

MATH 315: METHODS in APPLIED STATISTICS VIDEOS ON “YouTube” (2018)

This compendium of videos is provided as an **optional resource** to enhance a student’s understanding of topics covered in the MATH 315: *Methods in Applied Statistics* course program. **They are not required listening.** Those videos which use SPSS for illustration and explanatory purposes may be using different versions of the software – so watch the procedure sequences carefully and compare them with your particular version.

All of these presentations provide either theoretical discussions around statistical concepts or case studies of statistical analysis in various disciplines using SPSS. The case studies have been drawn from: social science, health studies, psychology, political science, management science, business, sports, engineering, manufacturing, medicine, veterinary medicine, biology, zoology, and education.

A good number of these videos have been developed by the Rocky Mountain University Health Professionals group (RMUoHP Biostatistics Resource Channel) or by Ray Cooksey, a professor from the University of New Zealand School of Business. Most of them include the use of the statistical software package, SPSS, for demonstration purposes. Some are simply overviews of various statistical methods and/or the logic behind their development. These mini-lectures have been chosen because of the clarity of presentation and the breadth of coverage (including complexities) of the topic at hand. In addition, reaching back a few decades, there are videos which were a part of the 1966 Design of Experiments learning series lectures given by statistician, author, and professor, J. Stuart Hunter. They have been presented courtesy of JMP software from SAS.

On each YouTube page, there are other web-casts which cover some of the same topics in slightly different ways. Please feel free to sample these videos at random.

Julie Peschke, MATH 315 Academic Coordinator

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➤ Different Designs in Statistical Research

(Unit 1: chapter 2 of the text pp. 16 – 48 – through another lens)

- [Statistics – Hypothesis Testing Mistakes](#) (DrCraigMcBridePhD)

Two data collection mistakes are discussed – the cart before the horse and mismatched data.

- [Experimental-Observational Methods](#) (Ray Cooksey)

In this video-cast, Professor Cooksey, from the Business School at the University of New Zealand, talks about variables involved in statistical analysis and their roles. He discusses the important difference between **independent and dependent variables**. In order to demonstrate cause and effect in a model, the video covers three important **must do's**, the issue of **covariance between variables** (when one variable affects the values of another) and other kinds of variables: namely, **moderator variables**, **mediating variables**, and **extraneous variables**.

- [Survey Methods](#) (Ray Cooksey)

Three types of survey methods are detailed: those that involve a **direct face-to-face interaction between researcher and participant**; **electronic interaction between researcher and participant**; and the self-administered survey techniques where the respondent has **little or no contact with the researcher**. Designs can be **cross-sectional** (one survey across the entire sample), **longitudinal** (same participants getting the survey instrument at different time periods), or a **panel study** (a series of cross-sectional studies where the respective samples are different but as similar as possible).

- [Cluster Analysis](#) (Ray Cooksey)

In this video, cluster analysis is presented as a data mining technique intended to discover patterns in a set of data. Most often data patterns of the variables can create a typology involving a categorization of respondents or cases. Respondents or cases are said to be similar if they are 'clustered' about a single point in the generalized Euclidean plane determined by the quantitative measures of TWO OR MORE variables (characteristics) and the Euclidean distance between them is within an acceptable limit. Ward's minimum variance hierarchical cluster technique as well as the *k*-means non-hierarchical clustering algorithm are discussed. Both methods may be done in SPSS.

- [What is Design of Experiments? – Part 1](#) (J. Stuart Hunter)

- [What is Design of Experiments? – Part 2](#) (J. Stuart Hunter)

In this two-part series, one can learn how statistical methods can be used to design experiments, based on mathematical models, which are useful for describing processes in science and engineering. These videos are a part of the 1966 Design of Experiments learning series presented by statistician and author, Professor J. Stuart Hunter. They have been presented courtesy of JMP software from SAS.

- [Experiments: What Can Go Wrong?](#) (Jeremy Haselhorst)

Three issues with experiments are discussed: the placebo effect, the double-blind experiment and the meaning of statistical significance.

➤ The Theoretical Basis for Inferential Statistical Methods

(top-down review of important foundational concepts from Introductory Statistics)

- [Quantitative Data Analysis Issues](#) (Ray Cooksey)

Quantitative data analysis draws upon a **tool kit of statistical methods**. Each of those methodologies are **rules-driven** and those rules generally come with a **set of assumptions** about the data gathered. Understanding and strictly applying those assumptions is half the battle to obtaining credible and significant statistical results.

- [The Logic of Statistical Inference](#) (Ray Cooksey)

This video provides a review of the conceptual logic of statistical inference as the fundamental decision making process behind hypothesis testing for the purposes of addressing certain kinds of research questions. In short, statistical inference is a generalization of single sample empirical evidence repeated many times.

- [Considering the Average – Part 1](#) (J. Stuart Hunter)

- [Considering the Average – Part 2](#) (J. Stuart Hunter)

Learn about multinomial distributions, **frequency density functions** and the **Central Limit Theorem**. Professor Hunter shows how taking averages using repeated trials of an experiment can lead to the **normal distribution**. He also discusses how the **Poisson distribution** came about - using a geiger counter. Note that the Greek letter indicating the mean of a distribution has changed from η (in 1966) to μ .

- [Sampling Distributions: An Introduction to the Concept](#) (jbstatistics)

This video helps explain why 'normally distributed' data is a pre-requisite for many statistical methods. The normal curve (or bell curve) is an idealized sampling distribution for the means and proportions of a surprising amount of quantitative data drawn from populations of statistical interest.

- [Estimating Sample Size using SPSS and Web-based Calculators](#) (RMUoHP)

- [PASS Software for Estimating Sample Size](#) (NCSS)

PASS can calculate optimal sample sizes for over 230 statistical tests and confidence intervals. Free trials are available.

- [Normality Test: How to check whether data points are normally distributed using SPSS](#) (RMUoHP)

Many of the statistical techniques mentioned in this document require that the data be AT LEAST approximately normally distributed. This video describes how to test your data for 'normality.'

- [Standard Scores and Shared Variance](#) (Ray Cooksey)

This is a review of the conceptual logic behind the use of standard or z-scores in statistical analysis. In the presentation, Dr. Cooksey also relates this logic to the concept of shared or common variance. It

explains why we sometimes use the standard normal distribution for hypothesis testing, instead of the normal distribution for each of the variables in question. In this way, we don't have to deal with a bunch of difference variances in the data across the groups of interest because each one has been standardized to have a mean of 0 and a standard deviation of 1 unit. A common variance simplifies statistical procedures used in many of the analytic methods.

- [What is the p-value of a Hypothesis Test? \(jbstatistics\)](#)

The video explains the concept of a statistical p-value and how it is used in hypothesis testing.

- [A Tool for Visualizing the p-value for Various Hypothesis Tests? \(statdistributions.com\)](#)

Visualizing the probability distributions and the positioning of the test statistic is an important part of understanding the hypothesis rejection regions. For example, this is an online application which, for a given p-value / test statistic and degrees of freedom, shows the different shapes of the Normal, the Standard Normal, the Student's t, the Chi-squared and the F- distributions in real time, the position of the test statistic and the area representing the given p-value.

➤ Statistical Analysis Techniques

- [Choosing the Appropriate Statistical Analysis Technique \(RMUoHP\)](#)

This presentation provides a step-by-step approach for choosing one or more appropriate statistical tests for data analysis. There are three types: descriptive, correlational or predictive, and group differences techniques.

- [How to Choose the Correct Statistical Test \(School of Surgery\)](#)

Here several criteria are used to determine which statistical test is best suited to a research question: the type of data collected, the number of samples/groups in the experiment and the purpose of the research. The flow charts for choosing a test, both parametric and non-parametric, are excellent.

- **Descriptive Analysis Techniques:** used in survey research or observational research designs, presented as preliminary top-down summaries of the data

These techniques involve finding frequencies of occurrence of a given variable (or characteristic), percentages or proportions of a population in a given category, percentiles, measures of central tendency (means, medians, modes, variances), and standard scores, such as a z-score. They may also include at-a-glance graphical presentations of the data, such as histograms, bar charts or pie charts.

- [How to Calculate and Interpret z-Scores using SPSS \(statisticsinstructor\)](#)
- [Displaying Group Data Using Box Plots and Bar Graphs using SPSS \(RMUoHP\)](#))

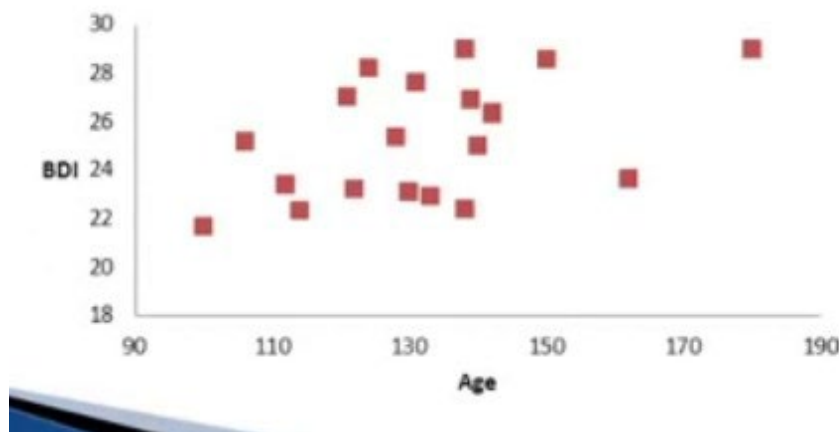
This video shows how to display both independent and dependent variable data.

- **Correlational / Predictive Analysis Techniques:** used to determine IF there exists a relationship between variables and, IF SO, its strength and direction

- **Finding Correlations or Relationships Between Quantitative Variables**

These techniques provide information as to whether a definable **dependence** or **relationship** exists between two **quantitative** variables and, if there is one, the **strength** and the **direction** (positive or negative) of that relationship. It should be noted that correlation does not necessarily imply causation.

Scatter plots of data points are often used to see possible correlations between two quantitative variables. They may be tested for linearity expressible as a straight line estimation (or non-linearity), for strength (the value of the slope of that estimated line) and for direction (whether that slope is negatively or positively oriented).



- **Preparing Quantitative Data for Statistical Analysis**

Data which is skewed, and therefore not (approximately) normally distributed, generally cannot be tested using statistical parametric methods. In order to report parametric statistics on that data, it may be necessary to transform the **continuous variables** using **logarithms** or other continuous invertible functions applied to the data so that it is more amenable to parametric testing.

(Unit 3.3: chapter 8, section 5 of the custom text pp. 75 – 82)

(Unit 4.1: chapter 11, section 1 of the custom text pp. 158 - 162)

- **[Transforming Skewed Data Sets using SPSS](#) (RMUoHP)**

This video discusses how to use log transformations to 'correct' or normalize skewed data sets.

- **[Reporting Log-transformed Data using SPSS](#) (RMUoHP)**

This video discusses how to prepare log-transformed data to be reported using the original units of measure.

- **[Data Aggregation using SPSS](#) (RMUoHP)**

This video discusses how to create new variables from old ones using sums, differences and products. For example, the final grade in this course is calculated using a formula which is composed from the grades on your assignments, your mid-term exam score and your final exam score.

PARAMETRIC TESTS: for (APPROXIMATELY) NORMALLY DISTRIBUTED DATA

(Unit 4.3: chapter 11, section 7 of the custom text pp. 190 - 198)

- [Pearson Correlation Coefficient using SPSS](#) (RMUoHP)

How to determine if there exists a **linear relationship** OR a **linear correlation** between TWO **continuous variables** that contain interval (can add or subtract) or ratio (can multiply and divide) scale data. The video also includes a demonstration of how to create a **scatter plot** of such data points in the plane.

NON-PARAMETRIC TESTS: for NON- NORMALLY DISTRIBUTED DATA

(Unit 2.6: chapter 15, section 8 of the custom text pp. 623 - 627)

- [Spearman Correlation Coefficient using SPSS](#) (RMUoHP)

How to determine correlations between TWO variables that contain EITHER **ordinal scale** (order or ranking) data OR **continuous interval** (can add or subtract) or **ratio** (can multiply and divide) scale data.

- [Kendall's Tau Correlation Coefficient using SPSS](#) (RMUoHP)

How to determine if a relationship exists between **TWO ordinal scale** variables. This test can be used as an alternative to the Spearman Correlation Coefficient.

- **Regression Techniques to Define Relationships Between Quantitative Variables**

These are more sophisticated extensions of correlation and are used to examine the predictability of ONE OR MORE independent variables on ONE **continuous, quantitative** measure. In these methods, the resulting relationship is expressed as a **mathematical equation** in which the **dependent variable is expressed as a linear combination of the independent variables** with a extra term of possible error.

- **Simple Linear Regression Analysis**

(Unit 4: chapter 11, sections 2 - 6 of the custom text pp. 163 - 190)

Simple regression analysis is a statistical method which uses ONE predictor/independent variable to predict a single (ONE) **continuous, quantitative** outcome. The regression process leads to a real-valued linear function in one independent variable with an error term - which, when graphed in the 2-dimensional plane, is **a line**.

- [Simple Linear Regression Analysis using SPSS](#) (RMUoHP)

A technique which uses ONE predictor/independent variable to predict a **single quantitative** outcome.

- [Regression and Prediction Equations using SPSS](#) (Dr. Ami Gates)

How to generate a prediction equation for TWO variables (one independent; one dependent) having a high enough (relatively close to 1) correlation using **linear regression** analysis.

- **Reducing Complexity in the Model (not suitable for categorical data)**

(Unit 5.6: chapter 13, section 2 of the custom text pp. 346 – 363)

FACTOR or COMPONENT ANALYSIS is one way of paring down the number of predictor /independent /explanatory variables (called factors) in certain research problems. The procedure is capable of identifying a small number of factors/independent variables which explain most of the variance exhibited in the outcome/dependent variable. This allows the researcher to screen variables for further analysis, in particular to **identify collinearity** before performing linear regression analysis. This method of statistical analysis can also be used to **generate hypotheses regarding cause and effect** amongst the variables.

Data: should be **quantitative and continuous (interval or ratio)**. In particular, factor analysis is suitable for **data for which Pearson Correlation Coefficients can be calculated**.

Assumptions: data, meaning the bivariate ordered pairs of (independent, dependent) for all such pairings or variables, should have a bivariate **normal** distribution. In addition, the observations should be **independent**.

Extraction Method: **principal component analysis (PCA)**

Options: allows **either a correlation or a covariance matrix** (a rectangular array of numbers)

- [Factor Analysis – An Introduction](#) (Lee Rusty Waller)

This video provides a conceptual overview of factor analysis. The presenter first defines factor analysis as “a correlational method used to find and describe the underlying factors driving data values for a large set of variables.” This process is used to reduce any highly correlated factors into a single factor. Finally, a general procedure is discussed for accomplishing this task.

- [Factor Analysis \(Principal Components Analysis\) using SPSS](#) (RMUoHP)

This video discusses the difference between ‘Standard Factor Analysis’ and ‘Principal component Analysis’ (PCA). It further demonstrates the PCA process, using SPSS, to determine which, out of a rather large set of predictor/independent variables, are most effective in their ability to measure a single construct.

- [Factor Analysis \(Principal Components Analysis\) using SPSS \(part 1\)](#) (Quantitative Specialists)
[Factor Analysis \(Principal Components Analysis\) using SPSS \(part 2\)](#)
[Factor Analysis \(Principal Components Analysis\) using SPSS \(part 3\)](#)
[Factor Analysis \(Principal Components Analysis\) using SPSS \(part 4\)](#)
[Factor Analysis \(Principal Components Analysis\) using SPSS \(part 5\)](#)
[Factor Analysis \(Principal Components Analysis\) using SPSS \(part 6\)](#)

This is a six-part series on how to perform ‘Principal component Analysis’ (PCA) for an experiment on satisfaction with one’s life. Five independent/predictive/explanatory variables were collected :

1. In most ways my life is close to ideal.
2. The conditions of my life are excellent.
3. I am satisfied with my life.
4. So far I have gotten the important things I want in life.
5. If I could live my life over, I would change almost nothing.

Each of the variables was to be given a score of 1 to 7 with the higher scores indicating a stronger agreement. From the data collected, this set of five was reduced in number by the PCA analysis.

- **Multiple Linear Regression Analysis**

(Unit 5: chapter 12, sections 1 - 7 of the custom text pp. 246 – 283
chapter 13, sections 1 – 6 of the custom text pp. 345 - 407)

Multiple regression analysis is a statistical method which uses multiple ($n \geq 2$) predictor/independent variables to predict a single (ONE) **continuous, quantitative** outcome. The regression process leads to a real-valued function in more than one or $n \geq 2$ independent variables with an error term – which, when graphed in $(n + 1) \geq 3$ Euclidean space, form a **straight plane** in that space.

- **The Logic of Multiple Regression** (Ray Cooksey)

An overview of the conceptual framework behind this statistical design for analyzing some data.

- **Types of Multiple Regression Analysis** (Ray Cooksey)

(Unit 5.6: chapter 13, section 3 of the custom text pp. 363 – 379)

This video discusses the conceptual underpinnings of different types of model building in multiple (MORE THAN ONE predictor/independent/explanatory variables) regression analysis: simultaneous regression, hierarchical regression and stepwise regression. While Professor Cooksey does not particularly encourage the use of stepwise regression, nonetheless it has its place in statistical methodology and is used by certain researchers.

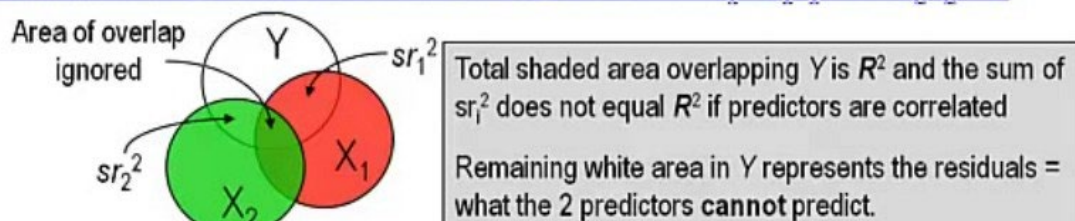
Simultaneous Regression (time 0:00 - 9:18)

Hierarchical Regression (time 9:19 - 16:46)

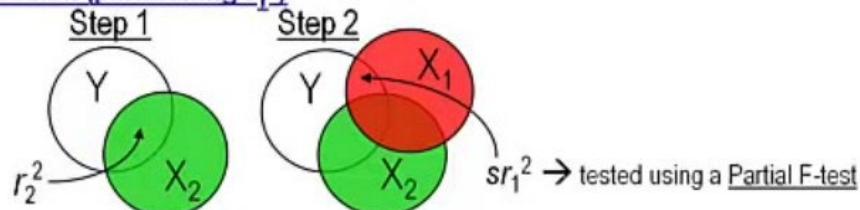
Step-wise Regression (time 16:47 - end)

Model Building in Multiple Regression Analysis

Simultaneous Regression (also Predictive Regression: $Y = b_0 + b_1X_1 + \dots + b_KX_K + e$)



Hierarchical Regression (partitioning s_y^2)



Total shaded area overlapping Y is R^2 and $sr_1^2 + r_2^2$ does equal R^2

Remaining white area in Y represents the residuals = what the predictors cannot predict.

Stepwise Regression (generally to be avoided as predictors in the model are chosen using an algorithm, rather than using theory)

- [Testing Multiple Regression Assumptions on Data Variables using SPSS](#) (Nikos Ntoumanis)
(Unit 5.6: chapter 13, section 4 of the custom text pp. 379 – 399)

Multiple regression analysis cannot be applied unless certain conditions have been met. This video discusses how to test these assumptions.

- [Standard Multiple Regression Analysis using SPSS](#) (RMUoHP)

This video provides a demonstration of simultaneous multiple regression which uses multiple (MORE THAN ONE) predictor/independent variables (either categorical using dummy variables or continuous) to predict a **single quantitative** outcome or continuous variable.

- [Multiple Regression – SPSS \(part 1\)](#) (how2stats)
- [Multiple Regression – SPSS \(part 2\)](#) (how2stats)

In this series, the presenter covers all of the main elements of a multiple regression analysis, including multiple R, R squared, model development (via stepwise method), intercept, unstandardized beta weights, standardized beta weights, semi-partial correlations, standard errors, as well as basic heteroscedasticity tests (equality of variances). Note that, in regression analysis, heteroscedasticity means a situation in which the variance of the dependent variable varies across the data groups. Heteroscedasticity complicates analysis because many methods in regression analysis are based on an assumption of equal variance.

- [Regression with Dummy Variables Part 1 using SPSS](#) (Stats199982)
- [Regression with Dummy Variables Part 2 using SPSS](#) (Stats199982)

These videos show how to create so-called ‘dummy variables’ in a multiple regression situation where one or more of the independent variables are categorical, rather than continuous quantitative variables. In this case, the categorical variable, gender (male, female), is replaced with the dummy variable in which male is coded as 0 and female as 1. The categorical variable, marital status (divorced, married, never married), is replaced with the dummy variable in which divorced is coded as 1; married as 2; and never married as 3.

- [Multiple Regression with SPSS](#) (Alliant International University)

In this video, one of the independent variables is “mathene,” a fake drug used to improve your understanding of mathematics. The other is “hours of study.” Multiple regression analysis is applied on these two variables against the dependent variable, math test scores.

- **Binary Logistic Regression Analysis**
(Unit 5.5: chapter 12, section 8 of the custom text pp. 290)

This kind of regression analysis uses ONE OR MORE **predictor/explanatory** variables (**either categorical or quantitative**) to predict a **dichotomous binary categorical** RESPONSE/OUTCOME variable, meaning an outcome in which there are only two possibilities. The null hypothesis of this test is that no relationships exist.

○ **Binary Logistic Regression Analysis using SPSS (LSE) (Political Science Research)**

In this case study, the researcher wants to know if a person's having signed a petition (**outcome/response variable**) has anything to do with any one of the following: their intention to vote in the next election, the number of volunteer groups in which they belong, their gender and their age (the **predictor/explanatory variables**). The null hypothesis is that there is no relationship between any of the predictor variables and the response variable.

FOUR EXPLANATORY VARIABLES (TWO categorical; TWO quantitative):

ONE categorical EXPLANATORY variable with TWO groups/levels: intention to vote (no, yes) using the dummy variable (0,1) where 0 = 'no'; 1 = 'yes';

ONE quantitative continuous EXPLANATORY variable: number of volunteer groups in which involved;

ONE categorical EXPLANATORY variable with TWO groups/levels: gender (female, male) using the dummy variable (0,1) where 0 = 'female'; 1 = 'male';

ONE quantitative continuous EXPLANATORY variable: age in years;

RESPONSE VARIABLE

ONE **dichotomous binary categorical** RESPONSE/OUTCOME variable with TWO groups/levels: signed a petition (no, yes) using the dummy variable (0,1) where 0 = 'no'; 1 = 'yes'.

○ **Binary Logistic Regression Analysis using SPSS (RMUoHP) (Health Studies Educational Research)**

In this case study, the researcher wants to know if students' having passed a certification exam (**outcome/response variable**) was related to any one of the following: their clinical experience evaluation score, their oral comprehensive exam score, their written comprehensive exam score, their overall GPA or their GPA in their major discipline (the **predictor/explanatory variables**). The null hypothesis is that there is no relationship between any of the predictor variables and the response variable.

SIX EXPLANATORY VARIABLES (ALL continuous quantitative):

ONE quantitative continuous EXPLANATORY variable: interview score;

ONE quantitative continuous EXPLANATORY variable: clinical experience evaluation score;

ONE quantitative continuous EXPLANATORY variable: oral comprehensive exam score;

ONE quantitative continuous EXPLANATORY variable: written comprehensive exam score;

ONE quantitative continuous EXPLANATORY variable: overall GPA (grade point average);

ONE quantitative continuous EXPLANATORY variable: GPA in major discipline;

RESPONSE VARIABLE:

ONE **dichotomous binary categorical** RESPONSE/OUTCOME variable with TWO groups/levels: pass or fail certification exam on first try using the dummy variable (0,1) where 0 = 'fail'; 1 = 'pass'.

- **Group Differences Techniques using Experimental Designs:** used to compare ONE OR MORE categorically organized groups to see if there are statistically significant differences between them on ONE (OR MORE) outcomes (either quantitative or categorical)

In determining which of the variables are independent and which are dependent variables, think of the independent variables as the ones (characteristics) which are influencing the outcomes/responses (characteristics or values of interest or study) and the dependent variables as the outcomes/responses being affected or measured.

- **Experiments: Modifications** (Jeremy Haselhorst)

While the completely randomized design for data collection is the simplest proper design for experiments, it doesn't always yield the best results. This video discusses splitting the data into similar or comparative groups and then using either a randomized block design or a matched pairs design.

- **Comparing Group Differences for Categorical Data**

One of the basic functions of statistical analysis is to determine the **frequency** of an action or characteristic occurring in a population. Often such data is gathered using surveys. It is **generally categorical** in nature whereby each variable has a fixed number of mutually exclusive choices, levels or groups into which individuals can be categorized or fitted - for example, gender, political preference, whether one smokes, education level and so on. The following tests are used to analyse such categorical data.

Goodness-of-Fit Tests – for Survey Data: NON-PARAMETRIC TESTS

Goodness-of-Fit tests examine if the measures of any of the OBSERVED **relative frequencies** for each of the categorical choices are significantly different from a **fixed EXPECTED relative frequencies** for each choice drawn from another known population or from another sample from the same population.

In short, a goodness-of-fit test compares ONE categorical variable of sample data with theoretical expectations of the same. The categorical groups are being compared using the relative frequencies of occurrence. This is a type of Chi-Squared Test of Independence having only ONE categorical variable being tested. **That is why goodness-of-fit tests are sometimes called Chi-squared tests of independence for ONE-WAY TABLES or a ONE-DIMENSIONAL Chi-squared test of independence.**

Assumptions:

ONE **sample** of randomly selected subjects, independent of one other;

Sample size should be large enough so that the observed frequency for each group/level to be tested is at least 5;

ONE **categorical independent variable** with TWO OR MORE choices/groups/levels which are mutually exclusive for each subject;

COMPARED TO: a **hypothetical, theoretical or EXPECTED outcome** for those same categorical groups;

USING: quantitative **relative frequency or proportion/ratio/percentages** of responses from the sample in each category choice.

○ [One-Way Chi-squared Test for Goodness of Fit using SPSS](#) (RMUoHP) (Health Science Research)

It compares the proportion of smokers in the study with the proportion from a previous study of the same population (the 'hypothesized' or 'expected' value which is fixed). Note that the study in question had collected categorical data on marital status, whether the individual had children, the educational level of the individual, nature of the sources of stress in the individual's life style and whether the person smoked or not.

ONE **categorical independent variable**: smoking status (smoker, nonsmoker);

COMPARED TO: a **hypothetical, theoretical or EXPECTED outcome** for those came categorical groups in a previous study of the same population;

USING: quantitative **relative frequency or proportion/ratio/percentages** of responses from the sample in each category choice.

The associated table for this design is:

	Independent Categorical Variable Groupings/Levels	
	SMOKER	NON-SMOKER
RELATIVE FREQUENCY		
Dependent Variable		

○ [Chi-squared Test for Goodness of Fit](#) (statslectures) (Sociology Research)

It compares the proportions of individuals (divided into THREE age groups) in a small town taken from a 2010 population census ('observed') to a previous census ('expected') done in 2000. This Chi-squared test was done without any statistical software.

ONE **categorical independent variable**: age (under 18 years, between 18 – 35 years, above 35 years);

COMPARED TO: a **hypothetical, theoretical or EXPECTED outcome** for those came categorical age groups in the 2000 census;

USING: quantitative **relative frequency or proportion/ratio/percentages** of responses from the sample in each category choice.

The associated table for this design is:

	Independent Categorical Variable Groupings/Levels		
	Under 18 years old	18 – 35 years old	Above 35 years old
RELATIVE FREQUENCY			
Dependent Variable			

Tests of Independence

In these experimental designs, the researcher wants to compare TWO categorical variables, each having TWO OR MORE groups/levels. A **Chi-squared test of independence** compares the frequencies of occurrence of ONE categorical variable with different values of ANOTHER categorical variable. These tests are sensitive to any **interrelation between two categorical variables** and can help **finding interactions** between them.

Also of note is that Chi-squared tests of independence do exist for THREE OR MORE categorical variables simultaneously but they are more complex. In those cases, researchers may opt for successive pair-wise Chi-squared independence tests for each of the categorical variables pairs.

Preparing Data for Chi-Squared Tests of Independence

Cross tabulation is a statistical process that **summarizes categorical data** to create a contingency table. A **cross tab** is any table showing summary statistics; they can also be called **contingency tables**. Some entries may be weighted. Tables in which all entries remain un-weighted are commonly known as **pivot tables**.

In this case, the collected data are summarized in an **R x C / cross tab / contingency table** where:

R = the numbers of rows in the table = # of groups/levels of categorical variable 1 and

C = # of columns in the table = # of groups/levels categorical variable 2.

** It is irrelevant which categorical variable is chosen as the row variable or the column variable. Both are independent variables in the design with the outcome/dependent variable as the relative frequency of occurrence of each of the groups.

The **null hypothesis for a test of independence** is that the row and column independent variables (collected at random) of the associated contingency table are independent of (not related to) one another.

Assumptions:

ONE **sample** of randomly selected subjects, independent of one other;

The **sample size** should be large enough so that the expected frequency for each group/level to be tested is at least 5;

COMPARISON OF:

TWO **categorical independent variable(s)** with TWO OR MORE choices/groups/levels which are mutually exclusive for each subject;

USING: quantitative **relative frequency or proportion/ratio/percentages** of responses from the sample in each category choice.

- [How to Use Chi-squared for Independence Tests or Cross Tabulation using SPSS \(RMUoHP\) \(Health Studies Research\)](#)

In this case study, the researcher had gathered data from a sample of individuals regarding two characteristics: smoking status (split into two levels) and alcohol consumption (broken into four levels).

The question of interest was whether a person's smoking habit had an effect on (explained) his/her consumption of alcohol (response).

Looking at this research from a 4 X 2 contingency table analysis:

COMPARISON OF:

TWO categorical independent variables: smoking status and alcohol consumption;

ONE categorical independent variable with TWO levels: smoking status (smoker, nonsmoker) ;

ONE categorical independent variable with FOUR levels: alcohol consumption or AC (none, light, moderate, heavy) ;

USING: quantitative **relative frequency or proportion/ratio/percentages** of responses from the sample in each category choice.

The associated table for this design is a 4 X 2 contingency table:

	Independent Categorical Variable Groupings/Levels	
Independent Categorical Variable: alcohol consumption	SMOKER	NON-SMOKER
Alcohol Consumption: none		
Alcohol Consumption: light		
Alcohol Consumption: moderate		
Alcohol Consumption: heavy		
Dependent Variable: measured using relative frequency		

Looking at this research from a 2 X 4 contingency table analysis:

COMPARISON OF:

TWO categorical independent variables: smoking status and alcohol consumption;

EXPLANATORY VARIABLE

ONE categorical independent variable with TWO levels:: smoking status (smoker, nonsmoker) ;

RESPONSE VARIABLE

ONE categorical independent variable with THREE levels: alcohol consumption (none, light, moderate, heavy) ;

USING: quantitative **relative frequency or proportion/ratio/percentages** of responses from the sample in each category choice.

The associated table for this design is a 2 X 4 contingency table (in this case, the dependent variable, relative frequency, is tacit, not explicit):

	Alcohol Consumption: Independent RESPONSE Variable Groupings/Levels			
	None	Light	Moderate	Heavy
SMOKER				
NONSMOKER				
Independent EXPLANATORY Variable				

In the SPSS cross tabulation process, the general rule to follow is that the **independent** EXPLANATORY VARIABLE (smoking status) is the row variable and that the **independent** RESPONSE VARIABLE (alcohol consumption) is the column variable. Therefore, the latter table, the 2 X 4 contingency table, will be the appropriate one to use when interpreting the SPSS output. HOWEVER, this rule is not in stone. A 4 X 2 contingency table could also have been used provided the appropriate changes in the SPSS variable choices have been made, accordingly.

- [\(Two-Way Cross Tab\) and Chi-squared for TWO Categorical Variables using SPSS \(Methodology LSE\)](#) (Political Science Research)

This case study examines whether a person's level of interest in politics is related to her/his willingness to take part in a peaceful demonstration or protest. This is actually a TWO-WAY CROSS TAB because it examines the relationship, if any, between TWO categorical variables.

COMPARISON OF:

TWO **categorical independent variables**: interest in politics and willingness to participate;

EXPLANATORY VARIABLE

ONE **categorical independent variable with TWO levels**: interest in politics ('not very or not at all interested', 'very or quite interested') ;

RESPONSE VARIABLE

ONE **categorical independent variable with THREE levels**: willingness to participate ('No, I would never do', 'I might do', 'Yes, I have done') ;

USING: quantitative **relative frequency or proportion/ratio/percentages** of responses from the sample in each category choice.

The associated table for this design is a 2 X 3 contingency table:

	Willingness to Participate in Peaceful Demonstration: Independent RESPONSE Variable Groupings/Levels		
INTEREST IN POLITICS	Never	Might	Have Done Already
LOW			
HIGH			
Independent EXPLANATORY Variable			

- **(Three-Way Cross Tab) and Chi-squared for THREE Categorical Variables using SPSS (Methodology LSE) (Political Science Research)**

This case study examines whether a person's level of interest in politics is related to her/his willingness to take part in a peaceful demonstration or protest USING the CONTROL VARIABLE of gender. This is called a THREE-WAY CROSS TAB because it examines the relationship, if any, amongst THREE categorical variables.

COMPARISON OF:

THREE **categorical independent variables**: interest in politics and willingness to participate, controlling for gender; where

EXPLANATORY VARIABLE

ONE **categorical independent variable with TWO levels**: interest in politics ('not very or not at all interested', 'very or quite interested') ;

RESPONSE VARIABLE

ONE **categorical independent variable with THREE levels**: willingness to participate ('No, I would never do', 'I might do', 'Yes, I have done') ;

CONTROL/BLOCKING VARIABLE

ONE **categorical independent variable with TWO levels**: gender (female, male) ;

USING: quantitative **relative frequency or proportion/ratio/percentages** of responses from the sample in each category choice.

The associated design has TWO (levels of control variable) of 2 X 3 contingency tables:

CONTROL/BLOCK Variable FEMALE	Willingness to Participate in Peaceful Demonstration: Independent RESPONSE Variable Groupings/Levels		
	Never	Might	Have Done Already
LOW INTEREST			
HIGH INTEREST			
Independent EXPLANATORY Variable			

CONTROL/BLOCK Variable MALE	Willingness to Participate in Peaceful Demonstration: Independent RESPONSE Variable Groupings/Levels		
	Never	Might	Have Done Already
LOW INTEREST			
HIGH INTEREST			
Independent EXPLANATORY Variable			

• Comparing Group Differences for Quantitative Data

Normality Tests for Data Sets – using SPSS

(Unit 3.2: chapter 8, section 4 pp. 70 - 75)

- [How to Check Whether Data are Normally Distributed](#) (Kent Loeffgren)

In order to conduct either the Independent Samples t test or the one-way ANOVA tests, one major assumption is that the data distribution is normal or approximately normal. This video illustrates how to check these conditions on data using SPSS.

Tests of Homogeneity (for Equality of Variances)

(Unit 3.2: chapter 8, section 4 pp. 70 - 75)

These videos cover the Homogeneity of Variance Test as a necessary condition to conduct either the Independent Samples t test or the one-way ANOVA tests and how to interpret it.

- [Levene's Test of Equal Variances \(Part 1\) using SPSS](#) (Quantitative Specialists)
- [Levene's Test of Equal Variances \(Part 2\) using SPSS](#) (Quantitative Specialists)
- [Tests for Equality of Variances: Parametric and Nonparametric Levene's Test using SPSS](#) (Kent Löffgren) (Educational Research)

t Tests: assumptions, parametric tests and non-parametric alternatives

These tests generally involve **ONE categorical variable with TWO groups/levels**, either TWO *INDEPENDENT* groups, such as {male, female}, or TWO *DEPENDENT/PAIRED* sets of data, such as {pre-intervention, post-intervention}, for which we are comparing the respective MEAN SCORES on ONE quantitative variable, called the **outcome/response variable**.

Note that these t-tests are a precursor to the more elaborate **one-way ANOVA tests** which involve **THREE or MORE groups/levels of ONE categorical variable** for which we are comparing the respective MEAN SCORES on ONE quantitative variable, called the **outcome/response variable**.

Assumptions of the t-Tests:

- Randomness:** samples are randomly drawn from the populations of interest;
- Normality:** the outcome data for each group is (approximately) normally distributed;
- Equal Variances:** variances for the outcome data for each group may be equal or not equal; and
- Independence:** samples drawn from *different* populations are independent.

The Independent Samples t-Test

This kind of t-test helps to determine if there is a difference in the mean values of TWO *INDEPENDENT* (not related to one another) GROUPS of ONE categorical variable with respect to ONE continuous quantitative variable.

- [Independent Samples t Test using SPSS](#) (Ami Gates) (time 0:00 – 4:99) (Biological Research)

The case study is whether, on average, a person's gender (EXPLANATORY variable) affects the person's height (RESPONSE/OUTCOME variable). Another way of looking at this is whether there is a significant

difference in the mean heights of males versus females in the sample. In SPSS, the t-test output will provide the results for both cases: when the variances of the two groups about their means are assumed to be equal and when they are assumed to be different. This is done using Levine's test on the variable in question. The t-test design includes the:

COMPARISON OF

EXPLANATORY VARIABLE:

ONE categorical independent variable : gender with TWO groups/levels (male, female);

RESPONSE VARIABLE:

ONE continuous dependent variable: height;

USING: mean scores.

The associated table for this design is a 1 X 2 cross tab (note the positions of the explanatory and the response variables):

	Gender Independent EXPLANATORY Variable Groupings/Levels	
	MALE	FEMALE
HEIGHT		
Dependent RESPONSE Variable		

- [Comparing Two Means– Part 1](#) (J. Stuart Hunter) (Engineering Research)
- [Comparing Two Means – Part 2](#) (J. Stuart Hunter) (Engineering Research)

These videos show how to use of the Student's t statistic in situations where you want to compare two means **without knowing the variances of the dependent variable of either population group about those means.**

In this case study, the researcher wants to compare two types of motors with respect to their hysteresis losses (amount of lag between input and output), a way of measuring engine performance. The statistical test is done using hand calculations. The structure of the experiment involves the:

COMPARISON/IMPACT OF

EXPLANATORY VARIABLE:

ONE categorical independent variable : types of motors with TWO groups/levels (motor A, motor B);

WITH/ON

RESPONSE VARIABLE:

ONE continuous dependent variable: hysteresis loss;

USING: mean scores of the dependent variable, hysteresis loss.

The associated table for this design is a 1 X 2 cross tab (note the positions of the explanatory and the response variables):

	Types of Motors	
	Independent EXPLANATORY Variable Groupings/Levels	
	Motor A	Motor B
HISTERESIS LOSS		
Dependent RESPONSE Variable		

NON-PARAMETRIC ALTERNATIVE: Mann-Whitney U Test

(Unit 2.1: chapter 15, section 2 pp. 593 - 600)

Assumptions:

- total sample size n of at least 8 subjects;
- sample of subjects has been randomly collected and randomly assigned to the groups;
- the groupings are mutually exclusive (each pair of groups has an empty intersection);
- unbiased and independent data collection of the outcome variable; and
- the outcome data is either an ordinal scale or is continuous but not (approximately) normally distributed. In the latter case, **the method converts the continuous data into an ordinal rank scale.**

○ Mann-Whitney U Test using SPSS (RMUoHP) (Physical Education Research)

The case study is whether an athlete's training program (EXPLANATORY variable) affects the person's placement in a race (RESPONSE/OUTCOME variable). Another way of looking at this is whether there is a significant difference in the race placement rankings between the two groups of athletes. The independent t-test design includes the:

COMPARISON OF

EXPLANATORY VARIABLE:

ONE **categorical independent** variable : training method with TWO groups (method 1, method 2);

RESPONSE/OUTCOME VARIABLE:

ONE **ordinal scale dependent** variable: finish place in a race;

USING: mean scores.

The associated table for this design is a 1 x 2 cross tab:

	Independent EXPLANATORY Variable Groupings/Levels	
	TRAINING METHOD 1	TRAINING METHOD 2
PLACEMENT RANK in RACE		
Dependent RESPONSE Variable		

The Dependent (or Paired) Samples t-Test

This kind of t-test measures the VARIANCE **in mean values** between TWO *DEPENDENT* (related to one another) or TWO *PAIRED* (each subject measured two times) groups with respect to ONE continuous quantitative variable.

○ **Dependent (Paired) Samples t test** (Ami Gates) (time 8:45 - end) (Educational Research)

The case study involves a sample of students, each of whom are asked to take two tests: one before the intervention; one after the intervention. The researcher wants to discover whether the intervention has been, *on average*, beneficial to the students' learning. Another way of looking at this is whether there is a significant difference in the mean pre-test scores versus the mean of the post-test scores for the same sample of students. The dependent (paired samples) t-test design includes the:

COMPARISON OF

EXPLANATORY VARIABLE:

ONE categorical independent variable: time period of measurement with TWO groups/levels (pre-test, post-test);

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent variable: test scores;

USING: mean scores.

The associated table for this design is a 1 X 2 cross tab:

	Time Period of Measurement	
	Dependent/Paired EXPLANATORY Variable Groupings/Levels	
	PRE-TEST	POST-TEST
TEST SCORE		
Dependent RESPONSE Variable		

NON-PARAMETRIC ALTERNATIVE: the Wilcoxon Signed Rank Test

(Unit 2.3: chapter 15, section 5 pp. 607 - 611)

Assumptions:

- total sample size n of at least 5;
- unbiased and independent data collection of the outcome variable;
- the outcome data are measured in either ordinal or continuous scale. If the outcome data is continuous but not (approximately) normally distributed, the method converts the continuous data into an ordinal rank scale.

○ **Wilcoxon Signed Rank Test for Matched Pairs** (RMUoHP) (Medical Research)

The case study involves a sample of patients, each of whom is asked to submit to a treatment for chronic pain and fill out two surveys: one before the treatment; one after the treatment. The researcher wants to discover whether the treatment has been, **on average**, effective in lowering the patients' pain levels. The matched pairs Wilcoxon Signed Rank test design includes the:

COMPARISON OF

EXPLANATORY VARIABLE:

ONE categorical independent variable: time period of self-evaluation with TWO groups/levels (before treatment, after treatment);

RESPONSE/OUTCOME VARIABLE:

ONE ordinal scale dependent variable: pain scale from 1 to 10, 1 being minimum and 10 being maximum;

USING: mean scores.

The associated table for this design is a 1 X 2 cross tab:

	Time Period of Self-Evaluation Independent EXPLANATORY Variable Groupings/Levels	
	BEFORE TREATMENT	AFTER TREATMENT
PAIN LEVEL		
Dependent RESPONSE Variable		

➤ The Analysis of Variance or ANOVA Family of Statistical Methods

○ [ANOVA MANOVA](#) (Ray Cooksey)

This presentation provides a top-down look at central concepts associated with analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA), the logic behind each method and their differences.

• ANOVA Tests

Assumptions: the **REINs** of ANOVA

- i. **Randomness:** samples are drawn randomly from either one or several different populations;
- ii. **Equal Variances:** variances in the outcome/response data across the various groups/levels are equal;
- iii. **Independence:** samples drawn from *different* populations are independent; and
- iv. **Normality:** the outcome/response data are at least (approximately) normally distributed.

One-Way (Single Factor) ANOVA Tests (Unit 3.1 – 3.5: chapter 8, sections 1 - 5 pp. 56 - 82)

The nomenclature 'one-way' means ONE independent categorical (or grouping) variable – called a **FACTOR**. Each **ONE FACTOR ANOVA** test provides the

COMPARISON/IMPACT OF

EXPLANATORY VARIABLE:

ONE **independent categorical variable/FACTOR**

having THREE OR MORE independent groups/levels/TREATMENTS;

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE **dependent continuous** variable;

USING observations and **mean scores** of the dependent variable.

ONE-Way (ONE Factor) Between Groups ANOVA

○ [Comparing \$k\$ Means – Part 1](#) (J. Stuart Hunter)

○ [Comparing \$k\$ Means – Part 2](#) (J. Stuart Hunter)

These presentations illustrate how to use different techniques for creating a randomized complete design and then using it to **estimate the variance within each treatment group**.

Included is a demonstration of a **one-way between-groups** ANOVA test. The question asked was: Is there a difference in the impact able to be absorbed by different plastics using a calibrated pendulum machine measuring that impact. The ANOVA design includes the:

COMPARISON/IMPACT OF

EXPLANATORY/PREDICTOR VARIABLE:

ONE **categorical independent variable/FACTOR:** type of plastic rods

Having **k** groups/levels/treatments (1, 2, 3, ..., k);

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent variable: calibration measurement for each plastic type;

USING mean calibration score of each plastic type over 4 repeats of the experiment.

The associated table for this design is a 1 X *k* cross tab:

	FACTOR: Type of Plastic Rod Independent Categorical Variable Groupings/Treatments			
Dependent RESPONSE Variable	1	2		k
MEAN CALIBRATION MEASURE				

○ [One-Way ANOVA using SPSS](#) (The Doctoral Journey) (Social Science Research)

There is a demonstration of a **one-way between-groups** ANOVA test. The question asked was: Is there a difference in high school students' level of satisfaction with their school based on their family's socio-economic status? The ANOVA design includes the:

COMPARISON/IMPACT OF

EXPLANATORY/PREDICTOR VARIABLE:

ONE categorical independent variable/FACTOR: socio-economic status

having THREE groups/levels/treatments (upper class, middle class, lower class);

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent variable: level of satisfaction with school;

USING mean scores of the level of satisfaction measurement.

The associated table for this design is a 1 X 3 cross tab:

	FACTOR: Socio-economic Status Independent EXPLANATORY Variable Groupings/Levels		
Dependent RESPONSE Variable	Upper class	Middle class	Lower Class
LEVEL OF SATISFACTION			

NON-PARAMETRIC ALTERNATIVE: the Kruskal-Wallis H Test

Assumptions:

- i. random sample of participants;
- ii. observations are independent (one outcome not influenced by another) ; and
- iii. data can be ranked data (ordinal) or skewed continuous data which can be ranked.

Compares the impact of: ONE categorical independent variable/FACTOR with THREE or MORE groups/levels on ONE ordinal or skewed continuous dependent variable.

- [Kruskal-Wallis H Test \(RMUoHP\)](#) (Health Sciences Research)
(Unit 3.4: chapter 8, section 6 pp. 82 - 85) (Unit 2.4: chapter 15, section 6 pp. 613 - 617)

The case study wants to determine whether any particular post-surgery rehabilitation technique (out of three possibilities) has an effect on the patients' quality of life. Surgery patients were randomly selected and randomly assigned to the various groups. The ANOVA design includes the

COMPARISON/IMPACT OF

EXPLANATORY VARIABLE:

ONE independent categorical variable/FACTOR: rehabilitation option

having THREE group options/levels/treatments: rehabilitation technique, labeled (1, 2, 3);

WITH/ON

RESPONSE VARIABLE:

ONE continuous dependent/outcome/response variable: quality of life measure which was NOT normally distributed but could be ranked;

USING mean scores of the quality of life measure.

The associated table for this design is a 1 X 3 cross tab:

	FACTOR: Rehabilitation Technique Independent EXPLANATORY Variable Groupings/Levels		
	Rehab Technique 1	Rehab Technique 2	Rehab Technique 3
QUALITY OF LIFE			
Dependent RESPONSE Variable			

Multiple Comparison Procedures

(Unit 3.6 – 3.8: chapter 9, sections 1 - 9 pp. 105 – 135)

- [One-Way ANOVA using SPSS \(RMUoHP\)](#) (Managerial Business Research)

The case study is whether age of a person has an effect on the number of days absent from work in a year. The ANOVA design includes the

COMPARISON/IMPACT OF

EXPLANATORY VARIABLE:

ONE independent categorical variable/FACTOR: age with THREE groups/levels/treatments

(group1: 18-30 yrs, group 2: 31-45 yrs, group 3: 45-65 yrs);

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent variable: days absent from work per year;

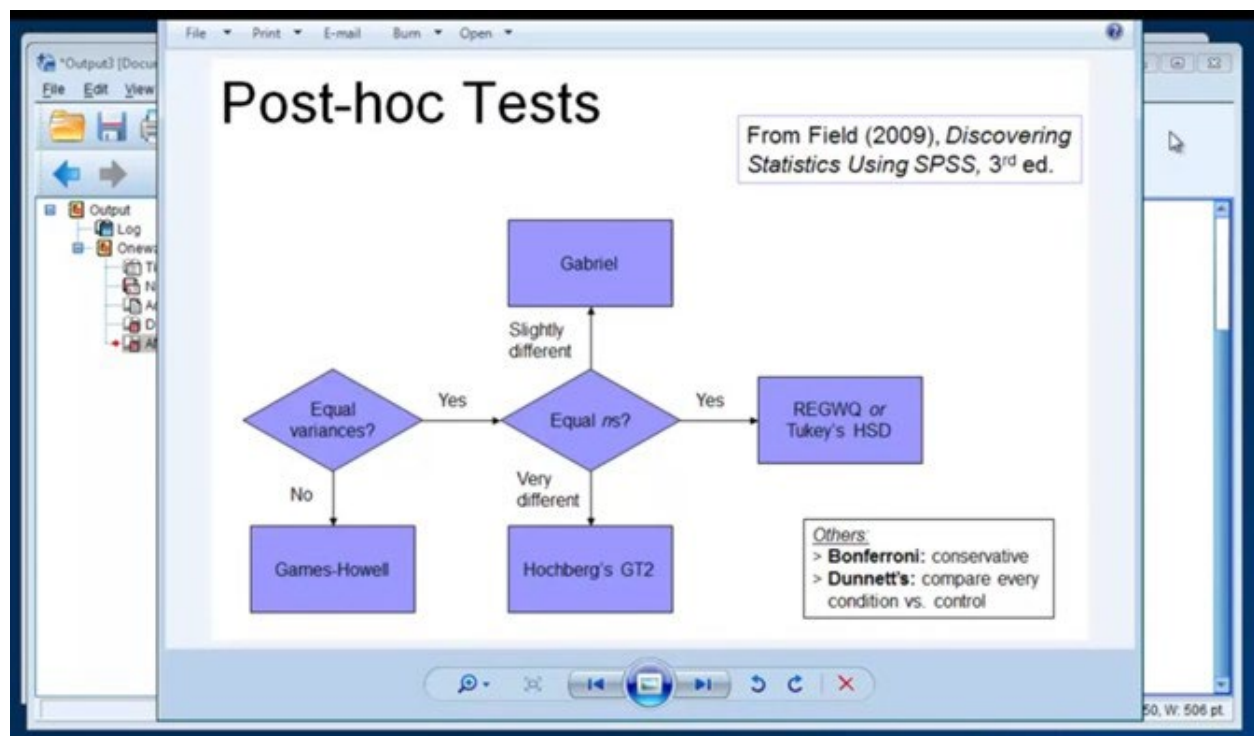
USING **mean scores** of the dependent variable.

The demonstration includes a discussion of **effect sizes**, the **power of the analysis** and post-hoc tests, including both **multiple comparisons** among the groups and **homogeneity tests**.

The associated table for this design is a 1 X 3 cross tab:

	FACTOR: Age Independent EXPLANATORY Variable Groupings/Levels		
Dependent RESPONSE Variable	18 – 30 years old	31 – 45 years old	46 – 65 years old
DAYS ABSENT FROM WORK			

- [Post Hoc Tests for Significant One-Way ANOVA using SPSS](#) (Doug Maynard)



This video discusses which of the *significant* one-way ANOVA post-hoc tests to use depending on **whether the groups have equal variances and/or equal sample sizes n** . In this presentation, Tukey's HSD test means the **Tukey's Honestly Significant Difference** test.

- [Fisher's LSD - An Attractive and Underused Post-Hoc Test](#) (how2stats)
(Unit 3.8: chapter 9, section 4 pp. 117 - 121)

This test can be used after the null hypothesis of a one-way ANOVA has been rejected and the researcher wants to make pair-wise comparisons among the means of THREE groups using a pooled error term.

[One-Way Between Groups ANOVA with Planned Comparisons](#) (RMUoHP) (Educational Research) (Unit 3.6: chapter 9, section 2 pp. 108 - 114)

This kind of ANOVA test uses **planned comparisons**, instead of post-hoc tests, to determine if any differences exist between particular groups, for example if one only wants to compare group 3 with groups 1 and 2.

The case study wants to determine whether any particular instructional technique (out of three possibilities) has an effect on a student's score on the final exam. The ANOVA design includes the

COMPARISON/IMPACT OF

EXPLANATORY VARIABLE:

ONE independent categorical variable/FACTOR: instructional technique with THREE group options/levels/treatment, simply labeled (1, 2, 3);

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent variable: score on a final exam;

USING mean scores of the final exams in each group.

The associated table for this design is a 1 X 3 cross tab:

	FACTOR: Instructional Technique Independent EXPLANATORY Variable Groupings/Levels		
Dependent RESPONSE Variable	Technique 1	Technique 2	Technique 3
SCORE ON FINAL EXAM			

ONE-Way (ONE Factor) Repeated Measures or Dependent Samples ANOVA

In repeated measures ANOVA designs, each sample subject is measured on the same ONE outcome (dependent variable) THREE OR MORE TIMES (groups/levels on the ONE categorical independent variable).

- [One-Way Repeated Measures ANOVA](#) (RMUoHP) (Health Sciences Research)

In this case study, 22 subjects are being given a particular treatment for high blood pressure. Their systolic blood pressures will be taken before, half-way, and at the end of the treatment period. The researcher wants to know the effect over time of the treatment on the blood pressure of the patients. The ANOVA design includes the

COMPARISON/IMPACT OF

EXPLANATORY VARIABLE:

ONE independent categorical variable/FACTOR: relative time period of measurement with THREE group options/levels being the before, during and after medical treatment;

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent variable: systolic blood pressure which is (approximately) normally distributed.

USING mean scores of the systolic blood pressure measurement.

The associated table for this design is a 1 X 3 cross tab:

	FACTOR: Relative Time Period of Measurement Independent EXPLANATORY Variable Groupings/Levels		
Dependent RESPONSE Variable	Before treatment	During Treatment	After Treatment
SYSTOLIC BLOOD PRESSURE			

NON-PARAMETRIC ALTERNATIVE: Friedman's Test

Assumptions:

- i. sample of participants randomly drawn;
- ii. observations are independent (one outcome not influenced by another) ; and
- iii. data can be ranked data (ordinal) or non-normal continuous data which can be ranked.

- [Friedman's ANOVA in SPSS \(Todd Grande\)](#) (Clinical Psychology Research)
(Unit 2.5: chapter 15, section 7 pp. 619 - 622)

The case study wants to determine whether a particular treatment with a psycho-educational component has had an effect on the participants' symptoms of depression. Ninety (90) participants were randomly selected and were independent of one another. The severity (measured on a Likert scale of 0 to 5 in ordinal numbers) of depressive symptoms of each participant were measured three times: one prior to the treatment, one just after the treatment and a third post-treatment 12 weeks later.

COMPARISON/IMPACT OF

EXPLANATORY VARIABLE:

ONE independent categorical variable/FACTOR: relative time period of measurement having THREE group options/levels being the before, after and after 12 weeks treatment;

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE dependent variable: the mean;

USING mean Likert scores.

The associated table for this design is a 1 X 3 cross tab is:

	FACTOR: Relative Time Period in Which Measurements were Taken Independent Categorical EXPLANATORY Variable Groupings/Levels		
Dependent RESPONSE Variable	before treatment	after treatment	12 weeks after treatment
MEAN			

Factorial ANOVA Tests – or the Two-Way or Three-Way or Four-Way ANOVAs

(Unit 6.2: chapter 14, sections 3 – 5 pp. 467 – 503)

A **factorial treatment structure** is often used to measure the *effects of differing levels* of more than one explanatory variable and their interactions on a response variable. This is a method whereby treatments are constructed from *combinations of several* FACTORS rather than just being *k* levels of a single factor.

The TWO (or **three** or **four**)-way ANOVA test compares the differences in the means of the outcome/response/dependent variable between TWO (or **three** or **four**) **independent variables** (called **FACTORS**) OF INTEREST, each having been split on at least TWO groups/levels.

In Factorial ANOVA designs,

the number of **treatments** =

of factors of interest (independent variables) X # of levels of each factor.

The primary purpose of a TWO (or **three** or **four**)-way ANOVA is to understand if there is an **interaction effect** between the TWO (or **three** or **four**) independent variables/FACTORS on the ONE dependent continuous variable.

In the following **TWO-way** or **TWO X TWO factorial** ANOVA design, the researcher wants to know if gender and/or body mass index (BMI) has an effect on a person's systolic blood pressure.

ONE dependent continuous	independent, categorical (two groups/levels)	
	BMI ≤ 25	BMI ≥ 25.1
	Mean SBP for males	
	Mean SBP for females	
	independent, categorical (two groups/levels)	

COMPARISON/IMPACT OF

EXPLANATORY VARIABLES:

TWO independent categorical variables/FACTORS OF INTEREST: gender and BMI (body-mass-index);

Each independent variable is split on TWO levels:

FACTOR 1: gender (male, female) and

FACTOR 2: BMI (below 25, above 25);

FOUR STATISTICAL treatments: no. levels in FACTOR 1 x no. levels in FACTOR 2 = 2 x 2 = 4;

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent variable: systolic blood pressure;

USING the means of the dependent variable, the systolic blood pressures.

- [Two-Way Factorial Repeated Measures ANOVA using SPSS](#) (Jim Grange) (Psychology Research)

This video illustrates the procedures for a **2x2 factorial ANOVA** of statistical data using SPSS. The example has TWO FACTORS (independent variables) and each factor has TWO levels. Each participant is given two cognitive tasks to do and the reaction time to complete the tasks is measured. The researcher wants to find out how the reaction time is affected by either the working memory load involved in the task or/and whether the second task is a repetition of the first or not.

COMPARISON/IMPACT OF

EXPLANATORY VARIABLES:

TWO independent categorical variables/FACTORS OF INTEREST: working memory load and task;

Each independent variable is split on TWO levels:

FACTOR 1: working memory load (high, low) and

FACTOR 2: task (group 1: repetition, group 2: switch);

FOUR STATISTICAL treatments: no. levels in FACTOR 1 x no. levels in FACTOR 2 = 2 x 2 = 4;

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent variable: reaction time to complete task;

USING the means of the dependent variable, the reaction times.

The associated table for this design is a 2 X 2 contingency table:

	FACTOR: Working Memory Load Independent EXPLANATORY Variable Groupings/Levels	
FACTOR: Task Independent EXPLANATORY Variable	HIGH	LOW
REACTION TIME for REPETITION		
REACTION TIME for SWITCH		
Dependent RESPONSE Variable: REACTION TIME		

- [Conducting a Two-Way ANOVA in SPSS](#) (Todd Grande) (Medical Research)

This video illustrates the procedures to conduct a **2x3 factorial ANOVA** of statistical data using SPSS. In this case study, the researcher wants to determine whether **either** a person's gender **or/and** the duration of the treatment has any effect on the symptom level experienced by the participant. Concepts such as main effects, interaction effects, post hoc tests, pairwise comparisons, Levene's test, effect size, and statistical significance are described.

The TWO-WAY or TWO FACTOR ANOVA design includes:

TWO independent categorical variables/FACTORS OF INTEREST: gender and duration of treatment;

ONE independent categorical variable/FACTOR is split on TWO levels: gender (male, female);

ONE independent categorical variable/FACTOR is split on THREE levels: duration of treatment (6 weeks, 12-weeks, 18 weeks);

SIX STATISTICAL treatments: no. levels in FACTOR 1 x no. levels in FACTOR 2 = 2 x 3 = 6;

ONE quantitative dependent/outcome variable: score indicating symptom level (lower values indicating fewer symptoms);

USING **mean scores** of the dependent variable.

The associated table for this design is a 2 X 2 cross tab:

	FACTOR: Duration of Treatment Independent EXPLANATORY Variable Groupings/Levels		
FACTOR: gender of participant Independent EXPLANATORY Variable	6 Weeks	12 Weeks	18 Weeks
Male			
Female			
Dependent RESPONSE Variable: SYMPTOM LEVEL			

- [Two-Way ANOVA, Part 1, using SPSS](#) (Dr. Ami Gates) (Educational Research)
- [Two-Way ANOVA, Part 2, using SPSS](#)

These videos illustrates the procedures for a **3x2 factorial ANOVA** of statistical data using SPSS. In this case study, the researcher wants to determine whether **either** a student's engagement with instructional videos **or/and** the student's gender has any effect on the students' total class score. The two-way ANOVA design includes:

TWO independent categorical variables/FACTORS OF INTEREST: engagement and gender;

ONE independent variable/FACTOR is split on THREE levels: engagement (all, half, none);

ONE independent variable/FACTOR is split on TWO levels: gender (male, female);

SIX STATISTICAL treatments: no. levels in FACTOR 1 x no. levels in FACTOR 2 = 3 x 2 = 6;

ONE continuous dependent/outcome variable: total class score;

USING **mean scores** of the dependent variable.

The associated table for this design is a 3 X 2 contingency table:

	FACTOR 2: gender of student Independent EXPLANATORY Variable Groupings/Levels	
FACTOR 1: engagement Independent EXPLANATORY Variable	males	females
CLASS SCORE: all videos		
CLASS SCORE: half of videos		

CLASS SCORE: no videos		
Dependent RESPONSE Variable: CLASS SCORE		

- [Factorial Repeated Measures ANOVA \(Split Plot ANOVA\) \(Mixed Between-within ANOVA\)](#)
(RMUoHP) (Clinical Psychology Research)

This video shows how to combine both between-groups and repeated measures within-subjects methods for a single case study. The researcher wants to split a sample of patients, who are known to be suffering from depression, into two equal-sized parts randomly. One of the sections will receive counseling for depression in one-on-one sessions, the second section in group counseling sessions. The split plot ANOVA design includes:

COMPARISON/IMPACT OF

EXPLANATORY VARIABLES:

TWO independent categorical variables/FACTORS OF INTEREST: counseling type and time;

FACTOR 1 measuring *between-groups effects*, split on TWO levels:
counseling type (one-on-one, group);

FACTOR 2 measuring *within-subjects repeated measures effects*, split on THREE levels:
time points of measurement for each subject (before, at conclusion, six months later);

SIX STATISTICAL treatments: no. levels in FACTOR 1 x no. levels in FACTOR 2 = 2 x 3 = 6;

WITH/ON

RESPONSE/OUTCOME VARIABLE:

ONE continuous dependent/outcome variable: depression level;

USING **mean scores** of the dependent variable.

The associated table for this design is a 2 X 3 contingency table:

	FACTOR 2 (Within Subjects): time Independent EXPLANATORY Variable Groupings/Levels		
FACTOR 1 (Between Groups): counseling type Independent EXPLANATORY Variable	Before Treatment	At Conclusion of Treatment	Six Months After Conclusion
DL: One-on-One Counseling			
DL: Group Counseling			
Dependent RESPONSE Variable: DEPRESSION LEVEL (DL)			

- [Experimental Design](#) (Peter Crickmore)

In this power point presentation, Dr. Crickmore discusses **full 2 level factorial** designs, **fractional 2-level factorial** designs, response surface designs, mixtures and Scheffe designs, sequential designs and the

Simplex Method. Some of this is beyond the scope of the Math 315 program but it does illustrate how these basic methods can be extended to more complex research experiments .

➤ **Block ANOVA Designs** (Unit 7: chapter 15, sections 1 – 7 pp. 532 – 570)

Review [What is Design of Experiments? – Part 1](#) (J. Stuart Hunter).

Randomized Block ANOVA Designs – an Overview

Blocking in an experiment is similar to stratifying a sample in an observational study.

For randomized block designs, there is ONE FACTOR or variable that is OF PRIMARY INTEREST which is to be quantitatively measured by means of ONE continuous DEPENDENT VARIABLE. However, there is also **at least** ONE NUISANCE/BLOCKING/CONTROL FACTOR present in the experimental data which the researcher wants to control in order to reflect relevant variation in the original sample. For example, age or gender may be used as a blocking factor in some experiments.

Blocking is the arranging of experimental units in groups (blocks) that are similar (homogeneous) to one another using values of an extraneous factor as sorting criteria. Typically, a BLOCKING FACTOR is a source of variability that is not of primary interest to the experimenter. The analysis of the experiment will focus on the effect of varying treatments of the primary factor within each block of the experiment.

Blocking is used to remove the effects of a few of the most important nuisance variables. Randomization is then used to reduce the contaminating effects of the remaining nuisance variables. For important nuisance variables, blocking will yield higher significance in the variables of interest than randomization.

A **balanced design** is an experimental design where all cells (i.e. treatment combinations) have the same number of observations.

○ [Randomized Block Design](#) (R Backman) (Medical Research)

The presenter shows how to set up a randomized block design for a medical researcher who is interested in studying how effective a particular flu vaccine is. TWO (2) treatment groups were suggested: a control group not given the vaccine and a second group, all of whose participants were to receive the vaccine. Since age may be a confounding factor in the effectiveness of a vaccine, the participants in the experiment sample were first divided into THREE(3) age groups or blocks: 18 – 40 years old; 41 – 60 years old; 61 and over. Then the treatments were assigned at random within each block. The dependent RESPONSE variable or what is used to measure “effectiveness” of the vaccine is not discussed. This design is associated with a 2 treatments x 3 blocks cross tab.

FACTOR of INTEREST: VACCINE TREATMENT	BLOCKING FACTOR (BF): Age		
	18 - 40	41 - 60	61 and over
NO VACCINE			
VACCINE			

○ [SPSS Wiki Script for Randomized Block Design ANOVA](#) (interactive)

Comparison of Completely Randomized Designs versus Randomized Block Designs

In a **completely randomized design**, objects or subjects are assigned to groups completely at random. (Unit 6.1: chapter 14, section 2 pp. 462– 467)

If a researcher is aware of group differences within a sample which may affect the outcome of an experiment, he or she may prefer a **randomized block design** to a completely randomized design. In a block design, experimental subjects are first divided into homogeneous blocks before they are randomly assigned to a treatment group. In a block design, both **control** and **randomization** are considered. (Unit 7.1 and 7.3: chapter 15, sections 2 and 4 pp. 533 – 545 and 556 - 560)

Example 1: Comparison of Completely Randomized ANOVA Design

- [Using ANOVA– Part 1](#) (J. Stuart Hunter) (Engineering Research)

This presentation teaches the four underlying assumptions (REINs) of an ANOVA, how to check your experimental results to see if the assumptions have been met and the mathematics behind the ANOVA design model.

In this video, Professor Hunter uses the one-way ANOVA design to study the effects (on a quantitative continuous variable) of FOUR different heat treatments on steel after rolling it (the ONE categorical variable/FACTOR having FOUR groups /levels/ treatments). This is a **completely randomized design** in which the order in which the four heat-treatment trials were run was completely random.

Versus Randomized Block ANOVA Design

- [Using ANOVA– Part 2](#) (J. Stuart Hunter) (Engineering Research)

In this follow-up video, Professor Hunter uses an ANOVA design to study the effects of the same FOUR different heat treatments to steel after rolling it BUT he BLOCKS the design to account for the day on which the heat treatment took place because of suspected day-to-day variation in the results of the heat-treatment processes. This is a **randomized block design** in which the order in which the heat- treatment trials ON EACH BLOCK DAY were run completely randomly, but EACH TREATMENT was, in fact, run on EACH DAY (the blocking/control variable).

Analysis:

ONE categorical independent variable/PRIMARY FACTOR with FOUR levels/TREATMENTS: types of heat treatments for steel (A,B,C,D);

FOUR treatments: no. levels in PRIMARY FACTOR = $4 = K$;

ONE CONTROL categorical variables/BLOCKING FACTOR, split on five levels: days of the week (1,2,3,4,5);

FIVE block levels: no. levels in BLOCKING FACTOR = $5 = b$;

ONE continuous dependent/outcome variable: measurement of effect on the steel.

The mathematical model split each of those observational measurements into the following components: the (grand) mean of the observations, the block effects for each of the days of the week, the treatment effects for each of the heat treatments and, finally, estimates of the residual/error effects.

NOTE: There is ONE PRIMARY FACTOR OF INTEREST (type of heat treatment) and the experimenter wants to control for ONE SOURCE of extraneous variation (day of the week).

This design is associated with a 4 treatments x 5 blocks cross tab.

FACTOR of INTEREST: HEAT TREATMENT	BLOCKING FACTOR (BF): Days of the Week				
	1	2	3	4	5
A					
B					
C					
D					

Example 2:

- [Using Randomization to Understand Variance– Part 1](#) (J. Stuart Hunter)
- [Using Randomization to Understand Variance– Part 2](#) (J. Stuart Hunter)

These videos discuss using randomized block designs to account for variability in the model and help determine the most significant variables. In this case study, the researcher wants to determine which of two kinds of gasoline (one with an additive; one without) provides better average performance (measured in miles per gallon) of a variety of cars. The premise or conjecture is that the presence of the additive did increase the performance of the vehicle – in other words, increased the mileage per gallon of the car in question.

Comparison of Completely Randomized ANOVA Design 1:

EXPERIMENTAL DESIGN 1: The experiment was first done for a sample of 20 cars, chosen randomly. Ten (10) of them were randomly chosen to use the gasoline with the additive, the remaining 10 were not given the additive. In this **completely randomized ANOVA** design, there was:

ONE categorical variable/FACTOR OF INTEREST having TWO groups /levels/ treatments – gas with additive, gas without additive;

ONE continuous dependent/outcome variable: mileage for 5 gallons of gasoline;

USING **mean scores** of the dependent variable across each treatment.

The ANOVA null hypothesis was that the mean mileage for each of the treatments was the same across all cars.

Versus Randomized Block ANOVA Design 2:

EXPERIMENTAL DESIGN 2: The experiment was subsequently done for a sample of 10 cars, chosen randomly. One trial used the gasoline with the additive in each of the 10 cars; the other trial used the gasoline without the additive in each of the 10 cars. However, the design was BLOCKED for the variability in the data due to the car-to-car differences (for example, engine size, weight).

In this **randomized block ANOVA** design, there was:

ONE categorical variable/FACTOR OF INTEREST having TWO groups /levels/ TREATMENTS – gas with additive, gas without additive;

TWO treatments: no. levels in PRIMARY FACTOR = 2 = k ;

ONE categorical variable/BLOCKING FACTOR having TEN groups /levels – one per car;

TEN block levels: no. levels in BLOCKING FACTOR = 10 = b ;

ONE continuous dependent/outcome variable: mileage for 5 gallons of gasoline;

USING **mean scores** of the dependent variable across each treatment, allowing for blocking effects.

Moreover, which gasoline was used in the first trial for each of the cars was determined by a toss of a coin. This introduced more randomness into the experiment by inherently, but not specifically, BLOCKING for the variability in the data due to gasoline usage for cold motors versus warm motors.

The mathematical model split each of those observed mileage measurements into the following components: the (grand) mean of the observations, the block effects for each of the cars used in the experiment, the treatment effects for each of the treatments (with and without the gasoline additive) and, finally, estimates of the residual/error effects.

Randomized Complete Block ANOVA Design

(Unit 7.1 and 7.3: chapter 15, sections 2 and 4 pp. 533 – 545 and 556 - 560)

Blocking is sorting the experimental units into similar groups (or blocks) using values of an *extraneous* factor as sorting criteria. Most often, a blocking factor is a source of variability that is not of primary interest to the experimenter. By blocking on a factor, the source of variability from this factor is controlled for, thus leading to greater reliability of the statistical results.

A randomized complete block design is an experimental design for comparing the k TREATMENTS /LEVELS of ONE FACTOR OF PRIMARY INTEREST split into b blocks (the LEVELS OF THE ONE BLOCKING FACTOR *not* of primary interest), *each block consisting of k homogeneous experimental units*.

This design is associated with a $k \times b$ cross tab. There is ONE FACTOR OF INTEREST with k groups/levels/TREATMENTS (rows) in which the experimenter wants to control for ONE SOURCE of extraneous variation having b groups/levels (columns). Treatments are randomly assigned to experimental units within a block, with **each treatment appearing exactly once in every block** (the completeness part of the design).

- [Designing Your Experiment Using Randomized Block Design](#) (UNL CropWatch) (Agricultural Research)

An experiment is conducted to compare two fungicides on a particular growth stage of corn crops. THREE (3) treatments are considered: a control group where no fungicide is applied and two treatment groups where fungicides A and B are, respectively, applied. The extraneous or confounding factor to evaluate the two fungicides may be the particular field or strip to which they are applied. The blocking factor is the strip of land used in the experiment. Four or, even better, FIVE levels (field strips) are recommended to make a solid comparison. Soil conditions within each block strip should be similar but soil conditions between the various blocks may vary.

Analysis:

ONE categorical independent variable/PRIMARY FACTOR with THREE levels/TREATMENTS: application of fungicide (none, fungicide A, fungicide B);

THREE treatments: no. levels in PRIMARY FACTOR = 3 = K ;

ONE CONTROL categorical variables/BLOCKING FACTOR, split on FIVE levels: field strips (1,2,3,4,5);

FIVE block levels: no. levels in BLOCKING FACTOR = 5 = b ;

ONE continuous dependent/outcome variable: crop yield.

NOTE: There is ONE PRIMARY FACTOR OF INTEREST (fungicide) and the experimenter wants to control for ONE SOURCE of extraneous variation (field strip). **Each treatment is applied exactly once in each block or strip. Hence the randomized COMPLETE block design.**

This design is associated with a 3 treatments x 5 blocks cross tab.

FACTOR of INTEREST: FUNGICIDE	BLOCKING FACTOR (BF): field strip				
	1	2	3	4	5
none					
A					
B					

○ [Randomized Block Design ANOVA in SPSS](#) (static pdf document) (Veterinary Medicine Research)

Digitalis is a medication used in some heart patients but it may have toxic side effects. Several veterinarians wanted to determine if the level of digitalis in the blood stream affects the mean level of calcium in dogs.

A study was conducted to compare the effect of three levels of digitalis on the level of calcium in the heart muscle of dogs. Because the general level of calcium uptake varies from one animal tissue to another, it was considered sufficient to compare calcium levels, blocked on heart muscles alone. Therefore, the effects of three levels of digitalis (A, B, and C) on calcium levels were compared based on the heart muscles of 4 individual dogs.

Analysis:

ONE categorical independent variable/PRIMARY FACTOR with THREE levels/TREATMENTS: level of digitalis (A,B,C);

THREE treatments: no. levels in PRIMARY FACTOR = 3 = K ;

ONE CONTROL categorical variables/BLOCKING FACTOR, split on four levels: dog (1,2,3,4);

FOUR block levels: no. levels in BLOCKING FACTOR = 4 = b ;

ONE continuous dependent/outcome variable: mean level of calcium in a dog's heart muscle.

NOTE: There is ONE PRIMARY FACTOR OF INTEREST (level of digitalis) but the experimenter wants to control for ONE SOURCE of extraneous variation (intrinsic differences between dogs).

This design is associated with a 3 treatments x 4 blocks cross tab.

FACTOR of INTEREST: LEVEL OF DIGITALIS	BLOCKING FACTOR (BF): DOG			
	1	2	3	4
A				
B				
C				

Incomplete Block ANOVA Designs (Unit 6.3: chapter 14, section 4 pp. 492 - 499)

Review [What is Design of Experiments? – Part 2](#) (J. Stuart Hunter).

A **fractional factorial design** is a screening process whereby the researcher tries to discover, from a relatively large list of explanatory variables, which of them have the greatest impact on the response variable.

Incomplete block designs for factorial treatment frameworks are based on the same principle as fractional factorial designs. They are used when circumstances dictate that it is not possible (for reasons of physical restraints, time or money) to test all possible treatments for all of the explanatory variables. However, there are ways to build a **balanced, incomplete block design** when *blocks aren't large enough to contain all possible treatments*. Recall that a **balanced design** is an experimental design where all cells (i.e. treatment combinations) have the same number of observations over all the cells, but not in each cell.

○ [Incomplete Block Designs](#) (Philip Ramsey) (Engineering Research)

This video illustrates a tool wear case study. The RESPONSE DEPENDENT VARIABLE of interest is a measurement of the amount of wear on a tool used to cut steel, thereby affecting the life expectancy of the tool itself. There are FOUR (4) EXPLANATORY INDEPENDENT VARIABLES or FACTORS of interest: cutting speed; cutting angle; blade height; blade material, each with TWO (2) LEVELS. Consequently, $2^4 = 16$ runs (factor-level combinations or TREATMENTS) would be required for a full experiment on the effect of all four factors on the response variable. BUT, in this machine shop it is possible to conduct at most eight trials per day. Therefore, it would take two days to complete the experiment. Because the engineers suspect that different environmental conditions in the shop may affect the results, a BLOCKING FACTOR of “day experiment conducted” with TWO (2) levels is included in the design. This is based on the number of times 4 things can be examined in triples $2^3 = 8$ over two days – hence the incomplete block design.

○ [Incomplete Blocks – Part 2](#) (J. Stuart Hunter) (Manufacturing Research)

In this presentation, Professor Hunter talks about **combinatoric balanced incomplete designs** which form a class of incomplete block designs. For example, the number of times 4 things ($k = 4$ treatments) can appear together in pairs ($b = 2 =$ number of levels in a blocking factor) is ${}_4C_2 = 4! / (2! 2!) = 6$ ways. This would imply 6 INCOMPLETE BLOCKS containing two of the four treatments. In another example, if we collect all possible combinations of 5 things ($k = 5$ treatments) taken 4 at a time ($b = 4 =$ number of levels in a blocking factor), then we would get ${}_5C_4 = 5! / (4! 1!) = 5$ INCOMPLETE BLOCKS containing four of the five treatments.

However, for the case study, he uses a **non-combinatoric, balanced, incomplete block design** in which there are 6 treatments in blocks of 3. The manufacturing firm wanted to test 6 kinds of carpets manufactured out of various combinations of artificial fibres ($k = 6$ treatments). The problem was that the single testing machine could only test 3 carpets at a time ($b = 3 =$ number of levels in a blocking factor). The dependent continuous variable was the amount of wear on each carpet as it went through the machine.

The number of runs necessary to test all 6 carpets, 3 at a time, in the balanced, incomplete design was 10. (Had the design used been combinatoric, the number of runs would have had to have been ${}_6C_3 = 6!$

$/(3!3!) = 20$ – the number of ways to choose 3 items out of 6.) Randomness was introduced into the design in the following ways:

1. The sequence of the rugs on the machine was randomly assigned;
2. the 10 block runs were chosen in random order.

Latin Square ANOVA Designs

(Unit 7.2: chapter 15, section 3 pp. 545 - 556)

The difference between a randomized complete block design and a Latin Square ANOVA design has to do with the number of BLOCKING FACTORS in the experiment. **Randomized block designs allow only ONE BLOCKING FACTOR**, whereas **Latin Square designs allow TWO BLOCKING FACTORS**.

Latin squares are $n \times n$ square arrays of n numbers/symbols (in other words, a square matrix) with the property that each row and each column must contain all of the n entries/treatments *without duplicates*.

○ [Incomplete Blocks – Part 1: An Intro to Latin Squares](#) (J. Stuart Hunter)

In this video, Professor Hunter discusses some cautions when using Latin Squares. In addition, he introduces Graeco-Latin Squares. Unfortunately, the presentation has been cut off prematurely but the preamble to Latin Square designs is worth the 5 minutes of listening time.

○ [Latin Squares – Part 1](#) (J. Stuart Hunter) ([Engineering Research](#))

In this video, Professor Hunter opens with a review of a randomized block design previously discussed in the video entitled: [Using ANOVA– Part 2](#) (J. Stuart Hunter). In that video, the experimenters wanted to test four different ways to heat-treat steel. It was suspected that there would be some day-to-day variation in the processes. Therefore, they ran the four treatments RANDOMLY on each of the five days of the week.

Analysis of the randomized block design with ONE BLOCKING FACTOR:

ONE categorical independent variable/**PRIMARY FACTOR** with FOUR levels/TREATMENTS: types of heat treatments for steel (A,B,C,D);

FOUR treatments: no. levels in PRIMARY FACTOR = 4 = K ;

ONE CONTROL categorical variables/**BLOCKING FACTOR**, split on five levels: **days of the week (1,2,3,4,5)**;

FIVE block levels: no. levels in BLOCKING FACTOR = 5 = b ;

ONE continuous dependent/outcome variable: observation of effect on the steel.

TOTAL NUMBER OF OBSERVATIONS/MEASUREMENTS: 20.

This design is associated with a 4 treatments x 5 blocks cross tab.

FACTOR of INTEREST: HEAT TREATMENT	BLOCKING FACTOR (BF): Days of the Week				
	1	2	3	4	5
A					
B					
C					
D					

○ [Latin Squares – Part 2](#) (J. Stuart Hunter) (Engineering Research)

Latin squares are $n \times n$ square arrays of n numbers/symbols (in other words, a square matrix) with the property that each row and each column must contain all of the n entries/treatments *without duplicates*. For an experiment to use a Latin Square design,

n = the number of treatments = number of levels in block factor 1 = number of levels in block factor 2.

In this follow-up video, Professor Hunter introduces a steel heat-treating experiment using a **3 x 3 Latin Square ANOVA design**.

Analysis of the Latin Square design with TWO BLOCKING FACTORS :

ONE categorical independent variable/**PRIMARY FACTOR** with **THREE** levels/TREATMENTS: types of heat treatments for steel (A,B,C);

THREE treatments: no. levels in **PRIMARY FACTOR** = $3 = n$;

TWO BLOCKING FACTORS of extraneous variation – the location and the variation in the type of furnaces used for the testing, each having 3 levels;

ONE CONTROL categorical variables/**BLOCKING FACTOR1**, split on **THREE** levels: location (I, II, III);

THREE block levels: no. levels in **BLOCKING FACTOR1** = $3 =$ number of rows in the Latin Square ;

ONE CONTROL categorical variables/**BLOCKING FACTOR2**, split on **THREE** levels: furnace (1,2,3);

THREE block levels: no. levels in **BLOCKING FACTOR2** = $3 =$ number of columns in the Latin Square ;

ONE continuous dependent/outcome variable: observation of effect on the steel.

TOTAL NUMBER OF OBSERVATIONS/MEASUREMENTS: 2 trials x 9 observations / trial = 18.

Two trials of the experiment were run so that the degrees of freedom of the experiment would not be too low for significant results.

The Latin Square design associated with this experiment is a 3×3 cross tab where $3 = n$:

BLOCKING FACTOR (BF2): Location	BLOCKING FACTOR (BF1): Furnace		
	1	2	3
I	A: 71; 61	B: 58; 56	C: 66; 58
II	C: 67; 58	A: 63; 57	B: 60; 55
III	B: 59; 54	C: 58; 59	A: 62; 58

○ [SPSS ANOVA for Latin Square Design](#) (static pdf document) (Engineering Research)

Goal: Comparing the performance (tire wear AS CONTINUOUS DEPENDENT VARIABLE) of four different brands of tires (A, B, C, and D) AS FOUR TREATMENTS.

Background: There are four cars available for this comparative study of tire performance. It is

believed that tires wear out at a different rate in different locations on a car. These are TWO sources of extraneous variation in the dependent variable.

Tires were installed in four different locations: Right-Front (RF), Left-Front (LF), Right-Rear (RR) and Left-Rear (LR). The measurements of the wearing of tires in this investigation are listed in the following table from a Latin Square Design setting.

Analysis of the Latin Square Design:

ONE categorical independent variable/PRIMARY FACTOR with FOUR levels/TREATMENTS: brand of tire (A,B,C,D);

TWO CONTROL categorical variables/BLOCKING FACTORS, each split on FOUR levels:
car (1,2,3,4) and tire position (RF,LF,RR,LR);

FOUR treatments: no. levels in PRIMARY FACTOR = $4 = n$;

ONE continuous dependent/outcome variable: tire wear;

USING mean scores of the dependent variable.

NOTE: There is ONE PRIMARY FACTOR OF INTEREST (brand of tire) and the experimenter wants to control for TWO SOURCES of extraneous variation (car and tire location).

TOTAL NUMBER OF OBSERVATIONS/MEASUREMENTS: 16.

The Latin Square design is associated with a 4×4 cross tab.

TWO sources of extraneous variation or BLOCKING FACTORS (car, tire location) form the rows and columns of the table, each having FOUR levels. The **FOUR** treatments (tire brands: A, B, C, D) are randomly assigned to experimental units within the rows and columns so that each treatment appears ONCE in every row and in every column. The tire wear is measured in brackets beside each treatment.

BLOCKING FACTOR (BF1) Car	BLOCKING FACTOR (BF2): Tire Position			
	RF	LF	RR	LR
1	A(32)	B(33)	C(47)	D(53)
2	B(36)	D(53)	A(42)	C(54)
3	C(51)	A(44)	D(62)	B(49)
4	D(81)	C(78)	B(72)	A(73)

Special Higher Order Latin Square ANOVA Designs

For the best statistical results using these designs, be sure to randomize the treatment units and the trial/run order, as much as possible. As one option, first, select at random one Graeco-Latin or Hyper-Graeco-Latin square design from those available; then randomize the run order.

- [Graeco-Latin Square Designs](#) (NIST/SEMATECH: Engineering Statistics Handbook)

Graeco-Latin squares are efficient designs to study the effect of ONE PRIMARY FACTOR on ONE continuous dependent variable in the presence of THREE BLOCKING FACTORS. These designs are restricted, however, to the case in which **all the factors have the same number of levels (anywhere from 3 to 10)**.

- [Hyper-Graeco-Latin Square Designs](#) (NIST/SEMATECH: Engineering Statistics Handbook)

Hyper-Graeco-Latin squares are efficient designs to study the effect of **ONE PRIMARY FACTOR** on ONE continuous dependent variable in the presence of **FOUR BLOCKING FACTORS**. These designs are restricted, however, to the case in which **all the factors have the same number of levels (either 4 or 5)**.

➤ **Analysis of CoVariance (ANCOVA)** (alluded to in Unit 1: page 45-46 of the text)

Analysis of covariance (ANCOVA) is a general linear model (GLM) which is a **blend of ANOVA design techniques and regression analysis**. ANCOVA evaluates whether population means of a dependent variable are equal across levels/treatments of a categorical independent variable, while statistically controlling for the effects of other continuous independent variables that are not of primary interest. The latter are known as COVARIATES.

In this context, the **covariate is always continuous**, always a control variable, and always observed (meaning that its values are not randomly assigned). They were measured as a part of the data.

Therefore, when performing ANCOVA, the MEANS of the DEPENDENT VARIABLE across the groups/treatments are adjusted to what they would be if all groups/treatments were equal on the COVARIATES.

This procedure compares the impact of ONE or MORE categorical variables (thereby giving rise to one-way, two-way, etc. ANCOVAs) on ONE quantitative dependent variable/outcome while accounting for ONE or MORE CONFOUNDING or COVARIATE variables.

Assumptions of ANCOVA

1. **Normality of Residuals:** The residuals (error terms) should be normally distributed.
2. **Independence of Error terms:** The error terms should be uncorrelated.
3. **Homogeneity of Variances:** The error variances should be equal for different treatment classes.
4. **Linearity of Regression:** The regression relationship between the dependent variable and concomitant independent variables must be linear.
5. **Homogeneity of Regression Slopes:** The slopes of the different regression lines should be equivalent - i.e. regression lines should be parallel among groups.

- [One-Way ANCOVA using SPSS](#) (RMUoHP) (Educational Research)

In this case study, the researcher wants to compare the impact of an instructional technique (one of three different methods) on students' understanding of statistics, measured by the scores on a final exam. Nonetheless, even within each training group, it was understood that there may be a good amount of variation in people's math ability. If a researcher doesn't control for that, it remains as unexplained variation in the model and it becomes difficult to see the actual effect of the instructional method. In order to control for that, all students in the sample were required to write a pre-test in statistics prior to the instructional intervention. In that way, the researcher could control for where the students started out and, thereby, be able to determine whether the students did well on the final exam due to the training technique or due to their innate and acquired mathematics ability.

Assumptions:

1. The covariate (pre-test score) was measured prior to the instructional technique intervention.
2. The covariate has been measured without error and as reliable as possible.
3. There must be a linear relationship between the dependent outcome variable (final exam score) and the covariate variable (pre-test score), meaning the covariate variable has to be correlated with the outcome variable. (**Linearity of Regression**)
4. The relationship between the covariate variable (pre-test score) and the dependent outcome variable (final exam score) must be the same in each of the groups/treatments of the factor of interest. (**Homogeneity of Regression**)

Analysis of the ONE-WAY ANCOVA design:

ONE categorical independent variable/ **FACTOR OF INTEREST** with THREE levels/TREATMENTS: types of instructional methods for learning Statistics (1,2,3);

THREE treatments: no. levels in PRIMARY FACTOR = 3 ;

ONE CONFOUNDING **continuous** variable/**COVARIATE**: score on pre-test on knowledge of Statistics;

ONE continuous dependent/outcome variable: score on final exam on knowledge of Statistics.

○ Two-Way ANCOVA using SPSS (RMUoHP) (Educational Research)

This presentation is an extension of the one-way ANCOVA done in the previous video. One more categorical independent variable/ FACTOR, gender, has been added to the model. The research questions in this case study are:

- i. Does gender influence the effectiveness of three different teaching methods on the students' final scores in statistics, by itself?
- ii. Does the intervention of three different teaching methods have an influence on the students' final scores by itself?
- iii. Is there an interaction between gender and the three different teaching methods on the final exam scores?

Note that gender is NOT a covariate factor because it is not continuous. The researcher classified it as a MODERATOR variable. Generally speaking, a moderator is a qualitative (for example, sex, race, class) or quantitative (such as level of reward) variable that affects the direction and/or strength of the relationship between an independent/explanatory variable and a dependent/response variable. In particular, in correlational analysis, a moderator is a third variable which has an influence on the correlation between the independent and the dependent variables.

Assumptions:

1. The covariate (pre-test score) was measured prior to the instructional technique intervention.
2. The covariate has been measured without error and as reliable as possible.
3. There must be a linear relationship between the dependent outcome variable (final exam score) and the covariate variable (pre-test score), meaning that the covariate variable has to be correlated with the outcome variable. (**Linearity of Regression**)

4. The relationship between the covariate variable (pre-test score) and the dependent outcome variable (final exam score) must be the same in each of the groups/treatments of the factor of interest. (**Homogeneity of Regression Slopes**)

Analysis of the TWO-WAY ANCOVA design:

TWO categorical independent variables/ **FACTORS** ;

ONE categorical independent variable/**PRIMARY FACTOR OF INTEREST** with THREE levels/groups: types of instructional methods for learning Statistics (1,2,3);

ONE categorical independent / **MODERATOR VARIABLE** with TWO levels/groups: gender (female 1, male 2);

SIX STATISTICAL treatments: no. levels in PRIMARY FACTOR X no. levels in MODERATOR VARIABLE = $3 \times 2 = 6$;

ONE CONFOUNDING continuous variable/**COVARIATE**: score on pre-test on knowledge of Statistics;

ONE continuous dependent/outcome variable: score on final exam on knowledge of Statistics.

In the first part of the following 7-part video series, the presenter demonstrates how to perform an analysis of covariance (ANCOVA) in SPSS. The method used was the ANCOVA test using the conventional approach by getting SPSS to estimate adjusted means through the General Linear Model (GLM) univariate (one variable) utility.

The hypothesis of this experiment was that males had a larger cranial capacity than females. The sample data was real data gleaned from a reliable source of medical records. The confounding issue was that the cranial capacity may be due to males simply having larger body sizes, in general, than females. Therefore, the experiment was set up to test the hypothesis but to control it for differences in body size. In other words, if body size is taken into account, then do males really have larger cranial capacity than females?

Analysis of the ANCOVA design:

TWO categorical independent variables/ **FACTORS** ;

ONE categorical independent variable/ **PRIMARY FACTOR** with TWO levels/TREATMENTS: gender (female 0, male 1);

SIX treatments: no. levels in PRIMARY FACTOR = 2 ;

ONE CONFUNDING continuous variable/**COVARIATE**: body size;

ONE continuous dependent/outcome variable: cranial capacity (in cubic centimeters).

Sample size: 60 females and 40 males.

STEP 1: The presenter uses an ANOVA procedure to test, from the sample data, if males and females have different cranial capacities, on average, not considering any other issues.

- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 1\)](#) (how2stats) (Medical Research)
- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 2\)](#) (how2stats) (0:00 – 1:53)

STEP 2: ONE quantitative continuous COVARIATE variable is created using Principal Component Analysis (PCA) on the three continuous body size variables in the data – weight, wrist size, body height – in order to obtain only ONE good variable representing body size. This ONE COVARIATE is formulated as a linear combination (sums of multiples) of the three collected data variables weighted by their component scores, respectively, in the PCA.

- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 2\)](#) (how2stats) (1:53 – end)
- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 3\)](#) (how2stats) (0:00 – 2:28)

STEP 3: The homogeneity of regression assumption was tested. It was checked if the relationship (the regression coefficient) between the COVARIATE variable (body size) and the dependent outcome variable (cranial capacity) was the same across each of the groups/treatments of the factor of interest – namely for both males and females.

- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 3\)](#) (how2stats) (2:28 – end)
- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 4\)](#) (how2stats) (0:00 – 3:02)

STEP 4: The ANCOVA was performed on the three variables – PRIMARY FACTOR, gender; COVARIATE FACTOR, body size; DEPENDENT VARIABLE, cranial capacity.

- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 4\)](#) (how2stats) (3:02 – end)
- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 5\)](#) (how2stats) (0:00 – 2:28)

NEXT STEPS: Some of the criticisms of ANCOVA are discussed and then the presenter goes through a step-by-step process showing how one can do multiple regression in ANCOVA.

The first step is to test the Homogeneity of Regression assumption by defining an interaction term.

- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 5\)](#) (how2stats) (2:29 - end)
- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 6\)](#) (how2stats) (0:00 – 2:43)

The presenter performs the multiple regression analysis testing if gender can really predict cranial capacity, above and beyond body size.

- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 6\)](#) (how2stats) (2:43 - end)

The presenter performs the multiple regression analysis testing if gender can really predict cranial capacity, above and beyond body size.

- [Analysis of Covariance \(ANCOVA\) – using SPSS \(Part 7\)](#) (how2stats)

In this last video of the series, the unstandardized regression coefficients are discussed, thereby pointing out the similarities between ANCOVA and multiple regression analysis.

➤ The General Linear Model (GLM) – an overview

(Unit 5.1: chapter 12, section 2 pp. 256 - 257)

The General Linear Model (GLM) is a statistical design model which **encompasses both regression and group differences techniques under one umbrella** - hence the adjective 'general.' This means that the independent variables/FACTORS OF INTEREST may be either:

- primary interest categorical factors (including numeric/continuous variables, string/categorical variables or a mixture of both types), as in ANOVA tests, or
- quantitative continuous covariates, as in regression techniques.

However, the **dependent variables are all continuous** (that is, quantitative interval or ratio data).

In the case of the regression techniques, it is called 'linear' because ANY linear **regression equations are linear equations** (highest power of the independent variable(s) is 1) in one or more independent variables. Graphically they represent either:

1. **one line** in 2-space (the XY -plane) with a linear equation having ONE independent/PREDICTOR variable X and ONE dependent variable Y ;
2. **one straight/ 'flat' plane** in higher dimensional space (3 or more dimensions) with a linear equation having TWO OR MORE independent variables/COVARIATES X_1, X_2, X_3 , etc. and ONE dependent variable Y ;
3. **a system of 'flat' planes** in higher dimensional space with a system of linear equations having TWO OR MORE independent variables/COVARIATES X_1, X_2, X_3 , etc. and TWO OR MORE dependent variables Y_1, Y_2, Y_3 , etc.).

For purposes of significance testing, all data are assumed to come from random samples. The variance(s) of the dependent variable(s) is/are assumed to be the same for each cell formed by categories of the independent variable factor(s). This latter condition is called the 'homogeneity of variances' assumption.

Its strengths include the following options:

- to be able to use fixed factors, random factors, and covariates as predictors/EXPLANATORY VARIABLES;
- to be able to analyze more than one dependent variable – thereby, in regression cases, leading to an ($m \times n$) system of linear equations;
- to be able to use multivariate (more than one dependent variable) tests of significance when modeling correlated dependent variables – thus reducing reliance on individual univariate (single dependent variable) tests as done in multiple regression techniques; and
- to be able to do repeated measures designs.

Finally, it can deal with redundant independent variables which would normally prevent solution in regular regression models. This is because the GLM uses a generalized inverse of the matrix of independent variables' correlations with each other.

The advantages of doing regression via the GLM procedure are that dummy variables are coded automatically, it is easy to add interaction terms, and it computes eta-squared (identical to R-squared when relationships are linear, but greater if nonlinear relationships are present). However, the SPSS regression procedure would still be preferred if the researcher wishes output of standardized regression (beta) coefficients, wants to do multicollinearity diagnostics, or decides to do stepwise regression or enter independent variables hierarchically, in blocks.

○ [Logic of the Generalized Linear Model – the GLM](#) (Ray Cooksey)

In this video Professor Cooksey presents a top-down view of the model, its strengths, its various components, and an explanation of its findings. He also shows how to code categorical data into dummy variables so that the 'essentially quantitative' model (because it creates an equation of dependence) can use them effectively.

- [GLM versus Linear Regression – using SPSS](#) (LearnViaWeb.com)

The presenter discusses the benefits of using the General Linear Model (GLM) over linear regression techniques using SPSS.

- [Introduction to Generalized Linear Models](#) (Actuarial Education) (Actuarial Research)

This video contains a review of the linear model and then does on to discuss how this model may be generalized to, for example, exponential models. A good understanding of the concepts presented here will require some knowledge of both exponentials and logarithmic functions and some experience with Calculus techniques. This video is included in this series because it provides some insights into more complex statistical methods which become necessary because the simple linear methods fail to explain satisfactorily the variations among the various groups of data.

➤ **Multivariate Analysis of Variance (MANOVA)** (optional)

MANOVA is a statistical procedure which is an extension of ANOVA and it is used when there are **MORE THAN ONE, BUT RELATED**, DEPENDENT variables/outcomes. In testing the statistical significance of three or more mean differences, the MANOVA mathematical model creates an aggregate dependent variable which is a linear combination of the two dependent variables of interest.

MANOVA is most effective when dependent variables are moderately correlated (0.4–0.7). If they are too highly correlated, the dependent variables may be measuring the same thing.

Some researchers prefer to do a sequence of ANOVA tests on the dependent variables, one at a time, rather use than the more complex MANOVA procedure. The sequential analysis, however, tends to increase the type I error of the experiment (when one rejects a true null hypothesis). However, one remedy for that is to use the Bonferroni adjustment on the sequence of ANOVAs which mitigates the type I error enlargement – sometimes called the family-wise error rate. The **Bonferroni correction** is done by dividing the significance level of the experiment (α) by the number of tests performed.

Assumptions: REINs of ANOVA apply to MANOVA

- i. **Randomness:** samples are drawn randomly from either one or several different populations;
- ii. **Equal Variances:** variances in the outcome/response data across the various groups/levels are equal;
- iii. **Independence:** samples drawn from *different* populations are independent; and
- iv. **Normality:** the outcome/response data are at least (approximately) normally distributed.

Additional Assumptions of MANOVA over ANOVA:

- v. The covariance matrices of the dependent variables (which measure the strength of the relationships between variables) are equal across all groups/levels/treatments of the independent variable(s).

○ **ANOVA MANOVA** (Ray Cooksey)

A top-down look at central concepts associated with analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA), the logic behind each method and their differences.

○ **One-Way MANOVA using SPSS** (RMUoHP) (Medical Research)

In this case study, one-way means testing the impact of:

ONE categorical independent variable with THREE LEVELS

on: **TWO quantitative dependent outcome variables (one continuous; one ordinal).**

COMPARISON/IMPACT OF

ONE independent categorical variables/PRIMARY FACTOR with THREE LEVELS: type of surgical technique on a shoulder injury (1,2,3);

THREE treatments: number of levels in PRIMARY FACTOR = 3;

WITH/ON

TWO quantitative dependent RESPONSE/OUTCOME VARIABLES:

ONE continuous dependent variable: recovery time in weeks;

ONE ordinal dependent variable: global rate of change (subjective patients' assessment of improvement after surgery) with values of -7 to + 7 in which 0 means no significant change;

USING the means of a linear combination of the dependent variables.

The associated table for this design is a 2 X 3 cross tab:

	PRIMARY FACTOR: Surgical Procedure Independent EXPLANATORY Variable Groupings/Levels		
Dependent RESPONSE Variables	Procedure 1	Procedure 2	Procedure 3
RECOVERY TIME (continuous)			
GLOBAL RATE OF CHANGE (ordinal)			

In the following 10-part video series, the presenter performs and interprets a MANOVA in SPSS in two different ways using between-groups designs with the same set of data.

METHOD 1: using a MANOVA in the most common way which helps protect the accuracy of the results from a series of Type 1 errors

- [MANOVA – using SPSS \(Part 1\)](#) (how2stats) (Educational Psychology Research)
- [MANOVA – using SPSS \(Part 2\)](#) (how2stats)
- [MANOVA – using SPSS \(Part 3\)](#) (how2stats)

Using SPSS, the presenter describes a one-way MANOVA testing the comparison of:

ONE categorical independent variable with THREE LEVELS/GROUPS (education level)
with: **NINE quantitative continuous dependent outcome variables** (intelligence subscales).

Analysis of the MANOVA design

COMPARISON/IMPACT OF

ONE independent categorical variables/PRIMARY FACTOR with THREE LEVELS:
education level of student (undergraduate, Master's degree student, Ph.D. student);

THREE treatments: number of levels in PRIMARY FACTOR = 3;

WITH/ON

NINE quantitative dependent RESPONSE/OUTCOME VARIABLES (all intelligence subscales):

THREE continuous dependent variables: verbal skills on THREE levels;

THREE continuous dependent variables: memory skills on THREE levels;

THREE continuous dependent variables: spatial skills on THREE levels;

USING the means of a linear combination of the dependent variables.

NEXT STEP:

- [MANOVA – using SPSS \(Part 4\)](#) (how2stats) (time 0:00 – 2:58)

If the MANOVA test is significant, meaning that the null hypothesis of equal means (or no significant differences across all three groups of education level) is rejected, one can apply a series of one-way ANOVAs to determine for which pair(s) of groups the test is significant. For the subsequent significant ANOVAs, the presenter walks through a series of t tests or post-hoc testing to clarify the relationships, if any, even further.

METHOD 2: There is a second way of conducting a MANOVA test which is more sophisticated but provides additional insights into the experimental results. This method is done using SPSS syntax which allows for an understanding of the discriminant function that is created by the MANOVA procedure.

- [MANOVA – using SPSS \(Part 4\)](#) (how2stats) (time 2:58 – end)
- [MANOVA – using SPSS \(Part 5\)](#) (how2stats)
- [MANOVA – using SPSS \(Part 6\)](#) (how2stats)
- [MANOVA – using SPSS \(Part 7\)](#) (how2stats)
- [MANOVA – using SPSS \(Part 8\)](#) (how2stats)
- [MANOVA – using SPSS \(Part 9\)](#) (how2stats)
- [MANOVA – using SPSS \(Part 10\)](#) (how2stats)

NOTE: Some SPSS syntax and code may be found on the [Institute for Digital Research and Education](#) (UCLA) statistics web site, under 'SPSS'. Some relevant URLs are: [SPSS Learning Modules](#) and [An Overview of Statistical Tests in SPSS](#).

- [Discriminant Analysis using SPSS](#) (RMUoHP)

The presenter outlines two main purposes for discriminant analysis:

1. to describe major differences among groups following a MANOVA analysis; and
2. to determine whether a set of variables is effective in predicting category membership, based upon one of more linear combinations of certain **UNCORRELATED** quantitative continuous measures. These latter linear combinations are called discriminant functions.

Assumptions of Discriminant Analysis: same as the MANOVA assumptions

Goal: out of a set of continuous variables which are deemed relevant to the task, if one can find the uncorrelated variables, then it is possible to discover those which discriminate between group membership. The process is similar to logistic regression, in the case of a binary outcome.

Analysis

In this case study, a set of FIVE predictor quantitative continuous variables was put forward as being a set of characteristics which could be used to discriminate or differentiate between students so as to predict which students would either pass or fail a certification exam.

SIX EXPLANATORY VARIABLES (ALL continuous quantitative):

ONE quantitative continuous EXPLANATORY/PREDICTOR variable: grade point average (GPA);
FOUR quantitative continuous EXPLANATORY/PREDICTOR variables: scores on each of four different standardized tests;

RESPONSE VARIABLE:

ONE **dichotomous binary categorical** RESPONSE/OUTCOME variable with TWO groups/levels: pass or fail certification exam using the dummy variable (0,1) where 0 = 'fail'; 1 = 'pass'.

- [Conducting a Discriminant Analysis in SPSS](#) (Todd Grande)

The presenter explains that Discriminant Analysis determines the probability of group membership based on predictor variables. He suggests that one way to think of Discriminant Analysis is to consider it as the MANOVA process in reverse.

In a MANOVA,
the INDEPENDENT VARIABLES are the GROUPS and the DEPENDENT VARIABLES are the PREDICTORS.

In DISCRIMINANT ANALYSIS,
the INDEPENDENT VARIABLES are the PREDICTORS and the DEPENDENT VARIABLES are the GROUPS.

The example used in the analysis concerns a way of calculating the probability of the successful graduation of students from a degree program based on three predictor variables measured and collected during the early part of the program: the grade on a pretest exam; a rubric score based on skills evaluated under counseling; and a grade obtained on the first course taken in the program. Therefore, there are THREE quantitative INDEPENDENT/EXPLANATORY /PREDICTOR variables and ONE categorical DEPENDENT/RESPONSE variable with TWO GROUPS/LEVELS: successful, not successful .

➤ **Mixed Methods Research (optional)**

This is included for those of you who are taking MATH 315 for purposes of learning more sophisticated statistical methods to be applied in your workplace or postgraduate research.

- [Managing Mixed Methods](#) (Ray Cooksey)

➤ **Cluster Analysis Techniques – a precursor to hypothesis testing (optional)**

- [Cluster Analysis](#) (Ray Cooksey)

In this video, cluster analysis is presented as a data mining technique intended to discover patterns in a set of data. The researcher will need a set of variables to form the basis for the search. Most often data patterns can create a typology involving a categorization of respondents or cases. Respondents or cases are said to be similar if they are 'clustered' about a single point in the generalized Euclidean plane determined by the quantitative measures of TWO OR MORE variables (characteristics) and if the Euclidean distance between them is within an acceptable limit. Ward's minimum variance hierarchical cluster technique as well as the *k*-means, non-hierarchical, clustering algorithm are discussed. Both methods may be done in SPSS.

In the following set of examples, we begin with hierarchical clustering. The researcher chooses a statistic that quantifies how far apart (or similar) two cases are. Then a method for forming the groups is selected. The final step is to determine how many clusters are required to represent the data. This is done by examining how similar clusters are when you create additional clusters or collapse existing ones.

- [Hierarchical Cluster Analysis in SPSS](#) (James Geskin)

The presenter performs a hierarchical cluster analysis on different kinds of burgers or sandwiches from a variety of restaurants. The clustering is done on the number of calories, the total grams of fat and the total milligrams of sodium in order to categorize them into groups of similar nutritional value in terms of these three characteristics (variables). Ultimately, he infers a hierarchical cluster relationships using a **dendrogram** (a tree diagram used to illustrate the arrangement of the clusters)..

- [SPSS Hierarchical Clustering Intro](#) (Stats-Lab Dublin)

The presenter uses SPSS to perform a hierarchical cluster analysis on different dogs in order to determine similarities and dissimilarities amongst them. The clustering is based on the weight (in kilograms) and the height (in centimeters) of each animal. Both an agglomeration schedule and a proximity matrix are used to detail the statistics. A **dendrogram** (a tree diagram) and a **vertical icicle plot** (a matrix whose rows are the cluster numbers and whose columns are the cases in each cluster) are used to present the results graphically. The algorithm used to decide which clusters may be joined together is Ward's method.

NOTE: **Ward's Method** is an alternative approach for performing cluster analysis – treating it as an analysis of variance problem. It does not use distance metrics or measures of association, as is the case with other methods. Ward's method is an iterative process which starts out with n clusters of size 1 and continues until all the observations are included into one cluster. Hence the hierarchy.

- [k-Means Non-Hierarchical Cluster Analysis in SPSS](#) (James Geskin)

Following up on his hierarchical cluster analysis video above, Dr. Geskin performs a non-hierarchical cluster analysis on the same set of sandwich/burger data using the same variables: the number of calories, the total grams of fat and the total milligrams of sodium. In this case, each of the data variables must be standardized in order to be compared and clustered into similar groups. The best way of standardizing each of these continuous quantitative data variables is the process of transforming them to their respective Z-scores. This is tantamount to scaling each variable so that its mean is 0 and its standard deviation is 1. An ANOVA table is one of the options used to detail the statistics indicating which of the variables are significant contributors to the cluster membership and which are not.

NOTE: In **k-means clustering**, the number of clusters desired is predetermined by the researcher. The algorithm iteratively estimates the cluster means and assigns each case to the cluster for which its distance to the cluster mean is the smallest.

- [Validating k-Means Cluster Analysis in SPSS](#) (James Geskin)

In this video, Dr. Geskin explains how to determine the optimal number of clusters into which to divide the given standardized data. A post-hoc multiple comparisons ANOVA test of means helps to validate the results.

- [k-Means Non-Hierarchical Cluster Analysis in SPSS](#) (Todd Grande)

In this second example, the presenter performs a non-hierarchical cluster analysis on a set of fifty (50) programs used to help patients with depression, anxiety and substance abuse. The quantitative data variables are positive integers with higher scores indicating increasingly more severe cases of patients' experiences. Each of the data variables, in order to be compared and clustered into similar groups, is

standardized to its respective Z-score. An ANOVA table is one of the options used to detail the statistics indicating which of the variables are significant contributors to determining which program belonged to which cluster.

- [Two-Step Cluster Analysis in SPSS](#) (James Geskin)

In this video, the presenter uses SPSS to create profiles of employees to see how they are clustered around a set of variables. Both quantitative and qualitative variables can be included. Through some experimentation, a 4-cluster analysis of the employees using the productivity and job satisfaction variables appears to create a meaningful analysis. After the clustering process, the clusters are analyzed for burnout using post hoc tests. Dr. Geskin also creates a cluster membership variable for each case/respondent which can be used as a moderation variable in other analyses such as **structural equation modeling** (SEM).

NOTE: **Two-step clustering** is used to simplify large intractable problem data sets. In the first step, cases are assigned to “pre-clusters.” In the second step, the pre-clusters are clustered using the hierarchical clustering algorithm. The researcher can specify the number of clusters or can allow the algorithm to decide the optimal number based on the preselected criteria.



[Choosing a Statistical Procedure](#) (The Doctoral Journey)

GLOSSARY of TERMS for EXPERIMENTAL DESIGNS

(Condensed from the NIST Engineering Statistics handbook: Section 5.7. A Glossary of DOE Terminology.) Courtesy of http://en.wikipedia.org/wiki/Analysis_of_variance.

Balanced design

An experimental design where all cells (i.e. treatment combinations) have the same number of observations.

Blocking

A schedule for conducting treatment combinations in an experimental study such that any effects on the experimental results due to a known change in raw materials, operators, machines, etc., become concentrated in the levels of the blocking variable. The reason for blocking is to isolate a systematic effect and prevent it from obscuring the main effects. Blocking is achieved by restricting randomization.

Design

A set of experimental runs which allows the fit of a particular model and the estimate of effects.

DOE

Design of experiments. An approach to problem solving involving collection of data that will support valid, defensible, and supportable conclusions.

Effect

How changing the settings of a factor changes the response. The effect of a single factor is also called a main effect.

Error

Unexplained variation in a collection of observations. DOE's typically require understanding of both random error and lack of fit error.

Experimental unit

The entity to which a specific treatment combination is applied.

Factors

Process inputs an investigator manipulates to cause a change in the output.

Lack-of-fit error

Error that occurs when the analysis omits one or more important terms or factors from the process model. Including replication in a DOE allows separation of experimental error into its components: lack of fit and random (pure) error.

Model

Mathematical relationship which relates changes in a given response to changes in one or more factors.

Random error

Error that occurs due to natural variation in the process. Random error is typically assumed to be normally distributed with zero mean and a constant variance. Random error is also called experimental error.

Randomization

A schedule for allocating treatment material and for conducting treatment combinations in a DOE such that the conditions in one run neither depend on the conditions of the previous run nor predict the conditions in the subsequent runs.

Replication

Performing the same treatment combination more than once. Including replication allows an estimate of the random error independent of any lack of fit error.

Responses

The output(s) of a process. Sometimes called dependent variable(s).

Treatment

A treatment is a specific combination of factor levels whose effect is to be compared with other treatments.

SUMMARY TABLE of EXPERIMENTAL DESIGNS

PARAMETRIC METHOD	DEPENDENT/ RESPONSE VARIABLE(S) *	INDEPENDENT/ EXPLANATORY VARIABLE(S) *	BLOCKING/ CONTROL VARIABLE(S) *	COVARIATE/ CONFOUNDING VARIABLE(S) *
Pearson Correlation Coefficient	Q (1)	Q (1)	(0)	(0)
Simple Linear Regression	Q (1)	Q or QC (1)	(0)	(0)
Multiple Linear Regression	Q (1)	Q or QC (≥ 2)	(0)	(0)
Binary Logistic Regression	BC (1)	Q or QC (≥ 1)	(0)	(0)
Goodness-of-Fit	compared using RF to a fixed outcome	C (1)	(0)	(0)
Test of Independence: two-way cross tab	compared using RF	C (2)	(0)	(0)
Test of Independence: three-way cross tab	compared using RF	C (2)	C (1)	(0)
t Tests: independent & dependent	Q (1)	QC (1) with 2 groups	(0)	(0)
Homogeneity Test	compared using RF	C (2)	(0)	(0)
One-Way ANOVA	Q (1)	QC (1) with ≥ 3 groups	(0)	(0)
Factorial ANOVA	Q (1)	QC (≥ 2) each with ≥ 2 groups	(0)	(0)
Completely Randomized ANOVA	Q (1)	QC (≥ 1)	(0)	(0)
Randomized Block ANOVA k treatments in b blocks	Q (1)	QC (1) with k groups	QC (1) with b groups	(0)
Latin Square ANOVA $n \times n$	Q (1)	QC (1) with n groups	QC (2) each with n groups	(0)
One-Way ANCOVA	Q (1)	QC (1)	(0)	Q (1)
Two-Way ANCOVA	Q (1)	QC (2) incl. moderators	(0)	Q (1)
MANOVA	Q (≥ 2)	QC (≥ 1)	(0)	(0)

*In the above table:

Q means quantitative, continuous (ratio or interval) outcome data;

C means categorical, generally split into groups having either numeric or string data;

QC means categorical, generally split into groups of numeric data (using dummy variables);

BC means binary categorical, having a dichotomous 0 or 1 outcome;

RF means relative frequency; and (n) is the specified number of variables of the type stated.

TABLE OF NON-PARAMETRIC ALTERNATIVE TESTS

PARAMETRIC METHOD	NON-PARAMETRIC ALTERNATIVE	DEPENDENT/ RESPONSE VARIABLE(S) *	INDEPENDENT/ EXPLANATORY VARIABLE(S) *
Pearson's Correlation Coefficient	Spearman Correlation Coefficient	OQ (1) Relationship determined by comparing ranks	OQ (1) or OC(1) with 2 groups
	Kendall's Tau Correlation Coefficient	O (1) Relationship determined by comparing ranks	OC(1) with 2 groups
Independent Samples t Test	Mann Whitney U Test	O(1) or OQ (1) Means compared using ranks	Q (1) or OC(1) with 2 groups
Dependent or Paired Samples t Test	Wilcoxon Signed-Rank Test for Matched Pairs	O(1) or OQ (1) Means compared using ranks	OQ (1) or OC(1) with 2 groups
Completely Randomized ANOVA	Kruskal-Wallis H Test	O(1) or OQ (1) Means compared using ranks	OQ (1) or OC(1) with ≥ 3 groups
	Friedman's Test	O(1) or OQ (1) Means compared using ranks	OQ (1) or OC(1) with ≥ 3 groups
Randomized Block ANOVA	Friedman's Test k treatments in b blocks	O(1) or OQ (1) Means compared using ranks	OQ (1) or OC(1) with k groups

*In the above table:

Q means quantitative, continuous (ratio or interval) outcome data;

C means categorical, generally split into groups having either numeric or string data;

O means ordinal or ranked data;

OC means categorical, generally split into groups of numeric data (or dummy variables);

OQ means quantitative continuous data converted into an ordinal rank scale;

(n) means number of variables.

Credits: This document, including the discovery and compilation of this magnificent collection of YouTube statistics videos (with some impetus from one of my students), was created by Julie Peschke, Academic Coordinator for the Math 315: *Methods in Applied Statistics* program at Athabasca University. Its purpose was to provide an overview of the numerous statistical methods available for analyzing data drawn from significantly diverse areas of disciplinary research. My personal analysis of the case studies and those of the presenters hopefully help to reveal the underlying structure and common thread of the statistical thought processes at work behind each method. Each case is presented with an emphasis on the dependent and independent variables of interest, their forms, and their roles.

ADDITIONAL VIDEOS on LOGISTIC REGRESSION**Logistic Regression, An Introduction (Brandon Foltz)**

<https://www.youtube.com/watch?v=zAULhNrnuL4>

Logistic Regression Probability, Odds, and Odds Ratio (Brandon Foltz)

<https://www.youtube.com/watch?v=ckkiG-SDuV8>

Logistic Regression, Estimating the Probability (Brandon Foltz)

<https://www.youtube.com/watch?v=gcr3qy0SdGQ>

Logistic Regression, Logit and Regression Equation (Brandon Foltz)

https://www.youtube.com/watch?v=NmjT1_nClzg