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EXPLORING THE METHODOLOGICAL FRAMEWORK AND IMPORTANCE OF STATISTICAL ANALYSIS IN QUANTITATIVE MANAGEMENT RESEARCH

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Purpose: This paper aims to examine the key stages and methodological considerations of quantitative research in management sciences. It focuses on how theoretical constructs are translated into measurable variables and investigates the effectiveness and challenges of operationalisation, hypothesis testing, and statistical interpretation.
Design/methodology/approach: The study adopts a structured, methodological approach to quantitative research, emphasizing statistical techniques such as correlation and regression analysis. It begins with a literature review, followed by hypothesis formulation, data collection, and statistical testing. The scope encompasses both theoretical underpinnings and empirical practices commonly applied in management research.
Findings: The research reveals that while quantitative methods enable the construction and validation of complex models, they also encounter challenges related to multidimensional constructs, sampling limitations, and the risk of statistical errors. Descriptive statistics provide a necessary foundation, but it is the application of inferential methods and careful hypothesis testing that ultimately determine the reliability of research conclusions. The analysis highlights the critical role of aligning research objectives with statistical techniques and managing risks associated with Type I and Type II errors.
Research limitations/implications: Limitations include potential sampling bias, issues of representativeness, and the constraints of data collection methods. Future research is encouraged to explore more diverse sampling strategies and integrate longitudinal studies to capture dynamic changes over time.
Practical implications: The study provides guidance for researchers and practitioners on enhancing the accuracy and validity of quantitative analysis. It offers methodological insights that can improve the design of data-driven decision-making processes in management and policy formulation.
Social implications: Improved methodological rigor in management research contributes to more effective policy-making and organizational practices, thereby supporting evidence-based strategies with broader societal impact.
Originality/value: This paper contributes to the literature by offering a critical, structured examination of the quantitative research process in management science. It provides value to

early-career researchers, academics, and practitioners seeking to improve the quality and applicability of empirical research.
Keywords: Quantitative research, hypothesis testing, operationalisation, statistical analysis, management science.
Category of the paper: Research paper.

1. Introduction

W. Dyduch (2016) highlights that the key distinction between qualitative and quantitative research lies in their starting points and methodological treatment. Qualitative research begins with data and information collection, treating findings as "texts", while quantitative research starts with theoretical foundations, applying specific theories and corresponding research methods, treating findings as "numbers". The primary divergence, however, is rooted in the research procedures.

Adopting theories from related disciplines, known as theoretical triangulation, can enrich the research; however, for dissertation work, it is advisable to remain within the boundaries of the primary discipline. Statistical analysis is a critical component of quantitative research, with its main purpose being to generalise the analysed information and maximise the insights drawn from collected data. This conceptualisation frames statistical analysis as a discipline of inference, utilising both primary and synthesized data to draw conclusions through probability theory and inductive reasoning.

A vital element of the research process is the operationalisation of the research problem, which involves thorough preparation. This preparation includes defining the target research community, choosing appropriate research methods and techniques, and selecting relevant indicators and variables.

This paper explores the intricate nature of conducting quantitative research with an emphasis on statistical analysis within management science. The discussion sheds light on the steps and considerations necessary to execute rigorous research that effectively translates theoretical constructs into measurable variables, allowing for deeper insights and robust findings.

The author emphasizes the need to conduct research in the described scope in order to provide guidance to researchers and practitioners on how to increase the accuracy and validity of quantitative analysis, which in turn can improve the design of data-driven decision-making processes in management.

2. Quantitative Research Operationalisation in Management Studies

Operationalisation is an essential part of the research process, with the decisions made during this stage directly influencing the outcomes of the research.

The procedure for conducting quantitative research can be outlined through the following steps (Babbie, 2007):

- analysis of the literature on the topic,
- identifying a research gap,
- development of a research model,
- formulation of research hypotheses,
- data collection – conducting the actual research,
- data analysis,
- drawing research conclusions – acceptance or rejection of hypotheses,
- creation of a new model,
- enriching theory through the research findings – contributing to the discipline's body of knowledge,
- highlighting the limitations of the conducted research,
- justification for further research.

The necessity of a research procedure arises from the nature of phenomena encountered in the management of organisations. According to E. Babbie (2007), these phenomena cannot be observed directly (where direct observations involve attributes of an object that can be seen straightforwardly) or indirectly (where indirect observations are based on examining attributes associated with the phenomenon that are of particular interest to the researcher). Constructs, however, represent theoretical interpretations of phenomena that are neither directly nor indirectly observable. In management science, this involves working with the development of a theoretical construct (Babbie, 2007).

A theoretical construct may have multiple dimensions, understood as groupings of similar attributes that are distinguishable from other groupings (Babbie, 2007).

M.H. Moriss and D.F. Kuratko (Czakon, 2016) demonstrated that organisational entrepreneurship is a construct comprising three dimensions: innovation, proactiveness, and risk-taking. Each of these dimensions can be represented by one or more attributes (Czakon, 2016). By defining and representing the dimensions of the construct, researchers can better grasp the complexity and multidimensionality of the phenomenon being studied (Babbie, 2007).

According to K.E. Weick (Dyduch, 2016), theory building involves the creation and subsequent testing of a series of statements that explain or predict a given phenomenon, which are then verified through specific examples. The objective of empirical research is to test these theses, which pertain to the relationships between variables within a theoretical model (Dzwigol, Kwilinski, Lyulyov, Pimonenko, 2024). Achieving this objective involves observing all independent and dependent measures within the created theoretical model that is to be tested. Empirical research aimed at testing a theoretical model can be exploratory (attempting to understand a previously unstudied phenomenon), descriptive, or explanatory (Babbie, 2007).

A literature review is conducted by examining journals and books published in recent years (ideally post-2000, with exceptions for classic works) in the relevant discipline (Babbie, 2007). Preferably, these sources should include journals from the so-called Philadelphia list, which features titles that have undergone rigorous evaluation and are indexed in the Institute for Scientific Information databases (Babbie, 2007). In Poland, the list of scored journals provided by the Ministry of Science and Higher Education serves as a suitable basis for such analyses. Professional journals, websites, and similar sources should be avoided as primary theoretical references in dissertations (Babbie, 2007). Literature analysis can reveal conclusions about certain phenomena; for instance, while entrepreneurship and efficiency are extensively covered in the literature, their combined analysis is less common, representing a research gap that quantitative researchers may seek to address (Babbie, 2007).

Designing a study necessitates the creation of a research model that describes the relationships between the variables under analysis. It is crucial to identify which variables are independent and which are dependent. In more complex models, contextual, mediating, or moderating variables may also be included (Babbie, 2007). The research model serves as a foundation for formulating research hypotheses—statements that articulate the relationships outlined in the model. Careful attention should be given to the wording of hypotheses, ensuring that multiple variables are not combined within a single hypothesis. Relationships between variables can be tested using methods such as correlation analysis, while the analysis of influence requires at least regression analysis (Babbie, 2007).

Once hypotheses are established, the next step is to collect data to describe the variables (Babbie, 2007). When transitioning from theory to empirical research, theorists and researchers must transform concepts into constructs that can be represented by variables. A concept does not necessarily need to be measured directly (Babbie, 2007).

According to M. Esterby-Smith, R. Thorpe, and A. Lowe (2002), there are several primary methods for data collection, which include interviews (commonly used in market research (Esterby-Smith, Thorpe, Lowe, 2002)), questionnaires (widely employed in quantitative research (Babbie, 2007)), tests (to gauge individuals' opinions on specific issues (Babbie, 2007)), and observations (primarily used in qualitative research but can be standardised and processed quantitatively, similar to questionnaire data (Babbie, 2007)).

The most frequently used techniques in quantitative research are survey questionnaires and interviews, aimed at collecting information about a particular group or population. When the population size ranges from a few dozen to several hundred subjects, it is possible to survey the entire group. For larger populations, a representative sample must be chosen, using either random or purposive sampling methods—or a combination of both for their respective advantages. Due to the typically low return rate of questionnaires, random sampling is not always feasible. Questionnaires may be distributed by post, allowing for a swift and reactive survey process. Additionally, the distribution should target a relatively homogeneous research group (Babbie, 2007).

Once the completed questionnaires are gathered (ensuring only fully returned questionnaires are used), the data is entered as variables into a spreadsheet for analysis. Depending on the research instrument, three types of variables can be obtained: qualitative (measured on a nominal scale), ordinal (measured on an ordinal scale), and quantitative (measured on an interval scale). The primary aim of employing these methods is to summarise the dataset and draw fundamental conclusions and generalisations from it (Babbie, 2007).

In quantitative analysis, descriptive statistical methods are often the initial and essential step. Commonly used techniques include tabular data description, graphical data presentation, and the calculation of distribution measures (such as measures of central tendency—mean, median, mode—and measures of variation—standard deviation, variance) (Babbie, 2007).

A frequently applied test in quantitative research is the chi-square test of concordance, used to test hypotheses where the test statistic follows a suitable distribution of a random variable (Babbie, 2007).

To assess the degree of relationship between two variables, correlation analysis can be utilised. The Pearson correlation coefficient (r) is the most widely used measure to determine the level of linear dependence between random variables. While correlation analysis indicates the relationship between variables, it does not imply causality (Babbie, 2007).

Regression analysis is employed to examine the simultaneous relationships between multiple variables. It allows researchers to explore the connections among different quantities in the dataset and use this knowledge to predict unknown values based on known quantities. In practice, regression analysis involves constructing a regression model—a function that describes how the expected value of the dependent variable relies on the independent variables. Multiple regression refers to a regression analysis with more than one explanatory variable. For better alignment of the function with the studied variables' relationships, curve fitting analysis may be conducted (Babbie, 2007).

It is worth noting that the outlined research procedure is not a perfect solution for operationalising a phenomenon within management sciences, i.e., converting data to ready variables for subsequent statistical processing. Certain limitations associated with the proposed methodology can also be highlighted. Firstly, given the time constraints, the proposed studies have a cross-sectional, statistical nature, unlike longitudinal studies that analyse the dynamics of the phenomenon over time. They offer a snapshot of the organisations examined and a single-time reflection of the phenomena present at that specific point. Secondly, due to challenges in accessing a sufficiently large group of respondents to form a representative research sample, surveys typically rely on random selection and are often limited to the scope of a single country. Lastly, the use of survey questionnaires results in numerical data that represent managerial attitudes and opinions, rather than directly measuring the phenomenon under study (Babbie, 2007).

An example of quantitative research operationalisation in management studies can be found in the works of notable researchers who have explored various aspects of the field. For instance, studies on sustainable development management have been conducted by prominent authors who provide valuable insights into how organisations integrate sustainability into their strategic frameworks (Kwilinski, 2023; Kwilinski, Trushkina, 2023; Kwilinski, Lyulyov, Pimonenko, 2024; Kwilinski, Lyulyov, Pimonenko, Pudryk, 2024; Kwilinski, Rebilas, Lazarenko, Stezhko, Dzwigol, 2023; Kwilinski, Abazov, Domaratskiy, Boiko, 2024; Lyulyov, Pimonenko, Chen, Kwilinski, 2023; Lyulyov, Chygryn, Pimonenko, Zimbroff, Makiela, Kwilinski, 2024; Mlaabdal, Kulish, Kwilinski, Chygryn, 2024; Morris, Kuratko, 2002; Weick, 1999; Zimbroff, 2023; Zimbroff, Jorgensen, Callan, 2021; Kwilinski, Vysochyna, 2024). In the area of digitalisation management, researchers have investigated the operationalisation of data collection and analysis to understand the influence of digital transformation on organisational structures and processes (Lee, Lee, Cha, 2023; Kwilinski, Kardas, 2023; Lyulyov, Pimonenko, Infante-Moro, Kwilinski, 2024; Kwilinski, Lyulyov, Pimonenko, 2023, 2024; Lyulyov, Pimonenko, Chen, Kwilinski, Yana, 2024; Kwilinski, Szczepańska-Woszczyna, Lyulyov, Pimonenko, 2024; Kwilinski, 2023, 2024a, 2024b; Kwilinski, Merritt, Wróblewski, 2024; Kwilinski, Pudryk, Eiba, Bourntoulis, 2024; Dzwigol, Kwilinski, Lyulyov, Pimonenko, 2024). Furthermore, entrepreneurship has been a focal point for scholars examining how entrepreneurial attitudes and behaviours can be quantitatively assessed to identify patterns and impacts within different business environments (Dzwigol, 2024, 2023a, 2023b, 2020, 2021; Kwilinski, Trushkina, Birca, Shkrygun, 2023; Zimbroff, Jorgensen, 2019; Zimbroff, Schlake, Anderson-Knott, Eberle, Vigna, 2017; Zane, Zimbroff, 2018). These studies exemplify the application of rigorous quantitative methodologies to various themes within management research.

3. Statistical Analysis

Many sciences, including management sciences, involve the observation of surrounding realities or, through experimentation, the verification of theories under study. In management sciences, such research typically pertains to the realities within existing enterprises and their various areas of activity (systems, subsystems). Considering that an enterprise comprises a collection of diverse elements operating together to achieve various functions, objectives, and requirements, a quantitative analysis often necessitates the collection, analysis, and interpretation of a substantial amount of data. To enable such analysis, an appropriate set of tools, grounded in statistical knowledge, is essential (Dźwigoł, 2018).

The term "statistics" originates from the Italian word *stato*, meaning "state". Related terms include *statista*, referring to a person involved with state affairs, and *statisticus*, derived from Latin, signifying a collection of information useful to "statisticians." Initially, "statistician" referred to tabular data collections about the state, a practice dating back to 16th-century Italy, which later spread to countries such as France, the Netherlands, and Germany. Notably, the practice of conducting population censuses and asset assessments can be traced back to ancient Egypt (Hald, 1990).

Statistical inference moves from the data, or sample, to the broader population. The population, seen as a kind of universe, can be defined as the total set of all measurement outcomes or elements that are of interest to the researcher. A sample, in contrast, is a subset of the population chosen according to criteria set by the researcher. The sample should accurately represent the population, with selection conducted randomly so that every possible sample of n elements has an equal chance of being chosen. Such a sample is referred to as a simple random sample. This sample is then studied, and the findings are generalised to the wider population.

A critical aspect of conducting statistical research is the systematisation of results, which should be based on measurement scales. This systematisation involves assigning numbers or symbols to objects (phenomena, etc.) according to established rules and principles (Bielecka, 2005).

This process is referred to as a measurement scale. Measurement scales are classified in a hierarchy from "weakest" to "strongest" (Stevens, 1946):

- nominal scale,
- ordinal scale,
- interval scale,
- ratio scale.

The nominal scale is the weakest measurement scale, where labels (groups, classes) are used instead of names. For instance, if the dataset comprises objects of different colours (e.g., yellow, green, red), each group of objects sharing the same colour is assigned the same number. Yellow objects may be labelled as 1, green as 2, and red as 3. These numbers merely replace the name of the group to which an object belongs. The nominal measurement scale is applied when the resulting observations are qualitative rather than quantitative in nature (Dźwigoł, 2018).

The ordinal scale, on the other hand, is used to rank objects of observation according to their size or importance. If a researcher evaluates three products based on a specific criterion, they can rate these products using the numbers 1 to 3. The researcher assigns these digits to indicate which product is the best and which is the worst (with 1 representing the best and 3 the worst). However, this scale does not inform the researcher by how much one product surpasses another.

An interval scale allows for the assignment of differences between observation results. The observations (expressed in appropriate units) are placed within a numerical interval, where the distance between objects corresponds to the difference in their observation results.

These scales are used for characterisation. For example, if the average value of the Dow Jones index was 3001 points in January 2012 and 2980 points in November 2012, the interval scale allows us to note that the difference between January and November was 21 points (Dźwigoł, 2018).

The quotient scale is the strongest of the scales mentioned. Unlike the interval scale, which measures distances between two observed objects, the quotient scale deals with distance quotients. This means that the relationships between two values (their differences or quotients) have a real-world interpretation. Examples of measurements on the quotient scale include wages (e.g., a salary of $100,000 is twice that of $50,000), prices in gold, electrical voltage, and inflation. The quotient scale includes an absolute zero, signifying that any quantity expressed on this scale can be represented as a multiple of another.

Once the measurement scale for a statistical survey is defined, the subsequent steps of statistical calculations can proceed, aiming to generalise the results from the research sample to the broader population. This process is encompassed within statistical inference, a branch of statistics that, beyond generalising study results, also estimates the errors involved in such generalisation. Reliable results require a proper approach to the analysis and interpretation of research findings, which means basing research on relevant empirical data, formulating appropriate research hypotheses, and verifying them.

To discuss the verification of statistical hypotheses, the basic concepts in this area must be defined. A statistical hypothesis is a conjecture made by the researcher about a population. Hypothesis verification is the process of determining whether the hypothesis posited by the researcher is true, based on results from a random sample (Dźwigoł, 2018).

There are several types of hypotheses, the most important being:

- null hypothesis,
- alternative hypothesis.

During the research process, the researcher proposes a hypothesis to be tested, known as the null hypothesis (denoted as H0). This hypothesis is assumed to be true until sufficient statistical evidence is provided to reject it in favour of an alternative. The alternative hypothesis, denoted as Hj or H1, opposes the null hypothesis by assigning population parameter values that differ from those proposed by the null hypothesis (Aczel, 2000). The null hypothesis and the alternative hypothesis together form a complementary pair covering all possible parameter values. An example of such a pair is:

$$H\_0: \mu = 50, H\_1: \mu \neq 50 \quad (1)$$

Here, the null hypothesis states that the mean of the population is 50, while the alternative hypothesis suggests otherwise. Only one of these hypotheses can be true. The null hypothesis reflects the researcher's assumption about a phenomenon or situation that they wish to test, determining whether this belief holds or should be rejected in favour of the alternative hypothesis.

The process of testing hypotheses set by the researcher is known as hypothesis testing or test statistics. This testing is conducted based on a test sample, from which the mean value derived from observations is used to determine whether the null hypothesis should be rejected. To make this decision, a predefined rule, known as the decision rule of the statistical hypothesis test, must be followed. This involves checking whether the result obtained from the random sample falls within the rejection region (Aczel, 2000). The rejection region is defined as a range of values such that, if the test result falls within this range, the null hypothesis (H0) should be rejected. For example, in the hypothesis (H0 = 50), a sample decision rule might state: "reject the null hypothesis if and only if x is not less than 45 or greater than 55" (Dźwigoł, 2018).

An important aspect of hypothesis testing is the potential for errors. Consider a courtroom scenario involving a murder trial. In this analogy, H0 could represent the hypothesis that the accused is innocent (assumed true unless proven otherwise), while H1 represents the hypothesis that the accused is guilty. The judge, who is unaware of the actual state of affairs, must decide between finding the accused innocent (not rejecting H0) or guilty (rejecting H0). The outcomes are as follows:

- If the judge rejects H0 (finding the accused guilty) when the accused is actually innocent, a Type I error, or "false positive", has been made.
- If the judge accepts H0 (finding the accused innocent) and the accused is indeed innocent, the decision is correct.
- If the judge accepts H0 (finding the accused innocent) but the accused is actually guilty, a Type II error, or "false negative", has been made.

These scenarios can be represented in Table 1.

Table 1.
Types of errors in hypothesis testing

Actual state **The decision to adopt one of the hypotheses**	**Ho**	**H1**
Ho	The right decision	Error of the second kind
H1	Error of the first kind	The right decision

Source: own study (Dźwigoł, 2018).

A Type I error occurs when the researcher rejects the null hypothesis (H0) when it is true. A Type II error occurs when the null hypothesis is not rejected even though it is false.

The probabilities of these errors are also significant. Let us denote the probability of making a Type I error as α (the significance level) and the probability of making a Type II error as β. For instance, in the hypothesis H0 = 50, if we do not know the true mean of the population and the mean is indeed 50 but we decide to reject H0, we commit a Type I error. Conversely, if H0 is not rejected and the true mean differs from 50, a Type II error is made.

Researchers should align the null hypothesis (H0) with prevailing assumptions and control primarily for the probability of a Type I error. Standard practice is to set the probability of a Type I error, α, at 0.05 or 0.01.

The probabilities α and β are relative probabilities. Probability α is the likelihood that the null hypothesis will be rejected after sampling and calculation, assuming it is true. Probability β is the likelihood that the null hypothesis will not be rejected after sampling and calculation, assuming it is false (Aczel, 2000). The relationships are as follows (Dźwigoł, 2018):

$$\alpha = P(H0 \text{ "rejected } | \text{ H0 is true"}) \tag{2}$$

$$\beta = P(H0 \text{ "not rejected } | \text{ H0 is false"}) \tag{3}$$

The decision made by the researcher regarding the acceptance or rejection of a hypothesis is part of the process of statistical inference. If the researcher decides not to reject the null hypothesis, it indicates insufficient evidence to reject it. Conversely, if the null hypothesis is rejected, it indicates strong conviction that the hypothesis should be discarded. Thus, a decision not to reject H0 leads to a tentative (weak) conclusion, whereas rejecting H0 leads to a firm conclusion.

The findings of this study reaffirm the critical role of statistical analysis in the effective execution of quantitative research in management science. The operationalisation of constructs—particularly those that are abstract and multidimensional—remains a methodological challenge that requires precise design and thoughtful interpretation. Despite advances in data processing tools and statistical techniques, the process of converting theoretical constructs into measurable indicators is still prone to oversimplification, which may compromise the richness of the original phenomena under investigation.

One of the central contributions of this study lies in the alignment of statistical methods with research objectives. While descriptive statistics offer foundational insights, the reliability and validity of findings largely depend on the careful application of inferential techniques such as correlation and regression analysis. These tools not only test hypotheses but also allow researchers to identify patterns, forecast trends, and assess relationships between variables within theoretical models.

Moreover, the discussion highlights the interplay between methodological precision and practical feasibility. The limitations identified—such as sampling biases, low response rates, and the constraints of cross-sectional studies—underscore the necessity of balancing methodological rigor with accessibility and cost-effectiveness in data collection. Integrating longitudinal approaches and expanding the diversity of samples could significantly enhance the robustness of future research.

The study also draws attention to the epistemological implications of statistical errors. Type I and Type II errors, often treated as purely technical concerns, reflect deeper issues of inference, decision-making, and risk management in empirical research. These errors remind us that statistical analysis, while objective in form, is inherently interpretive and dependent on the researcher's assumptions, thresholds, and theoretical orientations.

Finally, the broader implications of the findings suggest that quantitative methods—when carefully applied—can bridge theoretical constructs and managerial realities. However, this requires not only technical proficiency but also a philosophical awareness of the assumptions embedded in statistical practices. This reinforces the argument that methodological transparency, rigorous model specification, and theoretical grounding are indispensable to high-quality research in management science.

4. Conclusion

The application of research methods and techniques depends on the nature of the research, the construction of the research model, the formulated hypotheses, and the research sample. It is the researcher's responsibility to select methods that are appropriate for the planned study, bearing in mind the wide array of available options (Huizingh, 2007; Gatnar, 2000; Kolonko, 1980). Quantitative research, despite its widespread use in management sciences, has both proponents and critics who emphasise the strengths of their chosen approach, often overlooking alternative research perspectives (Babbie, 2007).

Today, statistics has evolved beyond merely collecting information for state purposes; it now focuses on methods of data collection, analysis, presentation, and practical application. Statistics is now recognised as a field of study that can encompass nearly all aspects of human activity. The gathering of numerical information, referred to as data, poses challenges in terms of analysis, synthesis, and multifaceted presentation. This necessity has led to the development of statistical tools, the most prominent of which is statistical analysis.

Quantitative research is an empirical approach involving the measurement of specific variables in a quantitative manner using suitable instruments. It is employed when both the research problem and the resulting findings can be expressed quantitatively (Niemczyk, 2011; Dźwigoł, 2018).

Further research could focus on enhancing the integration of quantitative methods with qualitative insights to provide a more comprehensive analysis of management phenomena. Additionally, exploring advanced statistical techniques and their applications in management studies could help improve the accuracy and depth of data interpretation. Investigating new data sources, such as big data analytics and machine learning, could also offer innovative perspectives and more robust decision-making tools in management science. Lastly, expanding comparative studies across different industries and countries would help reveal cross-contextual insights and improve the generalisability of research findings.

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