STATISTICS FOR BEHAVIORAL SCIENCES

by GRAVETTER AND WALLNAU · Language: EN

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Overview

Gravetter and Wallnau's "Statistics for Behavioral Sciences" is a foundational textbook designed to introduce students in psychology and other behavioral sciences to the principles and applications of statistical methods. The book emphasizes a conceptual understanding of statistics, moving beyond mere computational formulas to explain the 'why' behind statistical procedures. It covers both descriptive statistics, which summarize and organize data, and inferential statistics, which allow researchers to draw conclusions about populations based on sample data.

The text is structured to be accessible to students with varying mathematical backgrounds, employing a step-by-step approach, numerous examples, and practice problems rooted in real-world behavioral research scenarios. Key topics include measures of central tendency and variability, z-scores, probability, hypothesis testing, t-tests, ANOVA, correlation, regression, and chi-square tests. The authors consistently link statistical concepts back to the research process, helping students understand how statistics are integral to designing experiments, analyzing data, and interpreting findings in fields like psychology, education, and sociology. Its enduring popularity stems from its clear explanations, engaging presentation, and practical relevance, making complex statistical ideas manageable for its target audience.

Key Takeaways

- Understand the distinction between descriptive statistics (summarizing data) and inferential statistics (making predictions about populations) to correctly apply methods.
- Master the concept of hypothesis testing, as it forms the bedrock for drawing conclusions from research data in behavioral sciences.
- Recognize that variability is a fundamental aspect of behavioral data, and its measurement is crucial for accurate statistical analysis.
- Learn to interpret p-values and confidence intervals correctly to avoid common misinterpretations of statistical significance.
- Always consider the assumptions of a statistical test before applying it to your data, as violating them can lead to invalid conclusions.
- Practice applying statistical concepts to real-world research scenarios to solidify your understanding and develop critical thinking skills.

• Understand that statistics is a tool for understanding and interpreting data, not just a collection of formulas to memorize.

Chapter Summaries

Chapter 1: Introduction to Statistics

This foundational chapter introduces the field of statistics, defining key terms such as population, sample, parameter, and statistic. It differentiates between descriptive statistics, used to summarize data, and inferential statistics, used to make generalizations about populations based on samples. The chapter also covers different types of variables (discrete, continuous) and scales of measurement (nominal, ordinal, interval, ratio), which are crucial for selecting appropriate statistical tests. Furthermore, it briefly touches upon various research methods like experimental, correlational, and nonexperimental designs, emphasizing their role in behavioral science research. The chapter concludes with an explanation of summation notation (sigma notation), a fundamental mathematical tool used throughout the textbook for statistical calculations.

Chapter 2: Frequency Distributions

Chapter 2 focuses on methods for organizing and presenting data to make it more comprehensible. It introduces frequency distribution tables, which show the number of times each score or group of scores occurs in a dataset, including regular and grouped frequency distributions. The chapter then moves to graphical representations, explaining how to construct and interpret histograms, bar graphs, and polygons, each suited for different types of data. It also discusses the common shapes of distributions, such as symmetrical, skewed (positively or negatively), and normal distributions. Understanding these visual and tabular methods is essential for gaining initial insights into a dataset before performing more complex analyses.

Chapter 3: Central Tendency

This chapter delves into the concept of central tendency, which aims to find a single, representative score that best describes the center of a distribution. It thoroughly explains the three primary measures of central tendency: the mean, median, and mode. The mean is presented as the arithmetic average, the median as the middle score in an ordered distribution, and the mode as the most frequently occurring score. The chapter details how to calculate each measure and, importantly, discusses the conditions under which each measure is most appropriate. For instance, the median is often preferred for skewed distributions or when dealing with ordinal data, while the mode is suitable for nominal data. The impact of extreme scores on the mean is also highlighted.

Chapter 4: Variability

Chapter 4 introduces the concept of variability, a crucial measure that quantifies the degree to which scores in a distribution are spread out or clustered together. It covers several measures of variability, including the range, interquartile range, variance, and standard deviation. A significant portion of the chapter is dedicated to explaining the sum of squares (SS), which is the foundation for calculating variance and standard deviation. The distinction between population variance/standard deviation and sample variance/standard deviation is made clear, with emphasis on the n-1 correction used for sample statistics to provide an unbiased estimate of the population parameter. Understanding variability is critical for interpreting data and is a prerequisite for inferential statistics.

Chapter 5: z-Scores: Location of Scores and the Standardized Distribution

This chapter introduces z-scores as a powerful tool for standardizing and comparing individual scores within a distribution. A z-score indicates the exact location of a score relative to the mean, expressed in terms of standard deviation units. The chapter explains how to transform raw scores into z-scores and, conversely, how to convert z-scores back into raw scores. It details the properties of a z-score distribution, notably that it always has a mean of 0 and a standard deviation of 1. This standardization allows for meaningful comparisons of scores from different distributions, even if they have different means and standard deviations, by placing them on a common scale.

Chapter 6: Probability and the Normal Distribution

Chapter 6 connects the concepts of z-scores and distributions to probability, a fundamental element of inferential statistics. It introduces the normal distribution, a symmetrical, bell-shaped distribution that is frequently encountered in nature and statistics. The chapter explains how to use the unit normal table (often called the z-table) to find the proportion of scores (which corresponds to probability) associated with specific z-score values. Students learn to calculate probabilities for scores falling above, below, or between certain points in a normal distribution. This understanding is crucial for hypothesis testing, as it allows researchers to determine the likelihood of observing particular sample outcomes.

Chapter 7: Probability and Samples: The Sampling Distribution of the Mean

Building on probability, Chapter 7 introduces the critical concept of the sampling distribution of the mean. This distribution is formed by taking all possible random samples of a specific size from a population and calculating the mean for each sample. The chapter explains the Central Limit Theorem, a cornerstone of inferential statistics, which describes the shape, mean (expected value), or standard deviation (standard error) of the sampling distribution of the mean. The standard error of the mean is defined as a measure of the average distance between a sample mean and the population mean. This chapter is vital for understanding how sample data can be used to make inferences about populations.

Chapter 8: Introduction to Hypothesis Testing

Chapter 8 provides the foundational framework for hypothesis testing, a systematic procedure for evaluating the validity of a hypothesis about a population parameter using sample data. It introduces the null hypothesis (H0), which states there is no effect or no difference, and the alternative hypothesis (H1), which proposes an effect or difference. Key concepts covered include the alpha level (level of significance), critical regions, and the calculation of a test statistic. The chapter also discusses the potential for Type I and Type II errors, explaining the consequences of each. The z-test is introduced as the first example of a hypothesis test, applicable when the population standard deviation is known.

Chapter 9: Introduction to the t Statistic

This chapter introduces the t statistic, a crucial inferential tool used when the population standard deviation is unknown, a common scenario in behavioral research. It explains that the t statistic uses the sample standard deviation to estimate the population standard deviation, leading to the concept of estimated standard error. The chapter details degrees of freedom (df), which influence the shape of the t distribution, making it flatter and more spread out for smaller sample sizes. Students learn how to use the t distribution table to find critical t values for hypothesis testing. The single-sample t-test is presented as the primary application, allowing researchers to test hypotheses about a single population mean when the population variance is unknown.

Chapter 10: The t Test for Two Independent Samples

Chapter 10 extends hypothesis testing to compare the means of two independent groups or conditions, a common scenario in experimental research. It focuses on the independent-measures (between-subjects) design, where each participant is assigned to only one treatment condition. The chapter details the calculation of the independent-measures t statistic, which involves pooling the variances of the two samples to obtain a more accurate estimate of the population variance. It also explains the degrees of freedom for two independent samples. The interpretation of the results, including the calculation of effect size using Cohen's d, is thoroughly discussed, allowing researchers to quantify the magnitude of the observed difference between group means.

Chapter 11: The t Test for Two Related Samples

This chapter introduces the t-test for related samples, also known as the paired-samples t-test or dependent-measures t-test. This test is used when the two sets of data are related, such as in repeated-measures designs (where the same individuals are measured in two different conditions) or matched-subjects designs (where individuals in two groups are paired based on relevant characteristics). The core of this test involves calculating difference scores for each pair and then performing a single-sample t-test on these difference scores. The chapter discusses the advantages of related-samples designs, such as reducing individual differences, and explains how to calculate and interpret the t statistic and effect size for these designs.

Chapter 12: Introduction to Analysis of Variance (ANOVA)

Chapter 12 introduces Analysis of Variance (ANOVA), a powerful hypothesis testing procedure designed to compare two or more population means simultaneously. It explains why conducting multiple t-tests when comparing more than two groups is problematic due to an inflated Type I error rate. ANOVA uses the F-ratio as its test statistic, which is a ratio of variance between treatments to variance within treatments. The chapter details how to partition the total variability in a dataset into these components. The ANOVA summary table, which organizes the sums of squares, degrees of freedom, mean squares, and the F-ratio, is thoroughly explained for a single-factor independent-measures ANOVA.

Chapter 13: Repeated-Measures ANOVA

Building on the principles of ANOVA, Chapter 13 applies the analysis of variance framework to repeated-measures designs, where the same group of individuals is measured across all treatment conditions. The key advantage of this design is the ability to remove individual differences from the error term, leading to a more powerful test. The chapter explains how to partition the total variability into between-treatments, within-treatments, and between-subjects variability, and how to calculate the F-ratio for repeated-measures ANOVA. It also covers the use of post hoc tests, such as Tukey's HSD or Scheffé, which are necessary to determine specific mean differences when a significant F-ratio is obtained for more than two conditions.

Chapter 14: Two-Factor ANOVA (Independent Measures)

Chapter 14 introduces factorial designs and the two-factor independent-measures ANOVA, which allows researchers to evaluate the effects of two independent variables (factors) and their interaction on a dependent variable. The chapter explains the concepts of main effects (the effect of each independent variable by itself) and interaction effects (when the effect of one factor depends on the level of the other factor). It details how to partition the total variability into three distinct F-ratios: one for Factor A, one for Factor B, and one for the A x B interaction. Interpreting interaction effects, often through graphs and simple main effects analysis, is a central focus.

Chapter 15: Correlation

Chapter 15 introduces correlation as a statistical technique used to measure and describe the relationship between two variables. It explains three key characteristics of a relationship: its direction (positive or negative), its form (typically linear), and its strength (how consistently the variables are related). The chapter focuses on the Pearson correlation coefficient (r), detailing its calculation and interpretation. It also covers hypothesis testing for correlation and discusses various factors that can influence the correlation coefficient, such as range restriction and the presence of outliers. The Spearman correlation is also introduced as a non-parametric alternative for ordinal data.

Chapter 16: Regression

Building on correlation, Chapter 16 introduces linear regression, a statistical technique used to predict one variable from another. It explains the concept of a regression line (the line of best fit) and its equation, Y = bX + a, where 'b' is the slope and 'a' is the Y-intercept. The chapter details the method of least squares, which is used to determine the values of 'b' and 'a' that minimize the squared distances between the actual Y values and the predicted Y values. The standard error of estimate is introduced as a measure of the accuracy of the predictions. The relationship between regression and correlation, particularly the coefficient of determination (r-squared), is also discussed.

Chapter 17: The Chi-Square Statistic: Tests for Goodness of Fit and Independence

Chapter 17 introduces the chi-square statistic, a non-parametric test used for categorical data. It covers two primary applications: the chi-square test for goodness of fit and the chi-square test for independence. The goodness-of-fit test is used to assess whether observed frequencies for a single categorical variable differ significantly from expected frequencies based on a null hypothesis (e.g., equal proportions or a known population distribution). The test for independence examines whether there is a statistically significant relationship between two categorical variables. The chapter explains how to calculate observed frequencies (fo) and expected frequencies (fe), degrees of freedom, and how to interpret the chi-square value.

Chapter 18: Beyond Chi-Square: Nonparametric Tests

This concluding chapter explores additional nonparametric statistical tests, which are valuable alternatives to parametric tests when assumptions about population distributions (e.g., normality, homogeneity of variance) are violated, or when data are measured on nominal or ordinal scales. The chapter typically covers tests such as the Mann-Whitney U test (an alternative to the independent-samples t-test), the Wilcoxon signed-rank test (an alternative to the related-samples t-test), the Kruskal-Wallis test (an alternative to one-way ANOVA), and the Friedman test (an alternative to repeated-measures ANOVA). It discusses the rationale for using these tests, their computational procedures, and their advantages and disadvantages compared to their parametric counterparts.

Themes

- Statistical Literacy
- Research Methodology
- Data Interpretation
- Hypothesis Testing
- Variability in Data

Frequently Asked Questions

What is STATISTICS FOR BEHAVIORAL SCIENCES about?

This textbook provides a comprehensive introduction to statistical methods specifically tailored for students in psychology and other behavioral sciences. It covers both descriptive and inferential statistics, explaining how to organize, summarize, analyze, and interpret data from behavioral research studies, emphasizing conceptual understanding over rote memorization.

Is STATISTICS FOR BEHAVIORAL SCIENCES worth reading?

Yes, it is highly regarded as a clear and accessible textbook for introductory statistics courses in behavioral sciences. Its step-by-step explanations, numerous examples, and focus on practical application make complex statistical concepts understandable for students, even those with math anxiety. It's an excellent resource for building a solid foundation in statistical reasoning.

How does STATISTICS FOR BEHAVIORAL SCIENCES end?

Spoiler: As a textbook, it does not have a narrative ending. It typically concludes with advanced inferential statistics topics such as chi-square tests for categorical data or an introduction to more complex ANOVA designs, followed by a summary of key concepts and perhaps a review of the decision-making process for choosing appropriate statistical tests.

Who should read STATISTICS FOR BEHAVIORAL SCIENCES?

This book is primarily intended for undergraduate students in psychology, education, sociology, and other behavioral or social sciences who are taking an introductory course in statistics. It is also useful for anyone needing a clear, comprehensive guide to basic statistical concepts applied to human behavior and social phenomena.

How long does it take to read STATISTICS FOR BEHAVIORAL SCIENCES?

Given its nature as a comprehensive textbook with practice problems and conceptual exercises, a thorough reading and understanding of "Statistics for Behavioral Sciences" could take anywhere from 30 to 60 hours, or even more, depending on the reader's prior knowledge and study habits. It's designed for semester-long study.

Best Quotes

“A population is the entire set of individuals of interest in a particular study.”

Introduction to Statistics and Research Methods

This foundational definition introduces the concept of a population as the complete group a researcher wishes to understand. It's crucial for distinguishing between the larger group and the smaller, studied sample, setting the stage for inferential statistics.

“A sample is a set of individuals selected from a population, usually intended to represent the population in a research study.”

Introduction to Statistics and Research Methods

This definition clarifies that a sample is a subset of the population, chosen for practical reasons to conduct research. The goal is for the sample to be representative, allowing researchers to generalize findings back to the larger population.

“A variable is a characteristic or condition that changes or has different values for different individuals.”

Introduction to Statistics and Research Methods

This core definition explains what a variable is in statistical terms. It's fundamental to understanding data collection and analysis, as all measurements and observations in a study involve variables that differ among participants or conditions.

“Descriptive statistics are statistical procedures used to summarize, organize, and simplify data.”

Introduction to Statistics and Research Methods

This quote distinguishes descriptive statistics as methods for making sense of raw data, such as calculating averages or creating graphs. It's the first step in data analysis, providing an overview before making broader inferences.

“Inferential statistics consist of techniques that allow us to study samples and then make generalizations about the populations from which they were selected.”

Introduction to Statistics and Research Methods

This defines inferential statistics, highlighting their purpose: to draw conclusions about a larger population based on data from a smaller sample. This process involves hypothesis testing and estimation, accounting for sampling error.

“The null hypothesis (H0) states that there is no change, no difference, or no relationship; in the general population, the independent variable has no effect on the dependent variable.”

Introduction to Hypothesis Testing

This defines the null hypothesis, a critical component of hypothesis testing. It represents the default assumption that any observed effect is due to chance, serving as a baseline against which the alternative hypothesis is tested.

“The alternative hypothesis (H1) states that there is a change, a difference, or a relationship; in the general population, the independent variable does have an effect on the dependent variable.”

Introduction to Hypothesis Testing

This defines the alternative hypothesis, which proposes that there is a significant effect or relationship in the population. It's the research hypothesis that a study aims to support if the evidence is strong enough to reject the null hypothesis.

“A Type I error occurs when a researcher rejects a null hypothesis that is actually true.”

Introduction to Hypothesis Testing

This crucial definition explains a Type I error, often called a 'false positive.' It means concluding there is an effect when there isn't one, which is controlled by the alpha level (level of significance) set by the researcher.

“A Type II error occurs when a researcher fails to reject a null hypothesis that is actually false.”

Introduction to Hypothesis Testing

This defines a Type II error, or a 'false negative.' It means failing to detect a real effect or difference. This error is related to statistical power, and researchers aim to minimize both Type I and Type II errors.

“The alpha level, or level of significance, is a probability value that is used to define the concept of 'very unlikely' outcomes.”

Introduction to Hypothesis Testing

This explains the alpha level, a threshold set by researchers (e.g., .05 or .01) to determine if a sample outcome is statistically significant. If the probability of obtaining the observed data under the null hypothesis is less than alpha, the null is rejected.

“Degrees of freedom (df) describe the number of scores in a sample that are independent and free to vary.”

The t-Test for One Sample

This definition of degrees of freedom is essential for understanding various statistical tests, particularly t-tests and ANOVA. It reflects the number of pieces of information available to estimate a parameter, influencing the shape of sampling distributions.

“Effect size is a measure of the magnitude of a treatment effect, independent of sample size.”

The t-Test for Two Independent Samples

This quote highlights the importance of effect size, which quantifies the practical significance of a finding, unlike p-values that only indicate statistical significance. It tells researchers how large or important an observed effect truly is.

“The Central Limit Theorem states that for any population with mean μ and standard deviation σ, the distribution of sample means for sample size n will have a mean of μ and a standard deviation of σ/n and will approach a normal distribution as n approaches infinity.”

Probability and Sampling for Sample Means

This fundamental theorem is crucial for inferential statistics. It explains why the normal distribution is so important for hypothesis testing, even when the population distribution is not normal, especially with larger sample sizes. It underpins the use of z-scores and t-scores for sample means.

Questions & Answers

What is the primary distinction between a parameter and a statistic?

The book emphasizes that a parameter is a value that describes a population, such as the population mean (μ) or standard deviation (σ). It is typically unknown and estimated. In contrast, a statistic is a value that describes a sample, such as the sample mean (M) or standard deviation (s). Statistics are calculated from observed data and are used to make inferences about unknown population parameters. This distinction is fundamental to understanding the goals of inferential statistics.

Why is variability a critical concept in statistics, according to Gravetter and Wallnau?

Variability is crucial because it measures the spread or dispersion of scores in a distribution. Gravetter and Wallnau explain that high variability makes it difficult to see clear patterns or effects, potentially obscuring a real treatment effect. Conversely, low variability allows for more precise and reliable conclusions. Understanding variability, often quantified by variance or standard deviation, is essential for interpreting descriptive statistics and for the accuracy of inferential tests, as it directly impacts standard error and test statistics.

What is the main purpose of hypothesis testing as presented in the book?

The main purpose of hypothesis testing, as described by Gravetter and Wallnau, is to use sample data to make decisions or draw conclusions about a population. It's a formal procedure to

determine whether a treatment or relationship observed in a sample is statistically significant enough to infer that it exists in the larger population, or if it's likely due to random chance. This involves setting up null and alternative hypotheses and evaluating the probability of the observed data under the null.

How do t-tests differ from z-tests in their application?

Gravetter and Wallnau explain that z-tests are used when the population standard deviation (σ) is known, which is rare in behavioral science research. T-tests, on the other hand, are used when the population standard deviation is unknown and must be estimated from the sample standard deviation (s). This estimation introduces more variability, leading to the use of the t-distribution, which is flatter and more spread out than the normal distribution, especially with smaller sample sizes, to account for the increased uncertainty.

What is the significance of the p-value in hypothesis testing?

The p-value, or probability value, is highly significant in hypothesis testing as it quantifies the probability of obtaining the observed sample data (or more extreme data) if the null hypothesis were true. Gravetter and Wallnau teach that if the p-value is less than or equal to the predetermined alpha level (e.g., .05), the result is considered statistically significant, leading to the rejection of the null hypothesis. A small p-value suggests that the observed effect is unlikely to be due to chance alone.

What is the role of the standard error of the mean?

The standard error of the mean (σM or sM) quantifies the average distance between a sample mean (M) and the population mean (μ). Gravetter and Wallnau explain that it measures how much variability is expected among sample means if multiple samples were drawn from the same population. A smaller standard error indicates that sample means are more clustered around the population mean, leading to more precise estimates and greater power in hypothesis tests.

When is an ANOVA (Analysis of Variance) used instead of multiple t-tests?

Gravetter and Wallnau explain that ANOVA is used when a researcher wants to compare means from three or more groups or conditions. Using multiple t-tests in such a scenario would inflate the Type I error rate (the probability of falsely rejecting a true null hypothesis) across the series of tests. ANOVA provides a single, omnibus test to determine if there are any significant differences among the group means, controlling the overall Type I error rate.

What does a correlation coefficient (r) tell us about the relationship between two variables?

A correlation coefficient (r) tells us two main things about the relationship between two variables: the direction and the strength. Gravetter and Wallnau describe that the sign (+ or -) indicates the direction (positive: variables change in the same direction; negative: variables change in opposite

directions). The magnitude (from 0 to 1) indicates the strength, with values closer to 1 (either positive or negative) representing a stronger, more consistent relationship. It does not imply causation.

What are the assumptions for using a Pearson correlation coefficient?

Gravetter and Wallnau outline several assumptions for the Pearson correlation. The data should consist of pairs of numerical scores (interval or ratio scale). The relationship between the variables should be linear. The scores should be obtained from random sampling. Additionally, for hypothesis testing, the sampling distribution of r is assumed to be normal, which often implies that the underlying population distributions of the variables are normal, especially for smaller sample sizes.

How does the concept of 'degrees of freedom' apply to different statistical tests?

Degrees of freedom (df) are crucial for determining the critical values and shape of sampling distributions (like t, F, or chi-square distributions) for various tests. Gravetter and Wallnau illustrate that df typically relate to the number of scores that are free to vary after certain parameters have been estimated. For example, in a one-sample t-test, df = n-1. In ANOVA, there are separate df for between-groups and within-groups variability, each reflecting the number of independent pieces of information used in their respective calculations.

What is the difference between statistical significance and practical significance (effect size)?

Gravetter and Wallnau emphasize that statistical significance (indicated by a p-value) tells us whether an observed effect is likely real and not due to chance. Practical significance, often measured by effect size (e.g., Cohen's d, r-squared), tells us about the magnitude or importance of that effect. A statistically significant result might have a very small effect size, meaning it's real but not practically meaningful. Conversely, a large effect size might not be statistically significant if the sample size is too small.

Why is random sampling important in research studies?

Random sampling is crucial because it helps ensure that the sample is representative of the population, thereby minimizing sampling bias. Gravetter and Wallnau explain that when every individual in the population has an equal chance of being selected, it increases the likelihood that the sample's characteristics will mirror those of the population. This allows researchers to generalize findings from the sample to the population with greater confidence and validity, which is a cornerstone of inferential statistics.

What is the purpose of a post hoc test in ANOVA?

Gravetter and Wallnau explain that when an ANOVA yields a significant F-ratio, it indicates that there is at least one significant difference among the group means, but it doesn't specify which specific groups differ. Post hoc tests (e.g., Tukey's HSD, Scheffé) are then used to conduct

follow-up comparisons between all possible pairs of group means. These tests are designed to control the overall Type I error rate across multiple comparisons, preventing an inflated chance of false positives.

How does the concept of 'power' relate to hypothesis testing?

Power, as described by Gravetter and Wallnau, is the probability of correctly rejecting a false null hypothesis. In simpler terms, it's the probability of detecting a real effect or difference if one truly exists in the population. Researchers aim for high power (typically .80 or higher) to minimize the risk of a Type II error (failing to detect a real effect). Power is influenced by factors like sample size, effect size, and the alpha level, and is often considered during research design.

What is the difference between an independent variable and a dependent variable?

Gravetter and Wallnau define the independent variable (IV) as the variable that is manipulated or controlled by the researcher, or that naturally differentiates groups (e.g., gender, treatment condition). The dependent variable (DV) is the variable that is measured or observed to assess the effect of the independent variable. The researcher hypothesizes that changes in the IV will cause changes in the DV. This distinction is fundamental to experimental and quasi-experimental research designs.

What is the role of the F-ratio in ANOVA?

The F-ratio in ANOVA is the test statistic used to determine if there are significant differences among two or more group means. Gravetter and Wallnau explain that it is calculated as the ratio of the variance between groups (treatment effect plus error) to the variance within groups (error only). A large F-ratio suggests that the differences between group means are substantially greater than what would be expected by chance, leading to the rejection of the null hypothesis.

How is the chi-square test used in behavioral sciences?

Gravetter and Wallnau describe the chi-square test as a non-parametric test used for categorical data. It's primarily used in two main ways: the chi-square test for goodness of fit, which assesses whether observed frequencies for a single categorical variable differ significantly from expected frequencies; and the chi-square test for independence, which examines whether there is a significant relationship or association between two categorical variables in a population.

What is the purpose of a confidence interval?

A confidence interval provides an estimated range of values that is likely to include an unknown population parameter (e.g., the population mean). Gravetter and Wallnau explain that it is constructed around a sample statistic (e.g., sample mean) and indicates the precision of the estimate. A 95% confidence interval, for example, means that if we were to take many samples and construct an interval for each, 95% of those intervals would contain the true population parameter.