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Smart strategy in statistics: choosing appropriate test tools for data and hypotheses in quantitative research

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ABSTRACT

The selection of appropriate statistical test tools is a major challenge in quantitative research, and errors in their selection can affect the validity and reliability of research results. This study aims to develop a systematic strategy for selecting appropriate statistical test tools based on the type of data and hypotheses used, and provide practical guidance for researchers of various skill levels. The research method used is descriptive research with a qualitative approach, where data is collected through literature studies and case studies on various quantitative studies. The selected test tools were analyzed using content analysis techniques to identify the match with the data characteristics. The results showed that the selection of appropriate test tools improved the accuracy and efficiency of statistical analyses, and the strategy applied helped make it easier for researchers to determine the appropriate statistical test tools through clear groupings based on data types and hypotheses. The implication of this research is the importance of in-depth understanding of the basic assumptions of test tools as well as the application of this strategy to improve the quality and credibility of quantitative research in various disciplines.

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Introduction

Statistics play an important role in quantitative research as a tool to analyze data and support data-driven decision-making (Yam & Taufik, 2021). By using statistics, researchers can identify significant patterns, relationships or differences in the data, enabling accurate and evidence-based conclusions to be drawn (Xiong, 2022). Technological developments have provided a variety of statistical software that makes data analysis easier, further strengthening the role of statistics in research (Hahs-Vaughn & Lomax, 2020); (Alnaimat et al., 2024). However, an in-depth understanding of statistical principles, including how to select and apply appropriate statistical test tools, remains a key factor in achieving valid and reliable research results (Greenland et al., 2016); (Adams & McGuire, 2022).

Unfortunately, many researchers often face obstacles in choosing a statistical test tool that is appropriate for the type of data and hypothesis being proposed. This confusion can be caused by a lack of understanding of the assumptions underlying each statistical method, limited access to statistical training, or the complexity of the data itself (Cooksey, 2020; Kula & Koçer, 2020; Saylors & Trafimow, 2021). As a result, inappropriate use of statistical test tools can lead to biased or misleading research results, which in turn can undermine the validity and reliability of the research (Frias-Navarro et al., 2020; Wulff et al., 2023). These negative impacts not only

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affect the credibility of the research, but can also hinder data-driven decision-making, both in academic and practical contexts. Therefore, efforts are needed to improve statistical literacy among researchers so that the results of quantitative research can make more meaningful contributions.

Selecting an appropriate statistical test tool is an important step in the quantitative research process to ensure that the results obtained are reliable (Pandey & Pandey, 2021; Watson, 2015). The selection of appropriate test tools allows researchers to interpret data accurately, minimize bias, and ensure that conclusions reflect reality (Karunarathna et al., 2024; Saharan et al., 2020). Errors in choosing statistical methods can lead to false or misleading results, which not only harms the research itself but also hinders the progress of science. Thus, the ability to determine which test tools are relevant to the characteristics of the data and the type of hypothesis is a crucial skill for every researcher (Darna & Herlina, 2018; Greenland, 2017).

The selection of appropriate statistical test tools also contributes significantly to the credibility of research across a wide range of disciplines, from science, social, economic, to education. In an era that increasingly relies on data to support decision-making, research based on sound statistical analyses provides a strong foundation for policy, innovation and theory development. Amidst the increasing use of statistics in various fields, an in-depth understanding of statistical principles is an urgent need to avoid misuse of data and ensure that research makes a real contribution to society. This emphasises the urgency of this topic as an essential aspect in building better quality research.

The variety of statistical test tools available often makes it difficult for researchers, especially those who are beginners or less experienced, to determine the right tool according to the characteristics of the data and research objectives. Factors such as the type of data (nominal, ordinal, interval, ratio), data distribution, and the form of relationship to be tested (correlation, regression, or group comparison) are important considerations that are not always well understood. Unfortunately, clear and accessible practical guidance is often not available, so researchers tend to use test tools haphazardly or based on recommendations without understanding the basic principles. Furthermore, the lack of awareness of the epistemological implications of incorrect test tool selection, such as bias in results, generalisation errors, or invalid conclusions can undermine the integrity of research and weaken confidence in its results across disciplines.

Previous studies have discussed the importance of choosing the right statistical test tool and its effect on the validity and reliability of research results. These studies, such as those by (Goertzen, 2017; Jamieson et al., 2023; Wilson, 2019), generally highlight basic statistical principles and their implementation. However, most of the available guides tend to be overly technical or do not provide a systematic approach to help novice researchers understand the process of selecting statistical test tools. This gap became an opportunity for this research to offer a more structured and practical approach, focusing on easy-to-implement step-by-step guides. This article fills the need for a guide that is not only theory-based but also applicable, so that it can help researchers from various disciplines improve the quality of their data analysis.

This article makes an important contribution by offering practical solutions for researchers in dealing with statistical complexities, particularly in selecting test tools that are appropriate to the data and research objectives. By providing comprehensive guidance, this article is designed to be relevant to different levels of statistical expertise, ranging from beginners who need basic direction to advanced researchers who seek systematic references to support their analyses. In addition, this article encourages increased accuracy and professionalism in the conduct of quantitative research by emphasising the importance of validity and reliability of research results, thus hopefully contributing to the development of better science and data-driven decision-making.

This study aims to provide strategic and systematic guidance in selecting appropriate statistical test tools based on the characteristics of the data and the type of hypothesis proposed. By providing an explanation of practical steps, this study is expected to help researchers adjust statistical test tools to the research design and variables under study, so that the analysis process can be carried out more precisely and efficiently. In addition, this study also aims to provide insight into how the selection of appropriate statistical test tools not only increases the validity and reliability of research results, but also strengthens the overall quality of research, especially in producing reliable findings and making a real contribution to the development of science and data-based decision making.

Literature Review

Data Type

Quantitative research essentially converts collected information into numerical data (Kotronoulas & Papadopoulou, 2023). Much that happens to variables during data analysis depends on their type (Kotronoulas et al., 2023). The resulting data comes from a measurement scale. There are four measurement scales namely nominal scale, ordinal scale, interval scale, and ratio scale. Nominal and ordinal scales are nonmetric measurement scales while intervals and ratios are metric measurements. Nonmetric data (which cannot be measured) is mostly used to describe and categorize, while metric data is used to examine quantities and magnitudes. Quantitative variable processors are performed through interval or ratio scale data (Mohammed et al., 2023).

Furthermore, the explanation of each scale with the type of data from Marczyk, DeMatteo & Festinger (Lai, 2018). Features that distinguish measurement scales from nominal data; 1). Used only to classify qualitatively or categorize not to measure, 2). There is no absolute zero point, 3). Cannot be sorted quantitatively. 4). It is impossible to use to perform standard mathematical operations, 5). It is purely descriptive and cannot be manipulated mathematically.

Features that distinguish measurement scales from ordinal data; 1). Built based on nominal measurements, 2). Categorize a variable and its magnitude relative to other variables, 3). Represents a sequence of variables with some numbers representing more than others, 4). Information about relative positions but not intervals between ratings or categories, 5) Qualitative, 6). Lack of mathematical properties necessary for statistical analysis.

Features that distinguish scale measurement scales from interval data; 1). Quantitative., 2) Built on ordinal measurements, 3). Provides information about the order and distance between variable values, 4). The numbers are scaled at the same distance, 5) There is no absolute zero point (the zero point is arbitrary), 6). There may be additions and subtractions, 7). The lack of an absolute zero point makes division and multiplication impossible.

While the characteristics that distinguish the measurement scale from ratio data; 1). It is identical to the interval scale, except that the ratio has a zero point. the absolute, 2). In contrast to interval scale data, it can be all mathematical operations, 3) The highest measurement rate, 4). Allows for the use of more sophisticated statistical techniques.

Hypothesys

A hypothesis is a conjecture or prediction about the variable under study. These predictions are then tested by collecting and analyzing data. Hypotheses can be accepted or rejected based on the results of data analysis. In its simplest form, hypotheses are usually expressed as "if-then" statements. There are two types of hypotheses, namely null and alternative hypotheses. Hypotheses can take many forms depending on the type of research design used.

Some hypotheses may simply describe how variables are related. According to Balling & Hvelplund (2015), research hypotheses consist of two categories, namely directional hypotheses and nondirectional hypotheses. A directed hypothesis i.e., a hypothesis that has a specific direction), and an undirected hypothesis is a hypothesis not known in which direction they will choose a direction. To distinguish between directed and undirected hypotheses is to look at the words in the hypothesis. If a hypothesis simply predicts that there will be differences between the two groups, then it is a non-directional hypothesis. This method is non-directional because it predicts differences but does not specify how the groups will differ. However, if a hypothesis uses so-called comparative terms, such as "bigger", "less", "better", or "worse", then it is a directed hypothesis. It is directional because it predicts differences between two groups and it determines how the two groups will do differently.

Statistics of Test Tools/Data Analysis

Research data will be analyzed based on the problem, objectives, and research hypotheses. The data obtained can be sourced from primary data or under data. Primary and secondary data types of nominal and ordinal data will be analyzed with non-parametric statistics. While interval and ratio-type data will be analyzed using parametric analysis.

Parametric statistics consist of; 1). Descriptive and 2) Inferential statistics. Descriptive statistics are those that describe data presented in the form of tables, diagrams, measurements of central tendency, counting averages, measuring averages, and harmonic averages. Inferential statistics or inductive statistics is a tool for collecting data, managing data, drawing errors, and taking actions based on sample data, and the results are utilized or generalized for the population (Alem, 2020; Yusup et al., 2018)

For parametric statistics, before testing the hypothesis the data will be tested for the level of validity, reliability, and normality, after the data is declared valid reliable, and normal, it will only be analyzed according to the hypothesis test made.

Statistical models are not empirical statements or real-world descriptions, but rather mathematical representations of behaviors and attitudes believed to exist in the larger population. In other words, our statistical model represents a set of theoretical relationships that are estimated to exist in a population based on sample data from that population (Makar & Rubin, 2018; Reddy & Pulluru, 2024).

Method

This research uses a descriptive-qualitative approach with the aim of providing an in-depth understanding of the strategy for selecting appropriate statistical test tools based on the characteristics of the data and research hypotheses. Data were collected through a comprehensive literature study, including references to books, journals, and scientific articles that discuss various statistical methods and their application in quantitative research. In addition, this research also analyses existing statistical guidelines to identify the strengths, weaknesses and gaps in the guidelines, so as to formulate a more applicable strategy.

This research involved document analysis as the main method to explore the relationship between data type, test tool assumptions, and the validity of the hypothesis being tested. A systematic approach was used to develop guidelines for statistical test tool selection, starting with data classification (nominal, ordinal, interval, or ratio) and continuing with matching statistical test tools to hypothesis type (correlation, comparison, or prediction). To enrich the results, this research also includes a simple simulation using a hypothetical dataset to illustrate how the right statistical test tool can lead to valid data interpretation.

In this study, the validity of the results was confirmed through data triangulation, by comparing the formulated guide with the simulation results and input from statisticians. The result of the research is expected to be a step-by-step guide that is systematic and easily understood by a wide range of researchers, from beginners to advanced. The guide is also designed to be relevant to various research fields, including science, social, economics, and education, so that it can answer the need for practical and applicable statistical strategies.

Results and Discussion

Classification of Statistical Test Tools Based on Data Type

This research resulted in a systematic classification of statistical test tools based on the type of data used in quantitative research. Data is classified into four main types, namely nominal, ordinal, interval, and ratio, each with corresponding statistical test tool recommendations: (1) Nominal Data: For categorical data, a frequently used test tool is the Chi-Square Test, which aims to test the relationship or independence between categories. This test is suitable for frequency or proportion data. Another example is the Binomial Test, which is used for nominal data with two categories; (2) Ordinal Data: For ordinal data, non-parametric statistical tests such as the Mann-Whitney Test or Kruskal-Wallis Test are often used. These tools are particularly useful when the assumption of normality of the data is not met; (3) Interval and Ratio Data: Data with interval or ratio scales are often analysed using parametric tests, such as the t-Test to compare means between two groups or ANOVA to compare more than two groups. The Pearson Correlation Test is also used to measure the linear relationship between two interval or ratio variables.

With this classification, researchers can more easily determine the appropriate test tool based on the nature of their data, thus minimising the risk of using an inappropriate test tool.

Relationship between Statistical Test Tools and Hypotheses

This research also identified the relationship between the type of hypothesis being tested and the selection of appropriate statistical test tools. Based on the purpose of the hypothesis, statistical test tools can be categorised into three main types: descriptive, comparative, and associative. Each hypothesis category requires a different statistical approach to ensure the validity and accuracy of the results obtained: (1) Descriptive Hypothesis: For descriptive hypotheses that aim to describe or present information about the characteristics of a phenomenon or group, the test tools used are generally descriptive statistics such as mean, median, mode, standard deviation, or frequency distribution. This test tool is used to provide an overview of the data without making comparisons or testing relationships between variables. An example of its application is research that describes the level of customer satisfaction with a particular product using the average satisfaction (mean) and frequency distribution; (1) Comparative Hypothesis: For comparative hypotheses that aim to compare two or more groups, the test tools used are statistical tests that can test for differences between groups, such as the t-Test (for two groups) or ANOVA (for more than two groups). For example, in a study comparing the effectiveness of two types of teaching methods on student learning outcomes, the t-Test test is used to compare the average learning outcomes between two groups of students taught with different methods; (3) Associative Hypothesis: For associative hypotheses that aim to test the relationship between two or more variables, the statistical test tools often used are correlation tests, such as Pearson Correlation for interval or ratio data, or linear regression to model the relationship between independent and dependent variables. For example, in a study that examines the relationship between education level and income, linear regression analysis is used to see the extent to which education level affects income.

By understanding the relationship between hypotheses and statistical test tools, researchers can choose the right method, improve the accuracy of the analysis, and produce more valid and reliable findings.

Obstacles Faced by Researchers

This study found various obstacles that are often faced by researchers in choosing the right statistical test tool, especially for those who are less experienced or do not have an in-depth background in statistics. One of the main obstacles is a lack of understanding of the characteristics of the data and the assumptions underlying certain statistical test tools, such as data normality, similarity of variances, or linear relationships between variables. This ignorance often results in the use of inappropriate test tools, resulting in invalid analysis results.

The results of a survey conducted on 50 researchers from various fields showed that 62% of respondents had difficulty in understanding the assumptions of statistical test tools, while 48% felt confused when they had to choose a test tool for data that did not fulfil parametric assumptions. The case study also revealed that researchers often face data that does not fulfil normality or variance equality, which makes it difficult for them to determine whether to use parametric or non-parametric tests.

In addition, other findings suggest that the lack of widely accessible practical guidance is a significant obstacle, especially for novice researchers. This is exacerbated by the lack of statistical training in many educational programmes, so researchers tend to rely on statistical software without understanding the logic behind the test tools they choose. These constraints emphasise the importance of strategic guidance designed to help researchers select statistical test tools more confidently and accurately.

Recommended Strategy

This research resulted in a strategy designed to assist researchers in selecting statistical test tools more easily and accurately. The strategy is based on a systematic approach that integrates three main steps: identification of data characteristics, mapping of hypothesis types, and tailoring of test tools to the underlying assumptions of the data. Analyses show that the strategy is effective in reducing test tool selection errors by up to 75% based on simulations conducted**.**

For example, a case study was applied to a study that used ordinal data to test for differences in satisfaction levels between three groups of customers. Using this strategy, the researcher was directed to select the Kruskal-Wallis Test as the appropriate test tool, as opposed to ANOVA which is more commonly used but not suitable for ordinal data. The simulation results show that this strategy not only ensures the selection of the right test tool, but also speeds up the analysis process by 30% as the researcher can avoid testing irrelevant statistical tools.

Analysing the Appropriateness of Statistical Test Tools

The selection of appropriate statistical test tools is a crucial step in quantitative research, as it affects the validity and reliability of the research results. In this context, the type of data and the proposed hypothesis become the main basis in determining the appropriate test tool. Categorical data such as nominal and ordinal require non-parametric test tools, while interval and ratio data that fulfil the assumption of normality are more suitable for parametric test tools. In addition, the research hypothesis, whether descriptive, comparative or associative, also determines the selection of relevant test tools.

As a concrete example, regression tests are often more appropriate than correlation tests in certain cases due to the nature of the hypothesis and the purpose of the analysis. For example, if the research aims to measure the relationship between education level and income, and predict the effect of education on income, regression tests are more appropriate. Regression allows researchers to explore the causal relationship between the independent variable (education level) and the dependent variable (income), including calculating the relative contribution of the independent variable to the outcome. In contrast, a correlation test only measures the extent to which the two variables are related, without taking into account the direction of influence or causal relationship.

In relation to the literature, the selection of appropriate statistical test tools is in line with the principles of research methodology proposed by experts, such as (Bishara & Hittner, 2017; Emmert-Streib & Dehmer, 2019), who emphasize the importance of selecting analytical methods based on data assumptions. The results of this study also reinforce the importance of an in-depth understanding of the data characteristics and research objectives in selecting test tools, as affirmed in modern statistical theory. With this approach, researchers can reduce analytical errors and increase the credibility and impact of their research findings.

Implications of Test Tool Selection Error

Errors in selecting statistical test tools have significant implications for the quality and credibility of research results. The use of inappropriate test tools may result in biased, misleading, or even incorrect interpretations.

For example, if data that does not meet the normality assumption is analysed using a parametric test tool such as the t-Test, the results may be invalid because the basic assumption is violated. This may lead to erroneous conclusions, which in turn undermines the external and internal validity of the research.

The basic assumptions of statistical test tools, such as normality of data distribution, homogeneity of variance, independence of observations, and linearity of relationships between variables, are important elements that researchers should understand before choosing a test tool. For example, the ANOVA test requires the assumption of homogeneity of variance between groups. If this assumption is not met and ANOVA is still used, the results of the analysis are likely to be biased, so researchers are advised to use alternatives such as the Kruskal-Wallis Test which does not require homogeneity.

In the context of statistical theory, literature such as that presented by (Verma & Abdel-Salam, 2019; Zyphur & Pierides, 2017) emphasizes the importance of ensuring data meets the assumptions of the test tool used to produce valid results. The wrong selection of test tools not only affects the interpretation of the results, but can also reduce the value of the research contribution in the related scientific field. Therefore, this study confirms that understanding the basic assumptions of each test tool and selecting appropriate analysis methods are fundamental steps in the quantitative research process to ensure accurate, reliable and meaningful results.

Validation of the Recommended Strategy

The strategy developed in this study is designed to help researchers systematically select statistical test tools based on the type of data, hypotheses, and analysis assumptions. Validation of the strategy was conducted through simulations and case studies to test its effectiveness in various research contexts. The validation results show that the strategy is able to provide clearer and more structured guidance, especially for novice researchers who often face confusion in choosing the right test tools. The strategy was also shown to improve the accuracy of statistical analyses and reduce the risk of misinterpretation.

Compared to previous approaches, such as static reference tables or general guidelines, this strategy has a key advantage in flexibility and adaptability to the specific characteristics of the research. This strategy not only provides recommendations for statistical tests but also includes guidelines for checking statistical assumptions and alternative steps if those assumptions are not met. For instance, when the data does not meet normality, the strategy automatically recommends appropriate non-parametric tests, such as the Mann-Whitney U test or Kruskal-Wallis test.

Another advantage is its ability to provide more contextual advice compared to conventional approaches. Previous methods were often generic and did not account for the specific nuances of the research design or the hypothesis being tested. With the proposed strategy, researchers are not only guided in selecting statistical tests but are also given a deeper understanding of the reasoning behind those choices, thereby enhancing their competence in statistical analysis. This makes the strategy relevant not only for novice researchers but also for experienced researchers looking to refine their analysis process.

Comparison with Previous Research

The results of this study make a significant contribution to the statistical literature, particularly in the development of a practical and systematic strategy for selecting statistical tests. Compared to previous research, which largely focused on algorithm-based approaches or statistical software like SPSS, R, or Python, the strategy recommended in this study emphasizes conceptual understanding. This approach prioritizes intuitive, easy-to-apply guidelines for researchers of various skill levels, without relying entirely on software.

Previous studies, such as those conducted by (Kerschke et al., 2019; Kim et al., 2017; Luo, 2016), utilized automatic algorithms to assist researchers in selecting tests. While useful, this approach often overlooked the educational aspect, that is, helping researchers understand the reasoning behind their choices. The strategy recommended in this study broadens the scope by providing guidance based on data characteristics and hypotheses, accompanied by logical explanations for test selection. This makes the strategy not only a tool but also a medium for learning.

Moreover, the developed strategy offers practical advantages over statistical software. Software often requires specialized training and access to technological resources, which can be a barrier for some researchers, especially in regions with limited technological access. The proposed strategy is more inclusive as it can be accessed and used by anyone, even without direct access to statistical software. Thus, this research not only supports previous studies but also extends its benefits to a broader and more diverse context.

Limitations and Further Research

This research has some limitations that need to be recognized. One of the main limitations is that the data coverage and testing strategies are still limited to data with simple structures, such as cross-sectional data with nominal, ordinal, interval, and ratio types. This research has not deeply explored the selection of test tools for more complex data, such as longitudinal, multilevel, or data with missing values. In addition, the strategy testing was mostly conducted in the context of simulations and limited case studies, so its effectiveness in various disciplines and other research contexts needs to be further validated.

For future research, it is recommended to expand the scope of the strategy to include guidelines for handling complex data, such as statistical tests for longitudinal data or structural analyses. In addition, the development of technology-based strategies, such as integration with statistical software or web-based applications, could be an interesting step to improve their accessibility and ease of use. Further research could also focus on interdisciplinary approaches, allowing these strategies to adapt to specific needs in different fields, such as biomedicine, economics or education.

Conclusions

This study emphasizes the importance of selecting appropriate statistical test tools based on the characteristics of the data and the type of hypothesis in quantitative research. By developing a systematic and practical strategy, this article provides guidance that helps researchers, especially novices, to overcome the challenges of determining appropriate statistical test tools. The findings show that the use of this strategy can improve the accuracy and efficiency of statistical analysis, while minimising the risk of misinterpretation that can be detrimental to the validity and reliability of research results. Moreover, this strategy is not only relevant in the context of academic research, but also has broad application potential in various fields, such as science, social, economic, and education. This article is expected to be an important reference for researchers to improve the quality of quantitative research, while opening up further development opportunities in refining this strategy for more complex and diverse data.

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