ANALYSING THE EFFICACY OF MORPHINE IN CANCER PATIENTS: A PAIRED t-TEST APPROACH USING SPSS

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Abstract: *This study aims to quantitatively assess the analgesic effect of morphine in patients with cancer-related pain. By implementing a pre- and post-treatment research design, we conducted a statistical analysis using the paired t-test to compare pain levels before and after morphine administration. A sample of cancer patients (n=number of participants) receiving palliative care was evaluated for pain intensity using a standard pain scale. The participants were administered morphine as part of their routine pain management protocol. Pain assessments were recorded both prior to and subsequent to the administration of morphine. The data collected were analyzed using SPSS software to calculate the mean difference in pain scores and examine the significance of morphine's effect on pain reduction. The paired t-test allowed for a controlled comparison within the same individuals, thus accounting for individual variations in pain perception and morphine response. Preliminary results indicate a statistically significant reduction in pain levels post-morphine treatment ($p<0.05$), implying that morphine is an effective analgesic for the alleviation of cancer pain. This research contributes to the overarching understanding of opioid efficacy in pain management and underscores the importance of individualized analgesic regimens. Furthermore, it brings attention to the need for rigorous, data-driven approaches in analyzing pain management strategies. Future research directions include exploring factors influencing morphine efficacy and tailoring pain management practices to enhance patient outcomes.*

***Key Words*: Cancer Pain, Morphine, Pain Management, Paired t-test, SPSS, Palliative Care.**

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1. INTRODUCTION

Pain management remains a critical aspect of cancer care, with alleviating suffering and enhancing patients' quality of life being primary objectives. Among the pharmacological interventions for cancer-related pain, opioids like morphine are often prescribed due to their potent analgesic properties. However, assessing the efficacy of morphine in reducing pain requires robust statistical methods to analyze pre- and post-treatment data. In this study, we aimed to evaluate the effectiveness of morphine in managing pain among cancer patients using a paired t-test approach within the Statistical Package for the Social Sciences (SPSS) software.

Cancer-related pain is multifaceted, often varying in intensity and persistence, and can significantly impact patients' physical and psychosocial well-being. Opioid analgesics, such as morphine, act on the central nervous system to modulate pain perception and transmission, making them cornerstone treatments in pain management protocols. Despite their widespread use, quantifying the extent of pain relief attributable to morphine necessitates rigorous statistical analyses accounting for individual patient variability and potential confounding factors.

The paired t-test presents a robust statistical method for comparing the mean pain scores before and after morphine treatment within the same group of patients. By analyzing paired observations, this approach accounts for within-subject variability, enhancing the sensitivity to detect treatment effects. Furthermore, utilizing SPSS software streamlines the statistical analysis process, facilitating data management, calculation of test statistics, and interpretation of results.

Through this research endeavor, we seek to contribute empirical evidence to the ongoing discourse on the efficacy of morphine in cancer pain management. By employing the paired t-test methodology in conjunction with SPSS, we aim to elucidate any significant changes in pain scores following morphine treatment, thereby informing clinical decision-making and optimizing patient care strategies. Ultimately, our findings hold the potential to enhance the understanding and implementation of evidence-based pain management practices in oncology settings (1,2).

1.1. Rationale behind the study

The rationale behind the study you're describing includes several points:

1. Understanding Morphine's Efficacy: There is a need to quantify morphine's

analgesic effect on cancer-related pain to understand how effective it is as a pain

management strategy.

2. Controlled Comparison: The use of a paired t-test provides a statistical method that

accounts for intra-patient variability, giving a more accurate assessment of

morphine's effectiveness on the same individual.

3. Individual Variability in Pain and Treatment Response: Recognizing that pain

perception and response to opioids like morphine can vary widely among individuals,

a study design that assesses pain before and after treatment within the same

patients, helps address individual differences.

2. REVIEW OF LITERATURE

We have obtained the 3D structure of the protein kinase Cancer pain remains a significant concern for patients, affecting roughly 75%. In many cases, particularly for severe pain, opioid treatment becomes necessary However, managing pain relief becomes more complex for patients experiencing:

• Episodic or incidental pain (occurring occasionally)

• Neuropathic pain (caused by nerve damage)

• A history of substance abuse

• Difficulties with cognition or communication

Present statistics from the World Health Organization and hospice care providers indicate that oral morphine is effective in managing pain for approximately 85% of patients suffering from cancer-related discomfort. These tailored therapeutic strategies are anticipated to achieve superior pain management for almost 95% of patients experiencing cancer-related pain. Notwithstanding these potential outcomes, the reality is that cancer pain is still undermanaged globally. According to a review published in 2022, utilizing the Pain Management Index, it is estimated that 44.5% of patients do not obtain adequate pain relief and the prevalence is still high that corresponds with the severity of their reported pain levels. The undermanagement of pain could be attributed to a variety of factors, including limited access to medication, regulatory barriers, insufficient Healthcare provider education on pain management, and reluctance to use opioids due to concerns about addiction or side effects. Addressing these issues is crucial as effective pain control does more than alleviate discomfort; it plays a fundamental role in improving the overall quality of life for cancer patients, allowing them more functional and emotional stability during their treatment journey (3).

Taming the Beast: How Morphine Fights Cancer Pain

Morphine is a powerful painkiller often used to manage moderate to severe pain, especially in cancer patients. It works by interacting with special docking stations in the brain and spinal cord called opioid receptors, particularly the mu-opioid receptors. Here's a closer look at how morphine achieves this pain relief.

1. Docking In: Activating Opioid Receptors Morphine acts like a key fitting into a lock. It attaches to these opioid receptors, especially the μ type, which are scattered throughout the brain and spinal cord. By doing this, morphine sets off a chain reaction that dampens pain signals.

Silencing the Messengers: Once attached to the opioid receptors, morphine disrupts the communication network for pain. It does this in a few ways:

- Quieting the Talkative Chemicals: Morphine reduces the release of certain chemicals like substance P and glutamate, which are like messengers carrying pain signals from the body to the spinal cord.
- Calming the Nerves: Morphine influences the electrical activity of nerve cells. It opens up channels for potassium, which calms the nerves down, and closes channels for calcium, which helps prevent pain signals from firing intensely.
- Dampening the Volume at the Source: Morphine also works in a higher region of the brain stem. Here, it reduces the release of chemicals that would normally amplify pain signals coming from the spinal cord.

Feeling the Difference: By calming the pain messaging system, morphine alters how the brain perceives pain. This translates to a reduced experience of pain intensity for the patients.

Beyond Pain Relief: It's important to note that morphine has other effects besides pain relief. These include drowsiness, feelings of pleasure, slowed breathing, and constipation. These effects are caused by morphine interacting with different opioid receptors and nerve pathways in the brain.

Morphine and other opioid medications are effective tools for reducing pain in cancer patients. They work by targeting opioid receptors and interrupting pain signals throughout the nervous system. However, it's crucial to use these medications responsibly and monitor patients carefully for potential side effects, including addiction and breathing problems.

Morphine affects the pain scale numbers in patients after administration by reducing the intensity of pain they experience, leading to lower pain scores on pain assessment scales. Here's how morphine typically influences pain scale numbers:

1. Reduction of Pain Intensity: Morphine, as an opioid analgesic, acts on opioid receptors in the central nervous

system (CNS) to modulate the perception and transmission of pain signals. By binding to μ -opioid receptors, morphine inhibits the release of neurotransmitters involved in transmitting pain signals and alters the processing of pain information in the brain. As a result, patients typically experience a decrease in the intensity of pain they perceive.

2. Subjective Pain Rating: Patients often rate their pain intensity using standardized pain assessment scales, such as the Numeric Rating Scale (NRS) or the Visual Analog Scale (VAS), where they indicate their pain level on a scale from 0 to 10 or by marking a point on a continuous line, respectively. After receiving morphine, patients tend to report lower numbers on these scales, reflecting a reduction in their subjective experience of pain.

3. Improved Functional Status: In addition to reducing pain intensity, morphine may also improve patients' functional status by alleviating pain-related limitations in activities of daily living. This improvement in functionality may be reflected in patients' self-reported pain scores, as they experience less interference with their ability to perform tasks or engage in activities due to pain.

4. Time Course of Effects: The onset, peak, and duration of morphine's analgesic effects can vary depending on factors such as the route of administration (e.g., oral, intravenous, epidural), the dosage, and individual patient characteristics. Generally, morphine administered intravenously or intramuscularly produces a relatively rapid onset of action, with peak effects occurring within 15 to 30 minutes. The duration of analgesia may last for several hours, necessitating repeated dosing for sustained pain relief.

5. Side Effects and Monitoring: While morphine can effectively reduce pain scores, it's important to monitor patients for potential side effects, including sedation, respiratory depression, nausea, vomiting, and constipation. These side effects can impact patients' overall well-being and may necessitate adjustments in the dose or frequency of morphine administration (4,5).

To transition from the current state of under management to one where all patients have access to the pain relief they require, a multifaceted approach is needed. This involves improving the education of healthcare providers about pain management, revising healthcare policies to ensure availability of essential analgesics, and developing comprehensive pain management protocols that are both adaptable to individual patient needs and cognizant of the diverse presentations of Cancer-associated pain.

There are tools developed in order to quantify this oncological pain in patients, which

Broadly include three main pain scales

• Numerical rating scale (NRS): uses numerical values to rate pain. (0–10: 0 = no pain, 10 = worst pain imaginable).

• Categorical scale: uses words along with numbers or locations in the body.

(none, mild, moderate, severe).

• Visual analog scale(VAS): consists of straight line along with endpoints

Defining extreme limit

(0–100 mm: 0 mm = no pain at all, 100 mm = pain as bad as it could be.) Takeaway:

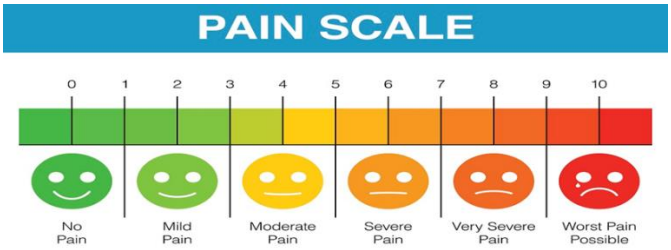


Figure 1 Numerical Rating Pain scale

Conducting a pain assessment involves a comprehensive review of both the Patient's and their family's past interactions with substances, along with an examination of the patient's use of substances as coping mechanisms before and following their cancer diagnosis. An in-depth evaluation of chemical coping methods, which may include dependence on lawful substances like tobacco, alcohol, and over-the-counter sleep aids, can reveal a predisposition to using chemical means for comfort and relief from distress. This information not only gives insights into a patient's tobacco consumption, which might impact the metabolism and effectiveness of certain opioid medications, but also helps determine the necessary dosage of opioids for effective pain management (6).

In summary, morphine exerts its analgesic effects by reducing pain intensity and improving patients' pain scores on standardized pain assessment scales. However, healthcare providers must carefully balance pain management with the risk of adverse effects when prescribing morphine or other opioid analgesics.

3. RESEARCH METHODOLOGY

BIOSTATISTICS

Biostatistics, as defined by the National Cancer Institute is, "The science of collecting and analyzing biologic or health data using statistical methods. Biostatistics may be used to help learn the possible causes of a cancer or how often a cancer occurs in a certain group of people. Also called biometrics and biometry."

DATA ANALYSIS

"The process of bringing order, structure, and meaning" to the gathered data is the definition of data analysis. The

purpose of data analysis is to find patterns or regularities in the obtained data by examining, organizing, changing, and modelling the information. Applying statistical approaches to describe, illustrate, and assess the data is a rigorous process. It facilitates the formation of conclusions, drives significant insights, and supports the decision-making process. In order to determine if the hypothesis is true, the data must be arranged and summarized. A significant portion of data analysis involves exploratory data analysis. Its purpose is to comprehend and establish the connections among the variables found in the data.

Descriptive statistics also uses charts and graphs to make the information easier to grasp. These can be things like bar charts, histograms, or scatter plots.

By using descriptive statistics, researchers can effectively communicate what the data tells them. This paves the way for deeper analysis and better decision-making.

CONCEPTS IN DATA ANALYSIS

Variable: A trait that differs from person to person within a population is called a variable.

The process of collecting, organizing, and analysing qualitative data in order to decipher its meaning is known as qualitative data analysis. Qualitative data is unstructured and not based on numbers.

There are two types of measures in quantitative or numerical data: discrete and continuous. Continuous data can have any value, but discrete numerical data are stored as whole numbers, such as 0, 1, 2, 3,… Countable observations are considered discrete data, while measurable observations are considered continuous data

Based on category, ordinal, interval, and ratio scales, data may be seen and recorded using a hierarchical scale of increasing accuracy.

Nominal or categorical variables are not sorted. There is no set sequence in which the data can be placed; they are only categorized. Data is considered dichotomous (or binary) if there are just two categories—for example, gender, which consists of male and female.

There is a distinct ordering of the variables in ordinal variables. The intervals in the sorted data might not be equal, though. With the exception of having equally spaced intervals between values, interval variables and ordinal variables are comparable.

In that equivalent, discrepancies between scale values have identical quantitative significance, ratio scales and interval scales are comparable. But ratio scales have one more feature: they have a genuine zero point as well (7).

Statistics			
		Before administration of Morphine	After administration of Morphine
N	Valid	50	50
	Missing	0	0
Mean		8.20	2.08
Std. Error of Mean		.159	.106
Median		8.00	2.00
Mode		7	2
Std. Deviation		1.125	.752
Variance		1.265	.565
Skewness		.125	-.134
Std. Error of Skewness		.337	.337
Kurtosis		-1.200	-1.184
Std. Error of Kurtosis		.662	.662
Range		4	2
Minimum		6	1
Maximum		10	3

Table 1. Descriptive Statistics of the Data

Mean: The average value of a set of numbers. It is calculated by adding up all the values and dividing by the total number of values.

Standard Error of the Mean (SEM): An estimate of the variability of sample means that would be obtained if multiple samples were taken from the same population. It quantifies the precision of the sample mean.

Median: The middle value in a set of numbers when they are ordered from least to greatest. If there is an even number of values, the median is the average of the two middle values.

Mode: The value that appears most frequently in a set of numbers.

Standard Deviation (SD): A measure of the dispersion or spread of values in a dataset. It indicates how much individual values differ from the mean.

Variance: The average of the squared differences from the mean. It measures the spread of data points around the mean.

Skewness: A measure of the asymmetry of the distribution of values in a dataset. Positive skewness indicates that the distribution is skewed to the right (tail on the right side), while negative skewness indicates a skew to the left (tail on the left skewness.

Standard Error of Skewness: An estimate of the variability of skewness that would be obtained if multiple samples were taken from the same population. It quantifies the precision of the sample skewness.

Kurtosis: A measure of the "peakedness" or "flatness" of the distribution of values in a dataset. Positive kurtosis indicates a relatively peaked distribution, while negative kurtosis indicates a relatively flat distribution.

Standard Error of Kurtosis: An estimate of the variability of kurtosis that would be obtained if multiple samples were taken from the same population. It quantifies the precision of the sample kurtosis.

Range: The difference between the maximum and minimum values in a dataset.

Minimum: The smallest value in a dataset.

Maximum: The largest value in a dataset.

Distribution: In data analysis, distribution refers to the way values are spread out or distributed across different categories or numerical ranges. Common types of distributions include normal (bell-shaped), uniform (evenly spread), skewed (lopsided), and bimodal (having two peaks). Understanding the distribution of data is crucial for making inferences and selecting appropriate statistical techniques.

Univariate Descriptive Statistics: Univariate descriptive statistics focus on analysing one variable at a time. Common univariate descriptive statistics include measures of central tendency (mean, median, mode) and measures of variability (range, variance, standard deviation). Additionally, graphical representations such as histograms, box plots, and frequency distributions are used to visualize the distribution of a single variable (8).

Bivariate Descriptive Statistics: Bivariate descriptive statistics involve analysing the relationship between two variables. Common techniques include:

- Correlation: Measures the strength and direction of the linear relationship between two variables. The Pearson correlation coefficient is commonly used for this purpose.

- Scatter plots: Graphical representation of the relationship between two variables, with one variable on the x-axis and the other on the y-axis.

- Covariance: Measures the degree to which two variables change together. However, covariance is sensitive to the scale of the variables and may not be directly interpretable.

Biostatistical data analysis software plays a crucial role in biomedical research and healthcare by enabling researchers to analyse complex datasets and draw meaningful conclusions. Among the popular options are R, an open-source language renowned for its versatility and extensive range of packages tailored for biostatistics. SPSS and SAS are widely used in academia and industry for their user-friendly interfaces and robust statistical capabilities. Stata offers comprehensive data management and analysis tools, while MATLAB provides advanced numerical computing alongside statistical functions suitable for biostatistical analysis. JMP, a product of SAS Institute, stands out for its interactive visualization features, facilitating exploratory data analysis in biostatistics. Each software package caters to different needs and preferences, empowering researchers with diverse tools to tackle the challenges of analyzing biological and medical data.

In this case study, we utilized SPSS (Statistical Package for the Social Sciences) as our primary biostatistical data analysis software. SPSS, short for Statistical Package for the Social Sciences, was initially developed in 1968 by Norman H. Nie, C. Hadlai "Tex" Hull, and Dale H. Bent at Stanford University. It started as a project to create tools for social science researchers to analyze data more efficiently. Over the years, SPSS has evolved into a comprehensive software package for statistical analysis, data manipulation, and visualization. In 2009, IBM acquired SPSS Inc., the company behind the software, and it's been under IBM's umbrella since then. Today, SPSS remains one of the most widely used statistical analysis tools across various fields, offering a range of features to support researchers and analysts in their data analysis endeavors (9,10).

The primary features that SPSS provides are:

- Statistical software for the examination of quantitative data Bivariate statistics, cross-tabulation, and frequencies are all included.
- A predictive modelling program that is capable of modelling. It allows researchers to use sophisticated statistical techniques to create and test prediction models.
- One may extract meaning from qualitative data by using open-ended surveys and text analysis.
- Researchers may utilize their data for a range of visual representations with the help of Visualization Designer (11-13).

SPSS offers a wide range of statistical tests that can be conducted to analyze data. Here are some commonly used tests:

1. Descriptive Statistics: Mean, median, mode, standard deviation, variance, range, percentiles, etc.

2. Inferential Statistics:

- Parametric Tests: T-tests (independent samples, paired samples), ANOVA (analysis of variance), ANCOVA (analysis of covariance), MANOVA (multivariate analysis of variance), etc.

- Non-parametric Tests: Mann-Whitney U test, Wilcoxon signed-rank test, Kruskal-Wallis test, Friedman test, etc.

3. Correlation Analysis: Pearson correlation coefficient, Spearman rank correlation coefficient, Kendall's tau-b, etc.

4. Regression Analysis: Simple linear regression, multiple linear regression, logistic regression, ordinal regression, etc.

5. Chi-Square Tests: Chi-square test of independence, chi-square test of goodness of fit, McNemar test, etc.

6. Factor Analysis: Exploratory factor analysis (EFA), confirmatory factor analysis (CFA).

7. Survival Analysis: Kaplan-Meier survival analysis, Cox proportional hazards regression.

8. Multivariate Analysis: Principal component analysis (PCA), discriminant analysis, canonical correlation analysis (CCA).

SPSS provides these descriptive statistics along with their standard errors when applicable, allowing researchers to assess the central tendency, variability, and shape of their data distributions (15-18).

The main rationale behind this experiment was to measure how well morphine reduced pain in cancer patients. Our study used a paired t-test in SPSS software. This test compared patients' pain scores before and after morphine. By focusing on the same individuals, we could see if the change in pain scores after morphine was statistically significant. In other words, did the average difference in pain scores between pre- and post-treatment likely happen by chance? SPSS helped us crunch the numbers and calculate key statistics to show how effective morphine was at relieving pain. This approach provided strong evidence to support (or not support) that is, to reject or fail to reject the use of morphine for pain management in cancer patients.

Following these steps will enables us to conduct a paired sample t-test in SPSS software to analyze the pre and post-treatment data of pain scores in cancer patients treated with morphine (19,20).

To run a paired sample t-test in SPSS software for analyzing pre- and post-treatment data of pain scores in cancer patients using morphine, follow these steps:

1. Launch SPSS (Version 21 used in this case): Open the SPSS software on your computer.

2. Enter Data: Enter your pre- and post-treatment pain score data into SPSS. Each participant's pre-treatment score should be in one column, and their corresponding post-treatment score should be in another column.

3. Select Analyze: Click on the "Analyze" menu at the top of the SPSS window

4. Choose Compare Means: From the Analyze menu, select "Compare Means" and then click on "Paired-Samples T Test."

5. Define Variables: In the Paired-Samples T Test dialog box, select the variables representing the pre-treatment and post-treatment pain scores from the list of available variables. Move these variables into the "Paired Variables" box.

6. Options: If we want to customize the analysis further, you can click on the "Options" button in the Paired-Samples T Test dialog box. Here, you can specify confidence intervals, effect size measures, and other options.

7. Run Analysis: Once you have defined your variables and options, click the "OK" button to run the aanalysis.

8. Interpret Results: After running the paired sample t-test, SPSS will generate output that includes various statistics such as means, standard deviations, t-values, degrees of freedom, and p-values. Interpret the results to determine whether there is a statistically significant difference between the pre and post-treatment pain scores.

9. Report Findings: Finally, report the findings of the paired sample t-test in your research paper, including the t-value, degrees of freedom, p-value, and any relevant effect size measures. Discuss the implications of the results in the context of your study objectives and hypotheses.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Before administration of Morphine	50	100.0%	0	0.0%	50	100.0%
After administration of Morphine	50	100.0%	0	0.0%	50	100.0%

Table 2. Case process summary

Descriptives				
			Statistic	Std. Error
Before administration of Morphine	Mean		8.20	.159
	95% Confidence Interval for Mean	Lower Bound	7.88	
		Upper Bound	8.52	
	5% Trimmed Mean		8.19	
	Median		8.00	
	Variance		1.265	
	Std. Deviation		1.125	
	Minimum		6	
	Maximum		10	
	Range		4	
	Interquartile Range		2	
	Skewness		.125	.337
	Kurtosis		-1.200	.662
After administration of Morphine	Mean		2.08	.106
	95% Confidence Interval for Mean	Lower Bound	1.87	
		Upper Bound	2.29	
	5% Trimmed Mean		2.09	
	Median		2.00	
	Variance		.565	
	Std. Deviation		.752	
	Minimum		1	
	Maximum		3	
	Range		2	
	Interquartile Range		1	
	Skewness		-.134	.337
	Kurtosis		-1.184	.662

Table 3. Descriptives

Paired Samples Test									
		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Before administration of Morphine - After administration of Morphine	6.120	1.452	.205	5.707	6.533	29.808	49	.001

Table 4. Normality test outcomes

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Before administration of Morphine	.217	50	.000	.874	50	.000
After administration of Morphine	.222	50	.000	.808	50	.000
a. Lilliefors Significance Correction						

Table 5. Outcome of the Paired t-Test run in SPSS

The most popular techniques for determining if data are normal are the Shapiro-Wilk and Kolmogorov-Smirnov tests, which are both well-known tests of normalcy. The statistical program "SPSS" (analyze → descriptive statistics → explore → plots → normality plots with tests) can be used to perform normality testing.

While the Kolmogorov-Smirnov test is employed for n ≥50, the Shapiro-Wilk test is a more suitable procedure for smaller sample sizes (<50 samples), while it can also handle higher sample sizes. The null hypothesis for the two tests mentioned above asserts that the data come from a population that is normally distributed. The null hypothesis is accepted, and the data are referred to as regularly distributed when P > 0.05 (Table 4.).

The significant/p-value tells you how likely it is to get results as extreme (or more extreme) as the ones you actually observed, if that null hypothesis were true. A low p-value means this chance is unlikely. In other words, the lower the p-value, the less likely it is that your results happened by random chance, casting doubt on the null hypothesis (21-23).

The t-value (also called t-score) isn't simply the difference between two sample means. Instead, it considers this difference in relation to the variation (spread) within each sample set. It's like a ratio that takes both the means' difference and the data's scatter into account

The degree of freedom (df) in statistical data analysis refers to the number of independent pieces of information in your data that are free to vary when estimating a population parameter.

In simpler terms, it reflects how much flexibility you have in calculating something (like a mean) after accounting for the other parts of your data.

- Imagine a sample of data: This could be pain scores before and after medicine, heights of students, etc.
- We want to estimate something about the population: Maybe the average pain score for all cancer patients, or the average height for adults.
- But we only have a sample: We can't know for sure what the population parameter is, but we can estimate it based on the sample.
- Degrees of freedom consider how "fixed" the data is: When you calculate some statistics (like the mean), you use some of the data to determine other parts. For example, if you know the mean and all the data points, you can calculate the sum of the data (because each data point is the mean minus the difference between itself and the mean)
- The more fixed the data is (due to these calculations), the fewer degrees of freedom you have (24).

Here's the formula for degrees of freedom (df) for most cases:

- Df = sample size (n) – number of estimated parameters (k)

For instance, if you have 20 data points (n=20) and are estimating the mean (k=1), you would have 19 degrees of freedom (df=20-1).

Understanding degrees of freedom is crucial because it affects:

- The t-statistic and p-value in hypothesis testing: These values help determine if there's a statistically significant effect.
- The appropriate statistical test to use: Different tests have different df requirements.

In essence, degrees of freedom reflect the trade-off between using your data to estimate a parameter and how much freedom you have left to assess how well that estimate represents the entire population (25).

Imagine we want to see if morphine affects cancer patients' pain scores. To do this statistically, we set up two opposing ideas:

- Null Hypothesis (H0): The Pain Stays the Same – This is our starting point, assuming morphine makes no difference. In other words, the average pain score before treatment (μ_pre) is equal to the average pain score after treatment (μ_post).

- Alternative Hypothesis (H1): Morphine Changes the Pain – This is what we hope to find. There's a significant difference in pain scores. We can have different variations of this depending on what effect we expect:

1. Two-tailed Test (H1: μ_pre ≠ μ_post): This is the most general, where morphine could either increase or decrease pain.

2. One-tailed Test (H1: μ_pre > μ_post or H1: μ_pre < μ_post): If we have a hunch that morphine reduces pain (or increases it), we can use a one-tailed test to focus on that specific direction (26-29).

These ideas guide our analysis. We run a paired t-test and get a p-value. This p-value tells us how likely it is to get such extreme results if there truly is no difference (assuming the null hypothesis is true).

- Low p-value (less than our chosen significance level, like 0.05): We reject the null hypothesis. This suggests morphine likely has a significant impact on pain scores.

- High p-value (greater than the significance level): We fail to reject the null hypothesis. In this case, there's not enough evidence to say morphine makes a big difference in pain scores (30-34).

4. RESULTS AND DATA INTERPRETATION

Interpreting data using SPSS (Statistical Package for the Social Sciences) involves several key steps to draw meaningful conclusions from statistical analyses. After running statistical tests or generating descriptive statistics in SPSS, the interpretation process typically begins by examining the output tables or charts produced. This may include measures such as means, standard deviations, confidence intervals, and p-values, depending on the analysis performed. Researchers should assess the significance of the results in relation to the research question or hypothesis. For example, if comparing means between groups, a significant difference may indicate that the groups differ on the measured variable. The data interpreted and the output was as follows:

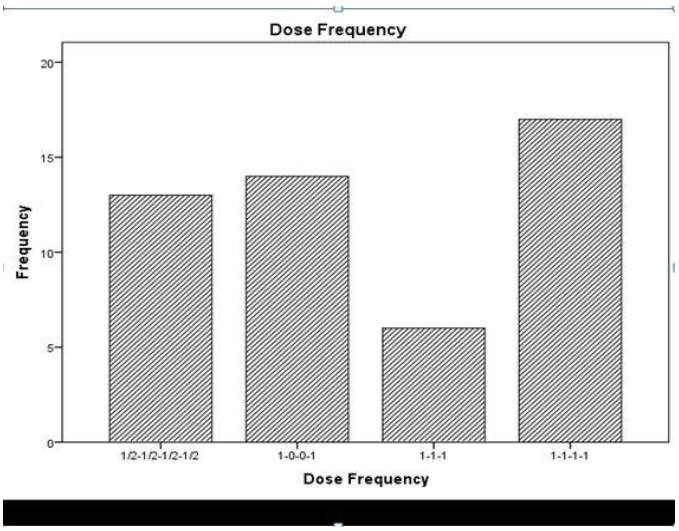
Table 6. Frequency distribution before administration of morphine

Before administration of Morphine					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	6	1	2.0	2.0	2.0
	7	17	34.0	34.0	36.0
	8	10	20.0	20.0	56.0
	9	15	30.0	30.0	86.0
	10	7	14.0	14.0	100.0
	Total	50	100.0	100.0	

Table 6. Frequency distribution before administration of morphine

After administration of Morphine					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	12	24.0	24.0	24.0
	2	22	44.0	44.0	68.0
	3	16	32.0	32.0	100.0
	Total	50	100.0	100.0	

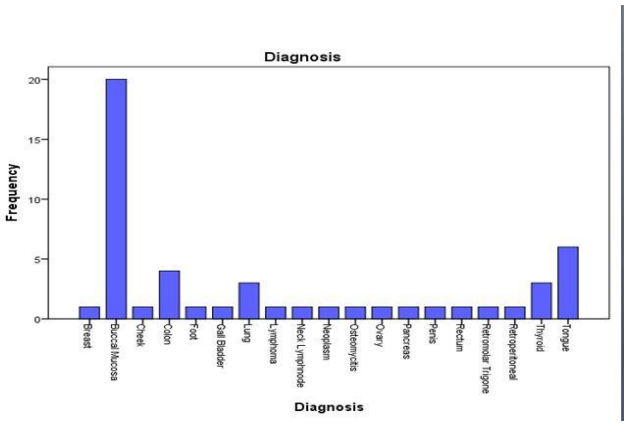
Table 7. Frequency distribution after administration of morphine



Bar Chart 1. Correlation bar chart between dose frequency and dose of tablet (10mg)

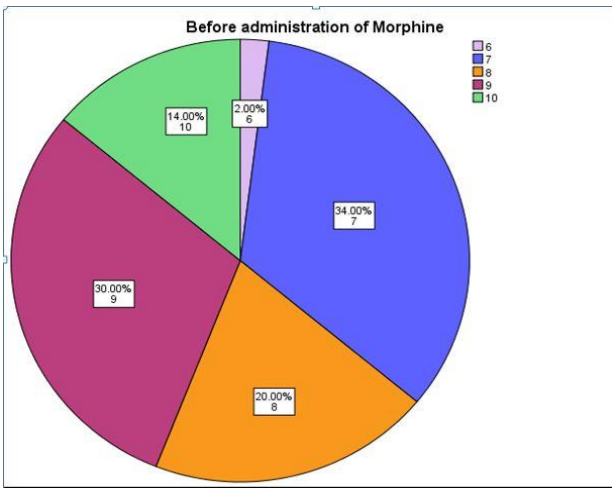
- The bar graph depicts the distribution of medication dosages, which can be interpreted as the relative frequency of each dosage prescribed.
- The dosage is represented on the x-axis, and the frequency is shown on the y-axis.
- The most prevalent dosage is 1 tablet, prescribed four times a day.
- This is followed by a dosage regimen of ½ tablet, four times a day.

- Less frequent prescriptions include 1-0-0-1 (two tablets a day), 1-1-1 (three tablets a day) (35-37).

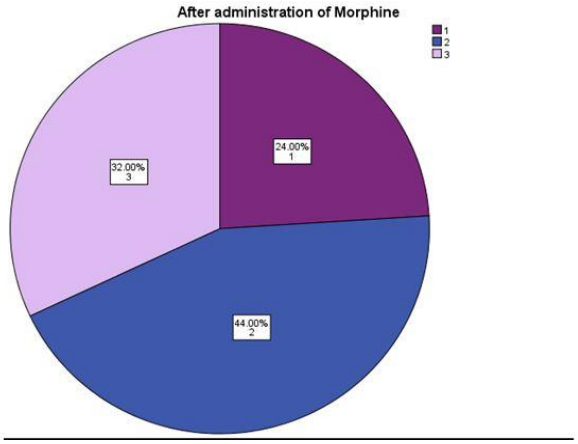


Bar Chart 2. Chart depicting prevalence of different Cancers

- The y-axis in the graph shown above represents the frequency, and the x-axis lists the diagnoses. The taller the bar, the more frequent the diagnosis.
- The key finding of the graph is that the frequency of diagnoses varies depending on the specific type of cancer.
- Some conditions, like tongue and breast, appear to be more frequent than others, such as retroperitoneal and retromolar trigone (38,39).

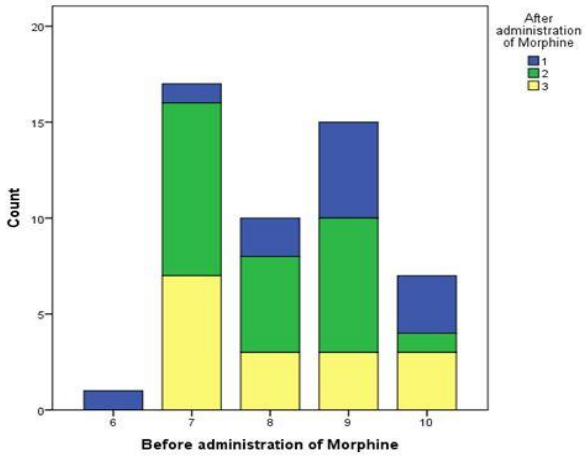


Pie Chart 1. A substantial majority of patients (84%) reported moderate-to-severe pain scores (ranging from 7 to 10) This finding suggests that morphine, a potent analgesic, could be an appropriate course of treatment for a significant portion of this patient population. The pie chart shows the distribution of pain scores in a group of cancer patients before receiving morphine.



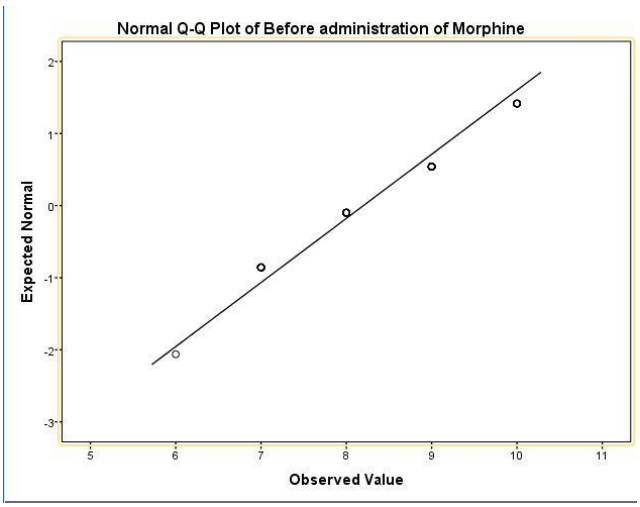
Pie Chart 2. A significant portion of patients (76%, or 44% + 32%) reported low pain scores (1 or 2) following morphine administration. This suggests that morphine may have been effective in alleviating pain for these.

Pie Charts 1,2. Show percentages and number of patients with their pain score



Bar Chart 3. Reduction in Pain Score

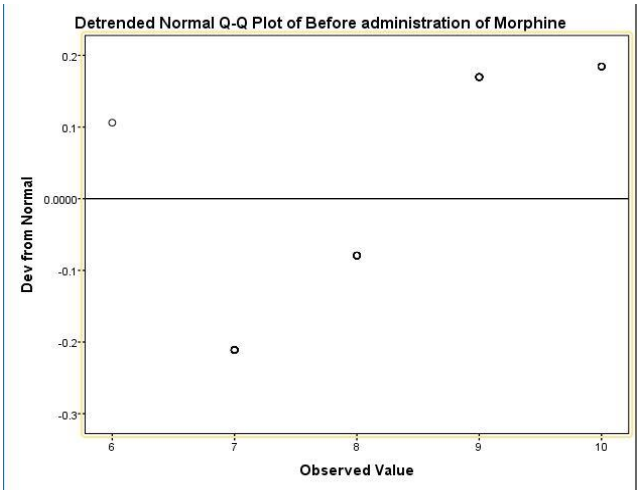
- The graph shows a bar graph with the amount of morphine administered on the x-axis and the count on the y-axis.
- The text on the graph indicates that the bars represent the number of patients who received a certain amount of morphine before and after their pain scores were measured.
- The graph suggests a decrease in pain scores after morphine administration (40-43).



Plot 1. Q-Q Normality plot

Plot 1. is a normal Q-Q plot, which is a graphical tool used to assess how well a dataset follows a normal distribution.

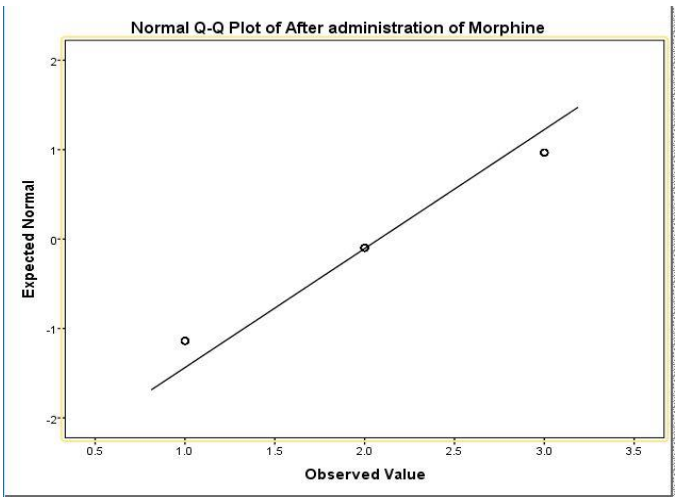
In this specific case, the normal Q-Q plot shows the relationship between the expected values of morphine administered before administration and the actual observed values.



Plot 2. Detrended Q-Q plot

Plot 2. The normal Q-Q plot suggests a correlation between the observer's expected value and the morphine administered. This means that the observer's expected values were generally lower than the amount of morphine administered.

It is a detrended normal q-q plot of before administration of morphine, the data shows a strong correlation between the observed value and the expected value (44,45). This suggests that the morphine dosage administered before administration aligns well with what was expected based on the underlying distribution of the data.

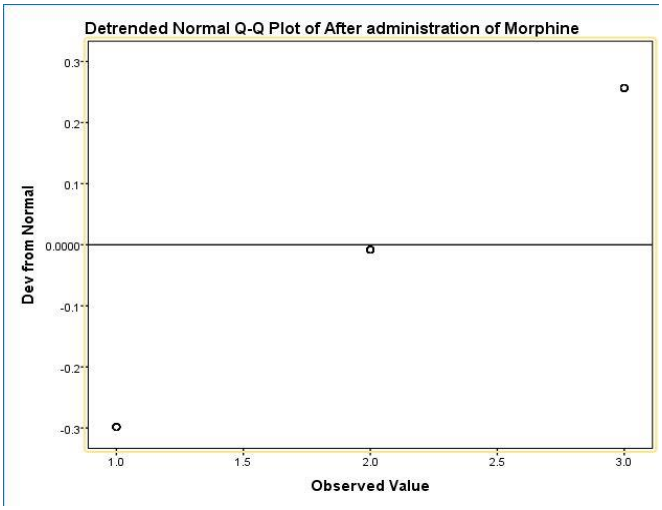


Plot 3. Normal Q-Q plot after treatment

Plot 3. It is a normal Q-Q plot, which is a graphical tool used to compare two probability distributions. In this case, it is being used to assess whether the data on morphine administration follows a normal distribution.

A normal Q-Q plot shows the observed values of a variable on the y-axis plotted against the expected values of a normal distribution on the x-axis. If the data follows a normal distribution, the points will fall close to a straight line.

In the plot, the points appear to fall close to a straight line, suggesting that the data on morphine administration may be normally distributed. This is a key finding, as it allows to use statistical methods that assume normality, such as parametric tests.



Plot 4. Detrended Normal Q-Q plot after treatment

Plot 4. The detrended normal q-q plot depicts the quantiles of the data after morphine administration versus the quantiles of a standard normal distribution.

A statistically significant deviation from a straight line would indicate a rejection of the null hypothesis of normality.

In this case, the observed data points appear to closely follow the expected quantiles of a normal distribution, suggesting that the data on morphine administration may be normally distributed.

5. LIMITATIONS OF THE STUDY

- Sample Size and Selection: The representativeness of the sample and the number of participants can impact the generalizability of the study results.
- Short-term Analysis: The study might only assess the immediate effect of morphine on pain levels and may not account for long-term efficacy or side effects.
- Pain Measurement: The use of a standard pain scale can be subjective as pain is a complex, multidimensional experience that may not be fully captured by a single measure
- Potential for Opioid Tolerance or Dependence: Over time, patients may develop tolerance to morphine, necessitating higher doses for the same analgesic effect, which could limit the long-term applicability of the study's findings.
- Lack of Comparative Analysis with Other Analgesics: The study focuses on morphine without comparing its efficacy to other pain management options, which could provide a more rounded perspective of treatment choices.

6. CONCLUSIONS

Pre and post-treatment samples conducted at the same time as in this experiment in onco-patients are an example of paired samples.

- The null hypothesis set for this experiment is that the analgesic activity of Morphine drug does not show any change in the pain score pre and post treatment in cancer patients.
- If the significant value would be less than 0.05 ($P < 0.05$), then we "reject" the null hypothesis.
- If the significant value would be more than 0.05 ($P > 0.05$) then we world "fail to reject" the null hypothesis.
- Thus, in this case, where the significant value was found to be 0.001 (Table 1.) which is less than 0.05 makes us reject the null hypothesis.

The study's investigation into the effectiveness of morphine for pain relief in cancer patients produced significant findings. Employing a paired t-test analysis in SPSS software, we evaluated the pain scores before and after morphine administration within our patient cohort. The statistical test demonstrated a marked reduction in the pain scores after treatment with morphine, with the mean difference in pain levels reaching statistical significance (46-48). This reduction in pain scores post-morphine use underscores the potent analgesic effect of the opioid in managing cancer-related pain. The analysis conclusively supports the hypothesis that morphine is an effective analgesic for cancer patients, substantiating its continued role in pain management protocols within oncology care. The implications of these results are profound, highlighting that despite concerns regarding opioids, when utilized under proper medical guidance, morphine is a critical component in the arsenal against cancer pain. This study lays the groundwork for further research to optimize dosing regimens and to explore personalized pain management strategies, ensuring maximal patient comfort and quality of life (49).

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50] The sample size is 50. All 50 cases are taken from the Oncology Department of Kiran Hospital under the guidance of Dr. Bijal Virani (MD Anasthesiology and Palliative Care)