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Factorial and Multivariate Analysis of Variance

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Dr. Kaywin LaNoue studied the difference in spiritual maturity in high school seniors across two independent variables. The first was whether seniors attended public or Christian high schools. The second was whether or not seniors were actively involved in Sunday School.[1]

She found no significant interaction between the independent variables (F=3.001, p=.086) allowing her to analyze the main effect F-ratios directly. She found no significant difference in spiritual maturity between Christian School and Public School seniors (F=0.217, p=0.642), but she found a significant difference between active and inactive seniors in Sunday School (F=13.918, p=0.000).[2] One hundred twelve seniors participated in this study.[3]

In Chapter 21, we studied ***one-way*** Analysis of Variance which extended the analysis of groups from two (t) to three or more (F). One-sample, two-sample, and one-way ANOVA designs all involve a single independent (controlled) variable and a single dependent (measured) variable.

In this chapter, we'll focus on ***Factorial ANOVA*** designs which extend the number of ***independent variables*** in a study. Factorial designs can involve two independent variables (two-way), or three independent variables (three-way) or more. I use the SYSTAT computer statistical package which can analyze designs involving up to eight independent variables (8-way).

Factorial designs offer greater efficiency for analyzing multiple independent variables simultaneously. We can also test for an ***interaction effect*** between independent variables — something not possible with multiple one-way studies. We will discuss the concept of interaction, illustrate 2- and 3-way ANOVA procedures, and finally introduce the ***Analysis of Covariance (ANCOVA)*** and ***Multivariate Analysis of Variance (MANOVA)*** procedures.

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[1]Kaywin Baldwin LaNoue, "A Comparative Study of the Spiritual Maturity Levels of the Christian School Senior and the Public School Senior in Texas Southern Baptist Churches with a Christian School," (Fort Worth, Texas: Southwestern Baptist Theological Seminary, 1987), 45

[2]Ibid., 46 [3]Ibid., 47

Two-Way ANOVA

Let's look at a study of the effect of reinforcement on developing vocabulary. One variable is ***reinforcement*** with two levels: "immediate" and "delayed." The second variable is subject ***socioeconomic class*** with two levels: "low" and "middle." The dependent (measured) variable is vocabulary test score. The two-factor table for this experiment is shown below.

The means in the table are identified as $\bar{X}_{r,c}$. Mean$_{row=1,col=1}$ is designated $\bar{X}_{1,1}$. The other three **cell means** are designated $\bar{X}_{1,2}$, $\bar{X}_{2,1}$, and $\bar{X}_{2,2}$. The **margin mean** for row 1 is designated $\bar{X}_{1\cdot}$. The dot (.) replaces the column number, indicating *all columns*. The other **margin means** are designated $\bar{X}_{2\cdot}$ (second row), $\bar{X}_{\cdot 1}$ (first column), and $\bar{X}_{\cdot 2}$ (second column).

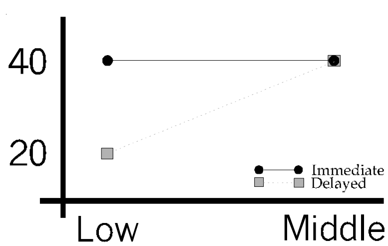
	Low	**Middle**	Row Means
Immediate	$\bar{X}_{1,1}=40$	$\bar{X}_{1,2}=40$	$\bar{X}_{1\cdot}=40$
Delayed	$\bar{X}_{2,1}=20$	$\bar{X}_{2,2}=40$	$\bar{X}_{2\cdot}=30$
Column Means	$\bar{X}_{\cdot 1}=30$	$\bar{X}_{\cdot 2}=40$	

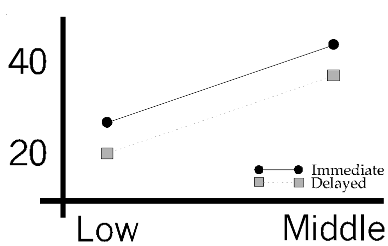
The 2x2 design above produces **three** **F-ratios**. It yields an **F**$_r$-ratio (row F-ratio) which compares $\bar{X}_{1\cdot}$ with $\bar{X}_{2\cdot}$ (Row mean 1 with Row mean 2). This F-ratio is the same as if we had computed a one-way ANOVA across ***reinforcement type*** alone.

The 2x2 design also yields an **F**$_c$-ratio (column F-ratio) which compares $\bar{X}_{\cdot 1}$ with $\bar{X}_{\cdot 2}$ (Column mean 1 with column mean 2). This F-ratio is the same as if we have computed a one-way ANOVA across ***socioeconomic status*** alone. ***These row and column F-ratios are called main effects***.

The 2x2 design also yields an **F**$_{rc}$-ratio, which tests whether there is an ***interaction*** between the two independent variables — in this case, reinforcement and socioeconomic status. This interaction cannot be tested in one-way ANOVA designs.

The Meaning of Interaction





The term "interaction" refers to the synergistic impact between independent variables on the dependent variable in an experiment. We can see this effect in our example above. When we graph the four values from our chart, we see that the ***type of reinforcement*** **affected mean vocabulary score differently** in the two ***SES groups***.

Immediate reinforcement (black line) showed no difference between the groups and produced consistently high results. ***Delayed reinforcement*** (gray line) was much less effective in the "Low" group than in the "Middle" group.

The conclusion of the study is that we should not use delayed reinforcement with children from a low socioeconomic status. It is clear the lines in the upper graph are **not parallel**. This indicates **interaction** between the two variables.

If there had been no interaction between reinforcement and socioeconomic status, the lines would be parallel, as shown in the lower left graph. In this (fictious) graph we see that the differences in vocabulary score are parallel across both reinforcement types and socioeconomic group. Let's look at some illustrations which show three types of interaction.

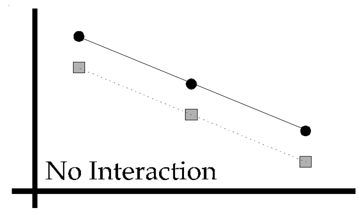
Types of Interaction

There are three basic kinds of interaction: **no** interaction, **ordinal** interaction, and **disordinal** interaction. Match the illustrations below with each description. For these examples we are using a 2x3 experimental design: Two levels in variable one and three levels in variable two.

No Interaction

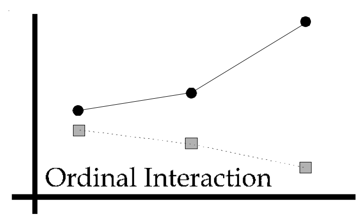
In data with **no interaction** between variables, the lines are parallel. Treatment effects are constant across variable levels. Notice that the difference between means (black circles and gray squares) is the same for the three levels of variable 2.

(Note: As with all statistical concepts, data can have some interaction -- and therefore slightly unparallel lines -- and still not have significant interaction.)



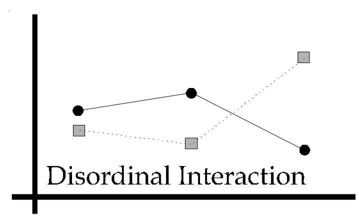
Ordinal Interaction

In **ordinal interaction**, the rank order of the cell means of one variable is the same within each level of the second variable. While the lines are not parallel, they do not cross. Notice that the difference between means (black circles and gray squares) varies, but remains in the same order, for the three levels of variable 2.



Disordinal Interaction

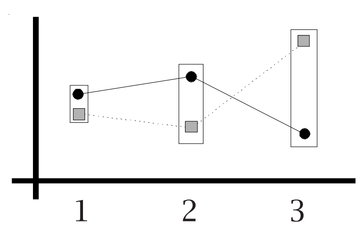
In **disordinal interaction**, the rank order of cell means is not consistent within each level of the second variable. The lines representing each variable cross. Effects of treatments are radically different across the two variables. Notice that the difference between means (black circles and gray squares) not only varies, but changes order across the three levels of variable 2.



A significant *ordinal* interaction shows that **one treatment is superior to another at every level of the second variable**. But when there is a significant *disordinal* interaction, one treatment is superior at one level of the second variable, but not at another.

In both cases, **interpretation of treatment effect must be made separately** for each level of the second variable. Such an analysis is called ***simple effects***. *Whenever there is a significant interaction,* ***main effects*** ***(*** F_r, F_c***)*** ***are meaningless*** *and* ***simple effects must be computed***.

In the diagram at right, simple effects computations would test the two means at level 1 for significance, then the two means at level 2, and then the two means at level 3, as indicated by the rectangles. There are special formulas for these computations, but we'll not address them here.



Sums of Squares in Two-Way ANOVA

In one-way ANOVA, we had three major SS terms: SS_t, SS_b, and SS_w. In two-way ANOVA we have six terms. The "between" portion of variance is further divided between variance in variable A and variable B, variance within cells, and variance due to interaction between A and B. We can summarize these terms as:

SS_t	total	SS_{cells}	within cells
SS_a	variable A	SS_{ab}	interaction
SS_b	variable B	SS_e	error

The Two-Way ANOVA Table

Dr. LaNoue's study can be reduced to the following two-way table[4] of the four group means, 175, 131, 157.5, 141.

	Sunday School Participation		
School	Active	Inactive	Row Means
Christian	**175**	**131**	153
Public	**157.5**	**141**	149.5
Col. Means	166.25	136	

The F_r-ratio tests the difference between row means 153 and 149.5 for significance, and the F_c-ratio tests the difference between column means 166.25 and 136 for significance. Analyzing this data by computer produces the following ANOVA table:

TABLE 3[5]

SUMMARY TABLE FOR THE TWO-WAY ANOVA

SOURCE	SUM-OF-SQUARES	df	MEAN-SQUARE	F-RATIO	P
C/P[6]	198.220	1	198.220	0.217	0.642
A/I[7]	12730.850	1	12730.850	13.918	0.000
C/P-A/I	2745.269	1	2745.269	3.001	0.086
Error	98787.740	108	914.701		

denominator for all three F-ratios

df_r = r-1 = 2-1 = 1. df_c = c-1 = 2-1 = 1. df_{rc} = (r-1)(c-1) = 1.
df_e = k(n-1) where k is the number of cells (equal cell n's)
= df_t - (df_a + df_b + df_{ab}) = 111-3 = 108. (unequal cell n's)
df_t = N-1 = 112-1 = 111

MS terms are given by the respective SS/df terms.

F-ratios are given by MS_x/MS_e

$F_r = MS_r/MS_e$	= 198.22 / 914.701	= 0.217	Main Effect
$F_c = MS_c/MS_e$	= 12730.85 / 914.701	= 13.918	Main Effect
$F_{rc}=MS_{rc}/MS_e$	= 2745.269 / 914.701	= 3.001	Interaction Effect

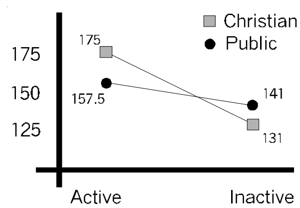
The first F-ratio to consider is the interaction F-ratio. This is F_{rc} (3.001) in the table. The computed value of 3.001 is *not significant* (p=0.086). Therefore, the interaction between **School Type** and **Participation** is not significant. *Had the interaction been*

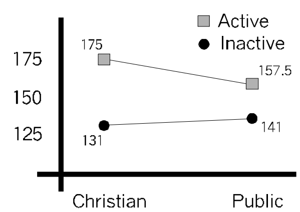
[4]Data drawn from LaNoue, pp. 107-109 [5]Ibid., p. 46 [6]Christian or Public School
[7]Active or Inactive in Sunday School

significant, the main effects values would have been meaningless, and we would have had to compute simple effects values. Because the interaction F is not significant, we can interpret main effect F-ratios directly.

The first main effect is **School Type**. This F-ratio tests whether the two row means (153, 149.5) are significantly different. Its value is **0.217** (p=0.642). Because the p value is greater than 0.05, these row means are declared **not significantly different.** *The spiritual maturity scores did not differ between seniors in Christian and public high schools.*

The second main effect is **Active Participation in Sunday School**. This F-ratio tests whether the column means (166.25, 136) are significantly different. Its value is **13.918** (p=0.000). Because the p value is less than 0.05, the column means are declared **significantly different.** *Seniors who were active in Sunday School were significantly more mature spiritually than seniors who were inactive, regardless of school type attended.* Two graphs of these means is shown below.





The graph at left above orders the means in the same ways as the two-way table. We can see some disordinal interaction, but since the interaction F is not significant (p=0.086), these differences are explained by sampling error. We can also see small (non-significant) differences between the Christian school and Public school seniors (squares and circles close together).

By re-ordering the means in the graph above right, we can focus on the activity variable. The difference between the Active seniors and Inactive seniors is clearly seen here. We also see the slight (non-significant) interaction. *Notice also that the **highest** mean of spiritual maturity is found in Christian-School-**Active** seniors (175, n=46). The **lowest** mean of spiritual maturity is found in Christian-School-**Inactive** seniors (131, n=13).*

These findings are strengthened by the fact that they are based on eleven Christian schools and their sponsoring churches in the state of Texas.[8] Dr. LaNoue raised the following questions in her proposal: *Does the Christian school accomplish the administrative goal of growth in Christ-likeness or spiritual maturity, or does that public school Christian grow as much or more in spiritual maturity as the Christian school student? Is the Christian school accomplishing something that is not being accomplished in another way?*[9] What she found should focus our attention on how active our teenagers are in Sunday School, not on whether they attend a private Christian school. It should also send a wake-up call to administrators of private Christian schools that spiritual growth may be more related to the school's publicity than to its students.

[8]Ibid., pp. 71-74 [9]Ibid., p. 19

Three-way ANOVA

Let's extend these ideas to ***three*** independent variables. Suppose you wish to measure the level of **test anxiety** in seminary students (dependent variable).

One independent variable is "school"; the categories are "theology", "educational ministries," and "music."

Another independent variable is "gender"; the categories are "male" and "female."

The third independent variable is "year in seminary"; the levels are "1st", "2nd", "3rd", "4th+" years.

With one analysis we can test the following:

1. Is there a significant difference in test anxiety (F_1) across schools, (F_2) between genders, or (F_3) across length of study? (3-way main effects)

2. Is there an interaction between school and gender (F_{12}), school and years of study (F_{13}), or gender and years of study (F_{23})? (2-way interactions)

3. Is there an interaction among all three variables (F_{123})? (3-way interaction)

A Three-way ANOVA table looks like the table below. (These table values are not related to seminary problem above, but are given merely as an example.)

Source	df	SS	MS	F
1	1.00	1,302.09	1,302.09	F_1 = 48.79*
2	2.00	1,016.67	508.34	F_2 = 19.05*
3	1.00	918.75	918.75	F_3 = 34.42*
12	2.00	116.66	58.33	F_{12} = 2.18
13	1.00	468.75	468.75	F_{13} = 17.56*
23	2.00	50.00	25.00	F_{23} <1
123	2.00	50.00	25.00	F_{123} <1
Error	36.00	961.00	26.69	
Total	47.00	4,883.92		

*p<0.05

The table shows that all three main effects and the AC interaction term are significant. Only F_2 can be directly interpreted because the a-c interaction renders F_1 and F_3 meaningless.

In graphing a three-way or higher order ANOVA, you must graph two variables at a time. For example, in graphing the means from the ANOVA table above, you might consider the two levels of A separately. Graph B and C for A1 and then B and C for A2. To show the significant interaction, graph A and C for each level of B. Graphing the ABC term is much more difficult, because it forms a plane in 3-dimensional space.

With each additional independent variable, the complexity of analysis and interpretation increases. Science likes simple solutions. Avoid overly complex designs, even if your computer software allows you to do them!

Analysis of Covariance

When intact groups must be used for a study, differences may exist between two groups before the treatment begins. Results of the experiment cannot be attributed confidently to the treatment. It would be helpful to have a way to statistically level the groups, adjusting for pre-treatment differences in the post-treatment tests. Fortunately, such a procedure exists.

The Analysis of Covariance (ANCOVA) procedure gets its name from the fact that it uses a known variable, called a ***covariate***, to adjust the means of the dependent (measured) variable before applying an ANOVA test. The adjustment to the means is done through the coefficient of determination ($\mathbf{r^2}$) and "variance accounted for" (See the end of Chapter 22).

Adjusting the SS Terms

Recall that the statistic ***r*** gives the degree of correlation between two variables. The statistic r^2 gives the amount of variability in one variable that is accounted for by another. So, if we have a pre-test that has a correlation of 0.80 with the post-test, its r^2 value is 0.64. Sixty-four percent of the variability found in the post-test scores can be explained by the variability in the pre-test scores.

The ***adjusted total sum of squares*** is adjusted as follows:

$$SS'_t = SS_t\,(1 - r^2_{total})$$

where SS'_t is the adjusted total sum of squares and r_{total} is the correlation coefficient between the covariate and the dependent variable for all pairs of observations.

The ***adjusted within sum of squares*** is given by

$$SS'_w = SS_w\,(1 - r^2_w)$$

where r_w is the within groups (pooled) correlation coefficient between the covariate and dependent variables. (Don't worry about where these terms come from. Computer programs calculate these terms from raw data automatically.)

Finally, the ***adjusted between sum of squares*** can be computed from the other two adjusted values:

$$SS'_b = SS'_t - SS'_w$$

These adjusted values are used in a one-way ANOVA design. The correlation between the covariate and the dependent variable reduces the amount of unknown error and makes the design more powerful.

Uses of ANCOVA

ANCOVA is employed where random assignment of subjects is not possible or permitted. This is frequently the case in schools, where classes must be studied as they are, intact. A simple approach is to give the intact groups a pretest, and then use the pretest as a covariate for posttest scores.

But there are many situations which lend themselves to ANCOVA: differences among religious, cultural, community, political, social, economic, or medical diagnostic groups; differences between alternative attitude, aptitude, or achievement groups; differences between vegetarians and non-vegetarians, smokers and non-smokers, users and non-users of a given product, criminals and non-criminals.

Measure the differing groups of interest on a large number of variables, and then analyze these variables to discover which ones best distinguish between the groups. This is done through a procedure called Discriminant Analysis. These differentiating

[10] Gene V. Glass, *Statistical Methods in Education and Psychology*, 2nd. (Englewood Cliffs, NJ: Prentice-Hall, Inc., 1984), 493-497

variables can then be used as covariates.

The strongest warning I've heard about ANCOVA came from my statistics professor at the University of North Texas. In defining what ANCOVA does, **Dr. William Brookshire** said, with a dry smile and somewhat sarcastically, "ANCOVA estimates what the experimental means would be if they weren't what they are." Be sure you understand both the research design and the statistical limitations of your study before you make strong statements about your findings. There lurk numerous pitfalls for researchers who fail to consider their findings carefully.

Example Problem

Gene Glass[10] provides this example of the benefits of ANCOVA.

An experiment was performed in twenty elementary schools of a large school district. Ten of the schools were randomly designated to be sites for adoption of an innovative science curriculum, "Science: A Process Approach" (SAPA). The SAPA materials were bought and placed in the **ten schools**; teachers were trained to use them. The **other ten** elementary schools continued to use the district's traditional science curriculum.

After two years of study in the respective programs, sixth-grade pupils in all twenty schools were given the Science Test (a 45-item measure of scientific methods, reasoning, and knowledge) of the Sequential Tests of Educational Process (STEP). Each student's score was expressed as a percentage. There were 50 to 120 6th graders in each school, but since the school itself (along with its teachers, administrators, surrounding neighborhoods, and the like) was randomly designated as either SAPA or Traditional (Experimental or Control), the **school was the experimental unit**. The twenty schools' means of sixth-grade pupils' STEP-Science scores were used as the observational unit in the statistical analysis. The collected data follows:

	"SAPA"	"Traditional"
	n = 10	n = 10
	77.63%	64.10%
	74.13	43.67
	67.20	50.40
	78.23	84.33
	57.93	44.93
	57.65	71.43
	83.30	71.10
	73.90	44.57
	45.90	68.23
	64.83	68.47
$\overline{X}$	68.07%	61.12%
s^2	134.60	201.50

Applying one-way ANOVA to this data produced the following table. **Was there a significant difference in the two curricula?**

Source	SS	df	MS	F
Between	241.30	1.00	241.30	**1.44**
Within	3,024.94	18.00	168.05	
Total	3,266.24	19.00		

F_{cv} (0.10, 1, 18) = **3.01**

The answer is no. The F-ratio is smaller than the critical value — ***even at α=0.10,*** *and inappropriate level of significance.* But what if we know something more about the schools that could explain some of the error variance, and in so doing, reduce the error term of the analysis? **IQ differences** between the schools might affect the results. It is reasonable to assume that schools with high scholastic aptitude (IQ) will tend to have higher means on the achievement test than schools with lower IQ means. IQ means for each of the twenty schools are shown with the achievement means below:

	"SAPA"		"Traditional"	
	IQ	ACH	IQ	ACH
	105.7	77.63%	101.2	64.10%
	100.3	74.13	97.6	43.67
	94.3	67.20	96.4	50.40
	108.7	78.23	109.6	84.33
	93.1	57.93	94.0	44.93
	96.7	57.65	105.4	71.43
	106.9	83.30	102.4	71.10
	100.3	73.90	100.6	44.57
	86.5	45.90	104.2	68.23
	96.1	64.83	112.6	68.47
$\overline{X}$	**98.86**	**68.07%**	**102.40**	**61.12%**
s^2	**47.94**	**134.60**	**33.60**	**201.50**

Using adjusted SS terms, an ANCOVA table can be built from this data which looks like this:

Source	SS'	df	MS'	F
Between	786.71	1.00	786.71	16.10
Within	830.88	17.00	48.88	
Total	1,617.59	18.00		

$F_{cv}(.01,1,17) = 15.7$

Now we find the groups significantly different ($p < 0.01$). This adjustment was possible because of the ***high correlation between mean IQ and mean science achievement scores*** (r = +.931, +.805 for the experimental and control groups respectively). ANCOVA used these correlations to reduce the error variance and provide a more powerful analysis than was possible through ANOVA alone.

Multivariate Analysis of Variance

When we extended one-way ANOVA to Factorial ANOVA, we added one or more ***independent*** variables to a design.

When we extend a one-way ANOVA to a Multivariate ANOVA (**MANOVA**), we add one or more ***dependent*** variables to a design. A one-factor MANOVA consists of one independent variable (treatment) and tests two or more dependent variables (measurements).

A **multi-factor MANOVA** tests two or more independent variables against two or more dependent variables (i.e., combines factorial and multivariate designs).

An educational researcher might be interested in the impact of three different questionning strategies on several learner variables. The three strategies form a one-way ANOVA design, but the multiple learner measurements — achievement, anxiety level, attitude toward the course, attitude toward the instructor — make the design a MANOVA.

A counseling researcher might be interested in the impact of group vs. individual counseling and level of social competence on four counselee variables. These two independent variables form a 2-way ANOVA design, but the four dependent variables make the design a multi-factor MANOVA. It is enough at this point to be aware of the existence of these procedures, and to know what has been done when you discover a MANOVA analysis in your reading.

Summary

In this chapter, you've been introduced to the concepts of factorial ANOVA, interaction, ANCOVA, and MANOVA. A basic understanding of these advanced techniques will help you understand the research articles you'll read as part of your literature analysis. The following table gives a summary of the key elements in these procedures.

Name of Analysis	*Number of Independent Variables*	*Number of Dependent Variables*
One-Factor ANOVA	**ONE** (Questionning strategy)	**ONE** (Achievement)
Multi-factor ANOVA	**MANY** (Questionning strategy, Structure, Variety, and Attitude of Teacher)	**ONE** (Achievement)
One-factor ANCOVA	**ONE plus COVARIATE** (Questionning strategy, IQ)	**ONE** (Achievement)
One-factor MANOVA	**ONE** (Questionning strategy)	**MANY** (Achievement, attitude toward class, anxiety level)
Multi-factor MANOVA	**MANY** (Questionning strategy, Structure, Variety, and attitude of Teacher)	**MANY** (Achievement, attitude toward class, anxiety level)

Example

Dr. Gail Linam's dissertation[11] was cited earlier for her use of the Kruskal-Wallis H Test to measure differences between three groups of ranks (see Chapter 24). Her use of the H Test was secondary to her primary statistic of two-way ANOVA. Her dependent variable was reading comprehension score. She used the **R**etelling Method and the **C**loze Test to produce reading comprehension scores for an Old Testament story (OT**R**, OT**C**), a New Testament story (NT**R**, NT**C**), and a Bible score, the average of the two stories (BIB**R**, BIB**C**). Her two independent variables were CAMP (church campus or mission campus) and VER (Bible version: KJV, NIV, NCV), as shown

[11]Information for these tables from Linam, pp. 174, 196, and 198-200

below:

	CAMP	
VERSION	**Church Campus**	**Mission Campus**
KJV	**xx.xxx**	**xx.xxx**
NIV	**xx.xxx**	**xx.xxx**
NCV	**xx.xxx**	**xx.xxx**

The two-way ANOVA table for **OTR** was:

DEP VAR: OTR N: 93 MULTIPLE R: 0.636 SQUARED MULTIPLE R: 0.405

ANALYSIS OF VARIANCE

SOURCE	SUM-OF-SQUARES	DF	MEAN-SQUARE	F-RATIO	P
CAMP	3591.258	1	3591.258	26.490	0.000
VER	3377.792	2	1688.896	12.458	0.000
CAMP*VER	175.082	2	87.541	0.646	0.527
ERROR	11794.434	87	135.568		

There is no interaction between CAMP and VERsion (p=.527), so we can test the two independent variables separately. There was a significant difference in OTR reading comprehension scores between the church campus and mission campus children (p<.001). Looking at the scores below, we can see the church campus children scored higher than mission campus children. This was true in every case.

There was a significant difference across translation (p<.001). The scores below show that the KJV produced the lowest comprehension scores. This was true in every case.

	CAMP	
VERSION	**Church Campus**	**Mission Campus**
KJV	**18.81**	**7.00**
NIV	**32.96**	**15.00**
NCV	**34.41**	**23.11**

The two-way ANOVA table for **NTR** was:

DEP VAR: NTR N: 92 MULTIPLE R: 0.649 SQUARED MULTIPLE R: 0.422

ANALYSIS OF VARIANCE

SOURCE	SUM-OF-SQUARES	DF	MEAN-SQUARE	F-RATIO	P
CAMP	3215.289	1	3215.289	29.485	0.000
VER	3406.045	2	1703.022	15.617	0.000
CAMP*VER	615.553	2	307.777	2.822	0.065
ERROR	9378.172	86	135.568		

There is no interaction (p=.065). Both CAMP and VER show significant differences. Here are the group means for NTR:

VERSION	CAMP: Church Campus	Mission Campus
KJV	25.55	7.25
NIV	37.55	21.56
NCV	34.60*	29.44

*See Linam, p. 105

The two-way ANOVA table for **OTC** was:

DEP VAR: OTC N: 93 MULTIPLE R: 0.718 SQUARED MULTIPLE R: 0.516

ANALYSIS OF VARIANCE

SOURCE	SUM-OF-SQUARES	DF	MEAN-SQUARE	F-RATIO	P
CAMP	1995.647	1	1995.647	39.754	0.000
VER	2239.649	2	1119.824	22.307	0.000
CAMP*VER	2.229	2	1.115	0.022	0.978
ERROR	4367.414	87	50.200		

There is no interaction (p=.978). Both CAMP and VER show significant differences.

VERSION	CAMP: Church Campus	Mission Campus
KJV	14.91	4.22
NIV	23.27	13.33
NCV	27.55	17.56

The two-way ANOVA table for **NTC** was:

DEP VAR: NTC N: 92 MULTIPLE R: 0.772 SQUARED MULTIPLE R: 0.595

ANALYSIS OF VARIANCE

SOURCE	SUM-OF-SQUARES	DF	MEAN-SQUARE	F-RATIO	P
CAMP	1873.493	1	1873.493	47.556	0.000
VER	2618.725	2	1309.362	33.236	0.000
CAMP*VER	119.222	2	59.611	1.513	0.226
ERROR	3388.047	86	39.396		

There is no interaction (p=.226). Both CAMP and VER show significant differences.

VERSION	CAMP: Church Campus	Mission Campus
KJV	11.05	0.38
NIV	23.50	10.78
NCV	22.82	16.11

In each case we see that church campus children scored significantly higher in reading comprehension than mission children, and readers of the KJV scored significantly lower than readers of either NIV or NCV versions -- in every condition. Specific computations of pair-wise differences were made using the FLSD procedure. See "Example" on page 21-8 for these findings.

Dr. Linam's findings indicate that teachers and curriculum writers need to avoid use of the King James Version of the Scriptures for older children (grades 4-6). Children of this age simply cannot understand the text as well as the New International of New Century versions.

Vocabulary

ANCOVA	Analysis of Covariance: uses pretest differences to adjust posttest means
disordinal interaction	factorial ANOVA: ranks of means differ across treatment levels
factorial ANOVA	designs which have 2 or more ind't variables (2-way, 3-way, k-way)
interaction effect	effects of one treatment not constant across levels of a second
main effects	Row and Column F-ratios in a factorial design
MANOVA	Multivariate Analysis of Variance: more than one dependent variable
multi-factor MANOVA	Factorial design (e.g., 2-way) with more than one dependent variable
ordinal interaction	factorial ANOVA: ranks of means constant across treatment levels
simple effects	testing differences of means of one treatment across all levels of the second

Study Questions

1. Define factorial ANOVA.

2. What is the advantage of using factorial ANOVA over multiple one-way ANOVA's?

3. Explain the term "interaction."

4. Compare and contrast ordinal and disordinal interaction.

5. If you discover a significant interaction in your data,
   A. What implications does this have for main effects interpretation?
   B. What further procedure must you employ?

6. Answer the questions below using this computer printout:

Source	*df*	*SS*	*MS*	*F*	*p*
Parity	1.00	11.24	11.24	2.70	0.11
Size	2.00	90.61	45.31	10.83	0.00
Parity x Size	2.00	16.32	8.16	1.95	0.15
Error	49.00	205.00	4.18		
Total	54.00	323.17			

A. How many subjects were involved in this study?
B. How many levels of PARITY were used?
C. How many levels of SIZE were used?
D. How many groups were tested?
E. Which term was used in the denominator of all the F-ratios?
F. Was the interaction between PARITY and SIZE significant?
G. Was PARITY a significant treatment variable? How do you know?

H. Was SIZE a significant treatment variable? How do you know?
I. In this case, would you
(a) interpret the main effects of PARITY and SIZE, or would you
(b) apply simple effects tests? Explain why.

7. Design a study in your field of specialty using the following research designs: factorial ANOVA, ANCOVA, or MANOVA.

Sample Test Questions

1. The row and column F-ratios in a two-way ANOVA are called
A. simple effects
B. side effects
C. interaction effects
D. main effects

2. Ordinal interaction is indicated on a graph of means by the fact that the lines
A. are parallel to each other
B. are not parallel, but do not cross each other
C. cross each other
D. intersect at the origin

3. The term used in the denominators of each F-ratio in a 2-way ANOVA, given variables A and B, is the term
A. MSa
B. MSb
C. MSab
D. MSe

4. All of the following suggest the use of ANCOVA except
A. intact school classrooms
B. differing religious groups
C. randomly selected subjects
D. criminals and non-criminals

5. The factor used to adjust the SS terms in ANCOVA is
A. MSw
B. N-k
C. r^2
D. n