interact in the effect on income and years of education.

Both IVs are categorical and include gender (*sex*) and job satisfaction (*satjob*). One should note that *satjob* represents four levels: very satisfied, moderately satisfied, a little dissatisfied, and very dissatisfied. The DVs are respondent's income (*rincom2*) and years of education (*educ*); both are quantitative. The variable, *rincom2*, is a transformation of *rincom91* from the previous example.

Method

Data should first be examined for missing data, outliers and fulfillment of test assumptions. The **Explore** procedure was conducted to identify outliers and evaluate normality. Boxplots (see Figure 6.5) indicate extreme values in *educ*. Consequently, *educ* was transformed to *educ2* in order to eliminate subjects with 6 years of education or less. **Explore** was conducted again to evaluate normality. Tests indicate significant non-normality for both *rincom2* and *educ2* in many categories (see Figure 6.6). Since MANOVA is fairly robust to non-normality, no further transformations will be performed. However, the significant non-normality coupled with the unequal group sample sizes, as in this example, may lead to violation of homogeneity of variance-covariance. The next step in examining test assumptions was to determine linearity between the DVs. A scatterplot was created; Pearson correlation coefficients were calculated (see Figure 6.7). Both indicate a linear relationship. Although the correlation coefficient is significant, it is still fairly weak (r=.337, p<.001). The final test assumption of homogeneity of variance-covariance will be tested with the MANOVA procedure. MANOVA was then conducted using **`Multivariate`**.

Figure 6.5 Boxplots for Years of Education by Gender and Job Satisfaction.



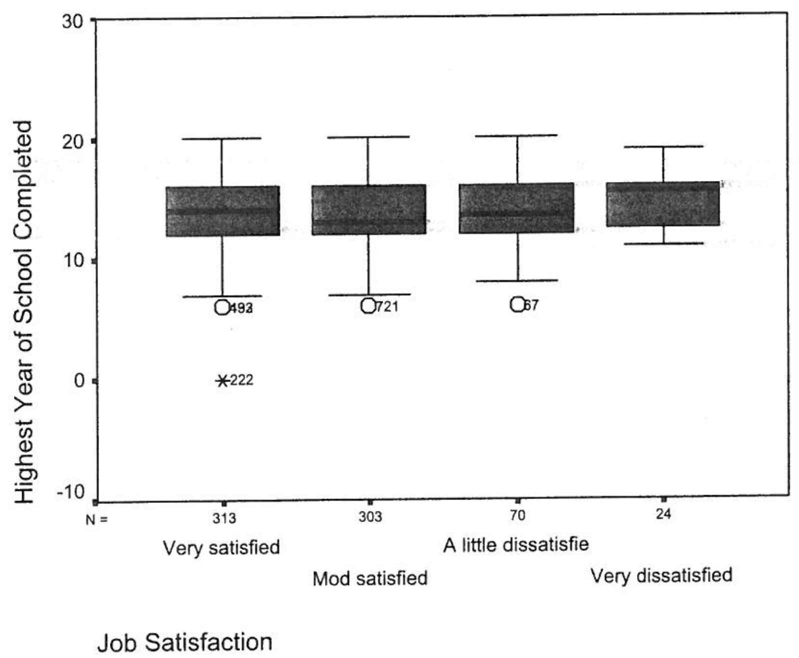


Figure 6.6 Tests of Normality of Income and Years of Education.

Tests of Normality

	SATJOB Job Satisfaction	Kolmogorov-Smirnov[a] Statistic	df	Sig.
RINCOM2	1 Very satisfied	.123	299	.000
	2 Mod satisfied	.080	291	.000
	3 A little dissatisfied	.086	67	.200*
	4 Very dissatisfied	.203	24	.012
EDUC2	1 Very satisfied	.148	299	.000
	2 Mod satisfied	.197	291	.000
	3 A little dissatisfied	.167	67	.000
	4 Very dissatisfied	.193	24	.021

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Some distributions of income by job satisfaction are significantly non-normal.

Distributions of education by job satisfaction are significantly non-normal.

Tests of Normality

	SEX Respondent's Sex	Kolmogorov-Smirnov[a] Statistic	df	Sig.
RINCOM2	1 Male	.100	374	.000
	2 Female	.110	307	.000
EDUC2	1 Male	.162	374	.000
	2 Female	.177	307	.000

a. Lilliefors Significance Correction

Gender distributions for income and education are significantly non-normal.

Figure 6.7 Correlation Coefficients for Income and Years of Education.

Correlations

		EDUC2	RINCOM2
EDUC2	Pearson Correlation	1.000	.337**
	Sig. (2-tailed)	.	.000
	N	742	681
RINCOM2	Pearson Correlation	.337**	1.000
	Sig. (2-tailed)	.000	.
	N	681	686

**. Correlation is significant at the 0.01 level (2-tailed).

Correlation coefficient indicates low relationship.

Output and Interpretation of Results

Figures 6.8 – 6.11 present some of the MANOVA output. The Box's Test (see Figure 6.8) is not significant and indicates that homogeneity of variance-covariance is fulfilled, $F(21, 20370)=1.245$, $p=.201$, so Wilks' Lambda test statistic will be used in interpreting the MANOVA results. The multivariate tests are presented in Figure 6.9. Factor interaction was then examined and revealed nonsignificance, $F(6, 1344)=.749$, $p=.610$, $\eta^2=.003$. The main effects of job satisfaction ($F(6, 1344)=3.98$, $p=.001$, $\eta^2=.017$) and gender ($F(2, 672)=8.14$, $p<.001$, $\eta^2=.024$) were both significant. However, multivariate effect sizes are very small. Prior to examining the univariate ANOVA results, the alpha level was adjusted to $\alpha=.025$ since two DVs were analyzed. Univariate ANOVA results (see Figure 6.10) indicate that income significantly differs for job satisfaction ($F(3, 673)=7.17$, $p<.001$, $\eta^2=.031$) and gender ($F(1, 673)=16.14$, $p<.001$, $\eta^2=.023$). Years of education do not significantly differ for job satisfaction ($F(3, 673)=2.18$, $p=.089$, $\eta^2=.010$) or gender ($F(1, 673)=1.03$, $p=.310$, $\eta^2=.002$). Scheffé post hoc results (see Figure 6.11) for income and job satisfaction indicate that individuals very satisfied significantly differ from those with only moderate satisfaction. Figures 6.12 and 6.13 present the unadjusted and adjusted group means for income and years of education.

Presentation of Results

The following narrative summarizes the results for the two-way MANOVA example.

A two-way MANOVA was conducted to determine the effect of job satisfaction and gender on the two dependent variables of respondent's income and years of education. Data were first transformed to eliminate outliers. Respondent's income was transformed to remove cases with income of zero or equal to or exceeding 22. Years of education was also transformed to eliminate cases with 6 or fewer years. MANOVA results indicate that job satisfaction (Wilks' $\Lambda=.965$, $F(6, 1344)=3.98$, $p=.001$, $\eta^2=.017$) and gender (Wilks' $\Lambda=.976$, $F(2, 672)=8.14$, $p<.001$, $\eta^2=.024$) significantly affect the combined DV of income and years of education. However, multivariate effect sizes are very small. Univariate ANOVA and Scheffé post hoc tests were conducted as follow-up tests. ANOVA results indicate that income significantly differs for job satisfaction ($F(3, 673)=7.17$, $p<.001$, $\eta^2=.031$) and gender ($F(1, 673)=16.14$, $p<.001$, $\eta^2=.023$). Years of education does not significantly differ for job satisfaction ($F(3, 673)=2.18$, $p=.089$, $\eta^2=.010$) or gender ($F(1, 673)=1.03$, $p=.310$, $\eta^2=.002$). Scheffé post hoc results for income and job satisfaction indicate that individuals very satisfied significantly differ from those with only moderate satisfaction. Table 1 presents the adjusted and unadjusted group means for income and years of education by job satisfaction and gender.

Table 1 Adjusted and Unadjusted Means for Income and Years of Education by Job Satisfaction and Gender

	Income		Years of Education	
	Adjusted *M*	**Unadjusted *M***	**Adjusted *M***	**Unadjusted *M***
Gender				
Male	14.95	15.15	14.37	14.07
Female	12.89	13.07	14.04	14.12
Job Satisfaction				
Very Satisfied	14.93	15.02	14.33	14.32
Mod. Satisfied	13.42	13.52	13.84	13.83
Little Dissatisfied	13.74	13.81	13.99	14.00
Very Dissatisfied	13.61	13.71	14.68	14.79

Figure 6.8 Box's Test for Homogeneity of Variance-Covariance.

Box's Test of Equality of Covariance Matrices[a]

Box's M	26.935
F	1.245
df1	21
df2	20370
Sig.	.201

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept+SATJOB+SEX+SATJOB * SEX

Box's Test is NOT significant. Use Wilks' Lambda criteria.

SECTION 6.5 SPSS "HOW TO" FOR MANOVA

This section presents the steps for conducting multivariate analysis of variance (MANOVA) using the **`Multivariate`** procedure for the preceding example, which utilizes the *gssft.sav* data set. To open the Multivariate dialogue box as shown in Figure 6.14, select the following:

`Analyze`
`General Linear Model`
`Multivariate`

`Multivariate` Dialogue Box (see Figure 6.14)

Once in this box, click the DVs (*rincom2* and *educ2*) and move each to the Dependent Variables box. Click the IVs (*satjob* and *sex*) and move each to the Fixed Factor(s) box. Then click **`Options`**.

`Multivariate Options` Dialogue Box (see Figure 6.15)

Move each IV to the Display Means box. Select **`Descriptive Statistics, Estimates of Effect Size`**, and **`Homogeneity Tests`** under Display. These options are described in Chapter 4. Click **`Continue`**. Back in the **`Multivariate`** Dialogue Box, click **`Post Hoc`**.

Figure 6.9 MANOVA Summary Table.

Multivariate Tests[c]

Effect		Value	F	Hypothesis df	Error df	Sig.	Eta Squared
Intercept	Pillai's Trace	.923	4042.110[a]	2.000	672.000	.000	.923
	Wilks' Lambda	.077	4042.110[a]	2.000	672.000	.000	.923
	Hotelling's Trace	12.030	4042.110[a]	2.000	672.000	.000	.923
	Roy's Largest Root	12.030	4042.110[a]	2.000	672.000	.000	.923
SATJOB	Pillai's Trace	.035	3.967	6.000	1346.000	.001	.017
	Wilks' Lambda	.965	3.984[a]	6.000	1344.000	.001	.017
	Hotelling's Trace	.036	4.002	6.000	1342.000	.001	.018
	Roy's Largest Root	.033	7.291[b]	3.000	673.000	.000	.031
SEX	Pillai's Trace	.024	8.135[a]	2.000	672.000	.000	.024
	Wilks' Lambda	.976	8.135[a]	2.000	672.000	.000	.024
	Hotelling's Trace	.024	8.135[a]	2.000	672.000	.000	.024
	Roy's Largest Root	.024	8.135[a]	2.000	672.000	.000	.024
SATJOB * SEX	Pillai's Trace	.007	.750	6.000	1346.000	.609	.003
	Wilks' Lambda	.993	.749[a]	6.000	1344.000	.610	.003
	Hotelling's Trace	.007	.748	6.000	1342.000	.611	.003
	Roy's Largest Root	.005	1.051[b]	3.000	673.000	.370	.005

a. Exact statistic

b. The statistic is an upper bound on F that yields a lower bound on the significance level.

c. Design: Intercept+SATJOB+SEX+SATJOB * SEX

Indicates that job satisfaction significantly effects the combined DV.

Indicates that gender significantly effects the combined DV.

Indicates that factor interaction is NOT significantly effecting the combined DV.

Figure 6.10 Univariate ANOVA Summary Table.

Indicates that job satisfaction significantly effects income but NOT years of education.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Eta Squared
Corrected Model	RINCOM2	1101.382[a]	7	157.340	9.676	.000	.091
	EDUC2	64.156[b]	7	9.165	1.358	.220	.014
Intercept	RINCOM2	47955.386	1	47955.386	2949.195	.000	.814
	EDUC2	49956.968	1	49956.968	7404.472	.000	.917
SATJOB	RINCOM2	349.728	3	116.576	7.169	.000	.031
	EDUC2	44.078	3	14.693	2.178	.089	.010
SEX	RINCOM2	262.463	1	262.463	16.141	.000	.023
	EDUC2	6.952	1	6.952	1.030	.310	.002
SATJOB * SEX	RINCOM2	26.942	3	8.981	.552	.647	.002
	EDUC2	15.304	3	5.101	.756	.519	.003
Error	RINCOM2	10943.317	673	16.261			
	EDUC2	4540.639	673	6.747			
Total	RINCOM2	149640.0	681				
	EDUC2	139907.0	681				
Corrected Total	RINCOM2	12044.699	680				
	EDUC2	4604.796	680				

a. R Squared = .091 (Adjusted R Squared = .082)

b. R Squared = .014 (Adjusted R Squared = .004)

Indicates that gender significantly effects income but NOT years of education.

<u>`Multivariate Post Hoc` Dialogue Box (see Figure 6.16)</u>

Under Factors, select the IVs (*satjob*) and move to Post Hoc Tests box. For our example, only *satjob* was selected since gender has only two categories. Under Equal Variances Assumed, select the desired post hoc test. We selected Scheffé.

Figure 6.11 Post Hoc Tests for Income and Years of Education by Job Satisfaction.

Multiple Comparisons

Scheffe

Dependent Variable	(I) Job Satisfaction	(J) Job Satisfaction	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
RINCOM2	1 Very satisfied	2 Mod satisfied	1.5045*	.3321	.000	.5739	2.4351
		3 A little dissatisfied	1.2174	.5450	.174	-.3101	2.7450
		4 Very dissatisfied	1.3151	.8555	.501	-1.0826	3.7127
	2 Mod satisfied	1 Very satisfied	-1.5045*	.3321	.000	-2.4351	-.5739
		3 A little dissatisfied	-.2871	.5464	.964	-1.8184	1.2443
		4 Very dissatisfied	-.1894	.8564	.997	-2.5895	2.2107
	3 A little dissatisfied	1 Very satisfied	-1.2174	.5450	.174	-2.7450	.3101
		2 Mod satisfied	.2871	.5464	.964	-1.2443	1.8184
		4 Very dissatisfied	9.764E-02	.9593	1.000	-2.5908	2.7861
	4 Very dissatisfied	1 Very satisfied	-1.3151	.8555	.501	-3.7127	1.0826
		2 Mod satisfied	.1894	.8564	.997	-2.2107	2.5895
		3 A little dissatisfied	-9.764E-02	.9593	1.000	-2.7861	2.5908
EDUC2	1 Very satisfied	2 Mod satisfied	.4929	.2139	.152	-.1066	1.0923
		3 A little dissatisfied	.3211	.3511	.841	-.6629	1.3050
		4 Very dissatisfied	-.4706	.5511	.866	-2.0150	1.0738
	2 Mod satisfied	1 Very satisfied	-.4929	.2139	.152	-1.0923	.1066
		3 A little dissatisfied	-.1718	.3520	.971	-1.1582	.8146
		4 Very dissatisfied	-.9635	.5516	.385	-2.5095	.5825
	3 A little dissatisfied	1 Very satisfied	-.3211	.3511	.841	-1.3050	.6629
		2 Mod satisfied	.1718	.3520	.971	-.8146	1.1582
		4 Very dissatisfied	-.7917	.6179	.650	-2.5234	.9401
	4 Very dissatisfied	1 Very satisfied	.4706	.5511	.866	-1.0738	2.0150
		2 Mod satisfied	.9635	.5516	.385	-.5825	2.5095
		3 A little dissatisfied	.7917	.6179	.650	-.9401	2.5234

Based on observed means.

*. The mean difference is significant at the .05 level.

II. MANCOVA

As with univariate ANCOVA, researchers often wish to control for the effects of concomitant variables in a multivariate design. The appropriate analysis technique for this situation is a multivariate analysis of covariance, or MANCOVA. Multivariate analysis of covariance is essentially a combination of MANOVA and ANCOVA. MANCOVA asks if there are statistically significant mean differences among groups after adjusting the newly created DV (a linear combination of all original DVs) for differences on one or more covariates.

SECTION 6.6 PRACTICAL VIEW

Purpose

The main advantage of MANCOVA over MANOVA is the fact that the researcher can incorporate one or more covariates into the analysis. The effects of these covariates are then removed from the analysis, leaving the researcher with a clearer picture of the true effects of the IV(s) on the multiple DVs. There are two main reasons for including several (i.e., more than one) covariates in the analysis (Stevens, 1992). First, the inclusion of several covariates will result in a greater reduction in error variance than would result from incorporation of one covariate. Recall that in ANCOVA, the main reason for including a covariate is to remove from the error term unwanted sources of variability (variance within the groups), which could be attributed to the covariate. This ultimately results in a more sensitive

F-test, which increases the likelihood of rejecting the null hypothesis. By including more covariates in a MANCOVA analysis, we can reduce this unwanted error by an even greater amount, improving the chances of rejecting a null hypothesis that is really false.

Figure 6.12 Unadjusted Means for Income and Years of Education by Gender and Job Satisfaction.

Descriptive Statistics

	SATJOB Job Satisfaction	SEX Respondent's Sex	Mean	Std. Deviation	N
RINCOM2	1 Very satisfied	1 Male	15.8193	3.7389	166
		2 Female	14.0301	4.0093	133
		Total	15.0234	3.9565	299
	2 Mod satisfied	1 Male	14.5157	4.3237	159
		2 Female	12.3182	4.0367	132
		Total	13.5189	4.3298	291
	3 A little dissatisfied	1 Male	15.2571	4.1398	35
		2 Female	12.2187	3.7566	32
		Total	13.8060	4.2184	67
	4 Very dissatisfied	1 Male	14.2143	5.0563	14
		2 Female	13.0000	2.8674	10
		Total	13.7083	4.2475	24
	Total	1 Male	15.1524	4.1183	374
		2 Female	13.0717	4.0376	307
		Total	14.2144	4.2087	681
EDUC2	1 Very satisfied	1 Male	14.2590	2.8856	166
		2 Female	14.3985	2.2086	133
		Total	14.3211	2.6030	299
	2 Mod satisfied	1 Male	13.7484	2.6766	159
		2 Female	13.9242	2.4762	132
		Total	13.8282	2.5847	291
	3 A little dissatisfied	1 Male	14.1429	2.7880	35
		2 Female	13.8438	2.5541	32
		Total	14.0000	2.6629	67
	4 Very dissatisfied	1 Male	15.3571	2.4685	14
		2 Female	14.0000	2.1602	10
		Total	14.7917	2.3953	24
	Total	1 Male	14.0722	2.7860	374
		2 Female	14.1238	2.3635	307
		Total	14.0954	2.6023	681

A second reason for including more than one covariate is that it becomes possible to make better adjustments for initial differences in situations where the research design includes the use of intact groups (Stevens, 1992). The researcher has even more information upon which to base the statistical matching procedure. In this case, the means of the linear combination of DVs for each group are adjusted to what they would be if all groups had scored equally on the combination of covariates.

Again, the researcher needs to be cognizant of the choice of covariates in a multivariate analysis. There should exist a significant relationship between the set of DVs and the covariate or set of covariates (Stevens, 1992). Similar to ANCOVA, if more than one covariate is being used, there should be relatively low intercorrelations among all covariates (roughly $< .40$). In ANCOVA, the amount of error reduction was a result of the magnitude of the correlation between the DV and the covariate. In

MANCOVA, if several covariates are being used, the amount of error reduction is determined by the magnitude of the multiple correlation (R^2) between the newly created DV and the set of covariates (Stevens, 1992). A higher value for R^2 is directly associated with low intercorrelations among covariates, which means a greater degree of error reduction.

Figure 6.13 Adjusted Means for Income and Years of Education by Gender and Job Satisfaction.

1. Respondent's Sex

				95% Confidence Interval	
Dependent Variable	Respondent's Sex	Mean	Std. Error	Lower Bound	Upper Bound
RINCOM2	Male	14.952	.338	14.288	15.615
	Female	12.892	.386	12.135	13.649
EDUC2	Male	14.377	.218	13.950	14.804
	Female	14.042	.248	13.554	14.529

2. Job Satisfaction

				95% Confidence Interval	
Dependent Variable	Job Satisfaction	Mean	Std. Error	Lower Bound	Upper Bound
RINCOM2	Very satisfied	14.925	.235	14.464	15.385
	Mod satisfied	13.417	.237	12.951	13.883
	A little dissatisfied	13.738	.493	12.770	14.706
	Very dissatisfied	13.607	.835	11.968	15.246
EDUC2	Very satisfied	14.329	.151	14.032	14.626
	Mod satisfied	13.836	.153	13.536	14.137
	A little dissatisfied	13.993	.318	13.370	14.617
	Very dissatisfied	14.679	.538	13.623	15.734

Figure 6.14 Multivariate Dialogue Box.

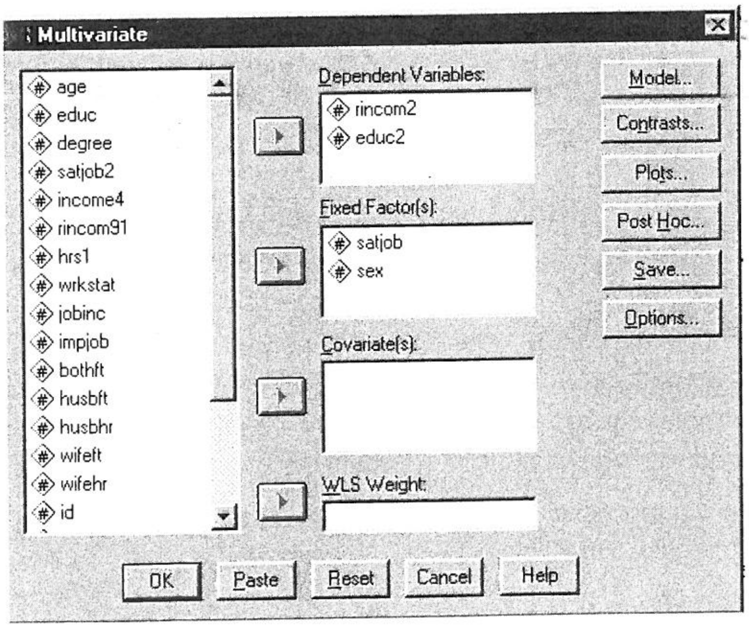


Figure 6.15 Multivariate Options Dialogue Box.

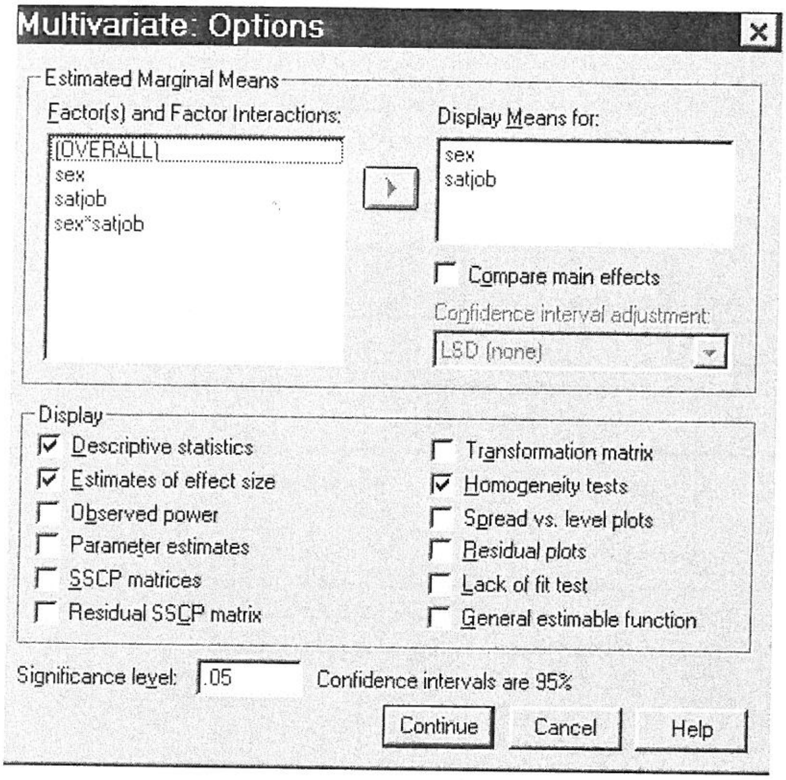
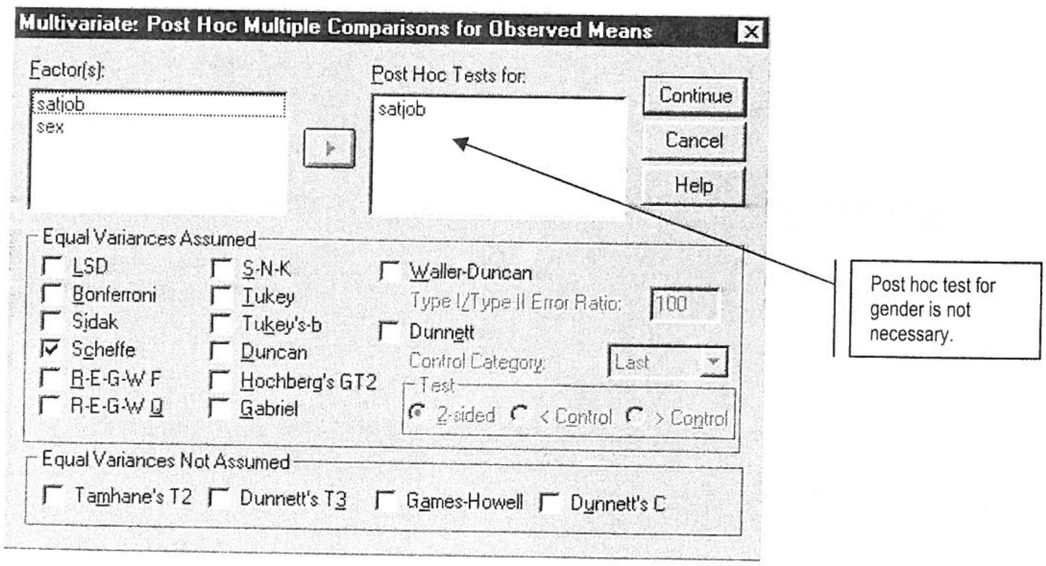


Figure 6.16 Multivariate Post Hoc Dialogue Box.



The null hypothesis being tested in MANCOVA is that the *adjusted* population mean vectors are equal:

$$H_0: \mu_{1_{adj}} = \mu_{2_{adj}} = \mu_{3_{adj}} = \ldots = \mu_{k_{adj}}$$

Wilks' Lambda (Λ) is again the most common test statistic used in MANCOVA. However, in this case, the sum-of-squares and cross-products (SSCP) matrices are first adjusted for the effects of the covariate(s).

The procedure to be used in conducting MANCOVA mirrors that used in conducting MANOVA. Following the statistical adjustment of newly created DV scores, the overall multivariate null hypothesis is evaluated using Wilks' Λ. If the null is retained, interpretation of the analysis ceases at this point. However, if the overall null hypothesis is rejected, the researcher then examines the results of univariate ANCOVAs in order to discover which DVs are being affected by the IV(s). A Bonferroni-type adjustment to protect from the potential of an inflated Type I error rate is again appropriate at this point.

The reader may recall from Chapter 5 explicit mention of a specific application of MANCOVA that is used to assess the contribution of each individual DV to any significant differences in the IVs. This procedure is accomplished by removing the effects of all other DVs by treating them as covariates in the analysis.

Sample Research Questions

In the sample study presented earlier in this chapter, we investigated the differences in worker productivity (measured by income level, DV_1, and hours worked, DV_2) for individuals in different age categories (IV). Assume that the variable of years of education has been shown to relate to both DVs and we want to remove its effect from the analysis. Consequently, we decide to include years of education as a covariate in our analysis. Therefore, the design we have is now a one-way MANCOVA. Accordingly, this study would address the following research questions:

(1) Are there significant mean differences in worker productivity (as measured by the combination of income and hours worked) for individuals of different ages, after removing the effect of years of education?

(2) Are there significant mean differences in income levels for individuals of different ages, after removing the effect of years of education?

(2a) If so, which age categories differ?

(3) Are there significant mean differences in hours worked for individuals of different ages, after removing the effect of years of education?

(3a) If so, which age categories differ?

For our second MANCOVA example, we will add a covariate to our two-factor design presented earlier. This two-way MANCOVA will investigate differences in the combined DV of income level (DV_1,) and years of education (DV_2) for individuals of different gender (IV_1) and of different levels of job satisfaction (IV_2), while controlling for age. Again, one should note that the following research questions address both the multivariate and univariate analyses within MANCOVA:

(1) a. Are there significant mean differences in the combined DV of income and years of education between males and females, after removing the effect of age?

b. Are there significant mean differences in the combined DV of income and years of education for different levels of job satisfaction, after removing the effect of age? If so, which job satisfaction categories differ?
c. Is there a significant interaction between gender and job satisfaction on the combined DV of income and years of education, after removing the effect of age?

(2) a. Are there significant mean differences on income between males and females, after removing the effect of age?
b. Are there significant mean differences on income among different levels of job satisfaction, after removing the effect of age? If so, which job satisfaction categories differ?
c. Is there a significant interaction between gender and job satisfaction on income, after removing the effect of age?

(3) a. Are there significant mean differences in years of education between males and females, after removing the effect of age?
b. Are there significant mean differences in years of education among different levels of job satisfaction, after removing the effect of age? If so, which job satisfaction categories differ?
c. Is there a significant interaction between gender and job satisfaction on years of education, after removing the effect of age?

SECTION 6.7 ASSUMPTIONS AND LIMITATIONS

Multivariate analysis of covariance rests on the same basic assumptions as univariate ANCOVA. However, the assumptions for MANCOVA must accommodate multiple DVs. The following list presents the assumptions for MANCOVA, with an asterisk indicating modification from the ANCOVA assumption.

(1) The observations within each sample must be randomly sampled and must be independent of each other.
(2*) The distributions of scores on the dependent variables must be normal in the populations from which the data were sampled.
(3*) The distributions of scores on the dependent variables must have equal variances.
(4*) Linear relationships must exist between all pairs of DVs, all pairs of covariates, and all DV-covariate pairs in each cell.
(5*) If two covariates are used, the regression planes for each group must be homogeneous or parallel. If more than two covariates are used, the regression hyperplanes must be homogeneous.
(6) The covariates are reliable and are measured without error.

The first and sixth assumptions essentially remain unchanged. Assumptions #2 and #3 are simply modified in order to include multiple DVs. Assumption #4 has a substantial modification in that we must now assume linear relationships not only between the DV and the covariate, but also among several other pairs of variables (Tabachnick & Fidell, 1996). There also exists an important modification to assumption number 5. Recall that if only one covariate is included in the analysis, there exists the assumption that covariate regression slopes for each group are homogeneous. However, if the MANCOVA analysis involves more than one covariate, the analogous assumption involves homogeneity of regression planes (for 2 covariates) and hyperplanes (for 3 or more covariates).

Our discussion of assessing MANCOVA assumptions will center on the two substantially modified assumptions (i.e., #4 and #5). Similar procedures, as have been discussed earlier, are used for testing the remaining assumptions.

Methods of Testing Assumptions

The assumption of normally distributed DVs is assessed in the usual manner. Initial assessment of normality is done through inspection of histograms, boxplots, and normal Q-Q plots. Statistical assessment of normality is accomplished by examining the values (and the associated significance tests) for skewness and kurtosis, and through the use of the Kolmogorov-Smirnov test. The assumption of homoscedasticity is assessed primarily with Box's Test or using one of three different statistical tests discussed in previous chapters (i.e., Chapters 3 and 5), namely Hartley's *F*-max test, Cochran's test, or Levene's test.

The assumption of linearity among all pairs of DVs and covariates is crudely assessed by inspecting the within-cells bivariate scatterplots between all pairs of DVs, all pairs of covariates, and all DV-covariate pairs. This process is feasible if the analysis includes only a small number of variables. However, the process becomes much more cumbersome (and potentially unmanageable!) with analyses involving the examination of numerous DVs and/or covariates—just imagine all of the possible bivariate pairings! If the researcher is involved in such an analysis, one recommendation is to engage in "spot checks" of random bivariate relationships or bivariate relationships in which nonlinearity may be likely (Tabachnick & Fidell, 1996).

Once again, if curvilinear relationships are indicated, they may be corrected by transforming some or all of the variables. Bear in mind that transforming the variables may create difficulty in interpretations. One possible solution might be to eliminate the covariate that appears to produce nonlinearity and replacing it with another appropriate covariate (Tabachnick & Fidell, 1996).

The reader will remember that a violation of the assumption of homogeneity of regression slopes (as well as regression planes and hyperplanes) is an indication that there is a covariate by treatment (IV) interaction, meaning that the relationship between the covariate and the newly created DV is different at different levels of the IV(s). A preliminary or custom MANCOVA can be conducted to test the assumption of homogeneity of regression planes (in the case of two covariates) or regression hyperplanes (in the case of three or more covariates). If the analysis contains more than one covariate, there is an interaction effect for each covariate. The effects are lumped together and tested as to whether the combined interactions are significant (Stevens, 1992).

The null hypothesis being tested in these cases is that all regression planes/hyperplanes are equal and parallel. Rejecting this hypothesis means that there is a significant interaction between covariates and IVs and that the planes/hyperplanes are not equal. If the researcher is to continue in the use of multivariate analysis of covariance, one would hope to fail to reject this particular null hypothesis. In SPSS, this is determined by examining the results of the *F*-test for the interaction of the IV(s) by the covariate(s).

SECTION 6.8 PROCESS AND LOGIC

The Logic Behind MANCOVA

The calculations for MANCOVA are nearly identical to those for MANOVA. The only substantial difference is that the sum-of-squares and cross-products (SSCP) matrices must first be adjusted for the effects of the covariate(s). The adjusted matrices are symbolized by **T*** (adjusted total sum-of-squares and cross-products matrix), **W*** (adjusted within sum-of-squares and cross-products matrix), and **B*** (adjusted between sum-of-squares and cross-products matrix).

Wilks' Λ is again calculated by using the SSCP matrices (Stevens, 1992). We can compare the MANOVA and MANCOVA formulas for Λ:

MANOVA

$$\Lambda = \frac{|\mathbf{W}|}{|\mathbf{T}|} = \frac{|\mathbf{W}|}{|\mathbf{B} + \mathbf{W}|}$$

MANCOVA

$$\Lambda^* = \frac{|\mathbf{W}^*|}{|\mathbf{T}^*|} = \frac{|\mathbf{W}^*|}{|\mathbf{B}^* + \mathbf{W}^*|} \qquad \text{(Equation 6.4)}$$

The interpretation of Λ remains as it was in MANOVA. If there is no treatment effect or group differences, then **B*** = 0 and Λ* = 1 indicating no differences between groups on the linear combination of DVs after removing the effects of the covariate(s); whereas, if **B*** were very large, then Λ* would approach 0, indicating significant group differences on the combination of DVs, after controlling for the covariate(s).

As in MANOVA, eta squared for MANCOVA is obtained in the following manner:

$$\eta^2 = 1 - \Lambda$$

In the multivariate analysis of covariance situation, η^2 is interpreted as the variance accounted for in the best linear combination of DVs by the IV(s) and/or interactions of IV(s), after removing the effects of any covariate(s).

Interpretation of Results

Interpretation of MANCOVA results is quite similar to that of MANOVA; however, with the inclusion of covariates, interpretation of a preliminary MANCOVA is necessary in order to test the assumption of homogeneity of regression slopes. Essentially, this analysis tests for the interaction between the factors (IVs) and covariates. This preliminary or custom MANCOVA will also test homogeneity of variance-covariance (Box's Test), which is actually interpreted first since it helps in identifying the appropriate test statistic to be utilized in examining the homogeneity of regression and the final MANCOVA results. If the Box's Test is significant at $p<.001$ and group sample sizes are extremely unequal, then Pillai's Trace is utilized when interpreting the homogeneity of regression test and the MANOVA results. If equal variances are assumed, Wilks' Lambda should be used as the multivariate test statistic. Once the test statistic has been determined, then the homogeneity of regression slopes or planes results are interpreted by examining the *F* ratio and *p* value for the interaction. If factor-covariate interaction is significant, then MANCOVA is not an appropriate analysis technique. If interaction is not significant, then one can proceed with conducting the full MANCOVA analysis. Using the *F* ratio and *p* value for a test statistic that was identified in the preliminary analysis through the Box's Test, factor interaction should be examined if two or more IVs are utilized in the analysis. If factor interaction is significant, then main effects for each factor on the combined DV is not a valid indicator of effect. If factor interaction is not significant, the main effects for each IV can be accurately interpreted by examining the *F* ratio, *p* value, and effect size for the appropriate test statistic. When main effects are significant, univariate ANOVA results indicate group differences for each DV. Since MANCOVA does not provide post hoc analyses, examining group means (before and after covariate adjustment) for each DV can assist in determining how groups differed for each DV.

In summary, the first step in interpreting the MANCOVA results is to evaluate the preliminary MANCOVA results that include the Box's Test and the test for homogeneity of regression slopes. If Box's Test is not significant, utilize the Wilks' Lambda statistic when interpreting the homogeneity of regression slopes and the subsequent multivariate tests. If Box's Test is significant, use Pillai's Trace. Once the multivariate test statistic has been identified, examine the significance (F ratios and p values) of factor-covariate interaction (homogeneity of regression slopes). If factor-covariate interaction is not significant, then proceed with the full MANCOVA. To interpret the full MANCOVA results, examine the significance (F ratios and p values) of factor interaction. This is necessary only if two or more IVs are included. Next evaluate the F ratio, p value, and effect size for each factor's main effect. If multivariate significance is found, interpret the univariate ANOVA results to determine significant group differences for each DV.

For our example that investigates age category (*agecat4*) differences in respondent's income (*rincom91*) and hours worked per week (*hrs1*) when controlling for education level (*educ*), the previously transformed variables of *rincom2* and *hrs2* were utilized. These transformations are described in Section 6.3. Linearity of the two DVs and the covariate was then tested by creating a matrix scatterplot and calculating Pearson correlation coefficients. Results indicate linear relationships. Although the correlation coefficients are statistically significant, all are quite low. The last assumption, homogeneity of variance-covariance, was tested within a preliminary MANCOVA analysis utilizing **`Multivariate`**. The Box's Test (see Figure 6.17) reveals that equal variances can be assumed, $F(9, 2827520)=.634$, $p=.769$; therefore, Wilks' Lambda will be used as the multivariate statistic. Figure 6.18 presents the MANOVA results for the homogeneity of regression test. The interaction between *agecat4* and *educ2* is not significant, Wilks' $\Lambda=.993$, $F(6,1342)=.815$, $p=.558$. A full MANCOVA was then conducted using **`Multivariate`** (see Figure 6.19). Wilks' Lambda criteria indicates significant groups differences in age category with respect to income and hours worked per week, Wilks' $\Lambda=.898$, $F(6,1348)=12.36$, $p<.001$, multivariate $\eta^2=.052$. Univariate ANOVA results (see Figure 6.20) reveal that age category significantly differs for only income ($F(3, 675)=24.18$, $p<.001$, partial $\eta^2=.097$) and not hours worked per week ($F(3, 675)=.052$, $p=.984$, partial $\eta^2=.000$). A comparison of adjusted means shows that individuals 18-29 years of age have income that is more than 3 points lower than those 40-49 and older than 50 (see Figure 6.21).

Figure 6.17 Box's Test for Homogeneity of Variance-Covariance.

Box's Test of Equality of Covariance Matrices[a]

Box's M	5.740
F	.634
df1	9
df2	2827520
Sig.	.769

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept+AGECAT4+EDUC2+AGECAT4 * EDUC2

Box's Test is not significant. Use Wilks' Lambda criteria.

Figure 6.18 MANCOVA Summary Table: Test for Homogeneity of Regression Slopes.

Multivariate Tests[c]

Effect		Value	F	Hypothesis df	Error df	Sig.	Eta Squared
Intercept	Pillai's Trace	.284	133.096[a]	2.000	671.000	.000	.284
	Wilks' Lambda	.716	133.096[a]	2.000	671.000	.000	.284
	Hotelling's Trace	.397	133.096[a]	2.000	671.000	.000	.284
	Roy's Largest Root	.397	133.096[a]	2.000	671.000	.000	.284
AGECAT4	Pillai's Trace	.004	.504	6.000	1344.000	.805	.002
	Wilks' Lambda	.996	.504[a]	6.000	1342.000	.806	.002
	Hotelling's Trace	.005	.503	6.000	1340.000	.806	.002
	Roy's Largest Root	.004	.833[b]	3.000	672.000	.476	.004
EDUC2	Pillai's Trace	.106	39.974[a]	2.000	671.000	.000	.106
	Wilks' Lambda	.894	39.974[a]	2.000	671.000	.000	.106
	Hotelling's Trace	.119	39.974[a]	2.000	671.000	.000	.106
	Roy's Largest Root	.119	39.974[a]	2.000	671.000	.000	.106
AGECAT4 * EDUC2	Pillai's Trace	.007	.816	6.000	1344.000	.558	.004
	Wilks' Lambda	.993	.815[a]	6.000	1342.000	.558	.004
	Hotelling's Trace	.007	.814	6.000	1340.000	.559	.004
	Roy's Largest Root	.005	1.169[b]	3.000	672.000	.321	.005

a. Exact statistic

b. The statistic is an upper bound on F that yields a lower bound on the significance level.

c. Design: Intercept+AGECAT4+EDUC2+AGECAT4 * EDUC2

Indicates that factor-covariate interaction is NOT significant.

Figure 6.19 MANCOVA Summary Table.

Indicates that the covariate significantly influences the combined DV.

Multivariate Tests[c]

Effect		Value	F	Hypothesis df	Error df	Sig.	Eta Squared
Intercept	Pillai's Trace	.298	142.742[a]	2.000	674.000	.000	.298
	Wilks' Lambda	.702	142.742[a]	2.000	674.000	.000	.298
	Hotelling's Trace	.424	142.742[a]	2.000	674.000	.000	.298
	Roy's Largest Root	.424	142.742[a]	2.000	674.000	.000	.298
EDUC2	Pillai's Trace	.126	48.428[a]	2.000	674.000	.000	.126
	Wilks' Lambda	.874	48.428[a]	2.000	674.000	.000	.126
	Hotelling's Trace	.144	48.428[a]	2.000	674.000	.000	.126
	Roy's Largest Root	.144	48.428[a]	2.000	674.000	.000	.126
AGECAT4	Pillai's Trace	.102	12.037	6.000	1350.000	.000	.051
	Wilks' Lambda	.898	12.356[a]	6.000	1348.000	.000	.052
	Hotelling's Trace	.113	12.673	6.000	1346.000	.000	.053
	Roy's Largest Root	.113	25.371[b]	3.000	675.000	.000	.101

a. Exact statistic

b. The statistic is an upper bound on F that yields a lower bound on the significance level.

c. Design: Intercept+EDUC2+AGECAT4

Indicates that age category significantly effects the combined DV when years of education is controlled.

Figure 6.20 Univariate ANOVA Summary Table.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Eta Squared
Corrected Model	RINCOM2	2411.930[a]	4	602.983	42.456	.000	.201
	HRS2	1490.452[b]	4	372.613	2.948	.020	.017
Intercept	RINCOM2	922.346	1	922.346	64.943	.000	.088
	HRS2	33502.664	1	33502.664	265.018	.000	.282
EDUC2	RINCOM2	1355.655	1	1355.655	95.452	.000	.124
	HRS2	1439.392	1	1439.392	11.386	.001	.017
AGECAT4	RINCOM2	1030.099	3	343.366	24.177	.000	.097
	HRS2	19.820	3	6.607	.052	.984	.000
Error	RINCOM2	9586.657	675	14.202			
	HRS2	85331.025	675	126.416			
Total	RINCOM2	149199.0	680				
	HRS2	1567026	680				
Corrected Total	RINCOM2	11998.587	679				
	HRS2	86821.476	679				

a. R Squared = .201 (Adjusted R Squared = .196)

b. R Squared = .017 (Adjusted R Squared = .011)

Indicates that age category significantly effects income but NOT hours worked.

Figure 6.21 Unadjusted and Adjusted Means for Income and Hours Worked per Week by Age Category.

Descriptive Statistics

	AGECAT4 4 categories of age	Mean	Std. Deviation	N
RINCOM2	1 18-29	11.8672	4.1438	128
	2 30-39	14.0315	3.8810	222
	3 40-49	15.3247	3.8660	194
	4 50+	14.9574	4.4173	141
	Total	14.1839	4.2155	685
HRS2	1 18-29	46.3203	10.3200	128
	2 30-39	47.0315	11.4182	222
	3 40-49	46.4897	11.7545	194
	4 50+	46.3262	11.5149	141
	Total	46.6000	11.3189	685

Figure 6.21 is continued on the next page.

Figure 6.21 Unadjusted and Adjusted Means for Income and Hours Worked per Week by Age Category. (*Continued*)

4 categories of age

Dependent Variable	4 categories of age	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
RINCOM2	1 18-29	11.993[a]	.333	11.339	12.648
	2 30-39	13.887[a]	.253	13.389	14.384
	3 40-49	15.356[a]	.272	14.822	15.890
	4 50+	15.165[a]	.321	14.535	15.795
HRS2	1 18-29	46.450[a]	.995	44.497	48.403
	2 30-39	46.882[a]	.756	45.398	48.366
	3 40-49	46.528[a]	.811	44.935	48.122
	4 50+	46.660[a]	.957	44.780	48.540

a. Evaluated at covariates appeared in the model: EDUC2 = 14.0985.

Writing Up Results

The process of summarizing MANCOVA results is almost identical to MANOVA; however, MANCOVA results will obviously include a statement of how the covariate influenced the DVs. One should note that although the preliminary MANCOVA results are quite important in the analysis process, these results are not reported since it is understood that if a full MANCOVA has been conducted, such assumptions have been fulfilled. Consequently, the MANCOVA results narrative should address the following:

(1) Subject elimination and/or variable transformation;
(2) Full MANCOVA results (test statistic, *F* ratio, degrees of freedom, *p* value, and effect size);
  (a) Main effects for each IV and covariate on the combined DV;
  (b) Main effect for the interaction between IVs;
(3) Univariate ANOVA results (*F* ratio, degrees of freedom, *p* value, and effect size);
  (a) Main effect for each IV and DV; and
  (b) Comparison of means to indicate which groups differ on each DV.

Often a table is created that compares the unadjusted and adjusted group means for each DV. For our example, the results statement includes all of these components with the exception of factor interaction since only one IV is utilized. The following results narrative applies the results from Figures 6.17 – 6.21.

> Multivariate analysis of covariance (MANCOVA) was conducted to determine the effect of age category on employee productivity as measured by income and hours worked per week while controlling for years of education. Prior to the test, variables were transformed to eliminate outliers. Cases with income equal to zero and equal to or exceeding 22 were eliminated. Hours worked per week was transformed; those less than or equal to 16 were recoded 17 and those greater than or equal to 80 were recoded 79. Years of education was also transformed to eliminate cases with 6 or fewer years. MANOVA results revealed significant differences among the age categories on the combined dependent variable, Wilks' Λ=.898, $F(6,1348)=12.36$, $p<.001$, multivariate η^2=.052. The covariate (years of education) significantly influenced the combined

dependent variable, Wilks' Λ=.874, F(2,674)=48.43, p<.001, multivariate η^2=.126. Analysis of covariance (ANCOVA) was conducted on each dependent variable as a follow-up test to MANCOVA. Age category differences were significant for income, (F(3, 675)=24.18, p<.001, partial η^2=.097) but not hours worked per week (F(3, 675)=.052, p=.984, partial η^2=.000). A comparison of adjusted means revealed that income of those 18-29 years differs by more than 3 points from those 40-49 years and those 50 years and older. Table 1 presents adjusted and unadjusted means for income and hours worked per week by age category.

Table 1 Adjusted and Unadjusted Means for Income and Hours Worked per Week by Age Category

	Income		Hours Worked per Week	
Age	**Adjusted *M***	**Unadjusted *M***	**Adjusted *M***	**Unadjusted *M***
18-29 years	11.99	11.87	46.45	46.32
30-39 years	13.89	14.03	46.88	47.03
40-49 years	15.36	15.32	46.53	46.49
50+ years	15.17	14.96	46.66	46.33

SECTION 6.9 MANCOVA SAMPLE STUDY AND ANALYSIS

This section provides a complete example that applies the entire process of conducting MANCOVA: development of research questions and hypotheses, data screening methods, test methods, interpretation of output, and presentation of results. The SPSS data set *gssft.sav* is utilized. Our previous example demonstrates a one-way MANCOVA, while this example will present a two-way MANCOVA.

Problem

Utilizing the two-way MANOVA example previously presented, in which we examined the degree to which gender and job satisfaction affects income and years of education among employees, we are now interested in adding the covariate of age. Since two IVs are tested in this analysis, questions must also take into account the possible interaction between factors. The following research questions and respective null hypotheses address the multivariate main effects for each IV and the possible interaction between factors.

Research Questions		***Null Hypotheses***
RQ1: Do income and years of education differ by gender among employees when controlling for age?	→	$H_0$1: Income and years of education will not differ by gender among employees when controlling for age.
RQ2: Do income and years of education differ by job satisfaction among employees when controlling for age?	→	$H_0$2: Income and years of education will not differ by job satisfaction among employees when controlling for age.
RQ3: Do gender and job satisfaction interact in the effect on income and years of education when controlling for age?	→	$H_0$3: Gender and job satisfaction will not interact in the effect on income and years of education when controlling for age.

Both IVs are categorical and include gender (*sex*) and job satisfaction (*satjob*). The DVs are respondent's income (*rincom2*) and years of education (*educ2*); both are quantitative. The covariate is years of age (*age*) and is quantitative. One should note that the variables *rincom2* and *educ2* are transformed variables of *rincom91* and *educ*, respectively. Transformations of these variables are described in section 6.3 of this chapter.

Method

Since variables were previously transformed to eliminate outliers, data screening is complete. MANCOVA test assumptions should then be examined. Linearity between the DVs and covariate is first assessed by creating a scatterplot matrix and calculating Pearson correlation coefficients. Scatterplots and correlation coefficients indicate linear relationships. Although three of the four correlation coefficients are significant ($p<.001$), coefficients are still fairly weak. The final test assumptions of homogeneity of variance-covariance and homogeneity of regression slopes will be tested in a preliminary MANCOVA using **`Multivariate`**. For our example, Box's Test (see Figure 6.22) indicates homogeneity of variance-covariance, $F(21,20374)=1.24$, $p=.204$. Therefore, Wilks' Lambda will be utilized as the test statistic for all the multivariate tests. Figure 6.23 reveals that factor and covariate interaction is not significant, Wilks' $\Lambda=.976$, $F(14, 1332)=1.143$, $p=.315$. Full MANCOVA was then conducted using **`Multivariate`**.

Figure 6.22 Box's Test for Homogeneity of Variance-Covariance.

Box's Test of Equality of Covariance Matrices[a]

Box's M	26.868
F	1.242
df1	21
df2	20374
Sig.	.204

Box's Test is not significant. Use Wilks' Lambda.

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept+SEX+SATJOB+AGE+SEX * SATJOB * AGE

Output and Interpretation of Results

Figure 6.24 presents the unadjusted group means for each DV, while Figure 6.25 displays the adjusted means. MANCOVA results are presented in Figure 6.26 and indicate no significant interaction between the two factors of gender and job satisfaction, Wilks' $\Lambda=.993$, $F(6, 1340)=.839$, $p=.539$. The main effects of gender (Wilks' $\Lambda=.974$, $F(2, 670)=9.027$, $p<.001$, multivariate $\eta^2=.026$) and job satisfaction (Wilks' $\Lambda=.972$, $F(6, 1340)=3.242$, $p=.004$, multivariate $\eta^2=.014$) indicate significant effect on the combined DV. However, one should note the extremely small effect sizes for each IV. The covariate significantly influenced the combined DV, Wilks' $\Lambda=.908$, $F(2, 670)=33.912$, $p<.001$, multivariate $\eta^2=.092$. Univariate ANOVA results (see Figure 6.27) indicate that only the DV of income was significantly effected by the IVs and covariate.

Figure 6.23 MANCOVA Summary Table: Test for Homogeneity of Regression Slopes.

Multivariate Tests[c]

Effect		Value	F	Hypothesis df	Error df	Sig.	Eta Squared
Intercept	Pillai's Trace	.399	220.855[a]	2.000	666.000	.000	.399
	Wilks' Lambda	.601	220.855[a]	2.000	666.000	.000	.399
	Hotelling's Trace	.663	220.855[a]	2.000	666.000	.000	.399
	Roy's Largest Root	.663	220.855[a]	2.000	666.000	.000	.399
SEX	Pillai's Trace	.001	.173[a]	2.000	666.000	.841	.001
	Wilks' Lambda	.999	.173[a]	2.000	666.000	.841	.001
	Hotelling's Trace	.001	.173[a]	2.000	666.000	.841	.001
	Roy's Largest Root	.001	.173[a]	2.000	666.000	.841	.001
SATJOB	Pillai's Trace	.010	1.100	6.000	1334.000	.360	.005
	Wilks' Lambda	.990	1.100[a]	6.000	1332.000	.360	.005
	Hotelling's Trace	.010	1.100	6.000	1330.000	.360	.005
	Roy's Largest Root	.009	1.947[b]	3.000	667.000	.121	.009
AGE	Pillai's Trace	.029	9.912[a]	2.000	666.000	.000	.029
	Wilks' Lambda	.971	9.912[a]	2.000	666.000	.000	.029
	Hotelling's Trace	.030	9.912[a]	2.000	666.000	.000	.029
	Roy's Largest Root	.030	9.912[a]	2.000	666.000	.000	.029
SEX * SATJOB * AGE	Pillai's Trace	.024	1.143	14.000	1334.000	.315	.012
	Wilks' Lambda	.976	1.143[a]	14.000	1332.000	.315	.012
	Hotelling's Trace	.024	1.142	14.000	1330.000	.315	.012
	Roy's Largest Root	.018	1.702[b]	7.000	667.000	.105	.018

a. Exact statistic

b. The statistic is an upper bound on F that yields a lower bound on the significance level.

c. Design: Intercept+SEX+SATJOB+AGE+SEX * SATJOB * AGE

Factor-covariate interaction is NOT significant.

Presentation of Results

The following narrative summarizes the results from this two-way MANCOVA example.

A two-way MANCOVA was conducted to determine the effect of gender and job satisfaction on income and years of education while controlling for years of age. Data were first transformed to eliminate outliers. Respondent's income was transformed to eliminate cases with income of zero and equal to or exceeding 22. Years of education was also transformed to eliminate cases with 6 or fewer years. The main effects of gender (Wilks' Λ=.974, F(2, 670)=9.027, p<.001, multivariate η^2=.026) and job satisfaction (Wilks' Λ=.972, F(6, 1340)=3.24, p=.004, multivariate η^2=.014) indicate significant effect on the combined DV. The covariate significantly influenced the combined DV, Wilks' Λ=.908, F(2, 670)=33.91, p<.001, multivariate η^2=.092. Univariate ANOVA results (Figure 6.27) indicate that only the DV of income was significantly effected by gender (F(1, 671)=17.73, p<.001, partial η^2=.026), job satisfaction (F(3, 671)=5.64, p=.001, partial η^2=.025) and the covariate of age (F(1, 671)=54.16, p<.001, partial η^2=.075). Table 1 presents the adjusted and unadjusted group means for income and years of education. Comparison of adjusted income means indicates that those very satisfied have higher incomes than those less satisfied.

Table 1 Adjusted and Unadjusted Group Means for Income and Years of Education

	Income		Years of Education	
	Adjusted *M*	**Unadjusted *M***	**Adjusted *M***	**Unadjusted *M***
Gender				
Male	15.00	15.15	14.37	14.07
Female	12.92	13.05	14.04	14.13
Job Satisfaction				
Very Sat.	14.80	15.00	14.35	14.33
Mod. Sat.	13.51	13.52	13.83	13.83
A Little Dis.	13.73	13.81	13.99	14.00
Very Dis.	13.80	13.71	14.67	14.79

Figure 6.24 Unadjusted Group Means for Years of Education and Income.

Descriptive Statistics

	SEX Respondent's Sex	SATJOB Job Satisfaction	Mean	Std. Deviation	N
EDUC2	1 Male	1 Very satisfied	14.2590	2.8856	166
		2 Mod satisfied	13.7484	2.6766	159
		3 A little dissatisfied	14.1429	2.7880	35
		4 Very dissatisfied	15.3571	2.4685	14
		Total	14.0722	2.7860	374
	2 Female	1 Very satisfied	14.4167	2.2070	132
		2 Mod satisfied	13.9242	2.4762	132
		3 A little dissatisfied	13.8438	2.5541	32
		4 Very dissatisfied	14.0000	2.1602	10
		Total	14.1307	2.3642	306
	Total	1 Very satisfied	14.3289	2.6039	298
		2 Mod satisfied	13.8282	2.5847	291
		3 A little dissatisfied	14.0000	2.6629	67
		4 Very dissatisfied	14.7917	2.3953	24
		Total	14.0985	2.6029	680
RINCOM2	1 Male	1 Very satisfied	15.8193	3.7389	166
		2 Mod satisfied	14.5157	4.3237	159
		3 A little dissatisfied	15.2571	4.1398	35
		4 Very dissatisfied	14.2143	5.0563	14
		Total	15.1524	4.1183	374
	2 Female	1 Very satisfied	13.9773	3.9779	132
		2 Mod satisfied	12.3182	4.0367	132
		3 A little dissatisfied	12.2187	3.7566	32
		4 Very dissatisfied	13.0000	2.8674	10
		Total	13.0458	4.0185	306
	Total	1 Very satisfied	15.0034	3.9479	298
		2 Mod satisfied	13.5189	4.3298	291
		3 A little dissatisfied	13.8060	4.2184	67
		4 Very dissatisfied	13.7083	4.2475	24
		Total	14.2044	4.2037	680

Figure 6.25 Adjusted Group Means for Years of Education and Income by Gender and Job Satisfaction.

1. Respondent's Sex

Dependent Variable	Respondent's Sex	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
EDUC2	1 Male	14.374[a]	.218	13.946	14.802
	2 Female	14.043[a]	.249	13.555	14.532
RINCOM2	1 Male	14.996[a]	.325	14.358	15.633
	2 Female	12.921[a]	.371	12.193	13.649

a. Evaluated at covariates appeared in the model: AGE Age of Respondent = 40.34.

2. Job Satisfaction

Dependent Variable	Job Satisfaction	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
EDUC2	1 Very satisfied	14.345[a]	.152	14.046	14.643
	2 Mod satisfied	13.830[a]	.153	13.530	14.131
	3 A little dissatisfied	13.994[a]	.318	13.370	14.618
	4 Very dissatisfied	14.666[a]	.538	13.609	15.723
RINCOM2	1 Very satisfied	14.798[a]	.226	14.353	15.242
	2 Mod satisfied	13.507[a]	.229	13.058	13.955
	3 A little dissatisfied	13.727[a]	.474	12.797	14.658
	4 Very dissatisfied	13.801[a]	.803	12.225	15.378

a. Evaluated at covariates appeared in the model: AGE Age of Respondent = 40.34.

Figure 6.26 MANCOVA Summary Table.

Multivariate Tests[c]

Effect		Value	F	Hypothesis df	Error df	Sig.	Eta Squared
Intercept	Pillai's Trace	.670	679.424[a]	2.000	670.000	.000	.670
	Wilks' Lambda	.330	679.424[a]	2.000	670.000	.000	.670
	Hotelling's Trace	2.028	679.424[a]	2.000	670.000	.000	.670
	Roy's Largest Root	2.028	679.424[a]	2.000	670.000	.000	.670
AGE	Pillai's Trace	.092	33.912[a]	2.000	670.000	.000	.092
	Wilks' Lambda	.908	33.912[a]	2.000	670.000	.000	.092
	Hotelling's Trace	.101	33.912[a]	2.000	670.000	.000	.092
	Roy's Largest Root	.101	33.912[a]	2.000	670.000	.000	.092
SEX	Pillai's Trace	.026	9.027[a]	2.000	670.000	.000	.026
	Wilks' Lambda	.974	9.027[a]	2.000	670.000	.000	.026
	Hotelling's Trace	.027	9.027[a]	2.000	670.000	.000	.026
	Roy's Largest Root	.027	9.027[a]	2.000	670.000	.000	.026
SATJOB	Pillai's Trace	.028	3.231	6.000	1342.000	.004	.014
	Wilks' Lambda	.972	3.242[a]	6.000	1340.000	.004	.014
	Hotelling's Trace	.029	3.252	6.000	1338.000	.004	.014
	Roy's Largest Root	.026	5.894[b]	3.000	671.000	.001	.026
SEX * SATJOB	Pillai's Trace	.007	.840	6.000	1342.000	.539	.004
	Wilks' Lambda	.993	.839[a]	6.000	1340.000	.539	.004
	Hotelling's Trace	.008	.838	6.000	1338.000	.540	.004
	Roy's Largest Root	.005	1.189[b]	3.000	671.000	.313	.005

a. Exact statistic

b. The statistic is an upper bound on F that yields a lower bound on the significance level.

c. Design: Intercept+AGE+SEX+SATJOB+SEX * SATJOB

The covariate of age significantly influences the combined DV.

Gender significantly influences the combined DV.

Job satisfaction significantly influences the combined DV.

Factor interaction is NOT significant.

Figure 6.27 Univariate ANOVA Summary Table.

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Eta Squared
Corrected Model	EDUC2	69.142[a]	8	8.643	1.280	.251	.015
	RINCOM2	1917.923[b]	8	239.740	15.958	.000	.160
Intercept	EDUC2	9098.497	1	9098.497	1347.329	.000	.668
	RINCOM2	4331.310	1	4331.310	288.305	.000	.301
AGE	EDUC2	3.586	1	3.586	.531	.466	.001
	RINCOM2	813.705	1	813.705	54.163	.000	.075
SEX	EDUC2	6.758	1	6.758	1.001	.317	.001
	RINCOM2	266.291	1	266.291	17.725	.000	.026
SATJOB	EDUC2	46.615	3	15.538	2.301	.076	.010
	RINCOM2	254.331	3	84.777	5.643	.001	.025
SEX * SATJOB	EDUC2	15.551	3	5.184	.768	.512	.003
	RINCOM2	29.773	3	9.924	.661	.577	.003
Error	EDUC2	4531.257	671	6.753			
	RINCOM2	10080.664	671	15.023			
Total	EDUC2	139763.0	680				
	RINCOM2	149199.0	680				
Corrected Total	EDUC2	4600.399	679				
	RINCOM2	11998.587	679				

a. R Squared = .015 (Adjusted R Squared = .003)

b. R Squared = .160 (Adjusted R Squared = .150)

Gender significantly effects income but NOT years of education.

Job satisfaction significantly effects income but NOT years of education.

SECTION 6.10 SPSS "HOW TO" FOR MANCOVA

This section describes the steps for conducting both the preliminary MANCOVA and the full MANCOVA using the **Multivariate** procedure. Again, the preceding example from the *gssft.sav* data set is utilized in these steps. The first series of steps describes the preliminary MANCOVA process for testing homogeneity of variance-covariance and homogeneity of regression slopes. To open the Multivariate dialogue box (see Figure 6.28), select the following:

```
Analyze
    General Linear Model
        Multivariate
```

Multivariate Dialogue Box (see Figure 6.28)

Once in this dialogue box, click each DV (*rincom2* and *educ2*) and move to the Dependent Variables box. Click each IV (*sex* and *satjob*) and move to the Fixed Factor(s) box. Then click each covariate (*age*) and move to the Covariate box. Then click **Model**.

Multivariate Model Dialogue Box (see Figure 6.29)

Under Specify Model, click **Custom**. Move each IV and covariate to the Model box. Then hold down the Ctrl key and highlight all IVs and covariate(s). Once highlighted, continue to hold down the shift key and move to the Model box. This should create the interaction between all IVs and covariate(s) (e.g., age*satjob*sex). Also check to make sure that Interaction is specified in the Build Terms box. Click **Continue**. Back in the **Multivariate** Dialogue Box, click **Options**.

Figure 6.28 Multivariate Dialogue Box.

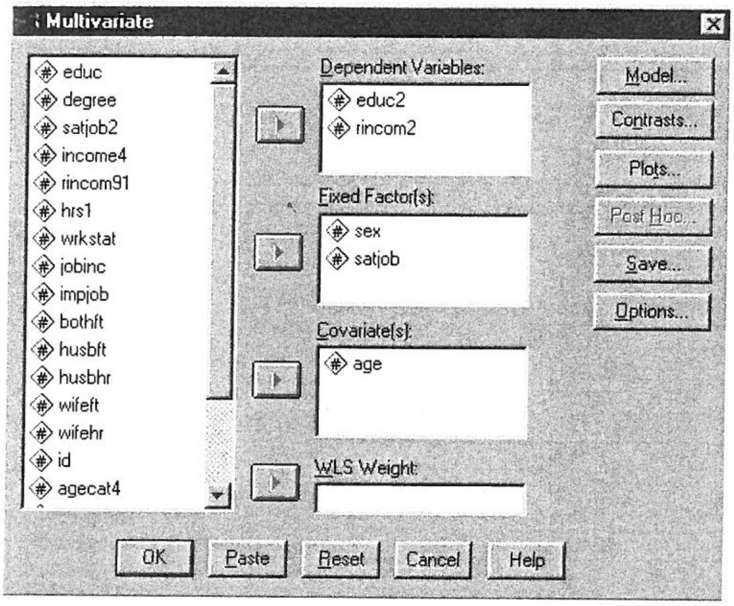
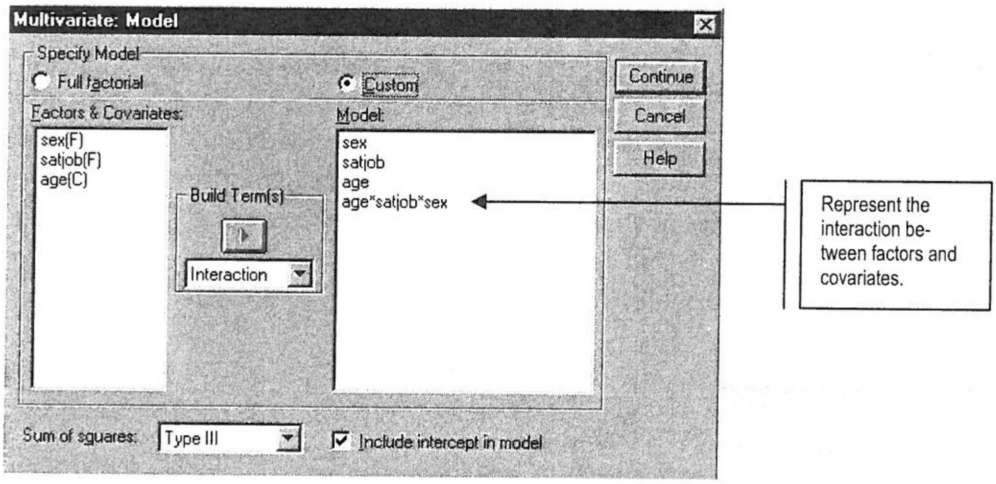


Figure 6.29 Multivariate Model Dialogue Box.



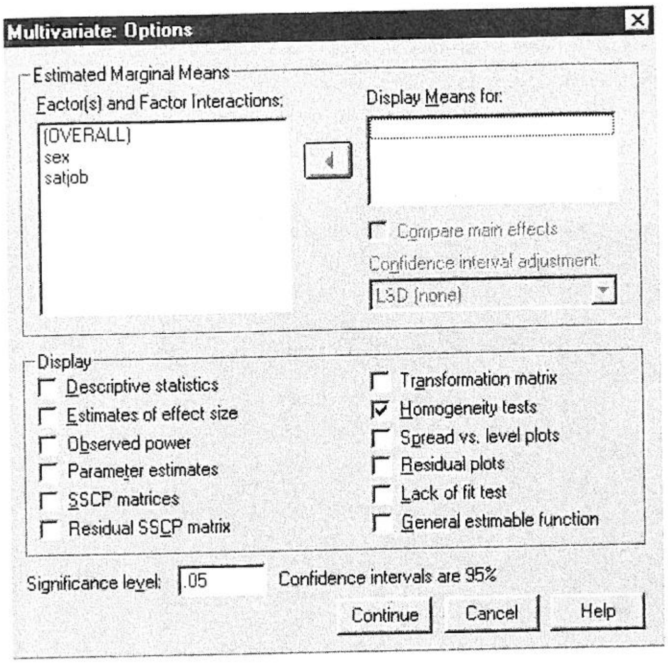
Multivariate Options Dialogue Box (see Figure 6.30)

Under Display, click Homogeneity Tests. Click **Continue**. Back in the **Multivariate** Dialogue Box, click **OK**.

These steps will create the output to evaluate homogeneity of variance-covariance and homogeneity of regression slopes. If interaction between the factors and covariates is not significant, then proceed with the following steps for conducting the full MANCOVA. The same dialogue boxes are opened, but different commands will be used. Open the Multivariate Dialogue Box by selecting the following:

Analyze
    General Linear Model
        Multivariate

Figure 6.30 Multivariate Options Dialogue Box.



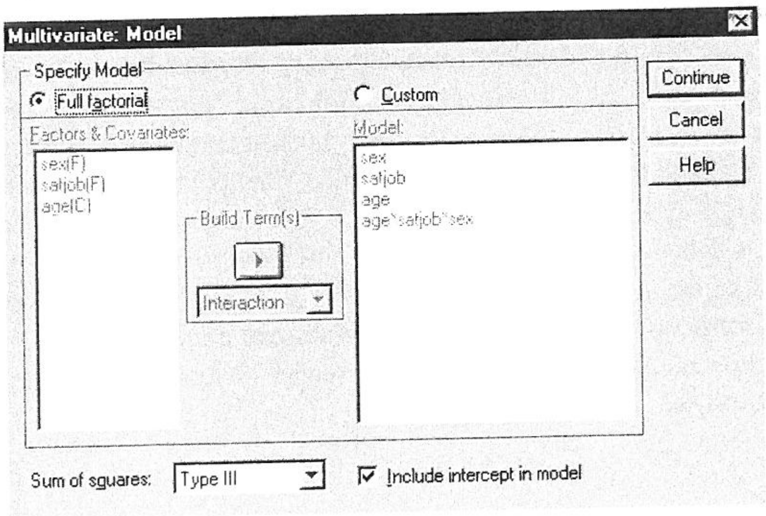
<u>**`Multivariate`** Dialogue Box (see Figure 6.28)</u>

If you have conducted the preliminary MANCOVA, variables should already be identified. If not, proceed with the following. Click each DV (*rincom2* and *educ2*) and move to the Dependent Variables box. Click each IV (*sex* and *satjob*) and move to the Fixed Factor(s) box. Then click each covariate (*age*) and move to the Covariate box. Then click **`Model`**.

<u>**`Multivariate`** Model Dialogue Box (see Figure 6.31)</u>

Under specify model, click Full. Click **`Continue`**. Back in the **`Multivariate`** Dialogue Box, click **`Options`**.

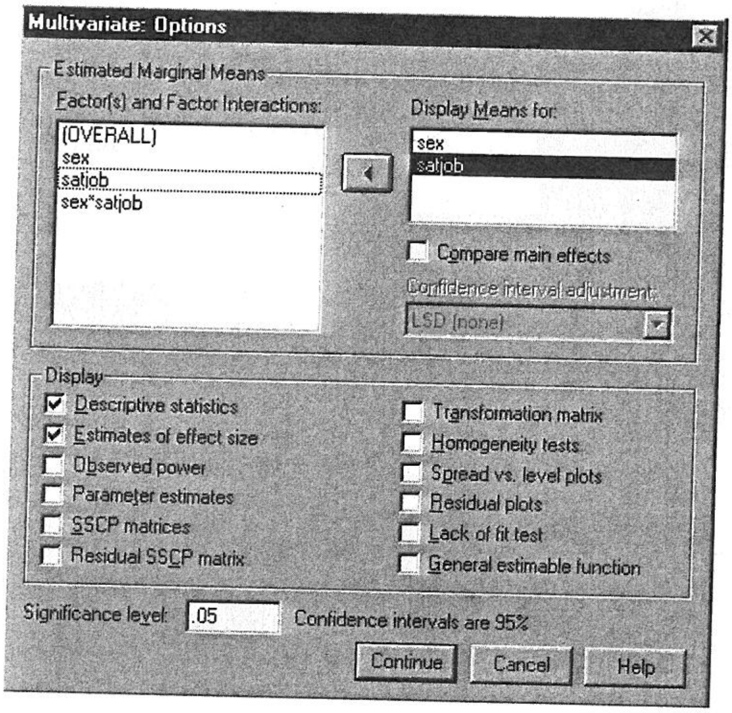
Figure 6.31 Multivariate Model Dialogue Box.



<u>**Multivariate Options** Dialogue Box (see Figure 6.32)</u>

Under Factor(s) and Factor Interaction, click each IV and move to the Display Means box. Under Display, click **Descriptive Statistics** and **Estimates of Effect Size**. Click **Continue**. Back in the **Multivariate** Dialogue Box, click **OK**.

Figure 6.32 Multivariate Options Dialogue Box.



SUMMARY

Multivariate analysis of variance (MANOVA) allows the researcher to examine group differences within a set of dependent variables. Factorial MANOVA will test the main effect for each factor on the combined DV as well as the interaction among factors on the combined DV. Usually follow-up tests, such as Univariate ANOVA and post hoc tests, are conducted within MANOVA to determine the specificity of group differences. Prior to conducting MANOVA, data should be screened for missing data and outliers. Data should also be examined for fulfillment of test assumptions: normality, homogeneity of variance-covariance, and linearity of DVs. Box's Test for homogeneity of variance-covariance will help determine which test statistic (e.g., Wilks' Lambda, Pillai's Trace) to utilize when interpreting the multivariate tests. The SPSS MANOVA table provides four different test statistics (Wilks' Lambda, Pillai's Trace, Hotelling's Trace, and Roy's Largest Root) with the *F* ratio, *p* value, and effect size that indicate the significance of factor main effects and interaction. Wilks' Lambda is the most commonly used criterion. If factor interaction is significant, then conclusions about main effects are limited. Univariate ANOVA and post hoc results determine group differences for each DV. Figure 6.33 provides a checklist for conducting MANOVA.

Figure 6.33 Checklist for Conducting MANOVA.

I. Screen Data

a. Missing Data?

b. Outliers?
  - ❑ Run Outliers and review stem-and-leaf plots and boxplots within **Explore**.
  - ❑ Eliminate or transform outliers if necessary.

c. Normality?
  - ❑ Run Normality Plots with Tests within **Explore**.
  - ❑ Review boxplots and histograms.
  - ❑ Transform data if necessary.

d. Linearity of DVs?
  - ❑ Create Scatterplots.
  - ❑ Calculate Pearson correlation coefficients.
  - ❑ Transform data if necessary.

e. Homogeneity of Variance-Covariance?
  - ❑ Run Box's Test within **Multivariate**.

II. Conduct MANOVA

a. Run MANOVA with post hoc test.
  1. 🖱 **Analyze**...🖱 **General Linear Model**...🖱 **Multivariate**.
  2. Move DVs to Dependent Variable box.
  3. Move IVs to Fixed Factor box.
  4. 🖱 **Model**.
  5. 🖱 **Full**.
  6. 🖱 **Continue**.
  7. 🖱 **Options**.
  8. Move each IV to the Display Means box.
  9. Check **Descriptive Statistics, Estimates of Effect Size** and **Homogeneity Tests**.
  10. 🖱 **Continue**.
  11. 🖱 **Post hoc**.
  12. Move each IV to the Post Hoc Test box.
  13. Select post hoc method.
  14. 🖱 **Continue**.
  15. 🖱 **OK**.

b. Homogeneity of Variance-Covariance?
  - ❑ Examine *F*-ratio and *p*-value for Box's Test.
  - ❑ If significant at $p<.001$ with extremely unequal group sample sizes, use Pillai's Trace for the test statistic.
  - ❑ If NOT significant at $p<.001$ with fairly equal group sample sizes, use Wilks' Lambda for the test statistic.

c. Interpret factor interaction.
  - ❑ If factor interaction is significant, main effects are erroneous.
  - ❑ If factor interaction is NOT significant, interpret main effects.

d. Interpret main effects for each IV on the combined DV.

e. Interpret Univariate ANOVA results.

f. Interpret post hoc results.

III. Summarize Results

a. Describe any data elimination or transformation.

b. Narrate Full MANOVA results.
  - ❑ Main effects for each IV on the combined DV (test statistic, *F*-ratio, *p*-value, effect size).
  - ❑ Main effect for factor interaction (test statistic, *F*-ratio, *p*-value, effect size).

c. Narrate Univariate ANOVA results.
  - ❑ Main effects for each IV and DV (*F*-ratio, *p*-value, effect size).

d. Narrate post hoc results.

e. Draw conclusions.

Multivariate analysis of covariance (MANCOVA) allows the researcher to examine group differences within a set of dependent variables while controlling for covariate(s). Essentially, the influence that the covariate(s) has on the combined DV is partitioned out before groups are compared, such that group means of the combined DV are adjusted to eliminate the effect of the covariate(s). One-way MANCOVA will test the main effects for the factor on the combined DV while controlling for the covariate(s). Factorial MANCOVA will do the same but will also test the interaction among factors on the combined DV while controlling for the covariate(s). Usually univariate ANCOVA is conducted within MANCOVA to determine the specificity of group differences. Prior to conducting MANCOVA, data should be screened for missing data and outliers. Data should also be examined for fulfillment of test assumptions: normality, homogeneity of variance-covariance, homogeneity of regression slopes, and linearity of DVs and covariates. A preliminary or custom MANCOVA must be conducted to test the assumptions of homogeneity of variance-covariance and homogeneity of regression slopes. Box's Test for homogeneity of variance-covariance will help determine which test statistic (e.g., Wilks' Lambda, Pillai's Trace) to utilize when interpreting the test for homogeneity of regression slopes and the full MANCOVA analyses. The test for homogeneity of regression slopes will indicate the degree to which the factors and covariate(s) interact to effect the combined DV. If interaction is significant, as indicated by the F ratio and p value for the appropriate test statistic, then the full MANCOVA should NOT be conducted. If interaction is not significant, then the full MANCOVA can be conducted. Once the full MANCOVA has been completed, factor interaction should be examined when two or more IVs are utilized. If factor interaction is significant, then conclusions about main effects are limited. Interpretation of the multivariate main effects and interaction is similar to MANOVA. Univariate ANOVA results determine the significance of group differences for each DV. Figure 6.34 provides a checklist for conducting MANCOVA.

Figure 6.34 Checklist for Conducting MANCOVA.

I. Screen Data
- a. Missing Data?
- b. Outliers?
  - ❑ Run Outliers and review stem-and-leaf plots and boxplots within **`Explore`**.
  - ❑ Eliminate or transform outliers if necessary.
- c. Normality?
  - ❑ Run Normality Plots with Tests within **`Explore`**.
  - ❑ Review boxplots and histograms.
  - ❑ Transform data if necessary.
- d. Linearity of DVs and covariate(s)?
  - ❑ Create Scatterplots.
  - ❑ Calculate Pearson correlation coefficients.
  - ❑ Transform data if necessary.
- e. Test remaining assumptions by conducting preliminary MANCOVA.

II. Conduct Preliminary (Custom) MANCOVA
- a. Run Custom MANCOVA.
  1. 🖱 **`Analyze...`** 🖱 **`General Linear Model...`** 🖱 **`Multivariate`**.
  2. Move DVs to Dependent Variable box.
  3. Move IVs to Fixed Factor box.
  4. Move covariate(s) to Covariate box.
  5. 🖱 **`Model`**.
  6. 🖱 **`Custom`**.
  7. Move each IV and covariate to the Model box.
  8. Hold down Ctrl key and highlight all IVs and covariate(s), 🖱 ▶ while still holding down the Ctrl key in order to move interaction to Model box.
  9. 🖱 **`Continue`**.
  10. 🖱 **`Options`**.
  11. Check **`Homogeneity Tests`**.
  12. 🖱 **`Continue`**.
  13. 🖱 **`OK`**.
- b. Homogeneity of Variance-Covariance?
  - ❑ Examine *F*-ratio and *p*-value for Box's Test.
  - ❑ If significant at $p<.001$ with extremely unequal group sample sizes, use Pillai's Trace for the test statistic.
  - ❑ If NOT significant at $p<.001$ with fairly equal group sample sizes, use Wilks' Lambda for the test statistic.
- c. Homogeneity of Regression Slopes?
  - ❑ Using the appropriate test statistic, examine *F*-ratio and *p*-value for the interaction among IVs and covariates.
  - ❑ If interaction is significant, do not proceed with Full MANCOVA.
  - ❑ If interaction is NOT significant, proceed with Full MANCOVA.

III. Conduct MANCOVA
- a. Run Full MANCOVA.
  1. 🖱 **`Analyze...`** 🖱 **`General Linear Model...`** 🖱 **`Multivariate`**.
  2. Move DVs to Dependent Variable box.
  3. Move IVs to Fixed Factor box.
  4. Move covariate(s) to Covariate box.
  5. 🖱 **`Model`**.
  6. 🖱 **`Full`**.
  7. 🖱 **`Continue`**.
  8. 🖱 **`Options`**.
  9. Move each IV to the Display Means box.
  10. Check **`Descriptive Statistics`** and **`Estimates of Effect Size`**.
  11. 🖱 **`Continue`**.
  12. 🖱 **`OK`**.
- b. Interpret factor interaction.
  - ❑ If factor interaction is significant, main effects are erroneous.
  - ❑ If factor interaction is NOT significant, interpret main effects.
- c. Interpret main effects for each IV on the combined DVs.
- d. Interpret Univariate ANOVA results.

Figure 6.34 continues on the next page.

Figure 6.34 Checklist for Conducting MANCOVA (*Continued*)

IV. Summarize Results

a. Describe any data elimination or transformation.
b. Narrate Full MANCOVA results.
  - ❑ Main effects for each IV and covariate on the combined DV (test statistic, *F*-ratio, *p*-value, effect size).
  - ❑ Main effect for factor interaction (test statistic, *F*-ratio, *p*-value, effect size).
c. Narrate Univariate ANOVA results.
  - ❑ Main effects for each IV and DV (*F*-ratio, *p*-value, effect size).
d. Compare group means to indicate which groups differ on each DV.
e. Draw conclusions.

Exercises for Chapter 6

The two exercises below utilize the data set *gssft.sav*, which can be downloaded from this Web site:

http://edhd.bgsu.edu/amm/datasets.html

1. You are interested in evaluating the effect of job satisfaction (*satjob2*) and age category (*agecat4*) on the combined DV of hours worked per week (*hrs1*) and years of education (*educ*).

   a. Develop the appropriate research questions and/or hypotheses for main effects and interaction.

   b. Screen data for missing data and outliers. What steps, if any, are necessary for reducing missing data and outliers?

   c. Test the assumptions of normality and linearity of DVs.

      i. What steps, if any, are necessary for increasing normality?

      ii. Are DVs linearly related?

   d. Conduct MANOVA with post hoc (be sure to test for homogeneity of variance-covariance).

      i. Can you conclude homogeneity of variance-covariance? Which test statistic is most appropriate for interpretation of multivariate results?

      ii. Is factor interaction significant? Explain.

iii. Are main effects significant? Explain.

iv. What can you conclude from univariate ANOVA and post hoc results?

e. Write a results statement.

2. Building on the previous problem in which you investigated the effects of job satisfaction (*satjob2*) and age category (*agecat4*) on the combined dependent variable of hours worked per week (*hrs1*) and years of education (*educ*), you are now interested in controlling for respondent's income such that *rincom91* will be used as a covariate. Complete the following.

   a. Develop the appropriate research questions and/or hypotheses for main effects and interaction.

   b. Screen data for missing data and outliers. What steps, if any, are necessary for reducing missing data and outliers?

   c. Test the assumptions of normality and linearity of DVs and covariate.

      i. What steps, if any, are necessary for increasing normality?

      ii. Are DVs and covariate linearly related?

   d. Conduct a preliminary MANCOVA to test the assumptions of homogeneity of variance-covariance and homogeneity of regression slopes/planes.

      i. Can you conclude homogeneity of variance-covariance? Which test statistic is most appropriate for interpretation of multivariate results?

      ii. Do factors and covariate significantly interact? Explain.

   e. Conduct MANCOVA.

      i. Is factor interaction significant? Explain.

      ii. Are main effects significant? Explain.

iii. What can you conclude from univariate ANOVA results?

f. Write a results statement.

3. Compare the results from problems number 1 and number 2. Explain the differences in main effects.