German Journal of Veterinary Research

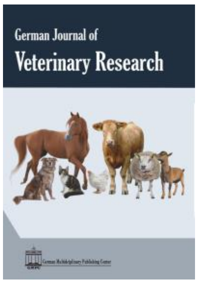
eISSN:2703-1322

Review article

Beyond the *p*-value: How descriptive statistics unlock insights in veterinary research?

Margarita Lušņičenko [1*], Alīna Zolova[2, 3], Jeļena Perevozčikova[1], Anna Gavrilova[4], Aleksandr Semjonov[5], Maksims Zolovs[1,6*]

[1] Statistics Unit, Riga Stradins University, Riga, Latvia
[2] Department of Rehabilitation, Riga Stradins University, Riga, Latvia
[3] Institute of Food and Environmental Hygiene, Latvia University of Life Sciences and Technologies, Jelgava, Latvia
[4] Department of Pharmaceutical Chemistry, Riga Stradins University, Riga, Latvia
[5] Institute of Veterinary Medicine and Animal Sciences, Estonian University of Life Sciences, Estonia
[6] Institute of Life Sciences and Technologies, Daugavpils University, Daugavpils, Latvia



Abstract

Veterinary research relies heavily on data analysis to understand animal health and disease. While inferential statistics are crucial for concluding, descriptive statistics form the foundation for effective data exploration and interpretation. This review delves into the importance of descriptive statistics in veterinary science. It outlines the key objectives of descriptive analysis and provides multiple examples of its application. The application of common measures like frequency distributions, central tendency, data spread, and visualization in veterinary contexts is explored. The review emphasizes the role of descriptive statistics in establishing a strong foundation for further statistical analysis of veterinary data.

Keywords: Data exploration, Animal Science, Effective data analysis, Veterinary data

Article History:
Received: 16 July 2024
Accepted: 21 Aug 2024

***Corresponding author:**
Maksims Zolovs
maksims.zolovs@rsu.lv

Citation: Lušņičenko, M., Zolova, A., Perevozčikova, J., Gavrilova, A., Semjonov, A., Zolovs, M. 2024. Beyond the *p*-value: How descriptive statistics unlock insights in veterinary research. Ger. J. Vet. Res. 4 (3): 140-150. https://doi.org/10.51585/gjvr.2024.3.0105

Introduction

Like in many other fields, descriptive statistics are often overshadowed by inferential statistical techniques in veterinary science. This article argues that a strong foundation in understanding and interpreting descriptive statistics is crucial for veterinarians and animal scientists to make sense of the vast amount of data collected in modern research.

Veterinary data can vary, for example, from the body weight measurements of a herd of cattle to the analysis of white blood cell counts of a dog with an infection. Without understanding descriptive statistics, this data is just a collection of numbers without the valuable insights it provides. Consider a scenario where we want to test a new deworming medication on a group of puppies. If we only report the number of parasites in each puppy, it wouldn't provide a complete understanding. By calculating the average parasite count, we establish a central point of reference. The standard deviation then helps us understand how much each puppy's parasite count differs on average from this central point, thereby allowing us to evaluate the overall effectiveness of the medication. Misinterpreting these values, for example, by assuming a normal distribution when the parasite counts are heavily skewed towards high numbers, could trigger misleading conclusions about the drug's efficacy.

This article explores the limitations of a superficial understanding of descriptive statistics in veterinary science. We highlight the importance of i) exploring the underlying assumptions behind each statistical measure, ii) showcasing real-world applications of descriptive statistics in veterinary research, and iii) demonstrating connections between descriptive statistics and more advanced statistical methods used in veterinary studies. All in the hope of reintroducing the whole scope of descriptive statistics and facilitating a diverse but mindful use of it in veterinary research.

We will demonstrate how descriptive statistics are universally applicable across various veterinary disciplines. They play a crucial role in understanding growth patterns and analyzing the prevalence of disease (Dong, 2023). Finally, we will present important measures clearly and concisely. We will prioritize conceptual understanding for veterinary professionals at all levels, including students, researchers, and educators, aiming to enhance their data analysis teaching skills.

Frequency and the measure of skewness and kurtosis

Frequency analysis is a fundamental step in exploring veterinary data. It simply counts how often each data value appears in the dataset. It's a quick and easy way to organize and understand the data. The results are typically presented in a frequency table and visualized with charts. For example, a bar chart or pie chart visualizes frequencies of nominal and ordinal variables, whereas a histogram is a highly informative chart of a continuous variable. A visual inspection of the histogram may provide information about the shape of data distribution, the mean value, data variation, and the presence/absence of outliers (Peck et al., 2016; Mendenhall et al., 2020). For frequency visualization, one can use a whole variety of chart formats: distribution polygon, dots plot, stem-and-leaf plot, bubble chart, multi-set bar chart, pictogram chart, violin plot, etc.

While a histogram (or any other chart) visually describes frequency data, the measure of skewness and kurtosis do the same, but only in numerical format. Skewness is a measure of symmetry in the data distribution. A positive skewness index shows that the right-hand tail of the histogram is longer than the left-hand tail, while a negative index indicates the opposite situation. The positive and negative values of skewness may be interpreted as previously described by Doane and Seward, 2011 in the following way: i) A perfectly symmetrical data set will have a skewness of 0; ii) If the skewness ranges from 0.01 to 0.50, the data are fairly symmetrical; iii) If the skewness ranges from 0.51 to 1.00, the data are moderately skewed; and iv) If the skewness is larger than 1.00, the data are highly skewed. For example, red blood cells (RBCs) are essential for transporting oxygen throughout the body. In healthy dogs, the RBC count falls within a specific range. However, certain diseases or conditions can cause a decrease in RBCs, which would negatively skew the data. For example, a smaller number of dogs will have significantly lower RBC counts, indicating potential anemia or other health problems. These low values will form the tail extending towards the left (negative side) of the distribution.

For example, understanding skewness can help calculate the dosage of medication required for treatment. Most pets will need a standard dose, but a few will require adjustments due to size or underlying conditions. These adjustments would typically be for higher doses, skewing the data positive.

Kurtosis

Kurtosis is a statistical measure to describe the “tail-heaviness” or the “tailedness” of data distribution (DeCarlo, 1997). A high kurtosis value indicates a sharp peak, fatter tails, and potential outliers, while a low kurtosis value indicates a rounded peak and thinner tails. For example:

Leptokurtic (high kurtosis)

The birthweight of puppies in a large litter may have an average weight at the center, but there could be a few very large puppies and a few runts, leading to a sharper peak around the average but with outliers on either side.

Mesokurtic (normal kurtosis)

The body temperature of healthy cats usually falls within a narrow range. It would likely follow a normal distribution, with most cats having temperatures close to the average and a few outliers with slightly higher or lower temperatures.

Platykurtic (low kurtosis)

The length of gestation for a specific breed of horse is usually quite predictable. Most pregnancies fall within a narrow timeframe, and there are minimal outliers on either side, resulting in a relatively flat distribution of the data.

Both skewness and kurtosis can be used to assess the normality of a data set. However, there is no consensus on the threshold values for a normal distribution. West et al. (1995) suggested a reference of significant departure from normality as an absolute excess kurtosis >4. Also, a normal distribution is not the only symmetrical distribution (Jupp et al., 2016). Moreover, statistics depend on the sample size. For a small sample size, it is not recommended to inspect measures of skewness and kurtosis (Cox, 2010). Therefore, skewness and kurtosis are not the sole tools for evaluating data normality. However, they can be valuable alongside other tests and visual inspection of the data.

Measures of central tendency

Veterinary science heavily relies on data analysis to understand animal health and develop treatment plans. Just as in any other field, measures of central tendency are crucial for summarizing and interpreting this data. In this discussion, we will explore the three main measures, "mean, median, and mode," and focus on their applications and limitations in veterinary settings.

Mean

The mean, also known as the average, is a commonly used measure. It is calculated by adding all the data points of the variable and then dividing by the total number of data points. Veterinarians often use the mean for various purposes: i) Body weight and growth rates: The average weight of a particular breed at different ages helps assess healthy growth patterns. ii) Blood test results: Mean values for red blood cell counts or white blood cell counts establish reference ranges for different species. iii) Drug dosages: Average body weight serves as a basis for calculating appropriate medication dosages for various animals. iv) However, the mean can be skewed by outliers (Lane, 2013). For instance, a single dog with a much higher than average white blood cell count due to an infection can inflate the mean for the entire group.

Median

The median is the middle value when data is arranged from lowest to highest (Lane, 2013). It offers a more robust alternative to the mean when outliers are present. Here are some veterinary examples: i) Parasite burdens: The median number of fleas or ticks found on pets in a particular area gives a more realistic picture of infestation levels compared to the mean, which heavily infested animals might inflate. ii) Length of hospitalization: The median duration of hospitalization after a specific surgery provides a better idea of typical recovery times than the mean, which a few animals with extended stays could influence.

Mode

The mode is a statistical measure that shows the most frequent value or values in a dataset. Even though it is not used as frequently as the mean and median, it has specific applications in veterinary science: i) Vaccinations: The mode can help identify the most commonly administered vaccinations in a clinic, which is useful for managing inventory. ii) Antibiotic resistance patterns: Identifying the most frequently occurring antibiotic-resistant bacterial strains in a particular region can help guide treatment decisions. However, the mode has its limitations. For example, there can be multiple modes (bimodal or multimodal data) if several values share the same frequency. Additionally, the mode does not consider the entire dataset and can be misleading if the most frequent value is an outlier (Cooksey, 2020). Choosing the most appropriate measure of central tendency depends on the specific data and the question you are trying to answer. Understanding the strengths and weaknesses of each measure allows veterinarians to interpret data and make informed decisions regarding animal health accurately (Peck et al., 2016; Mendenhall et al., 2020).

Measurement scales and measures of central tendency

The choice of the most appropriate measure of central tendency depends on the type of data you are analyzing (Table 1).

Continuous measurements scale

The first step in analyzing continuous data is to visualize its distribution. While histograms are great for showing the overall distribution of data, boxplots offer a different perspective. They can be particularly useful for highlighting key features (Peck et al., 2016; Mendenhall et al., 2020); for example, it provides a quick overview of the following aspects: i) ***Center***. The box represents the middle half of the data, with the line in the middle indicating the median (the value that separates the higher half from the lower half); ii) ***Spread.*** The whiskers extend from the box and show the range of most data points;

Outliers. Points outside the whiskers are considered outliers, potentially indicating unusual values; iii) ***Symmetry.*** The overall shape of the box and whiskers helps assess normality. An asymmetrical boxplot suggests a symmetric distribution (including normal) where the data points are clustered around the center.

Only continuous data should be tested for normal data distribution. Normality refers to how closely the data resembles a bell-shaped curve (normal distribution). While boxplots are valuable visualization tools, it is important to acknowledge their limitations. They can be misleading for small datasets or data with many outliers. Additionally, boxplots do not capture the entire data distribution. Complementary visualizations like histograms or density plots can provide a more detailed picture.

The normality of data can influence the choice of appropriate statistical tests. If the data is normally distributed, the arithmetic mean (average) is a good measure of the center. However, if the data is not normal, the median is a more robust measure. While the mode (most frequent value) can be informative, it does not necessarily represent the center of the data (Peck et al., 2016; Mendenhall et al., 2020).

The calculation of mode for continuous data is possible; however, it needs to make more sense. The probability of a specific value to occur more than one time is close to 0. Therefore, in the case of continuous scale data, a mode is used rarely, mostly to identify unusual data points of a discrete (countable) variable. For example, a distribution that has two modes indicates that the sample harbors data from two populations, as the difference in populations gets highlighted by these modes.

Table 1. Choosing descriptive statistics by measurement scale (Peck et al., 2016; Mendenhall et al., 2020).

	Nominal	**Ordinal**	**Continuous**
Frequency	X	X	X
Percentage	X	X	X
Percentiles	X	X	X
Quartiles		X	X
Mode	X	X	X
Median		X	X
Mean			X
Standard deviation			X
Interquartile range		X	X
Variance			X
Variation ratio	X		
Range			X
Standard error			X
Confidence interval			X
Skewness			X
Kurtosis			X

Ordinal scale

If a variable belongs to ordinal data, the best choice for determining its central tendency would be the median. The arithmetic mean would not be appropriate for ordinal data because it is a type of categorical data that is usually assigned numbers (as levels) to indicate the order of the list; however, these numbers are not mathematically determined. Additionally, the intervals between units on the ordered scale may not necessarily be of equal size. Mode is also appropriate for the analysis of ordinal data but is not as commonly used as the median because it carries less information about the distribution than the median (Peck et al., 2016; Mendenhall et al., 2020).

Nominal scale

When working with nominal data (categorical data with no intrinsic order), the most frequent category, or the mode, is the only appropriate summary statistic. The arithmetic mean cannot be calculated because it is not appropriate for categorical data. Also, the median cannot be calculated because categories of nominal variables do not have an ordered nature.

Percentage, percentiles and quartiles

Understanding how data is distributed is crucial in veterinary science. Percentiles and quartiles offer valuable tools for analyzing this distribution.

Percentiles divide data into 100 equal parts, indicating the position of a specific value within the dataset. For example, for a blood test, a red blood cell count at the 80th percentile means it is higher than 80% of other values in the ordered dataset (Peck et al., 2016; Mendenhall et al., 2020).

Percentages express a value as a proportion of 100, and they are often used for success rates or proportions. For example, an 80% success rate for a treatment indicates that 80 out of 100 animals responded positively. Percentiles help compare an individual value to the rest of the data, while percentages express a proportion of the whole.

Quartiles are a specific type of percentile, dividing data into four equal parts (each representing 25% of the data): Q1 (first quartile)=25th percentile, Q2 (second quartile)=50th percentile (median), Q3 (third quartile)=75th percentile.

Boxplots utilize quartiles to depict the spread and symmetry of data. For example, a boxplot of body temperature in a group of dogs might show the median (Q2) as the average temperature, with Q1 and Q3 representing the lower and upper limits of the normal range. Values outside these quartiles (below Q1 or above Q3) could indicate potential health issues.

By interpreting percentiles and quartiles, veterinarians can gain valuable insights into how data is distributed and identify potential abnormalities in animal health parameters.

The measure of the spread of data values

In veterinary science, analyzing data goes beyond finding the "average." Understanding how data points are distributed, or their variability is crucial for interpreting results. Here, we will explore some key measures of spread, along with their strengths and limitations, and see how they can be applied in veterinary settings.

Measures of central tendency (mean, median, mode) provide a single value summarizing the data. However, this single value does not tell the whole story. Spread measures show how much data points deviate from the central value, indicating how well the central tendency measure represents the entire dataset (Peck et al., 2016; Mendenhall et al., 2020).

Common measures of spread

Range

The range is the simplest measure that shows the difference between the highest and lowest values. It is useful for continuous data because it helps to identify potential data entry errors and assess the overall spread (Peck et al., 2016; Mendenhall et al., 2020). For example, a veterinarian might calculate the range of red blood cell counts in a group of cats. A large range could suggest a nutritional deficiency or other health issues in some cats. Some properties of the range are: i) It is measured in the same units as the data. ii) It is used with the mean. iii) It is sensitive to outliers and can be misleading.

Standard deviation (SD)

This reflects the average distance of each data point from the mean. A larger SD indicates greater variability (data points further from the mean). Useful for continuous data with normal distribution to assess how tightly data points cluster around the mean (Peck et al., 2016; Mendenhall et al., 2020). For example, a researcher might evaluate the SD of body weights in a litter of puppies to understand growth consistency within the litter. Properties of SD are i) Measured in the same units as the data. ii) Used with the mean. iii) Sensitive to outliers. iv) Requires normal data distribution for accurate interpretation.

Interquartile range (IQR)

This represents the spread of the middle 50% of the data, focusing on the "typical" range of values. Ideal for non-normal data or data with outliers, which is common in life science studies. It can be used for both continuous and ordinal data (Peck et al., 2016; Mendenhall et al., 2020). For example, a study might assess the duration of hospitalization after spaying in dogs. The IQR would provide a better idea of the typical recovery time for most dogs compared to the range, which a few animals with extended stays could skew. Properties of IQR are i) Measured in the same units as the data. ii) Used with the median. iii) Less affected by outliers than the range and standard deviation.

Variation ratio.

This is the simplest measure of spread for nominal data (categorical data with no inherent order). It expresses the proportion of cases that fall outside the most frequent category (mode) (Kader and Perry, 2007; Zedeck, 2014). Useful for understanding the diversity of categories in nominal data relevant to veterinary medicine, such as coat color distribution in a dog breed. For example, a shelter might calculate the variation ratio of dog breeds admitted in a month. A high ratio indicates a diverse range of breeds, while a low ratio suggests the dominance of a particular breed. Properties of variation ratio are i) Measured as a percentage. ii) Used with the mode. iii) Not applicable to other data scales.

Choosing the right measure

The most appropriate measure of spread depends on the type of data (continuous, ordinal, or nominal) and the characteristics of your dataset (normal distribution, presence of outliers) (Table 2). By understanding these measures, veterinarians can gain a more complete picture of their data and draw more informed conclusions about animal health. For instance, a veterinarian might use the SD of white blood cell counts to assess potential infections in a dog, while the IQR of fecal egg counts might be more informative for a group of horses to identify parasite burdens.

Table 2. Central tendency, spread, and assumptions for different measurement scales.

Central tendency	Measurement scale	Assumptions	Paired with a measure of the data spread
Mean	Continuous	Normally distributed data No outliers	Standard deviation or coefficient of variation
Median	Continuous Ordinal	-	Interquartile range (IQR by presenting Q1 and Q3)
Mode	Discrete Ordinal Nominal	-	Variation ratio

Note: Q1 – the first quartile and Q3 – the third quartile

Standard error and confidence interval

When conducting a study, it's common to work with a sample because data from the entire population are often not available for various reasons. As a result, it's not possible to know the true mean of a variable in the entire population, but it is possible to calculate an interval that includes the true mean of the population. Mean ± one standard error (SE) creates an interval that will include the true mean of the population with a probability of ~ 68%. However, it is a better practice to report the standard error as a 95% confidence interval (±1.96 standard errors) because it gives a meaningful interval where the true population mean lies (Peck et al., 2016; Mendenhall et al., 2020). It is the main reason why a 95% confidence interval (CI) is reported in scientific articles more often than standard error. Imagine you want to know the average lifespan of a specific dog breed. You cannot examine every single dog, so you take a sample of, say, 50 dogs and track how long they live. This sample gives you an estimate of the average lifespan, but it might not be perfect.

The standard error tells you how much your estimate might be off. It is like the margin of error around your guess. A smaller SE means your sample estimate is likely very close to the real average lifespan for that breed. The standard error tells you how much your estimate might be off. It is like the margin of error around your guess. A smaller SE means your sample estimate is likely very close to the real average lifespan for that breed across all dogs. A larger SE means your estimate could be further from the real average.

Think of it like throwing darts at a target. The bullseye is the real average lifespan, and your throws (sample estimates) will hopefully land close. The tighter your throws are grouped (smaller SE), the more confident you are that you're near the bullseye. Conversely, scattered throws (larger SE) mean you are less sure how far off you might be.

Confidence interval builds on this idea and tells you a range where the real population's average lifespan is likely to fall. It is like saying, "I am 95% confident the true average lifespan is between X and Y years."

For example, your sample of 50 dogs suggests an average lifespan of 12 years. The SE is 1 year. This means the real average (with a probability of ~68%) could be between 11 and 13 years (12 years +/- 1 year). With a 95% confidence interval, the range might be 10 to 14 years (you are 95% sure the real average falls within this broader range).

Data visualization

Data visualization is an integral part of descriptive statistics that offers a substantial amount of information about the data. This method of data mining should not be ignored or overlooked to quickly move to more complex and advanced methods of data processing. Even the use of all measures of descriptive statistics may not give the picture that the charts offer. Many data analyses start with the visualization of the raw data and end with the visualization of the results of statistical tests. Visualization is also used to test assumptions of statistical tests (Table 3).

The role of descriptive statistics alongside statistical tests

Descriptive statistics plays a crucial role not only in exploratory data analysis but also in interpreting the results of statistical tests. While statistical tests tell you whether an observed effect is likely due to chance or not, they do not tell you the magnitude of that effect. This is where descriptive statistics comes in (Peck et al., 2016; Mendenhall et al., 2020).

Let us say you perform an independent t-test to compare the average body weight between two groups (e.g., male vs female). The resulting *p*-value tells you if the observed difference in body weight is statistically significant (unlikely due to chance). However, the *p*-value does not tell you how much higher or lower the average body weight is for one group compared to the other.

This task calls for descriptive statistics. Together with the *p*-value, the mean body weight for each group should be reported, allowing readers to see the actual size of the difference.

Additionally, measures of spread, like the standard deviation, can be included to understand how much body weight varies within each group. This provides a much richer picture than just the *p*-value alone. This principle applies to various statistical tests. Here are some additional examples: i) Correlation analysis. Reporting the correlation coefficient (e.g., Pearson's r) reveals the strength and direction of the relationship between two variables; however, presenting the means and standard deviations of both variables provides a clearer understanding of the data distribution. ii) Regression analysis. In addition to the regression equation, including the R-squared value helps to understand how well the model explains the variability in the dependent variable. Descriptive statistics of the independent and dependent variables also assist in interpretation. By presenting both descriptive statistics and the results of statistical tests, you can provide a more comprehensive and informative picture of your data and analysis (Table 4).

Why is data visualization key?

Humans are highly visual beings. In the early days of our species, we preferred visual stimuli over all other types of information. We rely heavily on these, and our dependence on them has increased throughout evolution (Nilsson, 2013). Hence, our brains have evolved to absorb, manipulate, and respond to visual information more and more efficiently.

The human brain processes visual patterns faster than text or numerical data, making images an ideal way to communicate complex ideas. This ability comes from evolutionary adaptations that were necessary for survival in changing environments. As a result, we use built-in cognitive processes that aid quick perception, on which, for example, Gestalt psychology is based (Kubovy et al., 2003). Visuals can convey multiple layers of information, providing a deeper understanding. By leveraging shape, color, shadowing, and spatial orientation, visualizations present large amounts of data in a concise format, enabling us to perceive connections more effectively through our powerful cognitive abilities (Lan et al., 2023).

Visualizations can be a universal tool for surpassing language barriers and cultural and knowledge level differences, making information accessible to different audiences (Nida, 2018). Whether presenting research findings to colleagues or educating the public about proper animal care, visualizations are effective in communication (Brodbeck et al., 2009; Auber et al., 2024).

A culture of evidence-based science calls for the immense volume of information we witness today (Franconeri et al., 2021). The field of veterinary medicine relies on a wide range of important datasets, including animal physiology and pathology data, pharmaceutical statistics, and clinical care information. These datasets are essential for evaluating medical methods and driving innovation in the industry. Without ongoing research, veterinary medicine would stagnate.

Table 3. Common visualizations for assessing assumptions for statistical tests.

Assumption	Visualizations	Statistical tests
Normal data distribution	histogram, normal Q–Q plot,	Independent samples T-test, Welch test, Dependent samples T-test, One sample T-test, ANOVAs, Pearson's correlation, Linear regressions, Pearson's partial correlation, Point-biserial correlation,
The distribution of cases for groups of the independent variable has a similar shape	histogram, boxplot	Friedman test, Kruskal - Wallis H test Mann-Whitney U test, Rank-biserial correlation
The distribution of the differences between the two related groups is symmetrical in shape	histogram, boxplot	Wilcoxon signed-rank test
A linear relationship between variables	scatterplots	Linear regressions, Pearson's correlation Pearson's partial correlation
At least a monotonic relationship between variables	scatterplots	Spearman's correlation
Outliers	histogram, boxplot	Independent samples T-test, Welch test Dependent samples T-test, One sample T-test, ANOVAs, Pearson's correlation Linear regressions, Pearson's partial correlation, Point-biserial correlation

In addition to medical data, information about veterinarians themselves, including occupational diseases and burnout, as well as the business and economics of the industry, are crucial for the current vitality of veterinary science. This data, when used effectively, can provide valuable insights, guide priorities, and help solve problems. Data visualization also plays a key role in distilling complex data into easily understandable images (Sharma and Kandel, 2023; Sukhdeve and Sukhdeve, 2023; Kharakhash, 2023).
The objective is to present information in a way that is easy to understand, and design is crucial for achieving this goal. Design not only makes data more appealing but also serves as a strategic tool for conveying details and telling a story. By adjusting the structure of graphs, their placement on the page, descriptions, color schemes, fonts, and the potential for viewer interaction, one can direct the audience's focus (Schwabish, 2021).

Design principles for effective data visualization

Effective visualization design goes beyond just showing data. It involves a thoughtful synthesis of communication principles and aesthetics to achieve a comprehensive result (Midway, 2020). A good visualization saves time, has a clear purpose, includes only relevant information, and encodes it appropriately (Munzner, 2014). It's not easy to tick off all these. Sometimes, researchers do lack the technical skills or design basis to come up with good visual material. Research from 1984 found that approximately 30% of graphs in the journal "Science" had a minimum of one error (Cleveland, 1984).

Thirty years later, Gordon and Finch evaluated visuals used in best-rated journals in statistics and applied science (Gordon and Finch, 2014). Nearly 40% of the 97 graphs sampled were rated as poor. We invite you to learn from the mistakes of others and further explore the best practices of design in data visualization. The designer (researcher in need of visual design) should first understand the essence of the task, including its conceptual and, in a way, spiritual aspects. Failing to grasp the internal logic of a task can make it much easier to fail (Qayyum and Smith, 2019). When the idea of the message to convey is clear, proceed. The embodiment of this idea will be the image to create. Further, the core values that guide a researcher when visualizing data are: i) ***Context***. Who is the target audience? How much time do they have to view the image?

Considering the needs, preferences, and expectations of the target audience helps the message come across smoothly. ii) ***Consistency***. Using consistent color schemes, fonts, and other graphical conventions makes it easier to navigate complex information. iii) ***Simplicity***. Striving for simplicity ensures there is no double meaning in the data visual. The intended message must be deciphered in the same way by different people. Simplicity in design does not mean simplicity in data, though, and it takes effort to choose minimal yet enough information to present. Remember, "clutter and confusion are failures of design, not attributes of information" (Tufte, 1990). iv) ***Scaling***. When analyzing data, it is crucial to establish a benchmark. Visualizations are effective tools if they help us compare our data to a relevant reference point. (Tufte, 2006).

In order to accurately estimate quantities from a graph, the reader needs to grasp the scale used. Therefore, whenever feasible, opt for simpler solutions. Use a single linear scale and incorporate light gridlines to aid in precise estimation without burdening the image. Additionally, refrain from using pie charts with more than five slices, 3D pie charts, doughnut charts, and stacked bar charts. Consider transposing an image to enhance its clarity and ease of understanding). v) ***Interactivity***. Using interactive elements, such as filters and dynamic visualizations, engages the user. An image that flows is many images together. That is an advantage; much more information can be conveyed. However, one should pay double attention to keeping the graph simple (Bredbenner, 2021). vi) ***Inclusivity***. Design must be practical, i.e., accessible. Alternative text should be provided for images for people with visual impairments or disabilities, and sufficient color contrast should be ensured. If a visual is colorful and dynamic, the designer should make sure it is not dynamic enough to cause seizures in prone people.

Table 4. Descriptive statistics are reported along with the results of statistical tests (Peck et al., 2016; Mendenhall et al., 2020).

Descriptive statistics	Statistical tests	Example
Mean, SD, 95% CI	Independent samples T-test, Welch test, Dependent samples T-test, One sample T-test, ANOVAs, and other parametric tests	The study found a significant difference in body weight between cats fed a grain-inclusive diet (mean=5.2 kg, SD=0.8 kg) and those fed a grain-free diet (mean=4.8 kg, SD=0.7 kg). Cats on the grain-inclusive diet weighed an average of 0.4 kg more (95% CI: 0.1 kg – 0.7 kg). This difference was statistically significant (t(80)=2.56, p=0.012, d=0.54).
Median, IQR (as Q1 and Q3)	Friedman test, Kruskal - Wallis H test, Mann-Whitney U test, Wilcoxon signed-rank test and other non-parametric tests	The Kruskal-Wallis H test revealed a significant difference in fecal egg counts between the three deworming groups (H(2)=10.24, p=0.006). Post-hoc Dunn's test with Bonferroni correction for multiple comparisons identified the following significant differences: horses dewormed monthly (median=50 eggs per gram, IQR 20-100) had significantly lower fecal egg counts compared to those dewormed biannually (median=200 eggs per gram, IQR 150-300) (adjusted p=0.014). No significant difference was found between horses dewormed quarterly (median =100 eggs per gram, IQR 50-150) and the other two groups (adjusted p> 0.05).
Frequency, Percentage	Chi-square test	A chi-square test revealed a statistically significant association between spaying and overweight status (x^2 (1)=10.24, p=0.001). Spayed Cats (n=75): Overweight - 42% (n=31), Normal Weight - 58% (n=44). Intact Cats (n=25): Overweight - 20% (n=5), Normal Weight - 80% (n=20). A significantly higher proportion of spayed cats (42%) were overweight compared to intact cats (20%). This suggests spaying may be a risk factor for weight gain in cats, although further research is needed to explore the underlying mechanisms.
Mean, SD	Point-biserial correlation	Point-biserial correlation analysis revealed a statistically significant moderate correlation (r_{pb}=0.487, p=0.002) between hoof condition and lameness scores. Horses with good hoof condition (mean score=2.5, SD=0.8) had significantly lower lameness scores compared to those with poor hoof condition (mean score = 4.2, SD=1.1).
Median, IQR (as Q1 and Q3)	Rank-biserial correlation	Rank-biserial correlation analysis revealed a statistically significant negative association (rho=-0.412, p=0.014) between a history of abuse and trainability scores. Dogs with a documented history of abuse received lower trainability scores (median score=2; IQR 1.5 - 3) compared to those without such a history (median score =4; IQR 3.5 - 4.5).
Percentage, 95% CI of estimate or odds ratio (OR)	Any regression analysis	The binomial logistic regression model revealed a statistically significant association between deworming practices and fecal egg counts (FEC) results (x^2(2)=42.1, p< 0.001). Quarterly deworming (B=-1.234, z=-3.87, p<0.001, OR=0.29): Compared to sheep never dewormed, those dewormed quarterly had a significantly lower chance of having high FEC (OR=0.29). This translates to a 71% decrease in the odds of high parasite burden with quarterly deworming (95% CI of OR: 0.18 – 0.49). Biannual deworming (B=-1.842, z=-4.51, p<0.001, OR=0.16): Sheep dewormed biannually had an even lower chance of high FEC compared to the never dewormed group (OR=0.16). This indicates an 84% decrease in the odds of high parasite burden with biannual deworming (95% CI of OR: 0.09 – 0.28).

Obviously, one should be mindful of how genders, races, and other information are presented (Nind, 2016; Correll, 2019).

Aligning with the core values listed above assures that a researcher gets their message across flawlessly. On this foundation, any amount of complex research can be transformed into useful and exciting images and infographics. As the types of charts were described above, choosing the right one should not be an issue. The next step towards visualization would be to approach all details an image needs in alignment with these core values.

The anatomy of the graph, meaning size and layout, must be intuitive. While showcasing many categories of data, less saturated colors ensure mindful usage of the viewers' attention. Usually, when one shows the facts, they use black, prospects – blue. When one shows favorable tendencies, they use green, less so – red. Human instincts can and should be used as a guideline to what associations need attention drawn to. As annoying as advertisements can get, inspecting them can reveal shortcuts to planting an idea one wishes to plant inside other peoples' heads (Lan, et al., 2023).

Conclusion

Descriptive statistics offer a wide range of possibilities, but they are fundamentally a rigorous discipline. They are rooted in exacting rules, precise language, and careful application, allowing us to uncover the stories hidden within numbers. In the age of complex big data, descriptive statistics have become powerful tools for scientists due to their ability to represent underlying information accurately.

Article Information

Funding. This research received no external funding.

Conflicts of Interest. The authors declare no conflict of interest.

Authors contribution. All authors contributed equally to the work.

Publisher's Note. The claims and data contained in this manuscript are solely those of the author(s) and do not represent those of the GMPC publisher, editors, or reviewers. GMPC publisher and the editors disclaim the responsibility for any injury to people or property resulting from the contents of this article.

References

Auber, D., Bikakis N., Chrysanthis P., Papastefanatos, G., Sharaf, M. 2024. Interactive big data visualization and analytics. Big Data Research 36. https://doi.org/10.1016/j.bdr.2024.100445

Bredbenner K. 2021. Visualize your data with simplicity, accuracy, and beauty. The Biochemist. 43. https://doi.org/10.1042/bio_2021_170

Brodbeck, D., Mazza, R., Lalanne, D. 2009. Human-machine interaction: Interactive visualization - A survey. Springer Berlin, Heidelberg. 27 pp. https://doi.org/10.1007/978-3-642-00437-7_2

Cleveland, W. S. 1984. Graphs in scientific publications. The American Statistician 38(4): 261–269. https://doi.org/10.1080/00031305.1984.10483223

Correll M. 2019. Ethical Dimensions of Visualization Research. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19). Association for Computing Machinery, New York, NY, USA, Paper 188, 1–13. https://doi.org/10.1145/3290605.3300418

Cooksey, R. W. 2020. Descriptive statistics for summarizing data. Illustrating statistical procedures: Finding Meaning in Quantitative Data, 61–139. https://doi.org/10.1007/978-981-15-2537-7_5

Cox, J. N. 2010. Speaking Stata: The limits of sample skewness and kurtosis, The Stata Journal Number 3, pp. 482–495. https://doi.org/10.1177/1536867X100100031

DeCarlo, L.T. 1997. On the meaning and use of kurtosis. Psychological Methods, American Psychological Association, 2, 292-307. http://dx.doi.org/10.1037/1082-989X.2.3.292

Doane, D. P., Seward, L. E. 2011. Measuring skewness: A forgotten statistic? Journal of Statistics Education, 19(2). https://doi.org/10.1080/10691898.2011.11889611

Dong, Y. 2023. Descriptive statistics and its applications. Highlights in Science, Engineering, and Technology. 47. 16-23. https://doi.org/10.54097/hset.v47i.8159

Franconeri, S. L., Padilla, L. M., Shah, P., Zacks, J. M., Hullman J.2021. The science of visual data communication: What works. Psychological Science in the Public Interest 22(3): 110–161. https://doi.org/10.1177/15291006211051956

Gordon, I., Finch S. 2014. Statistician heal thyself: have we lost the plot? Journal of Computational and Graphical Statistics 24(4): 1210-1229. https://doi.org/10.1080/10618600.2014.989324

Jupp, P.E., Regoli G., Azzalini A. 2016. A general setting for symmetric distributions and their relationship to general distributions, Journal of Multivariate Analysis, Volume 148, Pages 107-119, ISSN 0047-259X. https://doi.org/10.1016/j.jmva.2016.02.011

Kader, G. D., and Perry, M. 2007. Variability for categorical variables. Journal of Statistics Education, 15(2), 1–17. https://doi.org/10.1080/10691898.2007.11889465

Kharakhash, O. 2023. Data visualization: transforming complex data into actionable insights. Automation of technological and business processes 15: 4-12. https://doi.org/10.47941/jts.1911

Kubovy, M., Epstein W., Gepstein S. 2003. Handbook of Psychology: Volume 3, Behavioral Neuroscience. Wiley. 85 pp. ISBN: 978-0-470-89059-2

Lan X., Wu Y., Cao N. 2023. Affective Visualization Design: Leveraging the emotional impact of data. IEEE Transactions on Visualization and Computer Graphics 30: 1 – 11. https://doi.org/10.48550/arXiv.2308.02831

Lane, D. M. 2013. Introduction to statistics: An interactive eBook. Rice University. https://books.apple.com/us/book/introduction-to-statistics-an-interactive-e-book/id684001500

Mendenhall W., Beaver R., Beaver B. 2020. Introduction to Probability and Statistics, 15th Edition (Metric Version). Cengage Learning. ISBN: 9780357114469

Midway, S. R. 2020. Principles of effective data visualization. Patterns 1(9): 100141. https://doi.org/10.1016/j.patter.2020.100141

Munzner, T. 2014. Visualization analysis and design (1st ed.). A K Peters/CRC Press, New York. https://doi.org/10.1201/b17511

Nida, I. 2018. Art of visual communication, evolution, and its impact. Indian Journal of Public Health Research & Development 9: 1725–1728. https://doi.org/10.5958/0976-5506.2018.02238.6

Nilsson, D.E. 2013. Eye evolution and its functional basis. Visual Neuroscience 30(1-2): 5–20. https://doi.org/10.1017/S0952523813000035

Nind M. 2016. The practical wisdom of inclusive research. Qualitative Research. 17. https://doi.org/10.1177/1468794117708123

Peck R., Olsen C., Devore J.L., 2016. Introduction to Statistics and Data Analysis, 5th edition. Cengage Learning. ISBN: 978-1-305-11534-7

Qayyum, A., Smith D. 2019. Improving the task understanding for knowledge creation in assessments. Journal of Information and Knowledge Management: 18(04). https://doi.org/10.1142/S0219649219500412

Schwabish, J. 2021. Better data visualizations : A guide for scholars, researchers, and wonks. New York: Columbia University Press. ISBN 9780231550154

Sharma, S., Kandel A. 2023. Data visualization and its impact on decision-making in business. https://doi.org/10.13140/RG.2.2.21906.12483

Sukhdeve, S. R., Sukhdeve S. S. 2023. Data visualization and business intelligence. Google Cloud Platform for Data Science. Apress, Berkeley. 121-147 pp. ISBN: 9781484296875. https://doi.org/10.1007/978-1-4842-9688-2_4

Tufte, E. R. 1990. Envisioning information. Graphics Press. London, pp 126 https://doi.org/10.1017/S0269888900005713

Tufte E. R. 2006. Beautiful Evidence. Graphics Press L.L.C. https://doi.org/10.1075/idj.15.2.13eng

West, S.G., Finch J.F., Curran P.J. 1995. Structural equation models with nonnormal variables: problems and remedies. In: Hoyle RH, editor. Structural equation modeling: Concepts, issues, and applications. Newbery Park, CA: Sage; pp. 56–75.

Zedeck, S. 2014. APA dictionary of statistics and research methods (1st ed.). Washington, DC: American Psychological Association. https://doi.org/10.1037/14336