EMERGENT ISSUES IN PRIMARY

EDUCATION STUDIES

Edited by

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DEDICATON

This book is dedicated to the Almighty God, The Rock, whose work is perfect and all His ways are judgment, a God of truth and without iniquity, just and right is He;

The staff members of PES Department, School of Education and College at Large And All PES Students in Nigeria Colleges of Education.

CONTENTS

Chapter 4
DESIGNING A RESEARCH

BY
Dr. J. G. Adewale

INTRODUCTION

Designing a research is an important aspect of any research process. The decision to select a research design is usually guided by many factors acting independently or combining with other factors. Every type of research is designed specifically to suit its own purposes; hence, it is important to note the design chosen must not be the one that will mal the validity of the result. Research design is the plan and structure of investigation, conceived so as to obtain answers to research questions. The design specifically outlines the various procedures of collecting and analyzing data relevant to the problem under investigation. It can be defined as the strategy or plan which a researcher adopts to enable him carry out his problem of investigation. The plan is the overall scheme or programme of the research which includes an outline of what the investigation will do. from writing the hypotheses and operational implications to the final analysis of data.

The structure of research according to Kerlinger and Lee (2000) is difficult or harder to explain because the word structure is not easily defined clearly and unambiguously. Since it is a concept that becomes important, the explanations and examples will give clear picture of the word in a more concrete manner. A structure is the framework, organisation or configuration of elements of structure related in specified ways. The best way to specify a structure is to write a mathematical equation that relates the parts of the structure to each other. Such a mathematical equation, since its terms are defined and specifically related by the equation or set of equations, is unambiguous, in a nutshell, a structure is a paradigm or model of the relations among the variables of a study. A paradigm is a model, an example, diagrams, graphs, and verbal outlines. A research design expresses both the structure of the research problem and the plan of investigation used to obtain empirical evidence on the relations of the problem.

PURPOSES OF RESEARCH DESIGN.

From the concepts given above, Research design has two basic purposes: (i) to provide answers to research questions, (ii) to outline and demonstrate how various variables of the research can be controlled or manipulated in order to generate the necessary primary data for research work. Primary data arise as a result of either a direct observation of events or phenomena or through manipulation of variables in the design.

Design helps investigators obtain answers to the questions of research and also to control the experimental, extraneous, or error variances of any research activity it is possible to omit this purpose from the discussion and to say that research design has one grand purpose to control variance. Research designs are invented to enable researchers answer questions as validly, objectively, accurately and economically as possible. Research plans are deliverable and specifically conceived and executed to bring empirical evidence to bear on the research problem.

Research problem: This can be and are stated in the form of hypotheses. At some point in the research, they are stated so that they can be empirically tested. Designs are clearly and carefully worked put to yield dependable and valid answers to the research questions epitomized by the hypotheses. We can make one observation and infer that the hypothesized relation exists on the basis of this one observation, but it is obvious that we cannot accept the inference so made. On the other hand, it is also possible to make hundreds of observations and to infer that the hypothesized relation exists on the basis of these many observations. In this case we may or may not accept the inference as valid. The result depends on how the observations and the inference were made. An adequately planned and executed design helps greatly in permitting us to rely on both our observations and our inferences.

How does design accomplish this? Research design sets up the framework for study of the relations among variables. Design tells us, in a sense, what observations to make, how to make them, and how to analyse the quantitative representations of the observations. Strictly speaking design does not 'tell' us precisely what to do, but rather 'suggests' the direction of observation making and analysis.

An adequate design suggests for example, how many observations should be made, and which variables are active and which one attributes. We can then act to manipulate the active variables and to categorize and measure the attribute variables. A design suggests to us which type of statistical analysis to use. Finally, an adequate design outlines possible conclusions to be drawn from the statistical analysis.

To control variance, a research design is, in a manner of speaking, a set of instructions to the investigation to gather and analyse data in certain ways, it is, therefore, a control mechanism. The statistical principle behind this mechanism, as stated earlier, is:

Maximize systematic variance, control extraneous variance, and minimize error variance. In other words, we must control variance.

According to this principle by constructing an efficient research design the investigator attempts to:
(i) Maximize the variance or variables of the substantive research hypothesis (ii) control the variance of extraneous or 'unwanted' variables that may have an effect on the experimental outcomes, and (iii) minimize the error or random variance, including so called errors of measurement.

FACTORS AFFECTING THE CHOICE OF DESIGN

Before a research design is chosen, the researcher must endeavour to consider the following which could affect the success or otherwise of his investigation. the factors include: types of research, the research population, the type of data required, the variables to control, the facilities / resources available.

Population: This aspect is important that researcher defines his/her population taking into consideration such factors as duration of time, expertise involved and money to be expended in the process. The population is the set of people or entities to which findings are to be generalized. The population must be defined explicitly before a sample is taken. Care must be taken not to generalize beyond the population. Doing so is a common error in social science writing. If you are interested in collecting data from every person or entity in the population, then you are conducting enumeration or census

SAMPLING TECHNIQUES

a. Random sampling is data collection in which every person in the population has a chance of being selected. Normally this is an equal chance of being selected. There are various types of random sampling, discussed below.

TYPES OF RANDOM SAMPLING

There are several types of random sampling, each of which affects how significance is computed.

Simple random sampling is common when the sampling frame is small. Starting at an arbitrary point in a table of random numbers, such as found in most statistics books, sets of random numbers are read and associated with members of the sampling frame. The first three digits might be 712, for instance, and thus the 712th person in the sampling frame might be selected. If the sampling frame had over 999 people, then four-digit random sequences would be used. Selections outside the range of members of the frame would be ignored. Using pseudo random number generating software (used to construct tables of random numbers found in books), such as that built into SPSS, a simpler, more modern method is simply to request such software generate n random digits between 1 and N, where n is sample size and N is population size.

Systematic sampling also involves the direct selection of subjects or other primary sampling units from the sampling frame. The researcher starts at a random point and selects every nth subject in the sampling frame. The random starting point equals the sampling interval, n, times a random number between 0 and 1, plus 1, rounded down. In systematic sampling there is the danger of order bias: the sampling frame list may arrange subjects in a pattern, and if the periodicity of systematic sampling matches the periodicity of that pattern, the result may be the systematic over- or under-representation of some stratum of the population. If, however, it can be assumed that the sampling frame list is randomly ordered, systematic sampling is mathematically equivalent to and equally precise as simple random sampling. If the list is stratified (e.g, all females listed, then all males), systematic sampling is mathematically equivalent to stratified sampling an is more precise than simple random sampling.

Repeated systematic sampling is a variant which seeks to avoid the possibility of systematic biases due to periodicity in the sampling frame. This is done by taking several smaller systematic samples, each with a different random starting point, rather than using one pass through the data as in ordinary systematic sampling. Repeated systematic sample has the side benefit that the variability in the subsample means for a given variable is a measure of the variance of that estimate in the entire sample.

Stratified simple random sampling is simple random sampling of each stratum of the population. For instance, in a study of college students, a simple random sample may be drawn from each class (freshman, 200L, 300L) in proportion to class size. This guarantees the resulting sample will be proportionate to known sizes in the population. One may simultaneously stratify for additional variables, such as gender, with separate simple random samples of freshman male, freshmen female 200L, female, etc. The finer the stratification, the more precision compared to un-stratified simple random sampling. That is, confidence intervals will be narrower for stratified sampling than for simple random sampling of the same population. The more heterogeneous the means of the strata are on a variable of interest, the more stratified sampling will provide a gain in precision compared to simple random sampling. Stratified sampling, therefore, is preferred to simple random sampling.

Multi-stage sampling is where the researcher divides the population into strata, samples the strata, then stratifies the samples, and then resample, repeating the process until the ultimate sampling units are selected at the last of the hierarchical levels. When the strata are geographic units, this method is sometimes called area sampling. For instance, at the top level, states may be sampled (with sampling proportionate to state population size); then cities may be sampled; then schools; then classes; and finally students. Probability proportional to size sampling (pps) is a related variant in which each of the hierarchical levels prior to the ultimate level is sampled according to the number of ultimate units (eg., people or households) it contains.

Overall, multi-stage or cluster sampling is usually less precise than simple random sampling, which in turn is less precise than one-stage stratified sampling. Warning: Since multistage sampling is the most prevalent form for large, national surveys, and since most computer programs use standard error algorithms based on the assumption of simple random samples, the standard errors reported in the literature often underestimate sampling error. See the discussion below regarding estimation and software for complex samples.

b. Non-random sampling is widely used as a case selection method in qualitative research, or for quantitative studies of a preliminary and exploratory nature where random sampling is too costly, or where it is the only feasible alternative. . However, random samples are always strongly preferred as only random samples permit statistical inference. That is, there is no way to assess the validity of results of non-random samples.

Availability sampling is where the researcher selects subjects on the basis of availability. Also called haphazard sampling, examples include interviewing people who emerge from an event or location, interviewing a captive audience such as one's students, and mail-in surveys printed in magazines and newspapers.

i. Quota sampling is availability sampling, but with the constraint that proportionality by strata be preserved. Thus the interviewer(s) will be told to interview so many white male Muslims, so many black female Christians, and so on, to improve the representativeness of the sample. Maximum variation sampling is a variant of quota sampling, in which the researcher purposively and non-randomly tries to select a set of cases, which exhibit maximal differences on variables of interest. Further variations include extreme or deviant case sampling or typical case sampling.

ii. Expert sampling, also called judgment sampling, is where the researcher interviews a panel of individuals' known to be expert in a field. Expertise is any special knowledge, not necessarily formal training. Depending on the topic of study, experts may be policy issue academics or devotees to a popular culture fad. Critical case sampling is a variant of expert sampling, in which the sample is a set of cases or individuals identified by experts as being particularly significant (e.g., award winners in a given field).

iii. Chain referral sampling, also called snowball sampling or network sampling, is where the researcher starts with a subject who displays qualities of interest (e.g., being a private militia member), then obtains referred subjects from the first subject, then additional referred subjects from the second set, and so on. (Note chain referral sampling is different from chain sampling in quality control applications. Chain sampling in this sense refers to basing acceptance of a given production lot based not only on a sample of that lot, but also on samples of the previous 10 or so lots.)

The sampling frame is the list of ultimate sampling entities, which may be people, households, organizations, or other units of analysis. The list of registered students may be the sampling frame for a survey of the student body at a university. Problems can arise in sampling frame bias. Telephone directories are often used as sampling frames, for instance, but tend to under-represent the poor (who have fewer or no phones) and the wealthy (who have unlisted numbers). Random digit dialing (RDD) reaches unlisted numbers but not those with no phones, while over-representing households owning multiple phones. In multi-stage sampling, discussed below, there will be one sampling frame per stage (eg. a list of the 50 states, lists of Census tracts for sampled states, lists of Census blocks for sampled tracts, and finally a list or residences for sample blocks).

Significance is the percent chance that a relationship found in the data is just due to an unlucky sample, and if we took another sample we might find nothing. That is, significance is the chance of a Type I error: the chance of concluding we have a relationship when we do not. Social scientists often use the .05 level as a cutoff: if there is 5% or less chance that a relationship is just due to chance, we conclude the relationship is real (technically, we fail to accept the null hypothesis that the strength of the relationship is not different from zero). Significance testing is not appropriate for non-random samples or for enumerations/censuses. Any relationship, not matter how small, is a true relationship (barring measurement error) for an enumeration.

Confidence intervals are directly related to coefficients of significance. For a given variable in a given sample, one could compute the standard error, which, assuming a normal distribution, has a 95% confidence interval of plus or minus 1.96 times the standard error. If a very large number of samples were taken, and a (possibly different) estimated mean and corresponding 95% confidence interval was constructed from each sample, then 95% of these confidence intervals would contain the true population value, assuming random sampling. The formula for calculating the confidence interval, significance levels, and standard errors, depends on the type of random sampling, discussed below.

The design effect (D) is a coefficient, which reflects how sampling design affects the computation of significance levels compared to simple random sampling. A design effect coefficient of 1.0 means the sampling design is equivalent to simple random sampling. A design effect greater than 1.0 means the sampling design reduces precision of estimate compared to simple random sampling (cluster sampling, for instance, reduces precision). A design effect less than 1.0 means the sampling design increases precision compared to simple random sampling (stratified sampling, for instance, increases precision).

Unfortunately, most computer programs generate significance coefficients and confidence intervals based on the assumption of formulas for simple random sampling. Formulas for all types are found in Kalton (1983).

DEALING WITH SAMPLING PROBLEMS

1. Mismatched Sampling Frames. Often, the sampling frame does not match the primary sampling unit. For instance, the sampling frame may be a list of residences, but the ultimate sampling units are individuals. The interviewer needs instruction on just which individual within a residence to select as a subject. This is handled by a selection grid (Kish, 1965). The selection grid may be of a variety of forms. For instance, in a survey of taxpayers, for simplicity assume that a residence can have a maximum of three taxpayers. Let the researcher number the taxpayers from 1 to 3 by age and use the selection grid below:

	If no. of taxpayers in residence is			
		1	2	3
Survey form	% of all forms	Interview taxpayer #		
A	1/3	1	1	1
B	1/6	1	1	2
C	1/6	1	2	2
D	1/3	1	2	3

In this example, there are four different forms of the survey (A, B, C, D), printed and randomly distributed in the proportions in the table above. Each survey form would have one of the rows in the table. For instance, in form B, if there were two taxpayers in the residence then the interviewer would interview taxpayer number 1. For forms C or D, taxpayer number 2 would be interviewed. For form A, taxpayer number 1 would be interviewed. Kalton (1983: 61) presents the table for the assumption of a maximum of four selectable subjects per residence. Similar tables can be constructed for any assumption. All such selection grid tables equalize the probability of any appropriate individual being chosen for inclusion in the sample. A similar, simpler approach is the "last birthday" method, whereby the researcher asks the number of adults in the household, then interviews the sole adult in one-adult households; every other time interviews the adult with the most recent birthday in two-adult households, and every other time the other adult; every third time in three-adult households, etc. Asking about birthdays rather than ages may be less sensitive. Some evidence suggests that in telephone surveys, these methods may require additional time screening and interview time, and may generate too many callbacks or refusals. In face-to-face interviews there is greater subject tolerance for such screening questions.

2. Increasing the response rate. Response rates for face-to-face interviews are typically in the 75% range, and for mail surveys 10% is considered good in some marketing surveys. However, "good" depends of purpose and resources of the polling organization. The Office of Management and Budget's minimal standards require a 75% expected response rate, and federal data collected with response rates under 50% should not be used except if a special OMB waiver is granted. The OMB guidelines point up the salient point, that high response rate, like random sampling, is essential to reliable statistical inference. Response rate can be increased by

- Having legitimating sponsorship for the survey, geared to sponsors who are highly-regarded in the community being surveyed
- Having a good, short explanation justifying the survey
- Notifying individuals in advance that a survey is coming
- Keeping the survey instrument short, and letting prospective subjects know this.

- Assure confidentiality and anonymity.
- Offer to reschedule to a time at the subject's convenience.
- Make call backs (four is typical) where needed. In mail surveys, provide a new copy of the instrument each time.
- Start the instrument with non-threatening questions, which arouse interest.
- Offer to provide final results later on.
- In mail surveys, use certified and expresses mail. In e-mail surveys, use priority e-mail. Postcard and e-mail reminders also help. In mail surveys, plan to wait about six weeks for all responses to drift in.
- Offer token remuneration (eg., N1 enclosed in mail surveys; N5 in face-to-face interviews; or use pens, key chains, calendars, or other tokens to make respondents feel like they are getting something in return). Linking the return of the survey to entrance into a lottery for a substantial prize (eg., N1,000) can also boost response rates.

3. **Sample size** often needs to be estimated in the design phase of research. The size of the sample will need to be larger if one or more of the following applies: the weaker the relationships to be detected, the more stringent the significance level to be applied, the more control variables one will use, the smaller the number of cases in the smallest class of any variable, and the greater the variance of one's variables. Combinations of these factors create complexities, which, in combination with lack of knowledge about the population to be sampled, usually make sample size estimation, just that -- an arbitrary estimate. Online sample size calculators may be found on the web. Note that needed sample size does not depend at all on the size of the population to be sampled and even in the most complex analyses, samples over 1,500 are very rarely needed. Sample size is discussed further below.

ASSUMPTIONS

Significance testing is only appropriate for random samples.

Random sampling is assumed for inferential statistics (significance testing). "Inferential" refers to the fact that conclusions are drawn about relationships in the data based on inference from knowledge of the sampling distribution. Significance tests are based on a sampling theory which requires that every case have a chance of being selected known in advance of sample selection, usually an equal chance. Statistical inference assesses the significance of estimates made using random samples. For enumerations and censuses, such inference is not needed since estimates are exact. Sampling error is irrelevant and therefore inferential statistics dealing with sampling error are irrelevant. Significance tests are sometimes applied arbitrarily to non-random samples but there is no existing method of assessing the validity of such estimates, though analysis of non-response may shed some light.

HOW CAN ONE ESTIMATE SAMPLE SIZE IN ADVANCE?

As mentioned above, sample size calculation depends on a number of complex factors. In practice, researchers use specialized software designed for these calculations. One rule of thumb is based on standard error as used in normal curve tests: Sample size = ss = s*z/T)2, where s is the standard error of the variable with the largest variance (perhaps estimated in a pretest sample), z is the number of standard units corresponding to the desired proportion of cases (z = 1.96 for two-tailed tests at the .05 significance level), and T is the tolerated variation in the sample. For instance, this formula might be used to compute the necessary sample size such that the variable with the largest standard deviation will have a sample mean within t=2 years of the true population mean, with .05 significance.

CONCLUSION

In this chapter, we explained that designing a research is an important aspect of a research process which is the plan and structure of investigation, conceived so as to obtain answers to research questions and to control variances. It also expresses both the structure of the research problem and the plan of investigation used to obtain empirical evidence on the relations of the problem. Basically, research design has two purposes: to provide answers to research questions, and to outline and demonstrate how various variables of the research can be controlled or manipulated in order to generate the necessary primary data for research work. In research design, the research problem must be clear which could be stated in the form of hypotheses. To accomplish this, a research design sets up the framework for study of the relations among variables. Design tells us, in a sense, what observations to make, how to make them, and how to analyse the quantitative representations of the observations. There are both adequate and inadequate research designs; an adequate design suggests for example, how many observations should be made, and which variables are active and which one attributes. It suggests which type of statistical analysis to use and it outlines possible conclusions to be drawn from the statistical analysis. The design of a research could be affected by: types of research, the research population, the type of data required, the variables to control, the facilities / resources available, choosing the right population, selecting the appropriate samples, the design effect. If all these factors are considered appropriately before a research is designed, it is likely that the research design will be an adequate one, otherwise extra efforts have to be put in for the design not to be an inappropriate one.

BIBLIOGRAPHY

Kalton, Graham (1983). Introduction to survey sampling. Quantitative Applications in the Social Sciences Series, No. 35. Thousand Oaks, CA: Sage Publications. This work is a recognized authority.

Kerlinger, N.K. and Lee, H.B (2000) Foundations of Behavioural Research. Australia: Earl McPeek. Wadsworth Thomson Learning 4th Edition.

Kish, L. (1965). Survey sampling. NY: John Wiley. Cited with regard to selection grids.