



STATISTICAL TOOLS AND METHODOLOGY IN SUSTAINABLE PROCUREMENT, ENVIRONMENTAL AND SOCIAL STANDARD PRACTICES

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Article History

Received: 05/03/2025

Accepted: 25/03/2025

Published: 27/03/2025

Vol – 2 Issue – 2

PP: -23-27

DOI:10.5281/zenodo.
15120492

Abstract

This study attempts to give researchers the knowledge and tools they need to approach their scientific investigations with confidence, methodological rigor, and an unshakable dedication to knowledge advancement by examining the intricacies of statistical analysis. By making it easier for researchers to comprehend a thorough process for selecting statistical methods based on the variables of interest and research hypothesis, this work aims to increase methodological precision. Statistics tools are indispensable in procurement and environmental, social standards studies due to their role in enhancing decision-making, managing risk, improving efficiency, ensuring compliance, and effectively communicating insights. The literature in these domains confirms that the thorough analysis these tools offer, leads to more informed, calculated decisions that support sustainability and economic objectives. The recommended statistical tools and process of selecting an appropriate statistical analysis/method is based on the context of the study and the unique properties of the data in line with the objective.

Keywords: Statistical Tools, Questionnaire Design, Procurement, Environment, Social Standards.

1. INTRODUCTION

The search for the right statistical tools in these three areas of development really deserves our attention. When it comes to evaluating and selecting procurement suppliers, having the right insights can be a game changer for success. Statistical methods play a crucial role in assessing supplier performance by analyzing data on delivery times, defect rates, pricing, and other important performance indicators. Techniques such as regression analysis and weighted scoring models can effectively quantify the risks and benefits associated with suppliers. In the realm of Environmental Standards Studies, like Environmental Impact Assessment (EIA), statistics are essential for gathering and analyzing environmental data—think air and water quality, and biodiversity metrics—to gauge the impact of various projects or policies. Statistical models are also used for modelling and prediction, helping to forecast potential environmental changes and outcomes under different scenarios, which ultimately aids in making informed decisions about conservation and resource management. When it comes to Social Standards Studies, such as Social Impact Assessment (SIA), statistics are invaluable for

measuring and evaluating the social effects of projects and policies. This includes looking at how they impact the quality of life in communities, employment rates, and social equity. Surveys and Data Collection: When it comes to understanding what communities need, what they prefer, or how policies affect social structures, surveys are key. They rely on statistical sampling and data analysis to uncover valuable insights. With so much data out there and research topics becoming more intricate, having a solid understanding of statistical methods is more important than ever. It's essential to realize that statistical analyses are vital for ensuring that research findings are both valid and clear. However, picking the right statistical analysis technique isn't always easy; it's a dynamic process shaped by the intricate relationships between various datasets and the subtleties of the research idea.

The importance of each methodological choice stands out when researchers face a multitude of options, especially since these choices can significantly impact the validity and reliability of their findings. Often, datasets come with a vast array of potential predictors, which is why techniques like principal components, partial least squares, and various forms

of regularized regression are applied to make the most of big data. The pace of innovation in statistical measurement and modelling is picking up speed. It's crucial to first grasp why each method works in practice, when it's appropriate to use it, and how to assess its statistical performance. Otherwise, diving into comparisons or discussions could lead to misleading applications. Plus, it's essential to use specialized software with care, as the effectiveness of many modelling techniques hinges on the tools you choose. Data can come from an experimental study known as a designed investigation or an observational study also referred to as a natural study or a collected-over-time data set that comprises measurements to be taken on the same experimental unit.

The hypothesis crafted for this analysis outlines the statistical methods and hypothesis testing techniques we'll be using. Discriminant analysis stands out as a practical and reliable way to categorize Nigerian students applying to universities in the country. It also provides a quantitative approach to predicting students' admission scores [1]. Given the sheer volume of data and the growing complexity of research topics, it's clear that a solid understanding of statistical methods is essential. It's important to recognize that statistical analyses are key to validating and clarifying research findings, which is a crucial part of this intricate process [2,3]. Selecting the right statistical analysis technique isn't a simple task; it's a dynamic journey shaped by the intricate relationships between various datasets and the subtleties of the research idea [4,5].

The Global Reporting Initiative (GRI) is a go-to for many organizations looking to measure their environmental and social impacts. By using GRI standards, they can gather important statistical metrics and indicators that highlight areas of concern and help set goals for sustainable procurement. On another note, when it comes to understanding how respondents perceive questions, cognitive interviewing techniques come into play [6,7,8]. These techniques are great for pretesting questions to make sure they're clear and understood as intended, helping to spot any issues with how questions might be interpreted. Lastly, reliability is key; it's all about ensuring that the questionnaire delivers stable and consistent results [9]. This often means running pilot tests and applying statistical measures like Cronbach's alpha to check for internal consistency.

Validity is all about whether a questionnaire measures what it's supposed to measure. There are a few key types to keep in mind, like content validity, construct validity, and criterion validity [10]. When it comes to choosing between open-ended and closed-ended questions, it affects the kind of data you gather. Closed-ended questions are a breeze to analyze statistically, while open-ended ones can give you deeper, more qualitative insights [11]. Now, let's talk about clarity and simplicity: your questions should be clear and easy to understand, steering clear of complicated language or jargon. The literature highlights the need to avoid double-barrelled questions (those that ask two things at once) and any vague wording [12].

2. RELATED LITERATURE

ANOVA, which stands for analysis of variance in one direction, is a statistical method used to test hypotheses. It helps us figure out whether the average values of three or more independent groups are the same. When comparing the averages of three distinct groups, the alternative hypothesis states that "all averages of groups A, B, and C are not the same," while the null hypothesis states that "all averages of groups A, B, and C are the same." Importantly, the alternative hypothesis states that "they are not the same" rather than "they are all different." Even though the three groups' averages may differ, the phrase "not the same" can also mean that two of the groups are the same and one is different.

If the null hypothesis is rejected, it's important to carry out a post-hoc analysis or multiple comparisons to dig into the differences among the various cases that are deemed "not the same" [14,15]. Plus, since the Bonferroni correction issue arises when the same hypothesis is tested multiple times, researchers need to keep an eye on the probability of a type 1 error, especially as they conduct more comparisons. When it comes to ANOVA, two related concepts are multivariate analysis of variance (MANOVA) and analysis of covariance (ANCOVA). ANCOVA helps us look at the true effect of an explanatory variable on a response variable while controlling for covariates that might influence the relationship between the two. On the other hand, MANOVA allows us to explore the relationships between two or more response and explanatory variables. If covariate is factored in MANOVA, the study refers to it as "multivariate analysis of covariance" (MANCOVA). This paper won't dive deeply into ANCOVA, MANOVA, MANCOVA, or the Bonferroni correction issue.

Analysis of variance (ANOVA) utilizing repeated measures with one or two factors involves the examination of one-factor repeated measurements. When data is collected three or more times, the ANOVA statistical hypothesis testing method is employed to determine whether the means of each measurement are identical. The phrase "repeated measurements" typically pertains to data collected multiple times over a period; however, it can also differ based on the context, such as in the operating room, post-anesthesia care unit, surgical critical care unit, and general ward. The singular factor that is consistently measured is time. The alternative hypothesis posits that "the means of the first, second, and third measurements are not equal," whereas the null hypothesis claims that "the means of the first, second, and third measurements are equal" when assessing the means of three repeated measurements. The alternative hypothesis for one-factor repeated-measures ANOVA, as previously discussed with one-way ANOVA, asserts that the means are "not identical." If the null hypothesis is rejected, it calls for a deeper examination of the specific cases that are "not identical." Repeated two-factor measurements ANOVA is a statistical technique employed to evaluate hypotheses based on data collected three or more times for each of two or more groups.

It's called "two-factor" because one factor represents the group, and the other factor indicates the time points that are often measured. In a two-factor repeated-measures ANOVA, three separate tests are conducted [16]. First, the analysis looks at the test variable without considering the group effect, focusing instead on how the means at each time point compare to see if they are consistent. Next, it shifts gears to examine how the test variable changes between groups, while ignoring the time point, to check if the means for each group are similar. Finally, the analysis digs into the patterns of change in the test variable between groups to see if these patterns hold steady across different time points, specifically looking at the interaction effects between the time factor and the group factor.

The primary goal of using a two-factor repeated-measures ANOVA in research design is to identify how patterns among groups change over different time intervals. The alternative hypothesis suggests that "the averages of the first, second, and third measurements differ," whereas the null hypothesis, which focuses solely on the time points, claims that "the averages of the first, second, and third measurements are the same" when looking at the averages from three repeated measurements across two groups. If the study finds reason to reject the null hypothesis, there is a need to dive deeper into the analysis to understand the differences among the cases that are considered "not identical". "The null hypothesis posits that "the means of the two groups are identical," while the alternative hypothesis asserts that "the means of the two groups differ." Additionally, the null hypothesis regarding the change patterns between the two groups states that "the change patterns remain consistent as time progresses from the first to the third point." Conversely, the alternative hypothesis claims that "the change patterns between the two groups vary as time advances from the first point to the third point." Should the null hypothesis be rejected, further investigation is necessary to identify the specific time points at which the change patterns of the two groups diverge. Analytical methods such as Fisher's exact test and the chi-squared test can be employed. The chi-squared test can be utilized for both independence and homogeneity assessments to determine whether two categorical variables are independent or homogeneous, respectively, as well as for goodness-of-fit tests to evaluate if the observed frequencies conform to a specified distribution [17].

When dealing with a small sample size, the Fisher's exact test serves as a statistical method to assess the relationship between two categorical variables within a 2×2 contingency table. The following conditions must be satisfied to perform the Fisher's exact test: 1) At least one cell should have an expected frequency of less than 5, 2) a 2×2 contingency table is necessary (indicating that both categorical variables must consist of two levels), and 3) the total sample size must be fewer than 40 participants. Once these three criteria are fulfilled, the Fisher's exact test can be executed. If any of these conditions are not met, the chi-square test should be utilized instead. In the context of correlation analysis, two key steps are involved: 1) calculating a correlation coefficient that

quantifies the strength of the linear relationship between the two variables, and 2) testing the significance of this correlation coefficient to determine if it is statistically different from zero [18].

3. METHODOLOGY

Researchers need to step up their research techniques when it comes to methodology. It's not just about slapping on some statistical techniques; it's about diving deep into the assumptions, theories, and pros and cons of each method. To truly navigate this intricate landscape, it's crucial to not only pick the right statistical tool but also to understand why it fits a particular scenario. So, just giving a rundown of statistical methods isn't going to cut it for researchers trying to make sense of this complex process.

Correlation Analysis, the goal is to dig into how closely related different variables are, such as how procurement practices might influence environmental performance. Some common techniques used here include Pearson correlation for data that follows a normal distribution and Spearman correlation for non-parametric data. On the other hand, Regression Analysis aims to predict or explain one variable based on another or even several variables. Techniques often employed in this area include logistic regression for categorical outcomes, as well as multiple and linear regression. Researchers need to step up their game and embrace a level of methodological sophistication that goes beyond just applying statistical techniques to handle this complexity effectively. It's crucial to have a solid understanding of each method's underlying assumptions, theories, strengths, and weaknesses [14]. This way, navigating the statistical landscape isn't just about picking a tool; it's about knowing why that tool is the right fit for the situation at hand. So, simply listing out statistical methods won't cut it when it comes to guiding researchers through this intricate process.

The logistic regression analysis encompasses the following steps: 1) assessment of the model's significance, 2) calculation of the odds ratios for each explanatory variable, 3) evaluation of the significance of these odds ratios, and 4) construction of the final logistic regression model. In the significance test of the logistic regression model, the alternative hypothesis posits that "at least one odds ratio differs from one," while the null hypothesis states that "all odds ratios are equal to one." If the null hypothesis is rejected, it can be concluded that "not all odds ratios can be considered statistically equal to one at the designated significance level." Consequently, the logistic regression model is deemed significant, indicating that at least one odds ratio is not equal to 1.

Factor Analysis and Principal Component Analysis (PCA) is objective is to reduce dimensionality by identifying underlying factors in environmental or social practices data.

When it comes to ANOVA and MANOVA, the goal is to compare the means of various groups. For instance, we might look at the environmental impact scores from different

procurement departments that are using various sustainable practices.

In Time Series Analysis, we focus on examining trends and changes over time, which is especially helpful for longitudinal data. This could involve tracking how waste reduction or energy consumption evolves after sustainable procurement policies are put into place.

Survival Analysis, on the other hand, aims to understand the timing of specific events, such as when sustainable practices are adopted. Here, we might evaluate how long it takes for different suppliers to comply with new social standards following policy changes.

4. RESULTS AND DISCUSSION

A statistical method known as the one-sample t-test is employed to assess whether the mean of a particular group is equal to or differs from a specified value. The null hypothesis posits that "the group's mean is equal to the specified value," while the alternative hypothesis asserts that "the group's mean is different from the specified value." If the null hypothesis is rejected, it indicates that "the group's mean cannot be statistically equal to the specified value at the established significance level."

Similarly, the two-sample t-test is a statistical hypothesis-testing method used to evaluate whether the means of two independent groups are identical or distinct. The null hypothesis states that "the means of group A and group B are identical," whereas the alternative hypothesis claims that "the means of group A and group B are different." If the null hypothesis is rejected, it can be concluded that "the means of group A and group B cannot be considered statistically identical at the significance level," indicating a difference between the two groups' averages.

The paired t-test is a statistical method used to determine whether the mean difference between two related groups, typically measured before and after an intervention, is statistically significant. This test is applicable when the same subjects are assessed at two different points in time, resulting in data from two dependent groups. Initially, a measurement is taken, followed by a second measurement after an intervention, which may include training, education, surgery, or medication. The primary objective of this analysis is to evaluate the effectiveness of the intervention by calculating the change for each subject between the two assessments. According to the null hypothesis, "the mean difference between the two dependent groups is equal to zero," while the alternative hypothesis posits that "the mean difference is not equal to zero." If the null hypothesis is rejected, it indicates that the average difference between the two groups is statistically significant, suggesting that the intervention implemented between the two measurements has had a meaningful effect.

In summary, linear regression analyses require adherence to five key assumptions: 1) the residuals should follow a normal distribution; 2) the residuals must exhibit homoscedasticity; 3) the residuals need to be independent; 4) the relationship

modelled must be linear; and 5) there should be no multicollinearity among the independent variables. If any of these assumptions are violated, the linear regression model is not appropriate for use. Therefore, the following steps should be undertaken to ensure that all five assumptions are met, thereby creating a reliable linear regression model: 1) develop a linear regression model; 2) assess whether the five assumptions hold true; and 3) modify the linear regression model as necessary.

5. CONCLUSION AND RECOMENDATIONS

Statistical models predict potential environmental changes and outcomes under various scenarios, supporting better conservation and resource management decision-making. They also present a structured questionnaire intended to act as a useful resource for researchers in exploring the different methodological choices available. Statistical practices provide the quantitative framework needed to integrate, monitor, and improve procurement with environmental and social standards. This approach drives transparency, aligns with regulatory requirements, and fosters sustainable, ethical sourcing. Literature highlights that procurement processes are complex and involve various uncertainties, such as supplier reliability and market volatility. Statistical tools enable organizations to make data-driven decisions by analyzing past data, forecasting trends, and comparing supplier performance. Techniques like time series analysis, regression models, and probability distributions help in understanding cost structures, demand patterns, and lead times. Statistical tools enable clear data interpretation through the use of charts, graphs, and statistical summaries, making complex data understandable for policymakers, stakeholders, and the general public. This is particularly relevant in both procurement reports and environmental impact assessments, where communicating findings effectively is crucial for buy-in and implementation.

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