RELEVANCE AND APPLICATION OF MULTIVARIATE STATISTICAL TECHNIQUES IN CONTEMPORARY BUSINESS MANAGEMENT RESEARCH: A STRATEGIC DISCOURSE

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Abstract

The study strategically explored various multivariate statistical techniques in contemporary business management research. Multivariate statistical techniques and analysis refer to a group of statistical techniques often put in use simultaneously to analyze three or more variables. The classification is categorized into dependency and interdependency assumptions. Whereas in dependency techniques, both dependent and independent variables exist, while in interdependency assumption, no single variable or group of variables is defined as being dependent or independent. The dependency techniques include: Multiple regression analysis, Discriminant analysis, Multiple analysis of variance (MANOVA) and Canonical analysis; while the independency in brevity is made up of: Factor analysis, Cluster analysis and Multidimensional scaling. In multivariate statistical techniques analysis, data could also be viewed and measured by ratio or interval scale i.e. being metric and interdependency techniques adopted. On the other hand, a nonmetric measure scale refers to ordinal and nominal, and dependency techniques assumptions come to play. In each case, investigations into their techniques usefulness, relevancy and adoption in contemporary business management research were also strategically explored in our present study and possible recommendations advanced.

Key words: ***Multivariate Statistical Techniques; Dependency Techniques; Independency Techniques; Metric Techniques; Nonmetric Techniques; Strategic Review; Business Management Research.***

Introduction

Multivariate Statistical Techniques Analysis is a family of statistical techniques that allow a researcher to do an evaluation of complex simultaneous relationships among three or more variables or phenomena. Multivariate analysis includes multiple regression, discriminant analysis, part and partial correlation, and canonical correlation (Borders and Abbott, 2002).

Multivariate statistical techniques may be classified as dependency and interdependency techniques (Kervin, 1992). This classification is viewed necessary and important, because the understanding of the distinction by the researcher enables him to make the selection and application of an appropriate technique feasible. In the process of selecting an appropriate technique, if it is discovered that the associated research questions have both criterion and predictor variables, such will quickly inform the researcher of the assumption of dependency techniques.

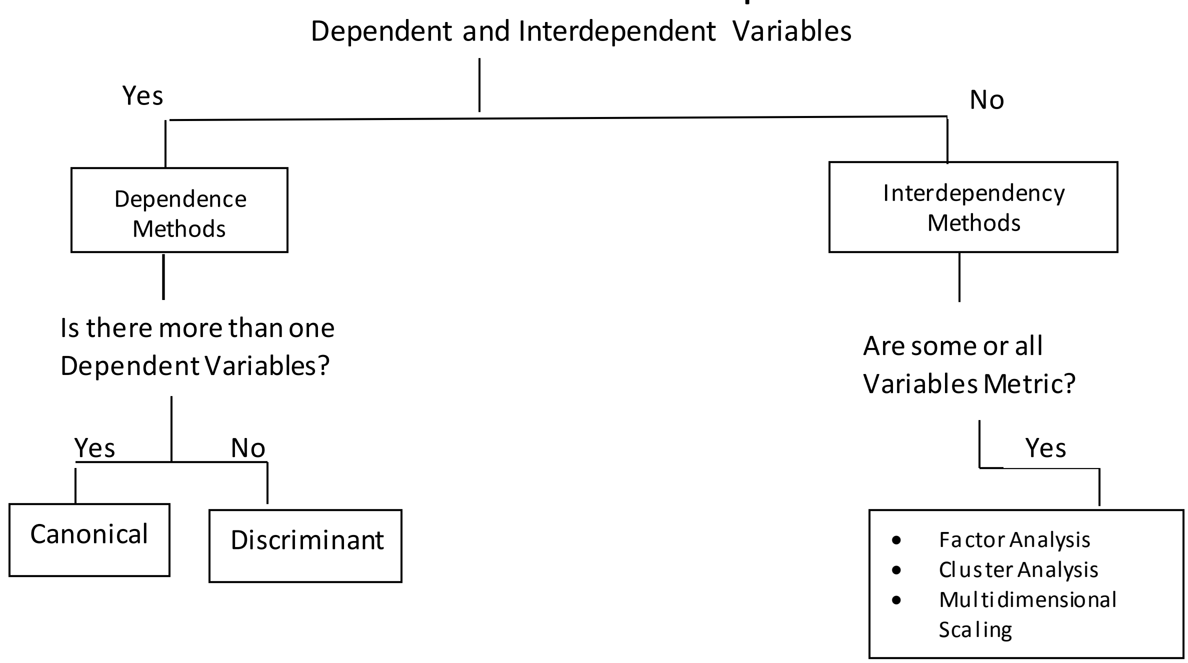
Techniques such as multiple regression, multivariate analysis of variance (MANOVA), and discriminant analysis are areas where criterion variables and predictor variables exist. On the other hand, if there are the interrelatedness of the variables without designating some as dependent and others as independent, the assumption of the interdependence of the variable comes into play. With this understanding, it is important to note that techniques such as Factor Analysis, Cluster Analysis, and Multidimensional Scaling are therefore taken as examples of interdependency techniques. The brief discussions of these and relevance in Contemporary Business Research are attempted as hereunder presented.

Criteria for Classification and Application of Multivariate Statistical Techniques

Multivariate statistical techniques analysis is a group of statistical techniques used when there are two or more measurements on element and the variables are analyzed simultaneously. In effect, it is concerned with the simultaneous relationships among two or more phenomena. The process of classifying multivariate statistical techniques may be based on three criteria concerning the nature and use of the data as hereunder expressed (Hair, Bush and Ortinau, 2003).

- Whether some of the variables are dependent on others? For instance, there may be a need to know whether a person's age, education, lifestyle, or marital status affect his or her frequency of visits to a pub house?
- It should be made known of how many variables are treated as being dependent on others?
- How the variables are measured, as well as having the knowledge of whether the variables are being measured on a non (i.e. categorical) or metric (continuous) scale?

Schematic Classification of Multivariate Statistical Techniques



Source: Hair, J.F., Bush, R.F., Ortinau, D.J. (2000) Marketing Research: A practical Approach In the New Millennium, New York: McGraw-Hill Higher Education.

Dependency Techniques

This involves such statistical techniques as Multiple Regression, Multivariate Analysis of Variance (MANOVA), Discriminant Analysis and Canonical Analysis

Multiple Regression Analysis and Applications

This is a statistical technique which analyzes the linear relationship between a dependent variable and independent variable by estimating coefficients for the equation for a straight line. Multiple regressions is a straightforward expression of Bivariate regression. The relationship that exists between correlation and regression is the foundation for the relationship between multiple correlations and multiple regressions. As argued by Muchinsky (2000), just as regression permits prediction on the basis of one predictor, multiple regression permits prediction on the basis of multiple predictors. He noted that the logic for using multiple regressions is the same as the logic for using multiple correlations. It usually enhances prediction of the criterion. Multiple regressions combine several predictor variables into a single regression equation (Furlong, Lovelace and Lovelace, 2000). Multiple regression analysis in most practical purposes is applied in marketing to solve the problems often faced by marketing managers. For instance, in a situation of several independent variables where the manager may want to carry out examination of their influences on a dependent variable of interests, the use of multiple regression analysis is the most appropriate technique to use. In such a situation, multiple independent variables are entered into the same type of regression equation. It is also to be noted that for each variable there, a separate regression coefficient is calculated which may describe its relationship with the dependent variable. These coefficients may enable the marketing manager to do the examination of the relative influence of each independent variable. Multiple regressions have been found to be of use and applicability specifically in four basic types of situations (Hair et al., 2000):

- It is noted to be used in the development of a self-weighting estimating equation for the purpose of predicting values for a criterion variable from the values, For instance, the marketing department may decide to predict the sales of their units based on the newly advertised products sales, income, a time factor, annual disposable income.
- Another relevance and use of multiple regressions in contemporary business management research is in the area of testing and explaining causal theories. This approach which is often referred to as path analysis, and the description of the entire structure of linkages that have been advanced from a casual theory, becomes accessible by the use and application of multiple regression analysis.
- A descriptive application of multiple regression assists in the controlling of confounding variables, and such helps in the evaluation of the contribution of other variables. For instance, a researcher might wish to study and control the brand of a product and the geographical locality where it is bought for the purposes of evaluating the effects of price and as an indicator of product quality.
- Multiple regression in addition to being a descriptive tool in contemporary business management research, is also relevant and is in use as an inference tool in the testing of hypotheses, as well as the estimation of population values.

In multiple regression analysis, the regression equation has the following form (Bordens and Abbott, 2002):

$\gamma_i = a + b_1X_1 + b_2X_2 + b_3X_3 + \ldots\ldots b_nX_n + \ell_i$

γ_i = Dependent variable for the ith observation

a = intercept coefficient

b_i = slope coefficient for dependent variable X_i

X_1 = independent variable 1

b_2 = slope coefficient for independent variable X_2

X_2 = independent variable 2

b_3 = slope coefficient for independent variable X_3

X_3 = independent variable 3

bn = slope coefficient for independent variable Xn

Xn = independent variable n

ℓ_i = Error term for the regression equation for the ith observation.

From the above multiple regression equation, it is important to note that the relationship existing between each independent variable and the dependent is still linear; but with the addition of multiple independent variables, the researcher has to think of multiple independent dimensions rather than the straight-line description. It is important to note that the first step in a regression analysis is to evaluate the data to see whether they meet the assumptions of test. However, we understand that the easiest way to carry out the analysis of the relationships is to examine the coefficient for each independent variable. When more then one independent variable is added, the situation is bound to have a couple of new issues for consideration. Under this situation, one major concern which the researcher has to battle with is the fact that, each independent variable may be measured using a different scale. For example, if a researcher has the intention to predict the sales volume for a newly designed and produced computer machine distributorship in a geographical area, using of sales force (x_1), amount of promotional budget (x_2), and consumer attitudes towards the company's product (x_3). It is likely, that each of these independent variable would probably be measured in different units. In such a situation, the size of the sales force would most probably be measured by the number of salespeople, the amount of promotional budget would be naira, and the attitude of consumer might be measured by making use of a five-point scale, from "Very Poor" to "Very Good". By way of application of the above, if we assume that some data have been collected (as specified below) and multiple regression analysis exercise carried out, it may result to the following regression equation:

$\gamma_i = 1125.43 + 0.65X_1 + 846.81X_2 + 1.32X_3 + \ell_i$ where

γ_i = observed sales volume for the ith observation

X_1 = size of the sales force

X_2 = Amount of the promotional budget

X_3 =consumer attitude score towards brand

By measuring multiple independent variables with different scales, it would not be possible to carry out a relative comparison between regression coefficients as to ascertain which independent variable has the most influence in the dependent variable. To solve the problem, what the researcher may need is to find a way of making the regression coefficients comparable. It is of note that the standardized regression coefficient or beta coefficient would be calculated from the normal regression coefficient, as well as the recalculation of the regression coefficient to have a mean of 0 and a standard deviation of 1. By this standardization process, the effects of different scales would then be removed. This understanding indicates that the researcher can make direct comparisons between independent variable using beta coefficients to determine which variables have the most influence on the dependent measure.

Beta coefficient could simply be described as an estimated regression coefficient that has been recalculated to have a mean of 0 and a standard deviation of 1. We understand that such a change enables independent variable with different unit's measurement to be directly compared on their association with the dependent variable.

Statistical Significance of Regression Coefficient and Application

When the regression coefficients of the study must have been estimated, there would still be the need to examine the statistical significance of each coefficient (Kervin, 1992). The process of doing this as he argued is similar to what is obtainable in bivariate regression case. In the process, each regression coefficient will be divided by its standard error to produce a statistic, which invariably is compared against the critical value to determine whether the null hypothesis can be rejected. In some situations, not all independent variables in a regression equation will be statistically significant. In practical terms, it is important to note that if a regression coefficient is not statistically significant, such indicates that the independent variables do not have a relationship with the dependent variable and the slope describing that relationship is relatively flat. This implies that the value of the dependent variable does not change at all as the value of the statistically insignificant independent variable changes. The importance of statistical significance in the multiple regression analysis and application cannot be overemphasized. In the usage of multiple regression analysis, it is very relevant to examine the overall statistical significance of the regression model. With such understanding, it is relevant to note that the amount of variation in the dependent variable that the researcher has been able to explain with the independent measures should be compared to the total variation in the dependent measures. The result of this comparison will yield a statistic called a model F statistic (Trochim, 2006). This measure accordingly would then be compared against a critical value as to determine whether the null hypothesis will be rejected or not.

Model F statistic is a statistic that compares the amount of variation in the dependent measure "explained" or associated with the independent variables to the "unexplained" or error variance (Trochim, 2006). A large F statistic indicates that the regression model has more explained variance than error variance.

Multiple Regression and use of Dummy Variables in Regression Analysis

Dummy variables are artificial variables introduced into a regression equation to represent the categories of a nominally scaled variable (Hair, et al., 2000). In some cases, according to them in multiple regression analysis, the particular independent variable a researcher may want to use to predict a dependent variable may not be measured by making use of interval or ratio scales, which are the basic assumption for the use of regression analysis.

Under such situation as argued, there could still be a way out for the researcher to go on in the analysis by the inclusion of such variables needed through the use of dummy variables. For example, if a researcher wanted to include the gender of his customers to explain their annual purchases of particular product. It is quite certain that his measure would include two possible values, male and female. The use of dummy variables coding involves the choice of one category of the variable to serve as a reference category, while adding as many dummy variables, as there are possible values of the variables, less than reference category. In this case, the categories could be coded as either 0 or 1. For instance, as in the above example, if the researcher chooses the female category as the reference category, he would add a dummy variable for the male category. If the dummy variable is assigned the value of 1 for males and 0 for females, the regression equation would be of this form (Hair et al., 2000):

$\gamma_i = a + biDi + \ell_i$

Where:

γ_i = Annual purchases of the researchers product for the ith observation

a = intercept (represents the value of γ for the females)

b_i = regression coefficient (representing the difference in annual purchases between males and females)

D_i = Dummy variable representing males (0 for females, and 1 for males)

ℓ_i = Error term for the equation

It is to be noted from the above that, if the dummy variable Di is given the value 1 when the respondent is a male and 0 when the respondent is a female, and in consequent regressional analysis, the regression equation would reduce to:

$\gamma_i = a + \ell i$ (because Di = 0)

When Di = 1, it shows that the regression coefficient, bi, will represent the difference in annual purchases for males compared to females. Invariably, if the regression coefficient was, say, 0.33, it would mean that in comparison to females, on the average that males purchase will be 0.33 more of the product. It is also important to note that this change in interpretation for the regression coefficient analysis when using dummy variable is important to remember, in that it is entirely the sole choice of the researcher, as regards which response category to use as a reference category. In relation to the above example, the researcher could also easily use males as the reference category, and under such, the regression coefficient would represent the difference in annual purchases for females compared to males.

Discriminant Analysis Techniques and Application in Contemporary Business Management Research.

Discriminant analysis is a multivariate statistical technique usually used for predicting group membership on the basic of two or more independent variables. The purpose is to predict a variable from a set of independent variables. It is a technique for analyzing for instance, marketing research data when the criterion variable is categorical and the predictor variables are intervals. This implies that, it is used when the dependent variable is categorical. That is, the prediction of a categorical variable is the purpose of discriminant analysis. Statistically, this involves the study of the direction of group differences based on finding a linear combination of independent variables – the discriminant function that shows large differences in group means. As a result, discriminant analysis is a statistical tool for determining linear combinations of those independent variables.

For example, in a situation of male-female, old-young, boy-girl categorization and one may have several predictor variables. A researcher can use discriminant analysis to identify a simple rule for classifying participants into groups or to determine which of his predictor variables contributes most heavily to the separation of groups. Discriminant analysis understanding works best when discriminnant functions are being formulated. In this respect, for each dependent variable group, a discriminant function score is calculated according to the following formula (Tabachnick and Fidel, 1989; in Bordens and Abbott, 2002).

$D_i = di_1Z_2 + di_2Z_2 + \ldots\ldots + dinZn$

Where:

Di =the discriminant function score calculated for each participant

di = the regression weight

Zi = the standardized raw score on a particular predictor

The discriminant weight (dn), or discriminant function coefficients, are estimates of the discriminatory power of a particular independent variable. Discriminatory function coefficient is the multipliers of variables on the discriminant function when the variables are in the original units of measurement (Bordens and Abbott, 2002). These coefficients are said to be computed by means of the discriminant analysis computer program. The variance structure of the variables in the equation determines the size of the coefficients associated with a particular independent variable. It is important to note that independent variables with large discriminatory power will have large weights, and those, with little discriminatory power will have small weights.

Furthermore, in discriminant analysis, a new variable (Di) is calculated for each participant. This variable is the best linear combination of predictor variables, just as in multiple regression`. It is of note that when the discrimiant function score has been calculated for each group, a Centroid can then be determined (Bordens and Abbott, 2002). The Centriod is simply the average of the discriminant function scores within a group. Discriminant function is the linear combination of independent variables developed by discriminant analysis which will best discriminate between the categories of the dependent variable.

It is also important to note that one discriminant function can link ones predictors with his dependent variable (Hair et al., 2003). However, the number of functions is limited to the number of predictors or the number of levels of the dependent variable minus 1, whichever is smaller. For example, if one had seven predictors and three levels of the dependent variable, the number of possible function is 2 (i.e. 3-1). Each discriminant function represents a different linkage between the predictors and dependent variable. The first one calculated maximizes the separation between levels of the dependent variable. Subsequent functions represent progressively weaker linkages between the predictors and the dependent variable. Due to the fact that the computations needed to perform a descriminant analysis are complex, the need to use a computer program (SPSS-PC) to conduct a discriminant analysis arose. SPSS-PC conducts a discriminant analysis within its Analyze subprogram.

The output of the SPSS-PC analysis gives one several important pieces of information. In the first place, the output will indicate the number of discrminant functions extracted, along with tests of statistical significance. Secondly, one can request for several other statistics needed to interpret his results.

Other Applications of Discriminant Analysis in Business Management Research

A researcher can evaluate the amount of variability accounted for by each function (Hair et al., 2003). He would do this by conducting a dimension reduction analysis that provides a canonical correlation coefficient and significant tests for each function. In addition, a researcher as argued can evaluate the degree of contribution for each predictor (within a function) to the separation of groups.

In marketing research for instance, there are many situations where the researcher's purpose would be to classify objects group by a set of independent variables. In such a situation the dependent variable in discriminant analysis is nonmetric or categorical. Alternatively, the independent variables in discriminant analysis are metric and often include characteristics such as demographics and psychographics. In product research, discriminant analysis ensures the distinction between heavily, medium, and light users of a product in terms of their consumption habits and lifestyles.

Discriminant analysis makes use of independent variables to classify observations into mutually exclusive categories. A researcher can also use discriminant analysis to determine whether statistically significant differences exist between the average discriminant scores profiles of two or more groups.

In image research according to Bordens and Abbott (2002) the use of discriminant analysis can help in discriminating between customers who exhibit favorable perceptions of a store or company and those who do not. In advertising research, it is also noted that discriminant analysis can help in distinguishing how marketing analysis is important in distinguishing characteristics of consumers who respond to direct marketing solicitations and those who do not.

Multivariate Analysis of Variance (MANOVA)

Multivariate analysis of variance is a commonly used multivariate analysis technique in business management research. It assesses the relationship between two or more dependent variables and the classification of variables or factors. Its usage or relevance in business management research can be applied in the test of differences among samples of customers, employees, manufactured items, production parts, and so on**.**

Multivariate Analysis of Variance (MANOVA) process is similar to that of the univariate analysis of variance (ANOVA), with the former having the added responsibility to take care of several dependent variables. In situation where ANOVA is consecutively being used as a set of interrelated dependent variables, the conclusions may be erroneous; this erroneous conclusion would be corrected if MANOVA is applied appropriately by testing all the variables and their interrelationships (Cooper and Schindler, 2003).

In testing for differences among groups, MAVONA employs sums-of-squares and cross-product (SSCP) matrices. To determine the variance between groups, there would then be the partitioning of the total SSCP matrix and testing for significance. To test for equality among treatment groups, the F ratio, generalized to a ratio of within-group variance and total-group variance matrices is applied.

The examination of the similarities and differences among the multivariate mean scores of several populations is being ensured by the use of MANOVA techniques. It is important to note that the null hypothesis for MANOVA is that all of the centroids (i.e. multivariate means) are equal (Cooper and Schindler, 2003). This implies as argued that:

Ho: $\mu_1 = \mu_2 = \mu_3 = \ldots\ldots\mu_n$, while in the altermate hypothesis the reverse is the case. This implies that:

H_A: $\mu_1 \neq \mu_2 \neq \mu_3 \neq \ldots\ldots \mu_n$

MANOVA analysis techniques can be used to rectify situation occasioned by the rejection of null hypothesis. Under such a situation, additional tests would be done for the better understanding of data. In such cases, several conditions or alternatives must come to play as hereunder stated (Cooper and Schindler, 2003).

- Univariate F test can be run on the independent variables.
- Simultaneous confidence intervals can be produced for each variable.
- Step-down analysis, like stepwise regression, can be run by computing F values successively. In this case, each value is computed after the effects of the dependent variable are eliminated.
- Multiple discriminiant analysis can be used on the SSCP matrices. This as noted aids in the discovery of which variables contribute to the MANOVA's significance.

MANOVA Relevance and Applications

MANOVA operates by forming a new linear combination of dependent variables for each effect in a related subject design. For instance, for a two-factor between-subjects design, a different linear combination of scores is formed for each of the main effects and for the interaction.

MANOVA also solves the problem of a researcher, after conducting an experiment and is faced with the problem of how to analyze his three dependent measures. The researcher may be tempted to conduct three separate one-factor ANOVA's; but this might not solve the problem because he might miss some important relationships among his variables. In such situation, a viable alternative is to use a MANOVA to analyze his data.

Canonical Analysis

Just as multiple regression analysis is used to determine the relationship between a set of variables (predictors) and a single dependent variable, canonical analysis techniques on its own, is used to determine the relationship between a set of predictors and a set of dependent variables (Bordens and Abbott, 2003). Canonical analysis techniques work by creating two new variables for each subject called canonical variates. A canonical variate is computed both for the dependent and predictor sets. The canonical variate as noted is simply the score predicted from a regression equation based on the variables within a set. The correlation between the two canonical variates is the canonical correlation.

Canonical Analysis Application

Canonical analysis technique affords the researcher the opportunity to investigate the relationship between two sets of variables (Bordens and Abbott, 2003). For instance, a management scientist may want to compute the simultaneous relationship between three measures of scholarly publication ability in his faculty with four measures of success for promotion. Similarly, a sociologist who is interested in research on social mobility may decide to carry out a research on the relationship between two predictors of social mobility based on an interview with the actual subsequent social mobility measured by five different indicators in the research process. There are some computational researches that are involved in canonical analysis which are of significance in business management research. Such include canonical weights, canonical scores, favour structures and Eigenvalue, among others. Canonical analysis is also applied in ethnographic assessment of pain coping perceptions e.g. in psychosomatic Medicine and Nursing Research.

Interdependency Techniques

Interdependency analysis techniques are a specific type of multivariate techniques analysis. The purpose is to summarize and reduce a large number of variables or objects for a better understanding of the data, as opposed to the prediction of variable from a set of dependent variable as obtainable in dependency techniques (Hair et al., 2003). Examples of interdependency techniques analysis include factor analysis, cluster analysis and Multidimensional scaling (Hair, et al, 2000). These are accordingly briefly discussed below.

Factor analysis

Factor analysis is a statistical analysis techniques under interdependency techniques that is used for the purpose of summarizing information contained in a large number of variables, into a smaller and manageable number of subjects or factors. Factor analysis is a class of procedure primarily used for data reduction and summarization. The main purpose of factor analysis is the simplification of data, solves the problem of distinction between dependent and independent variables. In factor analysis application, all variables under investigation are analyzed together for the identification of the underlying factors. In factor analysis, the predictor-criterion relationship that was in existence in dependence situation is replaced by a matrix of inter-correlation among several variables, and none of which is viewed as being dependent on another.

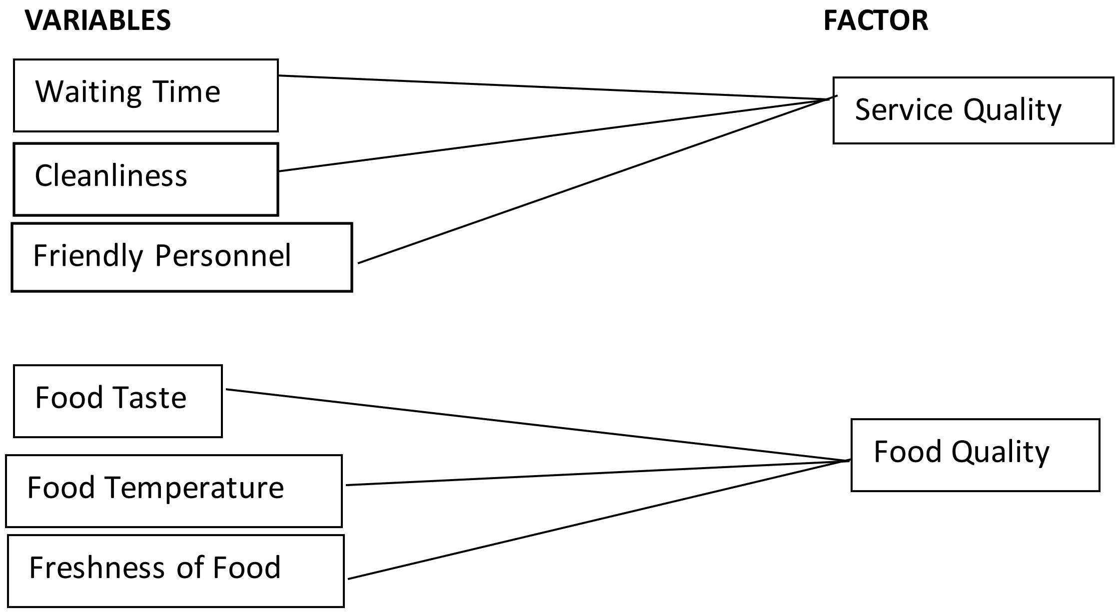
Factor analysis operates by extracting as many significant factors from ones data as possible, based on the bivariate correlation between the measures. A factor is a dimension of any number of variables. Factor analysis involves extracting one factor and then evaluating ones data for the existence of other factors. Under such situation, it is to be noted that, the successive factors extracted in factor analysis are not of equal strength. Each successive factor accounts for less and less variance. In specific terms, the first two or three factors will be strongest (i.e. they account for the most variance). The strength of a factor is indicated by its eigen value.

The starting point in interpreting the statistics of factor analysis lies in the understanding of factor scores. Factor score is composite scores estimated for each respondent on the derived factors. A factor is therefore a linear combination of variables or a weighted summary score of a set of related variables (Hair et al., 2000).

Factor Analysis Methodology

Factor analysis begins with the construction of a new set of variables based on the relationships in the correlation matrix. The analysis can be done in many ways but the most frequently used approach is principal components analysis. The use of this method helps in the transformation of a set variable into a new set of composite variables or principal components that are not correlated with each other.

Example of a Factor Analysis Application to a Fast Food Restaurant



Source: Adapted from, Hair, J.F., Bush, R.P. and Ortinau, D.J. (2000). Marketing Research: A Practical Approach in the new Millennium, New York: McGraw-Hill Higher Education.

Factor analysis application in marketing research (Hair et al., 2000).

- **Pricing-** The identification of the characteristics of price- sensitive and prestige-sensitive customers can be done with the help of factor analysis.
- **Advertising-** Factor analysis usuage in advertising is for the better understanding of media habits of various customers.
- **Product-** The identification of brand attributes that influences customer choice can be achieved by the use of factor analysis.
- **Distribution-**The better understanding of the channel selection criteria among distribution channel members can be achieved.

Cluster Analysis

Cluster analysis is a multivariate interdependence technique whose primary objective is to classify objects into relatively homogenous groups based on the set of variables considered. For instance, the classification or grouping of customers products, market areas, and so on.

It is important to note that cluster analysis originally developed as a classification device for taxonomy, and that its use has spread following classification work in areas such as medicine, biology and other sciences. The usefulness of cluster analysis in those fields with the help of high-speed computers for extensive calculations, the adoption has also spread in other areas like engineering, economics, marketing and a host of other areas (Cooper and Schindler, 2003). As Factor Analysis and elementary linkage analysis enable the researcher to group together factors and variables, cluster analysis enables the researcher to group similar and homogeneous samples of people (Cohen, Manion, and Morrison, 2007).

Cluster Analysis Methodology

As expressed by Cooper and Schindler (2003), five steps are basic to the application of most cluster studies:

- Selection of the sample to be clustered (e.g. buyers, medical patients, inventory, products, employees).
- Definition of the variables on which to measure the objects, events, or people (e.g. financial status, political affiliation, market segment characteristics, symptom classes, product competition definitions, productivity attributes).
- Computation of similarities among the entities through correlation, Euclidean distances, and other techniques.
- Selection of mutually exclusive clusters (maximization of within cluster similarity and between cluster differences) or hierarchically arranged clusters.
- Cluster comparison and evaluation. It is to be noted that different methods exist and do provide different solutions.

Cluster Analysis Relevance and Application in Business Management Research (Cooper and Schindler, 2003)

- The conduct of a cluster analysis helps a company to identify a target segment based on the data it has gathered.
- Test marketing: Cluster analysis does this by grouping test areas or location into homogeneous clusters for test marketing process.
- New-product research: The clustering of brands can enable a firm to examine its product offerings relative to competition. It is of note that brands in the same cluster compete more fiercely with each other than with brands in other clusters.
- Buyers Behaviour: The identification of similar groups of buyers who have similar choice criteria can be made by employing cluster analysis technique.
- Marketing Segmentation: The development of distinct market segment based on geographical areas, demographic, psychographic and behaviouristic variables can be achieved with the aid of cluster analysis.

Multidimensional Scaling

Multidimensional scaling is an interdependent multivariate statistical analysis technique. This technique is a class of procedures for representing perceptions and preferences of respondent spatially by means of a visual display (Cohen et al., 2007). Multidimensional scaling according to them develops a geometric picture or map of the location of some objects relative to others. This map as noted specifies how the object differs. The Multidimensional scaling technique provides the market researcher with a procedure for measuring objects in Multidimensional space, on the basis of respondents' perceptions of similarity (or preferences) among a set of objects. The perceived similarity or preference can be in the form of ranking data (i.e. non metric) or in form of customer ratings (i.e. metric). Multidimensional scaling does not include a predictor or dependent variable, just as is applicable in factor and cluster analyses.

Multidimensional Scaling Methodology

In terms of methodology adoption, three types of attribute space may be considered, each representing a Multidimensional map (Cooper and Schindler, 2003). In the first place as argued, an objective space in which an object can be positioned in terms of its measurable attributes i.e. its flavour, weight and nutritional value. In the second instance, there could be a subjective space whereby the perceptions of the objects flavour, weights, and nutritional value may be positioned. It is noted also that in rare cases, the objective-subjective attribute assessment may coincide. When a comparison of the two is made, such makes the researcher to judge how accurately an object is being perceived. Simultaneously, individuals may have different perceptions of an object; these perceptions may be averaged to be taken as a summary measure of perceptions.

By the availability of a third map as further noted, the researcher can describe the respondents' preferences with the aid of objects attributes. Under this circumstance, such will represent their ideal object. In essence, all such objects close to this ideal point are interpreted as being preferred by respondents to those that are more distant. With this in place, the ideal points from many people can be positioned in the preferences clusters. When this situation is achieved, it could then be compared to the subjective space for the assessment of how well the preferences correspond to perception clusters. In this regard or direction, it is of note that cluster analysis and Multidimensional scaling could be combined to map market segment as well as the examination of products designed for those segments.

Relatedly, Multidimensional scaling can also provide the researcher with a perceptual map of the data. A perceptual map could be described as a visual representation of customer perceptions of data. For instance, the ranking of brands or superstores. In other words, a perceptual map could be viewed as a graphic representation of respondent beliefs about the relationship between objects with respect to two or more dimensions, which could usually be attribute or features of the objects.

In addition, the ranking or similarity judgements could statistically be transformed into distances by placing the superstores. A similarity judgement is a direct approach to gathering perceptual data for Multidimensional scaling, where the respondents use a likert scales to rate all possible pairs of brands in terms of their similarity.

Example: Similarity ranking of super-stores

	A	**B**	**C**	**D**	**E**	**F**
A		2	16	14	12	8
B			6	7	9	5
C				1	8	10
D						
E					4	6
F						2

Source: Adapted from Hair, J.F., Bush, R.P. and Ortinau, D.J. (2002). Marketing Research: A Practical Approach for the New Millenium, New York: McGraw-Hill Higher Education.

Multidimensional Scaling Relevance and Application

Multidimensional scaling helps in a special description of a respondent's perception about a product, service, or other objects of interest. With the understanding of Multidimensional scaling, the business researcher can attend to the difficult-to-measure constructs such as, product quality or desirability. In Multidimensional scaling, many constructs are perceived and cognitively mapped in different ways by individuals. With the help of Multidimensional scaling, items that are perceived to be similar will fall close together in Multidimensional space, and those that are perceived to be dissimilar will be farther apart. Multidimensional scaling is also useful and is applied in theory and applications in behavioural sciences research.

Concluding Remarks and Recommendations

Multivariate Statistical Techniques Analysis is a group of statistical techniques or procedure most often used to simultaneously analyze three or more variables. Multivariate techniques are further classified into two categories: dependency and independency. The assumption of dependency operates when a problem reveals the presence or use of criterion and predictor variables, while the assumption of interdependence comes into play if the variables do not reveal dependent and interdependence characteristics techniques such as, multiple regression, canonical analysis, discriminant analysis and multivariate analysis of variance (MANOVA) as is applicable under dependency assumption, and applicability. Similarly, techniques such as factor analysis, cluster and multidimensional scaling fall under then interdependence techniques and applicability. Each of the aforementioned techniques has its practical relevance and applicability in contemporary business world and management research, as briefly noted in each case in this write-up. It is therefore recommended that researchers should strategically understand the assumptions in each multivariate statistical technique and feasibility before applicability in contemporary business management research. The strict adherence of these is recommended in order to enhance effective statistical analysis and respective management decision making.

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