THE CONSTRUCT VALIDITY OF PRE-BUILT LIKERT-TYPE ATTITUDE SCALES

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ABSTRACT

A number of survey research efforts in South Africa have neglected to examine the validity of attitude scales designed for and validated on other populations. Methods for testing the validity of attitude scales constructed using Likert's (1932) summated ratings method are discussed and demonstrated using Dean's (1961) Social Alienation Scale as an example. The use of factor analysis and cluster analysis in the construct validation of such a scale is examined. The results not only raise doubts about the validity of this particular scale when applied to a non-representative sample of 404 so-called Coloured and White respondents in Cape Town, but also indicate that extreme caution should be exercised when applying such an attitude scale in a population other than that for which it was originally designed and tested.

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CHAPTER ONE

INTRODUCTION AND RATIONALE

1.1 Statement of Purpose

The broad objective of this thesis is an examination of the use of factor analysis and related techniques such as correlation analysis, cluster analysis, and item analysis in the construct validation of attitude scales, using the particular case of a pre-built Likert-type scale as an example. This will involve a step by step look at the various procedures involved in the validation of attitude scales, and elucidation of some of the difficulties commonly encountered in the application of such procedures.

The secondary task of this study is to provide evidence relating to the construct validity of the particular scale being examined: Dean's (1961) Social Alienation Scale. This scale is ideally suited to our purpose as it is a multi-dimensional attitude scale with the proposed dimensions clearly demarcated. Moreover, it is a scale constructed using the Likert technique and standardised on American samples. All the major elements of construct validity are thus involved.

This thesis does not set out to be comprehensive in its coverage of the field of validation, nor to examine all the techniques available for determining validity, for this would require many volumes. Rather, it is aimed to highlight key issues involved in the process of construct validation and to try out some of the more commonly used techniques in a real-data situation, with the hopeful result that researchers will become less reluctant to use such techniques to create attitude scales that result in a valid contribution to our knowledge of society.

1.2 Rationale

One of the major assumptions running throughout this thesis is that validity and reliability are not only highly desirable, but are in fact an essential part of the scientific endeavour (a second major assumption is concurrence with Thurstone's (1967) claim that "attitudes can be measured"). Certain conditions must be fulfilled before the data obtained from any measuring instrument can be used in practical situations. Firstly, the measuring instrument, used on a given occasion and with a given purpose must really measure the object or idea it is intended to measure. Secondly the instrument must give a reliable measurement, so that the same result is obtained when the measurement is repeated under similar conditions. The resultant data should thus be dependable from two points of view: there should be consistency of meaning (validity) and there should be consistency of measurement (reliability).

In sociological research, these aspects are often lacking. This study has arisen out of an observed lack of effort on the part of researchers, both in South Africa and abroad, whether through insufficient time, money, expertise or other factors, to adequately determine the validity of attitude measures for the population under consideration. In many instances the conclusions drawn from such research are not justified. Commenting on the questionability of many research results, Lirtzman (1966 : 51) writes:

> It is my guess that much of this is due in part to misunderstandings and lack of understanding about the nature of attitude scales and measurement, and in part to the computational complexity, cost of adequate preparation of scales, and lack of time which constantly plagues us in our research work.

The availability of validation procedures not being an issue, there should be no excuse for a lack of attention to considerations of validity and reliability in our research endeavours. An intelligent combination of research design and analysis, item selection and pretesting, and proper utilization of the computer can go a long way to reduce the amount of unreliable information generated by the sometimes questionable use of attitude scaling and measurement techniques. The extra effort expended in striving for validity is worthwhile if the results are meaningful and contribute to our understanding of social phenomena.

Validity in comparative attitude research is even more imperative. Comparison is important to much of social research. Isolated measurements are meaningless, and absolutes extremely rare. However, comparison involves more than the difference between individuals in a homogeneous test group. Validity as consistency of meaning is important here. Much can be learnt from the field of intelligence testing in this regard. Likert (1967) argues that it is reasonable to suppose that just as an intelligence test which has been standardised upon one cultural group is not applicable to another, so too an attitude scale which has been constructed for one cultural group will hardly be applicable in its existing form to another cultural group.

Having established the importance of validity to attitude research let us look at the extent to which social science researchers are striving toward this goal. In their collection of 176 attitude scales, Shaw and Wright (1967) deplore throughout the lack of reported validity for published scales, and conclude that:

> ... attitude scales that purportedly are developed by one of the formal procedures, such as the Thurstone or Likert methods, often are only partially evaluated. Scale constructors often seem to ignore the assumptions underlying the scaling method employed, and evidence of reliability and validity is frequently lacking, and almost always incomplete.
>
> (Shaw and Wright, 1967 : 559)

It is also interesting to note that only six of these 176 scales report using some method of item analysis, and only four factor analysis, in the scale construction process.

Of the 90 attitude scales listed in Robinson, Rusk and Head (1968), 36 report no reliability estimates, and 52 have no reported validation procedures. Item analysis is reported for only five of the scales, and factor analysis for four. Similar pictures emerge from an examination of the scales in Robinson and Shaver (1970), Robinson, Athanasiou and Head (1969), and Miller (1970). If this is the situation in the initial scale construction, the problem is only compounded by the application of such scales to other populations. Once determined to be "valid" and "reliable", attitude scales are often thereafter treated as acceptable measures. Often little attention is paid to the characteristics of the sample on which reliability and validity were determined. Bardo (1976 : 403) notes:

> The result is a number of inventories of "pre-built", supposedly reliable and valid scales ... and a tendency for many researchers not to re-test, or report that they retested, for reliability and validity.

Extreme caution should be exercised in assuming that pre-built scales measure what they purport to measure for every population under consideration.

In South Africa the validity problem is further aggravated by the heterogeneous nature of the population, of which language is but one of the lines of cleavage. Establishing consistency of meaning for scales translated into various languages is an almost impossible task, yet it is essential that attitudes be compared across language groups and other dimensions.

Two approaches to this problem have been evidenced in attitude research in South Africa. The first assumes that comparison through equivalent measures is not possible, and proceeds to develop particular scales for the South African context. The second appraoch assumes that pre-built scales have consistency of meaning across cultures and thus are equally applicable to the South African situation. Neither approach, however, avoids the need for determining the reliability and validity of a scale for each population in which it is applied.

There is a disturbing trend in this country to accept without question the validity of attitude scales developed abroad. Evidence of this can be seen in the work of Lobban (1972), Orpen (1973; 1976), Nieuwoudt and Nel (1975), Pettigrew (1958), Serfontein (1966), Weichel (1977) and Wilson and Shutte (1973), amongst others. These comments refer particularly to scales of the Likert-type: the Bogardus Social Distance Scale, for instance, has been used with much success in this country and has been described by Lever (1972 : 204) as " ... probably the only attitude test that permits cross-national comparison". Heaven's (1978) work represents an attempt to establish the validity of a pre-built scale in the South African context (see also Heaven, 1980; Heaven and Stones, 1979). Concerning the first approach mentioned above, many authors regard some form of item analysis (usually Edwards' t-test) as sufficient evidence of the internal structure of a newly-constructed scale (Nel, 1978). Once accepted as part of a scale, items are then often arbitrarily assigned to various subscales (see, for example, Raubenheimer, 1972; Mouton, 1978). The use of multivariate techniques for scale construction or validation in South Africa is rare, possibly due to ignorance concerning the application of these methods or lack of expertise regarding their use. Some exceptions are Pravetz, 1976; Hotz, 1974; Sippel, 1978. The task of this thesis is to meet this shortcoming by demonstrating the use of such techniques for the validation of attitude scales in a real-data situation.

Because of the lack of resources available for this type of research in South Africa, the aim must be to produce the most useful measuring instrument in as short a time and with as little cost as possible. The task of this thesis is not to design a new scale to measure the particular attitude discussed, but rather to provide guidelines for the researcher concerned with obtaining the maximum reliability and validity within the given limitations, whether using a pre-built or self-constructed attitude scale. It should also be noted that this study is concerned with the exploratory stage of attitude research, in which an adequate measure of an often ill-defined attitude construct is being developed. The more common validity approaches (predictive and concurrent validity) will not be discussed thoroughly, nor will much attention be focused on reliability as such. These procedures have been adequately documented and need no elucidation here.

1.3 Structure of the Thesis

The key issues having being mentioned in the previous section, the remaining chapters will be structured as follows. Chapter Two is concerned with the concept attitude. The major approaches to attitude scale construction are discussed. In Chapter Three, validity is examined, with special emphasis on what is meant by construct validity. The following three chapters deal with methods for the determination of construct validity. Chapter Four concerns the analysis of internal consistency, including item analysis and reliability. Factor analysis is examined step by step in Chapter Five. Chapter Six is devoted to a discussion of cluster analysis. The concept of alienation and various attempts at the measurement of the concept are discussed in Chapter Seven, with particular emphasis being placed on Dean's (1961) Social Alienation Scale. Following this is the chapter concerning methodology (Chapter Eight) and the results of the present study (Chapter Nine).

In the final chapter (Chapter Ten) the results are discussed and conclusions reached.

Because of the interrelatedness of the various discussions, it was found difficult to arrange the chapters in a particular logical order. The chapter divisions and order of presentation of the first seven chapters is thus arbitrary and need not be rigorously adhered to.

CHAPTER TWO

ATTITUDES AND THEIR MEASUREMENT

2.1 Definition of Attitude

Allport (in Edwards, 1957 : 1) writes:

> The concept of attitude is probably the most indispensible concept in contemporary American social psychology. No other term appears more frequently in experimental and theoretical literature.

What constitutes an attitude is, however, still open to much debate, and the definitions of attitude are legion. Our aim is not to become embroiled in the argument over the meaning of attitude, and thus a definition will be offered without much discussion. Some of the key aspects of the definition will be examined briefly.

Most definitions agree that attitudes consist of affective, cognitive and behavioural components (see Shaw and Wright, 1967 : 2). The following summary definition which represents the views of a number of writers on attitude is thus offered:

> An attitude is an organized system of evaluative, affective expectations about an individual's environment that predisposes him to act in certain ways.

This definition take the above three aspects into account: the cognitive (an organized evaluative system), the affective, and the behavioural (predisposition to act). In addition to these components, attitudes have much in common with beliefs. Belief involves an expectancy or proposition which the individual accepts as true of an object or event (see Katz, 1970 : 459-460). A belief becomes an attitude when it is accompanied by an effective component which reflects the evaluation of the preferability of the characteristics or existance of the object (Shaw and Wright, 1967 : 4). All attitudes thus include beliefs, but not all beliefs are attitudes. This belief (expectational) component is also accounted for in the above definition.

The behavioural component includes both the verbal and non-verbal expression of attitude. Opinions are the verbal expression of an attitude (see Katz, 1970), and can be seen as intervening variables between abstract or hypothetical concepts (attitudes) and the empirical world. Objection to defining attitudes is sometimes made on the ground that they are too intangible and hypothetical to be amenable to satisfactory description and explanation (see Mouton, 1967 : 7). However, attitudes are no more hypothetical than psychological phenomena such as intelligence, aptitude and ability. The whole claim for the measurability of attitudes is based on the fact that they are made tangible through certain indicators, such as behaviour or the expression of opinion. Carter (1945 : 343) in fact argues that "opinion tests" is a more accurate term than "attitude tests". The latter term will be retained here, although it should be kept in mind that attitudes are not being measured directly, but rather by means of opinions that intervene between the concrete and the abstract.

A further assumption regarding attitudes that has important implications for their measurement concerns the cognitive component. Attitudes are organised in heirarchical groups or subsystems. These subsystems are interrelated with one another to form the total attitudinal system of an individual. Likert's approach to attitude measurement is based on the observation that a series of verbal propositions dealing with the same general social issue can be assumed to be more or less equivalent, or at least to be closely related, so as to permit prediction from a knowledge of a subject's attitude on one issue to his attitudes on other aspects of the same issue (Likert, 1932 : 9-10).

The heirarchical subsystems range from the specific to the general. Thus a person may not only hold specific attitudes about, say, political participation and community involvement, but may also have a systematic organisation of such beliefs and attitudes in the form of an attitude subsystem of alienation. The connection between such generalised dispositions and measurable components is often obscure, making validation of such measurements difficult.

2.2 Attitude Measurement

This study is not concerned with approaches to attitude measurement other than through the verbal expression of such attitudes, and thus only the latter will be discussed. LaPiere (1934) cautions that an individual's expressed attitudes are often not consistent with behaviour. However, it is felt that there are too many variables intervening between covert attitudes and overt behaviour for such a sweeping dismissal to be made, and that regardless of behavioural components, the expression of attitude in itself is of interest. Ferguson (1939 : 669) argues that actual behaviour is not an adequate criterion on which to base the validity of an attitude scale. He further notes that one can get no closer to the underlying physcial order of an attitude than its expression. Assuming, then, that the measurement of an individual's attitudes by means of his responses to items on an attitude rating scale is both possible and practical, some of the methods of constructing such scales will be examined.

2.2.1 Attitude Scales

Why attitude scales? Would not the response to a single penetrating question suffice? In a comprehensive review of early single-question opinion research, McNemar (1946) found that such research is extremely unreliable, and concluded that "single question opinion gauging be discarded in favour of opinion measurements by attitude scales" (see also: Eysenck, 1954 : 97-100; McKennell, 1977; Schuman and Duncan, 1974). A very specific opinion towards a single well-defined object in an individual's environment could probably be ascertained by the simple expedient of requesting his opinion regarding the object. However, more abstract attitude subsystems can only be indirectly elicited through the individual's response to a collection of opinion statements concerning the hypothesised domain of content of the attitude. Such a collection of statements (or items) is known as an attitude scale (test, inventory). The goal of attitude scaling is the development of a measuring instrument that is both valid and reliable: it measures accurately and consistently that which it was designed to measure.

Numerous techniques for the construction of scales for the measurement of attitudes have been suggested. Such scales are developed according to strict procedures which ensure that several responses can be summed to yield a single score representing an independent attitude domain (see Henerson, 1978). The procedures for constructing attitude scales ensure consistency by discarding erratic items or statements. Erratic items are those which produce responses that are inconsistent with an individual's responses to the other items. Some of the more well-known attitude scaling techniques used today include (in order of popularity): Likert's (1932) method of summated ratings, Thurstone's method of equal-appearing intervals (see Edwards, 1957: Chapter 4), Guttman's (1944, 1947a, 1947b) scalogram analysis, Osgood's semantic differential (see Shaw and Wright, 1967 : 29-30), the Bogardus social distance scale (see CRM Books, 1974 : 258-259), and latent structure analysis (Shaw and Wright, 1967 : 29).

The first three scale construction methods mentioned above warrant further discussion. In an informal inspection of the 176 attitude scales listed in Shaw and Wright,(1967), 82 are of the Likert type, 49 are Thurstone type equal-appearing interval scales, and 6 are scales constructed by Guttman's scalogram analysis, the remaining 39 scales being those constructed by the various less formal techniques. Similarly, of the 90 scales discussed in Robinson, Rusk and Head (1968), 21 are Likert, 4 Thurstone, and 13 Guttman scales. Seiler and Hough (1970 : 159) write:

> Two of the most important and enduring methods of attitude scale construction were introduced by Louis Thurstone and Rensis Likert. Despite more recent innovations, such as Guttman scaling, their methods remain in heavy use, and the discourse over the advantages of one vis-a-vis the other still continue.

These three methods of attitude scale construction will be discussed in turn.

2.2.2 Guttman's Scalogram Analysis

Although developed later than the other methods to be discussed, Guttman's scaling technique is mentioned first as its difficulty of application (especially with many variables and large samples) makes it less useful than either the Thurstone or Likert techniques. In actual fact scalogram analysis, developed by Guttman (1944, 1947a, 1947b; see also Edwards, 1948; Festinger, 1947), is not a method for constructing an attitude scale, although it has been used as such by many researchers. Scalogram analysis could best be described as a procedure for evaluating sets of statements to determine whether or not they meet the requirements of unidimensionality or homogeneity. This method is based upon the notion that items can be arranged in an order such that an individual who responds positively to any particular item also responds positively to all other items having a lower rank. If items can be arranged in this manner, they are said to be scalable.

Only in extremely rare cases will perfect scalability be attained. The degree of homogeneity is measured by the coefficient of reproducibility (CoR) which is given as:

$$\text{CoR} = 1 - \frac{\text{total number of errors}}{\text{total number of responses}}$$

(Note: for each item there are only two possible responses: positive and negative)

Theoretically, the coefficient of reproducibility is equal to the proportion of item responses than can be reproduced from knowledge of an individual's score (see Shaw and Wright, 1967 : 25). On the basis of this coefficient a large number of items is reduced until a group of items with a high degree of scalability is obtained. The Guttman procedure is thus limited in that it results in very short scales of high homogeneity which, in the words of Kerlinger and Kaya (1970 : 264), "probably rarely tap much of the richness of any complex attitude structure".

2.2.3 Thurstone's Equal-Appearing Intervals

First described in 1929, Thurstone's method of equal-appearing intervals (see Edwards, 1957: Chapter 4; Shaw and Wright, 1967 : 21-22; Thurstone, 1967) represents one of the earliest attempts at developing specific procedures for the construction of attitude scales. This method begins with the collection of a large number of statements of opinion toward a particular issue which is then reduced through editing according to certain criteria, such as ambiguity or irrelevance. The edited statements are then presented to a large group of judges. The judges sort the statements into eleven piles which represent a scale ranging from extremely unfavourable (1) through neutral (6) to extremely favourable (11) expressions of opinion about the issue in question. From this the scale value for each item, taken as the median of the position given the item by the judging group, is computed.

The Q value, which is a measure of the spread of the middle 50% of the judgements, is computed by obtaining the difference between the 25th and 75th percentile values. A large Q value indicates lack of agreement among judges, and is a basis for the rejection of items. Items are then selected according to the computed scale and Q values. An attempt is made to select about 20 to 22 items with low Q values and with scale values spread at more or less even intervals along the attitude continuum (hence equal-appearing intervals). These items then constitude the final scale. The individual's score on the scale is the median (or mean) scale value of the items he has checked as those with which he agrees.

One of the problems of this scaling technique is that the goal of equal intervals between items is rarely achieved. If judgements are normally distributed about a "true" value, intervals at the scale extremes will tend to be compressed in relation to intervals near the middle of the scale (see Shaw and Wright, 1967 : 22). There is also the question of whether scale values for statements derived from one population of judges is applicable to other populations of subjects (Allport, 2967 : 11).

2.2.4 Likert's Summated Ratings

Both Guttman's and Thurstone's methods are based upon the assumption that sets of attitude statements can be arranged along a continuum of "difficulty", the order being reflected by the relative frequency with which each item is endorsed (McKennell, 1977 : 187). Allport (1967 : 11) argues that attitudes are not necessarily arranged naturally along a single continuum. Rather, they are often discrete and highly individual. In Likert's method of summated ratings no attempt is made to assign items to positions along the attitude continuum and, in fact, good Likert items tend to fall at either extreme of the continuum rather than the middle. The Likert scale is a cumulative type of scale in which the subject responds in some way to all items (Loevinger, 1945). Likert's primary concern was with unidimensionality rather than with equal-appearing intervals (see Oppenheim, 1966 : 133).

Black and Champion (1976 : 187) write:

> The Likert measurement method is by far the most popular of all measurement methods presently used in social research. (see also Lemon, 1973; McKennell, 1977).

Developed by Likert (1932) in an attempt to obviate the costly and time-consuming judging group required by the Thurstone technique, the method is favoured by researchers because of its ease of construction, application and interpretation.

Likert's method is based on the assumption that an attitude towards a given object has many different but interrelated components, and that an individual's responses to the various components can be summated to elicit his response on the attitude sub-system itself. Another assumption made is that each item has equal weight (or equal contribution to the attitude structure being measured) in relation to every other item (Black and Champion, 1976 : 195). It is also assumed that individuals differ in their strength of agreement with a given attitude subcomponent (or belief statement), and that hypothetically continuous measures of that strength of agreement will be normally distributed in the population.

In this method a large number of attitude statements are collected according to the following general criteria:

1. Statements should be expressions of desired behaviour and not statements of fact.

2. Each statement should be clear, concise, and straightforward, avoiding any possible ambiguity.

3. It is desirable that statements elicit responses tending to the extremes of the attitude continuum, rather than clustering around the neutral point.

4. It is also desirable to have roughly half of the statements corresponding to the upper part of the reaction alternatives (e.g. "strongly agree"), and the other half having the same end of the attitude continuum corresponding to the lower part of the reaction alternatives (e.g. "strongly disagree").

5. Each statement should involve only a single attitude variable and not several (Likert, 1967 : 90-91) (for further criteria for attitude statements see: Ferguson, 1939 and Wang, 1937).

Having compiled a wide range of attitude statements, one then asks a sample of respondents from the target population to respond to each item on a five-point scale ranging from strongly agree through agree, undecided and disagree to strongly disagree (3-point and 7-point options have also been proposed: see Guttman, 1970; Guertin and Bailey, 1970; Guilford, 1954).

To obtain an individual's score on the attitude scale, numerical weights are assigned to the categories of each item. The total score is then the summed weights over all items for the respondent (hence summated ratings). There are two methods of assigning weights to response categories, namely the sigma (or normal deviate) method, and the arbitrary assignment of integral weights to categories. The sigma method is based on the observation that 5-point item responses yielded distributions resembling a normal distribution. Hence, normal deviates (areas under the normal curve) can be calculated on the basis of the proportion of subjects falling within each category for that item. The normal deviate or sigma values are then used as the respective category weights. To ease computation, the weights can be made positive by adding the absolute value of the largest negative value to all category weights, and rounding the weights off to the nearest integer (for further discussion of the sigma scoring method see Likert, 1932 : 21-25; Edwards, 1957 : 149-151). For an example of the calculation of sigma weights see Appendix A.

A simpler technique for scoring involves the assignment of values ranging from 0 to 4 (or 1 to 5, or whatever: the scoring system is independent of linear transformation) to each of the five respective categories, with the O (or lower) end always being assigned to the negative end of the attitude continuum, and the 4 (or higher value) end to the positive. Thus the higher an individual's score, the more positive or favourable his attitude is toward the object in question (it should be noted that in both the simple and sigma methods scoring is reversed for negatively-worded items). Likert has found that the simpler method of scoring correlated highly (.99) with the sigma method, and thus advocates the use of the former for ease of calculation (Likert, 1932 : 26).

Having calculated the total scale scores for the pilot group, items are selected for the final scale using the criterion of internal consistency. Criterion groups consisting of the upper and lower 10 per cent of the subjects in terms of the total scores are compared to find whether the individual items differentiate between the two groups. The means for each group are found, and items which show the largest difference between each pair of means are retained in the final scale. Alternatively, internal consistency can be based on item-total correlations (see Section 4.1 for a discussion of item analysis techniques). Scales constructed by the method of summated ratings usually contains about 20 to 25 items (Edwards and Kenney, 1943 : 74).

As has been mentioned, the usefulness of the Likert approach lies in its flexibility and ease of measurement. Guilford (1954) notes that Likert scales are among the easiest to construct and apply, and the simplest in terms of handling the results. He adds:

> If the rater takes his numbers seriously, and if he can apply number properties directly to his observations of the rated phenomena, the ratings themselves should represent measurements of a high order. (Guilford, 1954 : 265).

Another advantage of the Likert method is that it makes allowance for the measurement of the intensity of expression of an attitude. A further advantage is that Likert procedures can be adapted to attitudes of any degree of generality or specificity, ranging from highly abstract domains such as alienation or authoritarianism at one extreme, to attitudes toward very specific stimulus objects such as a particular occupation or political party at the other (see McKennell, 1977).

One disadvantage of the Likert technique concerns its lack of reproducibility (in the technical sense). The same total score may be obtained in many different ways and thus there is no consistent meaning that can be attached to the scores derived by such measurement (see Black and Champion, 1976 : 195; Oppenheim, 1966 : 140). Related to this is the assumption of a Likert scale that each item has identical weight in relation to every other item in representing the attitude being measured. This is not necessarily a valid assumption. Another disadvantage is that the scales are such that one cannot tell when scores in the middle ranges change from mildly positive to mildly negative. However, this obstruction can be overcome by adopting a comparative approach, in which an individual's score is considered relative to the scores of others on that scale, or by assuming a normal distribution and utilizing standard deviations as total score intervals. A more serious disadvantage of the Likert technique is its inability to detect when more than one dimension is represented in the item set (see McKennell, 1977 : 214). There is no way of easily ascertaining which items in a scale are the most intense, nor is there any guarantee that only one dimension is present. Thus this method can yield an apparently unidimensional scale which is actually multidimensional. In this study methods for counteracting the last-mentioned drawback are discussed.

2.2.5 Comparison of Approaches

Which method of constructing an attitude scale yields the best results in terms of reliability and validity? As the determination of comparative validity depends very much on the constructs being measured, more effort has been expended in the past on the comparative reliabilities of the various approaches. Likert has claimed that his method of scoring yields higher reliabilities when applied to a scale constructed by Thurstone's method (.94 as opposed to .88 for the 44-item Thurstone-Droba War Scale, N=54; see Likert, 1932 : 34-35) than when the Thurstone scoring method is used. This approach has been criticised by Ferguson (1941) on the grounds that reliability can be increased simply by increasing the number of steps in a scale. The proper approach suggested is a comparison of scale construction methods rather than scoring methods.

The evidence is still strongly in favour of scales constructed by the Likert technique when scale construction methods are compared. In a comparison of various approaches, Tittle and Hill (1967) found that not only were Likert scales better predictors of behaviour, but that they also yielded a higher split-half reliability (.95) than either the Thurstone (.67) or Guttman (.80) methods. Further studies (Edwards and Kenney, 1946; Poppleton and Pilkington, 1963; Seiler and Hough, 1970) lead to the conclusion that a high reliability (.90) can be achieved with 20-25 items in a scale constructed by Likert's method. For equivalent reliability, about 50 Thurstone-scale items would be needed. This fact together with ease of construction, makes Likert's approach the method preferred by most attitude researchers today.

A major limitation of both the Likert and Thurstone techniques is that, in and of themselves, they give little or no clue to the factors behind the attitudes purportedly being measured. Moreover, although they contain items associated with the attitude in question, there is no guarantee of unidimensionality. Furthermore, two or more identical scores on a scale may have totally different meanings. For this reason, the pattern of responses often becomes more interesting than the total score. These shortcomings can be overcome by the various multivariate techniques discussed in the chapters following.

2.3 Attitude Scales in the Comparative Context

Researchers attempting to measure a particular attitude are faced with the choice of developing their own measuring instrument or making use of an existing scale designed to measure the same attitude. Advantages of the latter approach are that it permits accumulation of findings and improves comparability of results (Shaw and Wright, 1967 : ix). Miller (1970 : 163), arguing for the use of pre-built scales, writes:

> Social scientists have often elected to construct new measures even when scales of high reliability and validity have been available. This practice is wasteful of time, energy, and money. In addition, it makes replication, and accumulation of research findings, difficult if not impossible.

However, the use of pre-built scales on populations other than that on which the measures were standardised is not without problems.

Bardo (1976 : 404) considers such an approach to have three underlying assumptions. These are:

1. Attitude scales are considered, <u>a priori</u>, to be generalizable beyond the group on which they were constructed.

2. The "scalability" of items is regarded as constant regardless of the respondents' backgrounds.

3. So long as the phenomenon being measured is generalizable to various groups, so should a standardised, highly reliable scale.

A number of authors (see Nunnally, 1970; Shaw and Wright, 1967) argue that Likert scales should always be standardised on a sample drawn from the target population. However, standardisation generally refers to criteria for score interpretation rather than item analysis. The items themselves and taken as given.

In studying this problem Bardo notes that the sociological literature contains a surprising number of studies using untested items or non-retested scales for the measurement of attitudes. He concludes:

> Of what validity are the results of these studies? There is no way of knowing. Without an estimate of the power of items to discriminate, in terms of internal response or test-retest consistency, it cannot be logically argued that study results are valid. (Bardo, 1976 : 413).

It is important to note that attitude measures are subject to cultural variation, and the validity of a scale in a particular situation is a function of that situation, and does not imply universal applicability.

This does not mean to say that pre-built attitude scales are worthless, but that the methodology involved in their use be re-examined. In the cross-cultural context validity refers to consistency of meaning. One of the first tasks in such research is to develop measuring instruments that represent equivalent stimuli in each population under consideration (see Almond and Verba, 1970). One way of doing this is to examine the structure of the scale for each population in which it is applied. The methods discussed in this thesis represent an attempt to establish the construct validity of a pre-built Likert-type scale in the cross-cultural context.

CHAPTER THREE

VALIDITY

3.1 Types of Validity

The problem of validity arises because measurement in the social sciences is, with very few exceptions, indirect. Attitudes, for example, are measured indirectly through their verbal expression in opinions. Under such circumstances, researchers are never completely certain that they are measuring the precise concept or property they intended to measure. Validity is concerned with the question "Is one actually measuring what one planned to measure?" There are a number of ways of attempting to answer this question. These are discussed in this chapter.

The first attempt to adequately conceptualise the various approaches to validity was the American Psychological Association's (APA) Committee on Psychological Tests (1954). The committee found it necessary to distinguish between four types of validity, namely predictive, concurrent, content and construct validity. The first three types will be briefly mentioned, but the fourth, construct validity, being the main concern of this thesis, will be examined more thoroughly.

3.1.1 Predictive Validity

This concerns the ability of an instrument to predict future behaviour and is the most sought-after when the attitude being measured has a strong behavioural component. According to an individual's response to a question or scale an expectation of future behaviour is hypothesised, and predictive validity is a measure of whether such behaviour correlates with that predicted. Intelligence tests make use of this type of validity, evaluating the accuracy of predictions regarding future academic achievement.

3.1.2 Concurrent Validity

This type of validity is used when the researcher wishes to compare an individual's score with some variable external to the measure being used. Concurrent validity is involved when one test or measure is proposed as a substitute for another or a test is shown to correlate with some contemporary criterion. Concurrent validity is the most common validity type, and is easy to establish when the construct being measured is shown to be related to other measurable phenomena.

Predictive and concurrent validity are similar in that they are both criterion-related, the former being concerned with future criteria and the latter with criteria that are currently accessible. In attitude research these forms of validity are usually concerned with some behavioural criterion, future or present, that can be inferred from the scale responses. Campbell (1960) has argued that these two validity types can be subsumed under the single title of practical validity.

3.1.3 Content Validity

Content validity is based on the assumption that the measure is a sample of the universe of situations. Thus the concern is with ensuring validity through the careful construction of scales or measures rather than with post hoc examination of the results. Here one is concerned with showing that the items of the scale are representative of the construct being measured, and that the full range of content or meaning of the construct is included among the items. Content validation is often an arbitrary affair, as quantitative evidence regarding the adequacy of sampling or representativeness of the scale content is not feasible. This type of validity has also been referred to as face validity (see Nachmias and Nachmias, 1976) in that it often involves a superficial examination of scale content.

These first three methods of validity all involve aspects external to the measuring instrument itself, and could thus also be regarded as measures of external validity as opposed to construct validity which is concerned with the internal validity of a scale or test. The above approaches to validity were already in common use before the APA's (1954) report, but the major innovation of the Committee was the introduction of the term construct validity.

3.1.4 Construct Validity

3.1.4.1 Pre-APA Developments

Although first conceptualised as such by the APA Committee, construct validity did not emerge out of a void in 1954. Its arrival was foreshadowed in several noteworthy articles preceding the Committee's Report, in which the inadequacies of the classical criterion-related notions of validity were emphasised and attempts at rectifying this situation were made.

Cronbach (1949) made a distinction between what he called "logical validity" and "empirical validity", the latter being the determination of validity through the comparison of test results with a criterion, whereas the former was concerned with the use of deductive and inductive methods of logical analysis in the validation process. Cronbach notes that logical analysis of a test or scale aims at understanding the processes that affect responses to items comprising a measure. Validity in this sense is not specific: only empirical validity is concerned with the usefulness of a test for some single purpose. Cronbach was concerned with only one of these two approaches to construct validity, namely logical analysis. However, empirical studies, both experimental and correlational, have since also become accepted methods for studying construct validity.

In an article entitled "Intrinsic Validity", Gulliksen (1950) deplored the then current tendency to choose and use the test with the highest correlation with the criterion without being concerned about what the test really measures. Many such correlations, he argued, should be disregarded because they do not reflect relationships that are direct and causal. Although criterion-oriented in his approach to validity, by expressing dissatisfaction with the current validity concept and pointing out the necessity for qualifying the relationships between tests and criteria, Gulliksen helped pave the way for the concept of construct validity.

Guilford (1954) distinguished between two types of validity: "practical validity", which has earlier been pointed out as corresponding to criterion-related validity procedures, and "factorial validity". The latter Guilford conceived of as being based on factor theory, the communality or common factor variance (these terms will be discussed later in the chapter on factor analysis) of a test being the foundation of its validity. The closeness of Guilford's concept of factorial validity to what is now known as construct validity can be evidenced in the following quotation:

> When one is aiming at factorial validity, however, the goal is to develop tests for general purposes and an immediate validation against practical criteria is not essential. A correlation study of some kind is necessary, however, and is the alternative to a practical validation study.
> (Guilford, 1954 : 402).

The factorial approach to validity, now only one aspect of construct validity, has important implications for cross-national research as well as for the search for unidimensional structures underlying a scale.

A further forerunner of the construct validity concept was Peak's (1958 : 249) notion of "functional unity". This she distinguished from validity as being psychological processes or behavioural events that have a functionally organised relationship. Peak discussed four ways of discovering the presence of such functional unity between processes or aspects of an event, these being primarily concerned with the internal structure of the scale under consideration. Another important point Peak makes is that the validity of a measuring instrument is demonstrated under a circumscribed set of conditions, and that a change of condition could affect such validity (Peak, 1953 : 291).

These then are the major developments leading up to the introduction of construct validity into the vocabulary of the social sciences.

3.1.4.2 The APA Report and After

We now come to the APA Committee's findings, in which construct validity is first referred to as such. No specific definition of construct validity is offered in the Report, but the essence of the term can be deduced from the following:

> Construct validity is evaluated by investigating what psychological qualities a test measures, i.e. by demonstrating that certain explanatory constructs account to some degree for performance on the test. To examine construct validity requires both logical

> and empirical attack. Essentially, in studies of construct validity we are validating the theory underlying the test ... Construct validity is ordinarily studied when the tester has no definite criterion measure of the quality with which he is concerned, and must use indirect measures to validate the theory. Here the trait or quality underlying the test is of central importance, rather than either the test behaviour or the scores on the criteria. (APA, 1954 : 14).

Construct validity is not discussed much further and it is left to two members of the Committee, Cronbach and Meehl, to elucidate the Committee's understanding of the term in a later article.

According to Cronbach and Meehl (1955), construct validation is involved whenever a test is to be interpreted as a measure of some attribute or quality which cannot be adequately operationally defined. Thus the construct validity of an instrument can be seen as the degree of assurance with which it can be claimed that the instrument represents the construct being measured. Put simply, whereas the other forms of validity are concerned with whether a test measures what it intends to measure, construct validity is in addition concerned with whether a test means what it intends to mean.

3.1.4.3 Constructs

To understand more fully what is meant by construct validity we need to look at the meaning of the term "construct". Cronbach and Meehl define a construct to be "some postulated attribute of people, as assumed to be reflected in test performance" (1955 : 283). To the extent that a variable is abstract rather than concrete in nature it is regarded as a construct. Such a variable is literally a construct as it is something put together by the researcher out of his own imagination, something that does not exist as an isolated, observable dimension of behaviour, verbal or non-verbal (see Nunnally, 1967 and 1970). Implied in a construct is the expectation that observable attributes (behaviours, opinions, etc.) will be organised in such a way as to provide evidence for the existence of the construct so defined (see Peak's functional unity).

Hotz (1974 : 2) describes hypothetical constructs and intervening variables as being on opposite ends of the construct continuum, the former being constructs with a low degree of operational validity, while the latter are constructs with the maximum possible operational validity and the greatest possibility of empirical investigation (see also MacCorquodale and Meehl, 1948; Marx, 1951; Ginsberg, 1951). Where a construct will be found on this continuum in part determines the validity approach to be used, the more hypothetical the construct, the less chance of using criterion-related procedures and the greater the need for a construct validation approach.

Confusion sometimes arises between the terms "construct" and "concept". The distinction between the two is often vague, and they have at times been used interchangeably (Cattell, 1978 : 280-281, refers to both conceptual and construct validity). Concepts are regarded as lying more on the theoretical side of the operational continuum than do constructs. Concepts tend to be theoretical entities, whereas constructs imply some hypothesis concerning their measurement. Thus alienation can be regarded as a concept, but the specific aspects of alienation measured by, say, Dean's (1961) Social Alienation Scale can be referred to as constructs, and the process of their validation as construct validity.

To ascertain whether a test measures a construct, a nomological network, defined as an "interlocking system of laws which constitute a theory" (Cronbach and Meehl, 1955 : 290), describing the relationship between aspects of the test and the construct must be developed. When a construct is in its infancy, these specifiable associations may be few. As the research proceeds, more evidence is contributed which adds substance to the initial framework of the construct, the eventual target being a fully integrated theory in which the construct can be identified by the specific relationships between it and the tests used to measure it.

3.1.4.4 Construct Definition

One of the initial opponents of construct validity was Bechtoldt, (1959 : 622), who warned that ...

> The "constructs" of construct validity appear to be "vague", open and "not explicitly defined" as matter of principle rather than as a matter of ignorance.

Thus construct validity is seen as a means of circumventing the need for adequate and explicit definition of terms. This is a very real danger in validation, but it should be kept in mind that the process of construct validity should lead to more precise definition of constructs and greater behaviour-relevance (integrated theory regarding the associations or relationships between the construct and specific empirically amenable phenomena). Construct validity is more often needed in the beginning stages of research, where these associations are not yet adequately specified. The need to use construct validity thus depends on the degree to which the variable is concrete or abstract.

In addition, Henerson (1978 : 136) notes that the first step in construct validation should be precise construct definition. This should include a list of the construct's distinctive features, including its subcomponents and their relationship to one another, a description of expected behaviours associated with the construct, and a list of closely-related constructs and the similarities and differences between these and the construct in question. In the initial stages of construct definition this is not easy but, as research proceeds, development of the nomonological net will occur, resulting in greater precision of definition.

Concerning construct definition, Cook and Campbell (1979 : 62-63) note that although acceptable definition of constructs is practically desirable, from a certain philosophical perspective the inability to achieve widely accepted definitions of many constructs is actually desirable. This is because propositions about constructs are more reliable if they have been successfully tested, not only across many overlapping operational representations of a single definition of a construct, but also across representations of many overlapping definitions of the <u>same</u> construct. Imprecise definition thus encourages investigation of the entire domain surrounding the construct. Thus various researchers persuing slightly different definitions of the same construct is preferable to a situation where all research proceeds from a perhaps limited initial definition.

3.1.4.5 Construct Validity in Relation to Other Validity Types

The various approaches to validity can be divided into two general types: internal validity and external validity (see Cook and Campbell, 1979 : 37). Predictive, criterion and, to a lesser extent, content validity, are external in that validity is sought through relating the test to external criteria. Construct validity is internal in that external criteria are often not available and validity is determined through an examination of the internal structure of the test. External validity requires in addition to the variable in question, the presence of at least one other variable (the criterion), whereas in construct validity the question is how a variable relates to a construct, as intended to embody the attribute or property in question (see De Groot, 1969 : 254-255). The choice of validity method depends on the evidence obtainable. Validity is a matter of degree rather than an all-or-nothing property, and validation is a never-ending process involving all possible approaches at the appropriate moments.

3.1.4.6 Measuring Construct Validity

Nunnally (1967 : 97) writes:

> In the ultimate analysis, the "measurement" and "validation" of constructs can consist of nothing more than the determination of internal structures and cross-structures.

None of the procedures specifically associated with the determination of construct validity are in fact new. Peak (1953) discussed four methods for discovering the presence of "functional unity" as she called it. These are:

1. Analysis of internal consistency,
2. scaling techniques,
3. correlations between tests or items, and
4. factor analysis of these intercorrelations.

The APA Committee (see Ekval, 1969 : 19) added two further methods, namely:

5. Studies of change over occasions, and
6. studies of process.

Cronbach and Meehl (1955 : 300) note that many types of evidence are relevant to construct validity, including inter-item correlations, interscale correlations, studies of group differences, studies of stability over time and stability under experimental intervention, factor analysis, and studies of internal structure.

As this study is concerned with specific statistical techniques, attention will be focused on multivariate analysis (including factor, cluster and correlation analysis) and analysis of internal consistency as the two internally oriented groups of procedures associated with construct validation. The specific roles of these various methods will be discussed in detail in the following two chapters where elucidation of the specific statistical procedures involved will also be undertaken. Before this is done, however, it remains necessary to look at the concept of reliability as it pertains to construct validity.

3.2 Reliability

Reliability is concerned with the consistency of measurement of a scale. A coefficient of reliability is the most common fact reported concerning a scale and it is certainly much easier to obtain than is a measure of validity. Reliability is the minimum information one should have regarding a test, but it is certainly not the most useful information. A test can be reliable without being valid, but a valid test must also be reliable. Thus reliability is an essential prerequisite of validity.

Reliability is actually a generic term for a number of distinct procedures. The several types of reliability coefficient do not attempt to answer the same questions and should be carefully distinguished from each other. Cronbach (1947) has referred to three categories of reliability estimates, these being:

1. A coefficient of stability,
2. a coefficient of equivalence, and
3. a coefficient of internal consistency (see also Guilford and Fruchter, 1978 : 414-416).

These three coefficients are also identified as such in the APA Committee Report (APA, 1954 : 28-33). Each will be discussed in turn.

3.2.1 Coefficient of Stability

This concerns the traditional test-retest approach to reliability, in which the same test is administered to the same subjects on two or more occasions after a suitable intervening period of time. The responses are then correlated with each other, the resulting error variance corresponding to the fluctuations in response from one test administration to the next. Thus the temporal dimension of reliability is investigated (see Anastasi, 1976 : 110-112). Test-retest reliability has also been referred to as a dependability coefficient (Cattell, 1973 : 352).

This approach to reliability has three major short-comings. First, the fact that the individual has been tested on one occasion may influence the measurement on subsequent tests. Secondly, human properties are in a constant state of flux. Changes in responses may be attributed to causes external to the test itself, giving a lowered estimate of reliability. This is especially true in the measurement of attitudes. Thirdly, this method of reliability determination is costly in time and administration, as well as in the difficulty of obtaining the same subjects after an elapsed period of time.

3.2.2 Coefficient of Equivalence

Heise and Bohrnstedt (1970 : 114) define reliability as "the correlation between two equivalent forms of a test". An alternative method that is far more simple than the above method is the so-called "split-half" technique in which the items of a test are separated into two equivalent subsets and the subjects' responses to these subsets compared. The well-known Spearman-Brown reliability formula is involved here (see Nachmias and Nachmias, 1976 : 67). One of the problems of this method of reliability calculation is that one cannot with any assurance claim the two forms of a test or scale to be equivalent. This is especially true of multidimensional tests measuring heterogenous attitude structures.

3.2.3 Coefficient of Internal Consistency

Internal consistency measures the efficiency with which the various parts of a scale (items, subscales, subvariables, etc.) support and complement one another (see De Groot, 1969 : 284). Wherry and Gaylord (1943 : 258) argue that approaches other than the internal consistency approach to test reliability are either less satisfactory or lead to the same general conclusions. Internal consistency reliability is most appropriately applied to tests of an homogeneous nature, that is, tests in which the items all measure the same construct to about the same degree. Methods of determining internal consistency reliability include item analysis and Cronbach's (1951) alpha coefficient. These will be discussed in more detail at a later stage. The Spearman-Brown formula can also be used as a measure of internal consistency.

It should be pointed out that internal consistency is also an important approach to the determination of construct validity. Before this relationship is examined further, a further reliability coefficient will be looked at.

3.2.4 Coefficient of Transferability

To the above three coefficients of reliability should be added a fourth, transferability (Cattell, 1973 : 282). Although not strictly a coefficient in that it cannot be directly computed, transferability is of vital importance to sociological research, especially research of a cross-cultural or cross-national nature. Transferability is concerned with consistency across populations or cultures. This is an oft-neglected aspect of comparative research.

Transferability is approached through the other reliability measures. The ease and simplicity with which attitude scales can be checked for split-half reliability and internal consistency would seem to make it desirable that such reliabilities are determined for each group upon which a scale is applied. In the same way that an intelligence test standardised upon one cultural group is not applicable to another so an attitude scale which has been constructed for one cultural group will hardly be applicable in its existing form to other cultural groups (see Likert, 1967 : 95). The comparison of reliability coefficients over populations gives an indication of transferability. The coefficient of transferability has important implications for construct validity.

3.2.5 Reliability: Internal or External

In the same way that validity has both internal and external dimensions, so too has reliability. The coefficients of equivalence and stability are concerned with the external aspects of reliability, whereas internal consistency coefficients emphasize the internal structure of a measuring instrument. The concern of this study is with the internal aspects of reliability and validity.

3.3 Reliability and Validity

It can be seen that internal reliability shares a number of distinct procedures with the internal construct validity approach. This is because both are concerned with the internal consistency of a test, construct validity referring to consistency of meaning and internal reliability to consistency of measurement. Both reliability and validity concepts require that agreement between measures be demonstrated. Transferability is concerned with construct validity as consistency of meaning because it questions whether a scale represents the same meaning across cultures and subcultures.

Campbell and Fiske (1967 : 283-287) argue that reliability and validity should be seen as regions on a continuum rather than discrete procedures. Reliability is the agreement between two efforts to measure the same trait through maximally similar methods (test-retest or alternate forms). Validity is represented in the agreement between two attempts to measure the same trait through maximally different methods. A split-half reliability is thus more like a validity coefficient than is a test-retest reliability, as the items are not quite identical. A correlation between dissimilar subscales is probably a reliability measure, but is still closer to the region called validity. This distinction probably causes confusion, and it seems better to stick with the internal/external dichotomy of validity and reliability (for an alternative conceptualisation of the validity-reliability domain see Cattell, 1973).

The aim of the above discussion was to point out that there are many areas of overlap between validity and reliability, and that the methods should be regarded as complementary rather than competitive. Terminological exactness is less important than comprehensive investigation of all aspects contributing to the usefulness and precision of an attitude scale.

3.4 Beyond Construct Validity

Because construct validity pertains almost exclusively to concepts that are not directly observable, there is a greater risk that the instrument is measuring some other phenomenon similar to the one under investigation. Compared to external validity procedures, there is no direct opportunity to correlate actual behaviours with scale scores as a means of demonstrating the construct validity of an instrument (Black and Champion, 1976 : 231-232). The research endeavour should never end with the construct validation of a scale. This merely provides evidence that the scale is a good indication of the construct, and should give rise to further definitions of the exact relationships between observable phenomen and the construct in question. Internal analysis of the scale is never an adequate substitute for external validation, but must often be used in the initial stages of research when the opportunities for external validation are still limited. It should be remembered that validity is a matter of degree rather than an all-or-nothing property, and validation is an unending process.

CHAPTER FOUR

ANALYSIS OF INTERNAL CONSISTENCY

We now turn to the first major group of methods identified earlier as being useful in the determination of construct validity for an attitude scale, namely the analysis of internal consistency. This includes such methods as item analysis, incorporating measures of discrimination, item-test and item-subtest correlations, and reliability. Measures of internal consistency differ from multivariate analysis in that whereas the latter are essentially post hoc analysis procedures, internal consistency analyses have their place in the initial development of an attitude scale, specifically in the selection of items. This does not, however, preclude their use on pre-built scales as an aid to determining construct validity. The latter approach is adopted here.

4.1 Item Analysis

Peak (1966 : 252) writes:

> Although item analysis has been used most often as a basis for selecting test items in the interest of improved prediction to a criterion, it may also be thought of as a device for establishing the existence of functional unity within a test.

Whether used for item selection or post hoc analysis of an existing scale, the methods of item analysis remain the same, the only difference being in the number of items analysed.

Item analysis is the most efficient test of whether subjects are responding to the items in the manner intended. Too often it has been assumed that an a priori division of scale items by the researcher corresponds to the way the respondents perceive them. The same applies to attitude scales standardised on one segment of the population. Without item analysis there can be no assurance that the items have equivalence of meaning across populations.

No matter for what *a priori* reasons the experimenter may consider an item to belong in a scale or subscale, if the item, when tried on a group, does not measure what the rest of the items measure, there is no justification for keeping that item in the scale. It is often found that the items do not form the groupings that were hypothesised for the scale. Thus item analysis is one of the most vital aspects in the construction of valid and reliable scales, and also in the examination of the validity of existing scales when applied to populations other than which were used for the selection of items.

Various methods of item analysis that have been proposed include the scale value difference ratio (Sletto, 1937), the t-test, described by Edwards (1957), and item-scale and item-subscale correlations. Each of these methods will be discussed in turn.

4.1.1 The Scale Value Difference Ratio

This method of item analysis, developed by Sletto (1937) in response to criticisms of Likert's method of scale construction mentioned earlier, is a refinement of the original item analysis procedure proposed by Likert (1932) in which the difference between means of high and low criterion groups are simply compared. The scale value difference ratio (SVD ratio) is based on the difference between the means of the upper and lower quartile (or any other proportion) of respondents when considering the item in isolation and as a part of a scale. The proportion of cases included in the upper and lower extreme groups varies from reserarcher to researcher. Sletto (1937), Vernon (1948) and other use quartiles (25%), Likert (1932) uses approximately 10% in each group, Thurstone (1931) 7% and so on. The present study will include 10% of the sample in each group (deciles).

The first step in obtaining the SVD ratios for the items of a scale is the calculation of the mean response for each of the high and low extreme groups for each item, using the total scale score to determine these extreme groups. The difference between these two means for a particular item then becomes the item scale value difference. The same method, but using the extreme groups on the item (not scale) yields the maximum potential difference value. This is the maximum difference between extreme group means that this item could attain regardless of the particular combination of items. The item scale value difference is the actual difference obtained in a specific combination of items.

The SVD ratio then becomes the item scale value difference divided by the maximum potential difference value. Expressed as a formula:

$$SVD = \frac{\bar{X}t_H - \bar{X}t_L}{\bar{X}i_H - \bar{X}i_L}$$

Where $\bar{X}t_H$ and $\bar{X}t_L$ are the means of the high and low groups respectively when selected on the basis of total scale scores; and $\bar{X}i_H$ and $\bar{X}i_L$ are the means of the high and low groups respectively when selected on the basis of item scores alone;

$\bar{X}t_H - \bar{X}t_L$ is the item scale value difference; and

$\bar{X}i_H - \bar{X}i_L$ is the maximum potential difference value.

Thus, what is being measured is whether the item acts consistently with the scale in discriminating between extreme criterion groups (deciles). This ratio is expressed as a proportion or percentage. For example, a SVD ratio of .41 means that the item attains 41% of its maximum possible decile discrimination for that sample when the item is scored on a particular scale (see Appendix B for an example of the calculation of SVD ratios).

One drawback of the SVD ratio, as with many other sociometric techniques at present, is that objective techniques for determining significance levels are lacking. Sletto suggests that a tentative lower limit of .50 for the ratio seems to provide some justification for combining a given item with other items in a single scale score. One must also be careful that the ratios are not too high, suggesting that the items are basically measuring the same thing, making some items redundant. A certain amount of heterogeneity is desirable. What can be achieved with this method is a ranking of items according to their contribution to the total scale. The cut-off point can be decided according to the needs of the researcher (length of scale, degree of homogeneity, etc.).

4.1.2 Edwards' T-value

A method similar to the SVD ratio is the t-value proposed by Edwards (1957). The t-value is also based on the differences between high and low group means, but is only concerned with the within-scale means. Edwards' formula (for the special case $n_H = n_L$) is as follows (1957 : 153):

$$t = \frac{\bar{X}_H - \bar{X}_L}{\sqrt{\dfrac{\sum(X_H - \bar{X}_H)^2 + \sum(X_L - \bar{X}_L)^2}{n(n-1)}}}$$

where: 1. $\sum(X_H - \bar{X}_H)^2 = \sum X_H^2 - \dfrac{(\sum X_H)^2}{n}$ and the same for $(X_L - \bar{X}_L)^2$

2. $\bar{X}_H$ is the mean of the high group for that item, and $\bar{X}_L$ the low

3. n is the number of subjects in each criterion group.

As with the SVD ratio, the value of t is a measure of the extent to which a given item differentiates between extreme groups. Significance levels for the t-value can be regarded as equivalent to those for Student's t-test for the difference between means, tables for which are obtainable in most statistical text books. For 40 subjects in each criterion group a t-value greater than 2.70 will be significant at the 1% level of confidence.

Both the above methods are concerned with evaluating the discriminative powers of items by comparing responses of high and low criterion groups. The aim is a ranking of items according to discriminative power which can be used for the selection of items for scales or subscales. The following methods, on the other hand, are based on the similarity of items to the total scale in terms of the complete profile of responses.

4.1.3 Item-Total Correlations

Item-total correlation methods of internal consistency provide some safeguard against the inclusion of unrelated items in a unidimensional scale, and in the *post hoc* situation identify those items which are not acting in concord with the items in the scale. Peak (1966 : 284) refers to these correlations as an index of item validity in that they indicate whether items act as hypothesised by scale definition.

With this method the correlations between respective items and the total scale score are computed, resulting in a coefficient which indicates the degree of correspondence between the two, in an attempt to determine whether the scale gains or loses anything by the inclusion of the item. Thus it is examined whether the item measures the same thing as the other items comprising a scale.

In order not to obtain a distorted coefficient, the item in question should be excluded from the total scale when the correlation is computed. If left in, the perfect correlation of the item with itself will inflate the resultant coefficient. With a large number of items this becomes a tedious process. However, the following formula has been developed (see Magnussen, 1966 : 211) for computing the correlation between a given item and the other items in a scale which necessitates computing only the correlation between the items and scale and the standard deviations for the items and the scale:

$$r_{i(t-i)} = \frac{r_{it} \; S_t - S_i}{\sqrt{S^2_t + S^2_i - 2r_{it}S_iS_t}}$$

where: S_i is the standard deviation of the item

S_t is the standard deviation of the total scale

S^2_i is the variance of the item

S^2_t is the variance of the total scale

r_{it} is the correlation between item and total scale

The significance levels for the coefficient are determined as for the normal product moment correlation coefficient. Wherry and Gaylord (1943 : 258) point out, however, that the value of the item-scale correlation does not approach unity as an upper limit as the items become more reliable, but approaches the value of $\sqrt{\frac{1}{k}}$ where k is the number of factors (if k = 1, $r_{i(t-i)}$ will approach 1.0). Thus the automatic rejection of items with lower $r_{i(t-i)}$ than would normally be accepted is not justified.

What one seeks for is a correlation that is high enough to confirm that there is some similarity of meaning between the item and the scale, yet not too high that the scale content becomes homogeneous, and the items tautological. The ideal is a scale that is homogeneous enough to conclude that the same construct is being measured by all the items, yet heterogeneous enough that all the aspects of the construct are covered by the items.

Wherry and Gaylord (1943) argue that item-subscale correlations are a more appropriate approach to item analysis. This is especially true when the construct is hypothesised to consist of a number of separate but interrelated aspects, each of which is measured by its own set of items. Item-scale correlations in this case would result in a distorted heterogeneity for the items, whereas item-subscale correlations would correctly disclose homogeneity within each sub-group. The correlations between subscales and the total scale in these instances could also be computed. Whether it is desirable or undesirable to have high subscale correlations depends on the nature and the purpose of the scale.

4.2 Reliability

In the chapter on validity it has been seen that there is no clear distinction between construct validity and reliability, especially concerning aspects of internal consistency. In this section, however, attention will be focused on the more traditional approaches to reliability as they pertain to internal consistency.

The most useful measure of internal consistency reliability is Cronbach's (1951) alpha coefficient. The alpha coefficient is a derivation of the split-half coefficient that avoids the shortcomings of the latter. The split-half approach has been criticised for its lack of uniqueness (see Cronbach, 1951 : 298). Instead of giving a single coefficient for a scale, the procedure gives different coefficients depending on which items are grouped when the scale is split into two parts. Especially in a scale with high heterogeneity, one can never be sure that the two halves are equivalent.

Alpha, however, can be seen as the average of all the possible split-half coefficients for a given scale.

The short-cut formula for alpha proposed by McKennell (1970 : 229) will be used here:

$$\text{Alpha} = \frac{n\bar{r}_{ij}}{1 + (n-1)\bar{r}_{ij}}$$

where: n is the number of items in the scale

$\bar{r}_{ij}$ is the average of all inter-item correlations.

This formula is easier to compute than Cronbach's original formula in that all the information necessary for the computation of alpha is available in the matrix of inter-item correlations. The resultant coefficient is an indication of the internal consistency reliability of the scale.

Alpha is useful not only as a measure of scale reliability, but also in subscale reliability, item analysis, and as an aid to factor and cluster analyses. Regarding the latter, the alpha coefficient is used to ascertain the reliability of a cluster, and items can be added to or subtracted from the cluster on the basis of their contribution to the reliability of that cluster. In this way inter-cluster heterogeneity can be accounted for (split-half reliability measures assume homogeneity of the total scale, and interpret heterogeneity as low reliability). In item analysis, the acceptance or rejection of items is based on the maximisation of scale reliability as measured by the alpha coefficient.

A reliability coefficient such as Cronbach's alpha helps us determine whether the designer of a scale was correct in expecting a certain collection of items to yield interpretable statements about individual differences. This information is of great importance to construct validity. The analysis of internal consistency, together with factor and/or cluster analysis, provides the information necessary to determine the construct validity of an attitude scale.

CHAPTER FIVE

MULTIVARIATE ANALYSIS I: FACTOR ANALYSIS

Factor analysis is but one group of statistical procedures that are multivariate in approach. Multivariate analysis involves the simultaneous analysis of three or more variables. Many of the techniques attempt to explain a dependent variable in terms of a series of independent variables. The need for external criteria are evident here. Some of these methods are multiple regression, partial regression, multiple correlation and path analysis (see Mueller, Schuessler and Costner, 1977 : 274-330). Other techniques, such as factor analysis and cluster analysis, involve the search for inter-relationships among any number of variables without the need for criteria or independent variables. The importance of these latter approaches to construct validity should thus be obvious. We shall now look at these two methods in depth.

It should be noted that this study is concerned more with the usefulness of the techniques of factor and cluster analysis to construct validity than with the actual methods employed. Because factor analysis without the aid of a computer is a time-consuming and impractical affair, detailed discussion of the statistical basis of and specific techniques involved in factor analysis becomes unnecessary, and will be kept to a minimum. As computer programmes for cluster analysis are not yet universally available, attention will be focused on techniques that do not require a high degree of statistical sophistication.

5.1 Factor Analysis

Factor analysis is a group of statistical techniques that aim at the orderly simplification of a number of interrelated measures into subgroups called factors. A factor is defined simply as any linear combination of the variables in a data matrix (matrix of correlations).

More simply, factor analysis is a procedure for investigating the possibility that a large number of variables have a small number of factors in common which account for their intercorrelations (Schuessler, 1971 : 10).

Thurstone (quoted in Cattell, 1952a : 15), one of the pioneers in the field, calls attention to the fact that factor analysis:

> ... has its principal usefulness at the borderline of science where fundamental concepts are still lacking and crucial experiments cannot be easily devised.

Factor analysis is at the heart of the measurement of psychological constructs (Nunnally, 1967 : 101). The explication of a construct consists mainly of determining the internal statistical structure of a set of variables said to measure the particular construct. Factor analysis is used directly to determine this. Guilford and Fruchter (1978 : 436) write:

> For many individuals concerned with construct validity, factorial validity provides the best answers.

5.2 Aims of Factor Analysis

The three main aims of factor analysis, according to Eysenck (1953 : 105-108), are similar to the aims of statistics in general, namely:

1. Factors as descriptive statistics (descriptive factor analysis);
2. factors suggesting an hypothesis (exploratory factor analysis); and
3. factors supporting or disproving an hypothesis (confirmatory factor analysis).

These three functions of factor analysis are not mutually exclusive. The descriptive nature of factor analysis is at the basis of all factor analytic research. Whatever else may be the function of a factor, it is always descriptive of a given sample or population. The hypothesis-testing and hypothesis-suggesting aims of factor analysis are similarly intertwined.

The construct validation of an attitude scale involves both the exploratory and confirmatory aspects of factor analysis. Comrey (1978 : 243) writes:

> One of the most common uses of factor analysis is to analyse the characteristics of a given measuring instrument or method to assess how well it is fulfilling its mission. This sometimes takes the course of a one-shot evaluation in which the investigator is checking on the adequacy of a particular measurement method of a construct .... Another related usage of factor analysis is by the developer of a measurement method who is trying to improve the excellence of his instrument.

Factor analysis suggests further hypotheses that result in possible improvements to the measuring instrument. The goal is the development of a highly reliable instrument that provides as pure a measure as possible of the construct in question. The important point is that construct validity consists of more than merely assessing the fit between the constructs and the instruments used to measure them. One can use the obtained pattern of data to edit one's thinking about both the cause and effects of constructs, and one can suggest, after the fact, other constructs that might fit the data better than those with which the investigation began (see Cook and Campbell, 1979 : 68-69).

5.3 Steps in a Factor Analysis

In any factor analytic design there are a number of steps to be taken before adequate results are attained, each step involving a number of decisions that could alter the final outcome of the analysis. Vaughan (1973 : 306) notes that, because of the widespread availability of computer programmes,

> ... many have been encouraged to turn out factor analyses of questionnaire items without first acquiring a sound apprenticeship in the demands of the method. The result has been that the true demands of experimental design and analysis in this field have often not been met.

Cattell (1973) has attempted to list the most essential steps involved in factor analytic research, some of which are appropriate only to the field of personality research. His steps will form the basis of a list of conditions for an effective factor-analytic design.

The conditions against which any factor analysis could be evaluated is as follows:

1. The data used as input in the factor analysis must be appropriate to the statistical techniques used, especially the correlation coefficient.

2. The appropriate factor analysis model should be chosen to suit the nature of the investigation.

3. Communalities, not unities, should be employed in the diagonals of the correlation matrix.

4. An objective test for extracting the optimum number of factors should be used.

5. An objective test for testing the significance of factor loadings should be used.

6. The appropriate method of rotation should be selected, with the aim of maximising simple structure.

7. Objective methods for matching the resultant factors with those from other studies should take preference over mere subjective judgement.

(see Cattell, 1973; Vaughan, 1973).

Failure to meet any one of these criteria (with the possible exception of the first) is sufficient to make the results of any factor analysis questionable. Numerous alternatives are open to the researcher wishing to make use of factor analytic methods, and the best way to reduce subjectivity is to approach the analysis systematically in terms of the steps listed above, carefully documenting all decisions made and, where possible, the results obtained at each stage of the analysis. In this way, one important scientific criterion can be satisfied, namely reproducibility of the results by independent investigation.

5.3.1 The Correlation Matrix

The first step in a factor analysis is to determine whether in fact the data are amenable to such analysis. Factor analysis requires that the underlying distribution of the data be of a multivariate normal type. This implies that, not only is each variable normally distributed, but that the relationships between all pairs of variables are linear. Once this has been determined, and the variables selected, the data are arranged in an mxn matrix, where the number of cases (n) should exceed the number of variables (m) by a ratio of at least 3 to 1, and preferably be more than 250 (Cattell, 1973 : 284). The correlation matrix between the variables is then prepared from the basic matrix of data.

The most common input for factor analysis is the Pearson product-moment correlation coefficient (r), computed from the data matrix using the following formula:

$$r = \frac{N\sum XY - (\sum X)(\sum Y)}{\sqrt{(N\sum X^2 - (\sum X)^2)(N\sum Y^2 - (\sum Y)^2)}}$$

where: r is the correlation between variables X and Y

N is the number of cases

X and Y are individual scores on the respective variables

An alternative formula which makes calculation of the coefficient easier is as follows (derived by dividing by N throughout):

$$r = \frac{\sum XY - \frac{(\sum X \sum Y)}{N}}{\sqrt{\left(\sum X^2 - \frac{(\sum X)^2}{N}\right)\left(\sum Y^2 - \frac{(\sum Y)^2}{N}\right)}}$$

The major assumptions underlying the product moment correlation are that variables should be continuous, linear, and of roughly normal distribution. In addition, data should be at least of an interval scale. This last point has met with much controversy, especially concerning the application of parametric techniques to ordinal data.

Most variables in attitude research are at best ordinal. That is, the relative positions of variable subclassifications can be defined but the interval between each unit is not necessarily of equal size (Black and Champion, 1976 : 178). The heart of parametric strategic is to assume equal distance between all rankings. This strategy obviously imputes scale properties that are not warranted under the assumptions of ordinal scaling. Strictly speaking, one cannot assign numbers to the subclassifications of an ordinal scale. Thus the use of Pearsonian correlation coefficients is strictly not permissable since addition and subtraction are possible only if at least an interval scale level has been achieved.

In spite of the arguments of purists, there is now much evidence to show that the advantages of using more sophisticated parametric statistical techniques on ordinal level data far outweigh the danger of violating assumptions. After putting this claim to the test, Labovitz (1967) concludes that parametric techniques (specifically the product moment correlation) are surprisingly robust in nature. Robustness means the ability of a statistical test to maintain its logically deduced conclusion when one or more assumptions have been violated. Many support this claim that the results obtained from assuming interval data have been useful (see Bohrnstedt, 1970; Labovitz, 1968; Nunnally, 1967; Anderberg, 1973; Baird and Noma, 1978; O'Brien, 1979; and Cohen and Cohen, 1975). For opposition to this view, see Henkel (1975a; 1975b), Krause and Vaitkus (1970), and Vigderhous (1971).

Morris (1968) objects to the argument for using parametric statistics on grounds of their superiority to nonparametric techniques. Advances in the nonparametric field have resulted in a number of measures that are highly powerful in comparison with their parametric equivalents. Two measures of concern to us here are Kendall's (1948) tau (see also Siegel, 1956) and Goodman and Kruskal's (1954) gamma, two measures of association for ordinal data (these two measures will be discussed in more detail in the following chapter). Another approach to the multivariate analysis of ordinal level data is thus to argue that an ordinal statistic (e.g. tau) calculated from ordinal level data may be used as an analogue to the correlation coefficient (see Hawkes, 1971). However, this approach has been criticised, and the approach discussed earlier (the calculation of interval level statistics directly from ordinal data) is considered to be superior (see Kim, 1975; Vigderhous, 1971; Wilson, 1974). Anderson (1961 : 315) concludes that:

> ... parametric procedures are the standard tool of psychological statistics, regardless of scale, and nonparametric tests should be seen as useful minor techniques.

This latter approach is adopted in this thesis.

Another approach to solving this problem is the transformation of the ordinal data into a scale approximating an interval scale. Likert's sigma scoring method, assuming a normal distribution, is claimed to result in a scale representing an interval level of measurement. Further evidence in favour of accepting ordinal data for analysis by parametric procedures is given by the high correlation (.99 with an N of 30) between total scores obtained using the sigma method and the arbitrary assignment of numbers to response categories (Likert, 1932 : 26). Likert consequently advocates the acceptance of the more simple ordinal scale as equally valid and less time-consuming than the sigma (quasi-interval) scaling method.

The three possible approaches to the problem of meeting the assumptions required by factor analysis are thus:

1. To assume that the acceptance of one's data as interval, linear, and of normal distribution will not seriously distort the results, and so use the product moment correlation as input into the factor analysis;

2. to use correlation procedures that meet the assumptions of the data but may be less powerful than the parametric techniques; and

3. to transform the data to approximate an interval scale so that parametric tests can be applied.

The first approach is the one adopted in the present study. However, nonparametric coefficients of correlation will be calculated for comparative purposes, as will the correlations based on transformed data (sigma scoring method).

5.3.2 Choice of Factor Model.

We now come to the point where the particular model of factor analysis is chosen, according to the aims of the analysis and the nature of the results desired. Factor analysis is a generic term referring to a number of distinct procedures, each with its own assumptions and methodological approaches. These methods include principal components analysis, common factor analysis, alpha factor analysis, canonical factor analysis, image analysis and maximum likelihood factor analysis, as well as a number of minor variations that do not warrant mention. A comprehensive discussion that would do justice to the various factor analysis models available would consume many pages, and thus cannot be undertaken here. For detailed discussion of the various procedures the reader is referred to such standard texts as Cattell (1978), Child (1970), Comrey (1973), Fruchter (1964), Gorsuch (1974), Harman (1960), Mulaik (1972), and Rummel (1970). In this section some of the major differences of procedure will be highlighted in order to demonstrate the choice that is available to the researcher.

The first major distinction in method is between principal components analysis (or simply component analysis) and common factor analysis. The former involves no reduction in the number of variables (n components account for n variables). Component analysis is a mathematically more appealing method than factor analysis, as the analysis is treated as a complete self-explanatory system with no purely statistical estimation (for e.g. unities are inserted in the diagonals rather than communality estimates). However, this method is an unrealistic one for the social sciences as however many variables are involved in the study, all the variance can never be entirely accounted for within these variables. Component analysis cannot take into account the influence of variables external to the study. For further discussion of the principal components model, see Cattell (1978) and Marriot (1974).

Common factor analysis involves more statistical assumptions regarding the data than does component analysis. Variables are assumed to approximate a normal distribution and have a linear relationship. Common factor analysis also assumes that data on a variable consist of both common and unique parts. The common factors account for the correlations among the variables, while each unique factor accounts for the remaining variance of a specific variable (usually only the common factors are reproduced in a factor matrix, the unique factors being easily calculated from the matrix). In common factor analysis, the number of factors is always less than the number of variables. The remaining procedures to be discussed are all refinements of the common factor analysis model.

Canonical factor analysis is a refinement of Lawley's (1943) maximum likelihood factor model developed by Rao (1955) and further refined by Harris (1956; 1964). However, maximum likelihood factor analysis has been further improved (see Jöreskog, 1967; Clarke, 1970) and now supercedes canonical factor analysis in popularity. Both methods involve complicated statistical manipulations and thus are beyond the scope of those researchers who are not experts in the field of factor analysis. It should be noted that, unlike common factor analysis, canonical factor estimates and factor scores are invariant of scale. Alpha factor analysis has a similar property. Invariance is an important property of a factor model as it relieves the researcher of making what are often arbitrary decisions about the appropriate scaling to apply (Rummel, 1970 : 122). Another advantage of canonical and maximum likelihood factor analysis is that the adequacy of the number of factors estimated at the outset can be tested with statistical precision after the analysis (Cattell, 1978 : 396).

Image analysis and alpha factor analysis are variations of the common factor analysis model developed in response to specific research needs. Image factor analysis, developed by Guttman (1953), is concerned with the dimensions of the common vector space of the data, ignoring that part unique to each variable. Image analysis makes use of the squared multiple correlation in contrast to the partial correlation of the common factor analysis model. Image analysis constructs with the multiple correlation matrix what can be described as an image of each variable as seen in the other variables. This image variance represents as much of the original variable as can be constructed by the multiple correlation from what it shares with other variables in the matrix. It then in effect constructs a new matrix which expresses the relationship among these images (Cattell, 1978 : 387-388).

Alpha factor analysis, developed by Kaiser and Caffrey (1965), is simply a way of implementing the common factor analysis model through a different weighting in the computational procedure. This method derives its name from its relation to the alpha coefficient for estimating homogeneity of items within a scale discussed earlier. Thus alpha factor analysis attempts to maximise validity, assuming that the criterion of validity is the factor as defined by the variables. Alpha factor analysis is a statistically appealing method not only because of its property of invariance, but also because the estimation of communalities and the number of factors to be extracted are intrinsic parts of the computational procedure.

Image and alpha factor analysis can be regarded as psychometric methods, as opposed to statistical methods, of factor analysis (Harman, 1976 : 229). In statistical studies the sampling elements or entities are usually persons. The attributes of these persons are the variables analysed for an understanding of the group being studied. This often involves generalisations from a sample to other groups of persons presumed to belong to the same population as the sample. Thus the concepts of sampling or generalisation refer to people, the variables being tacitly assumed to be determined or fixed. This is known as statistical inference. Psychometric inference, on the other hand, is concerned with variable generalisation. When the variables are the elements sampled, they may be presumed to belong to a universe of content and, when projections are made from such a sample, it is referred to as content-area or psychometric inference (Harman, 1976).

It can be seen from this brief discussion that the differences between various factor analysis models are often slight, being due to minor differences in emphasis or computational procedure. No one method should be chosen above the others and stuck to rigidly for all analyses. Each method yields different results under different circumstances. It is felt that alpha factor analysis is the most appropriate for the present study as it is concerned with generalisations from variables not subjects. It is, however, advocated that several factor analysis methods by employed to see whether roughly equivalent solutions emerge and to test what Harris (1967) calls the "robustness" of the factors. By this he means the regularity with which particular factors reappear for homogeneous cases irrespective of the analytical techniques adopted (Harris, 1967 : 61). Some of the differences between the various models of factor analysis will become more clear in the ensuing discussion of the determination of communalities.

5.3.3 Determining Communalities

Communality (h^2) can be defined as the sum of all the common factor variance of a variable, or the variance shared with other variables (Child, 1970 : 35). More simply, a communality is the correlation of an item with itself due to the common factors only. Since the common factors are unknown at this stage of the analysis, these values must be estimated.

The problem of communalities is that they cannot be known until the common factors are defined, yet the delineation of these factors depends on the correlations and the communality values in the principal diagonal of the correlation matrix. The traditional procedure for dealing with this inability to determine precise communalities is to insert in the principal diagonal some estimates of the communality values.

There are various methods of reaching these estimates. The first possibility is to utilise the average correlation of the variable with the other variables as the communality estimate for that variable.

This method is not often used, as it is too low an estimate of the true communality. A second method, advocated by Thurstone (1947 : 299-300, 318), is to use the highest correlation of a particular variable as its communality. The third and most popular method is estimating communality through refactoring. An initial estimate such as the average correlation or squared multiple correlation is employed in the matrix, which is then factored. New communalities are then inserted into the correlation matrix and the matrix refactored. The procedure can be reiterated until the successive communalities converge on a stable value (Rummel, 1970 : 317). This is also known as the iterative method of communality determination (for further discussion of the communality issue see Nunnally, 1967 : 348-355).

The choice of communality estimate for the common factor analysis model will depend on:

1. The estimate adopted by other factor studies against which results might be compared;

2. existing computing facilities;

3. the number of variables; and

4. the size of the off-diagonal correlations (Rummel, 1970 : 318-319).

With regard to the first consideration, it is presumed that the researcher will wish to compare his factor structure with others to determine the stability of the common factors. Especially when the number of variables is small, the findings are in part determined by the estimates adopted. In an experimental test of this question, Bechtoldt (1961 : 424) found that

> ... comparable analysis for the several sets of data of this study indicate that differences in the stability of factor loadings do result both from the method of factoring, and from the diagonal values used as communality estimates, as well as from the characteristics of the data.

Thurstone (1947) also presents evidence that the values in the principal diagonal can alter the factor loadings and the number of factors defined for the data. Regarding the second point mentioned earlier, computer programme availability and options should be investigated before deciding on the method of estimation. Estimation by the iterative method is impractical without a computer, but other methods can be estimated by hand. The number of variables also has an effect on the importance of communality estimates. The larger the number of variables, the smaller the effect of the diagonal elements on the factor results. Similarly, the larger the average off-diagonal correlations, the less the influence of the diagonal values on the final solution.

The estimate of communalities is applicable only to the common factor model. For other models the communality problem is already solved. The essential distinction between the principal components and factor analysis models is that the components solution accounts for the variance of all variables in terms of common factors alone, thus giving communalities of unity, whereas factor analysis also requires the aid of specific factors to account for this total variance and thus has communalities of less than unity (Cattell, 1978 : 64).

Neither image nor alpha factor analysis require communality estimates, the determination of the number of common factors being an integral part of the procedure. For image analysis the squared multiple correlation for each variable with the remaining variables is the precise communality value. In the alpha and canonical models communality estimates are employed, but the best estimates are known, and the analysis begins with these estimates, converging them to stable values through iteration (Rummel, 1970 : 312).

5.3.4 The Number of Factors

Determining the number of factors to be extracted constitutes the next major decision to be made. Instead of extracting all the factors present in the data, including spurious factors, factoring is usually stopped at the point where no additional significant or meaningful variance remains. How this significance is determined is important, as the number of factors extracted can influence results when factors are rotated.

For some models the decision as to the number of factors to be extracted constitutes no problem. In canonical factor analysis this number is determined by a significance test. In alpha factor analysis the factors extracted are those with eigenvalues greater than unity (an eigenvalue or latent root is the sum of squares of the loadings for each factor, and is a measure of the variance of that factor). In common, component and image factor analysis models, however, the best number of factors to extract depends on the researcher's judgement. Taking out the right number of factors, points out Cattell (1978 : 61), does not mean a number correct in some absolute sense, but rather in the sense of not missing a factor of more than trivial size (in the psychometric approach) or one that is statistically significant (in the statistical approach).

A number of procedures have been proposed that assist the researcher in deciding on the number of factors to be extracted. Three of the better-known procedures are as follows:

1. The Scree test.
2. The Kaiser-Guttman criterion.
3. Shifting the whole basis of factor extraction to the maximum likelihood method.

As the third alternative involves adopting the canonical or maximum likelihood approaches, discussion will be limited to the first two criteria for factor extraction.

5.3.4.1 The Kaiser-Guttman Criterion

This criterion, developed by Kaiser (1960b), has gained wide popularity for common factor analysis. The method involves retaining unities in the principal diagonal of the correlation matrix and limiting the factors to those with eigenvalues greater than unity. Thus it is also known as the eigenvalue-one criterion (Cattell, 1978 : 362). This criterion is neat and easy to apply, but should not be used without caution. An inspection of the eigenvalues should be undertaken, as a factor with an eigenvalue just below unity (say, .97) might be dropped, yet another with an eigenvalue of 1.02 retained. The difference between the factors seems hardly meaningful, yet one would be included in the analysis, and the other ignored. Thus a strict application of the criterion risks missing important factors.

5.3.4.2 The Scree Test

This criterion is based on the observation by Cattell (1966b) that factor variance levels off when the factors are largely measuring random error. If the eigenvalues for the successive factors were to be plotted on a graph, the point at which the curve straightens out into a more gentle slope (the scree) is the point below which error factors are predominant.

The interpretability of factors should not be overlooked in the extraction process. Rummel (1970 : 357) notes that:

> The researcher ... will first weigh the interpretability of a factor, its consonance with other research findings, the configuration of its loadings, and its proportional factor variance and then decide whether to accept or reject the factor.

Thus statistical or analytical considerations should not blind the researcher from using common sense in judging a factor according to its usefulness and meaning. Cattell (1978 : 55) warns that the conclusions of a factor analysis are more likely to be distorted by underfactoring than by overfactoring. Thus it is safer to include possible unwanted factors rather than risk excluding an important common factor through underfactoring.

5.3.5 Significance of Factor Loadings

We have now arrived at an unrotated or raw factor matrix in which the factor loadings represent the correlations between the factors and the variables. It is now necessary to determine the significance of the loadings of a particular variable upon a particular factor. Henrysson (1957 : 137) notes that the only acceptable tests of significance for loadings seem to be those introduced by Lawley. These tests are, however, based on the assumptions of maximum likelihood factor analysis. For the other methods one must attempt to approximate the levels of significance for factor loadings.

A rule-of-thumb method that is often used for large samples (N=50 at least) is $\pm$ .30 as an arbitrary level of significance, with loadings in the range -.10 to +.10 being regarded as zero loadings. This arbitrary level is based on the assumption that a squared value ($.30^2$) gives .09, which indicates that a data variable correlating with the factor less than .30 has less than 10% of its variance in common with the factor (Comrey, 1973 : 225). Compared with other criteria this is quite a rigorous significance level.

A more realistic approach is based on the observation that factor loadings are in effect correlation coefficients. For the purposes of specifying an acceptable level of significance, the loadings can be treated in similar fashion to correlations, using a table of significance levels for the correlation coefficient (Baggaley, 1964 : 189-190). Thus for N= 400, loadings of at least .098 and .128 are recommended for the 5% and 1% confidence levels respectively. For larger samples, this criterion is thus far less demanding than the arbitrary figure of $\pm$ .30.

Burt and Banks (in Child, 1970 : 45-46) have developed a formula that takes both the number of variables and the particular order of the factors into account when calculating the significance levels for a loading. They argue that as one progresses from the first factor to higher factors the acceptable level for the significance of a loading should increase (it should get harder for loadings to reach significance). The gradual intrusion of unique variance into later factors requires some adjustment in the level of significance. The Burt-Banks formula is as follows (Cattell, 1978 : 480):

$$\sigma_p = \sigma_r \left(\sqrt{\frac{n}{n + 1 - f}} \right)$$

where: σ_r is the standard error of a correlation (see Child, 1970 : 95)

σ_p is the standard error of a loading (significance level)

n is the number of variables in the analysis

f is the factor number (position of the factor after extraction) to use an example, suppose 400 individuals are tested on 23 variables. The standard error for a sample of 400 at the 1% level is .128. For the 5th factor extracted, n = 23, f = 5, thus:

$$\sigma_p = .128 \left(\sqrt{\frac{23}{24-5}} \right)$$

$$\sigma_p = .141$$

It can be seen that for the first factor, the standard error of the loading (σ_p) would equal the standard error of the correlation (σ_r). For the eighth factor the significance level for loadings would be .153 at the 1% level of confidence. Again one must warn against rigidity and the subsequent rejection of loadings that have interpretive value merely on the grounds of their lack of significance, or the acceptance of items whose loadings reveal no truly significant relationship. These tests of significance should be regarded as approximate guidelines, not as absolute criteria for the acceptance or rejection of a factor loading.

In exploratory studies such as this one, strict criteria for significance are not as necessary as when one intends to give substance to the resultant factors. However, when one is attempting to assign items to one group or another on the basis of factor loadings, to set significance levels too low will result in items loading on too many factors. Thus a level of significance should be chosen that will aid the assignment of items to groups. This is done after a careful examination of all factor loadings. It should be emphasised that the determination of significance levels is an arbitrary decision of the researcher based upon theoretical expectations regarding the data. Thus for certain analyses in this study the significance level is set at .30, with items loading over .20 on a factor being considered for inclusion where it makes sense to do so.

5.3.6 Rotation of Factors

The attainment of a matrix of factor loadings with desired communalities and the optimum number of factors is by no means the necessary end of the factor analytic process. This matrix is known as the raw or unrotated matrix. If the principal aim of the investigation is the parsimonious description of the data, the unrotated factor matrix would suffice. However, if the aim is to identify distinctive clusters of variables, rotation of the original factor loadings is necessary. This is because the initial unrotated solution will identify the principal patterns of variation and not necessarily distinctive variable groupings. What is sought is some pattern in the factor loadings that makes the factors more amenable to interpretation. To better understand the purpose of rotation we need to take a look at what is meant by simple structure.

5.3.6.1 Simple Structure

The earliest attempts at rotation could be attributed to Thurstone (1947 : Chapter 4), whose primary objective was to organize the factor loadings so that their meaning would make better sense in psychological terms. For him, the aims of factor analysis were that the factor solutions should be parsimonious, invariant, unique and in accordance with non-factorial research findings (see Child, 1970 : 55). Parsimony refers to the reduction of variables to a small number of related factors (this aim is met by the unrotated matrix). By invariance is meant the constancy of factor content from one analysis to another. Uniqueness occurs when the resulting matrix is the most appropriate description of the underlying causes of a factor.

In order to fulfil these requirements, Thurstone established several criteria against which rotations could be evaluated. These are the criteria of simple structure. The basic principle underlying simple structure is that each of the variables would be affected by only some of the factors, and that each of the factors would contribute to only some of the variables. The criteria are as follows:

1. Each variable should exhibit at least one zero or non-significant loading (because of sampling errors, a zero loading is regarded as ranging between -.10 and +.10).

2. If there are n common factors in the rotation, there should be at least n non-significant loadings in each factor.

3. For every pair of factors there should be several variables with non-significant loadings in one, but significant loadings in the other.

4. When there are four or more factors, for every pair of factors a large proportion of the loadings should be non-significant in both factors.

5. For every pair of factors there should only be a small proportion of significant loadings in both factors (Thurstone, 1947 : 156; see also Bennett and Bowers, 1976 : 28; Child, 1970 : 56; and Schuessler, 1971 : 123).

A number of techniques have been developed for determining the statistical significance of simple structure, the easiest being that of Sine and Kameoka (1980; see also Cattell, 1978 : 554-568) which considers the number of variables in the hyperplane for each factor.

A hyperplane variable is simply one with zero loading on a factor. However, because of the possibility of error, a variable with loading between -.10 and +.10 is regarded as being in the hyperplane for that factor. The literal variable loadings must be divided by the square roots of their respective communalities in order to determine whether the loadings, adjusted for communality size still fall in the ± .10 hyperplane. Using the tables in Cattell (1978), in a study with 23 variables and 8 factors, each factor would require 15 variables in the hyperplane to be considered significantly approximating simple structure at the 1% confidence level (14 variables in hyperplane for $p < .05$).

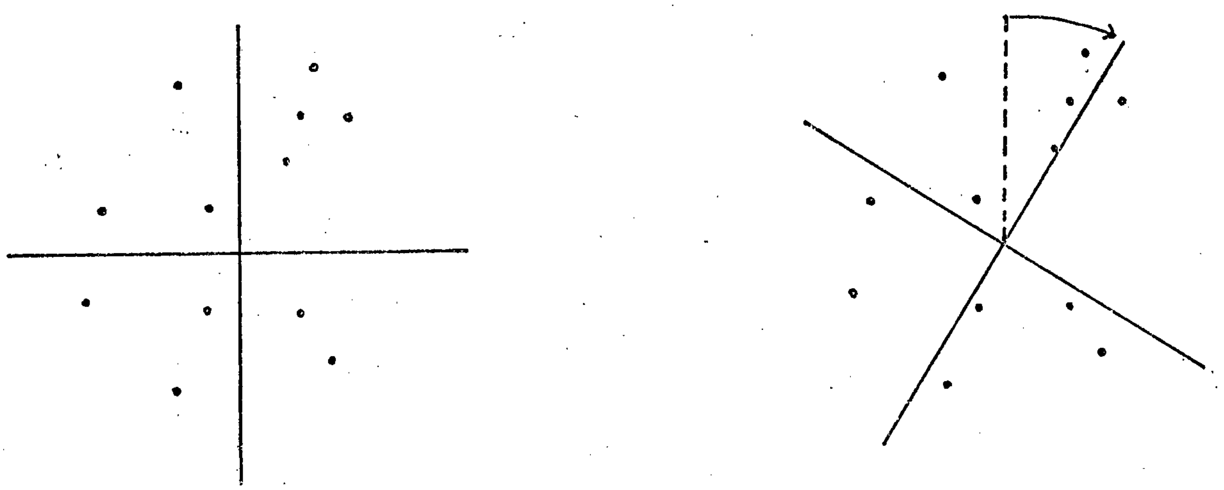
5.3.6.2 Geometrical Illustration of Rotation

In order to understand what is meant by rotation it is necessary to make use of graphs depicting variables plotted for two factors (the axes) by means of their loadings on each factor. The geometric aim of rotation is to align factor axes as close as possible to the major variable groupings.

Figure 5.1

Geometrical Representation of Orthogonal Rotation

Unrotated Axes | Orthogonally Rotated Axes



It can be seen from Figure 5.1 that, whereas the loadings of the variables on the factors change, their configuration in respect of each other remains invariant. Communalities also remain unchanged. In orthogonal rotation, illustrated above, the angle between the factor axes remains 90°, hence the term orthogonal. In oblique rotation this angle can assume any value. If only two factors were involved in an analysis, geometric rotation could be undertaken. However, most analyses involve more factors, and hence analytical methods are resorted to for the simultaneous rotation of a number of factors. The major decision that has to be taken is whether to rotate orthogonally or obliquely. We shall look at each choice in turn.

5.3.6.3 Orthogonal Rotation

If factor analysis is employed as a purely descriptive technique, then a model with uncorrelated factors is often easier, both to understand and to use. In addition, uncorrelated factors are statistically more appealing. Orthogonality ensures that factors will delineate statistically independent variation, thus the factors are necessarily uncorrelated with each other. It has been argued (Rummel, 1970 : 392) that the VARIMAX criterion of orthogonal rotation, developed by Kaiser (1958), comes closest to Thurstone's goal of simple structure. This method involves maximising the variance (hence vari-max) of the squared factor loadings. VARIMAX is now generally accepted as the best analytical orthogonal technique (Harman, 1976; Harris, 1964; Warbuton, 1963). A strong feature of VARIMAX is its ability to discern the same cluster of variables regardless of the number or combination of the variables in the analysis. Other programmes for orthogonal rotation include

QUARTIMAX, VARISIM (Rummel, 1970 : 390) and ORTHOMAX (Harman, 1976 : 299).

5.3.6.4 Oblique Rotation

Whereas in orthogonal rotation the final factors remain uncorrelated, in oblique rotation they are allowed to become correlated. Oblique rotation individually rotates the factor axes until each factor delineates a distinct variable cluster (Rummel, 1970 : 388). The empirical correlation between the clusters will determine the degree of correlation between the resultant factors. A common justification for oblique rotation is the argument that the world cannot be realistically treated as though basic functional unities represented by the factors are uncorrelated (Cattell, 1958 : 309). Phenomena, whether singly or in clusters, are interrelated, and the factors themselves must reflect this reality.

Oblique rotation allows for interrelated phenomena. If the factors do happen to be uncorrelated, oblique rotations will stop at the orthogonal position. It is argued (Guilford, 1954 : 508) that Thurstone's simple structure criteria can be more easily satisfied by oblique than by orthogonal rotations, although they can apply to both. Oblique rotation programmes available today included OBLIMAX, MAXPLANE, PROMAX and ROTOPLOT (Cattell, 1978 : 136-139).

There is still controversy regarding the best approach to rotation. Such noted psychometricians as Burt (see Rummel, 1970 : 386), Edwards (1957), Guilford (1954) and Horst (1965) have argued in favour of orthogonal rotation, while the main proponents of oblique rotation have been Thurstone (1947) and Cattell (1952a; 1978). The oblique rotation method is preferred in the present study as the nature of the scale under investigation leads one to expect factors with a degree of intercorrelation.

5.3.7 Factor Matching

The final step in the factor analysis of a data matrix has been reached. A factor matrix has been produced whose loadings provide a parsimonious and coherent description of the factors underlying a set of variables. However, one does not need to stop here. The comparison of factor patterns from different studies is vitally important, whether the aim is to derive or discover constructs or merely reduce multivariate data. Factor matching provides important evidence regarding the stability and cross-cultural validity of attitude scale constructs. Thurstone (1947) has proposed that generalisability or invariance of factors is a major goal of an adequate factor analytic design. The need for comparison, writes Rummel (1970 : 449),

> ... stems from a conviction that no theoretical-empirical study can by itself contribute to a science. It must be replicated and compared if its findings are to find a proper theoretical niche, and the researcher interested in contributing to building a science ... should try to construct a research design that will maximise the ability of himself or others to make this comparison.

Factor matching involves four possible situations:

1. Same variables, same subjects
2. same variables, different subjects
3. different variables, same subjects
4. different variables, different subjects.

Our discussion of factor matching procedures will be limited to the first two alternatives. A number of approaches have been proposed to deal with the problem of factor matching. Two of these approaches will be discussed further.

5.3.7.1 The Congruence Coefficient

One approach, adopted by Rummel (1970 : 461) is simply to compare factors on different studies by correlating the loadings of the variables on each pair of factors. One possible disadvantage of this method is that it measures only pattern similarity and not magnitude similarity as well, as does the congruence coefficient.

This latter approach, developed by Burt (1952) and refined by Wrigley and Neuhaus (1955), is similar to the correlation between loadings mentioned above. However, the congruence coefficient (r_c) avoids some of the defects of the ordinary correlation coefficient when finding the similarity of two sets of loadings. Wrigley and Neuhaus' (1955) formula for the congruence coefficient is as follows:

$$r_c = \frac{\sum_{j}^{j=n} b_{j1} b_{j2}}{\sqrt{\sum_{j}^{j=n} b_{j1}^2 \sum_{j}^{j=n} b_{j2}^2}}$$

where: b_{j1} and b_{j2} are the loadings of variable a_j on the compared factors F_1 and F_2.

The practical problem of r_c is that there is as yet no clear test of its significance. Attempts to obtain significance levels through Monte Carlo simulation (randomly-generated data) have been undertaken by Korth and Tucker (1975) and Schneewind and Cattell (see Cattell, 1978). For example, for 23 variables in common between two factors, the critical ($p < .01$) values of r_c by Schneewind and Cattell's method would be -.63 and +.68. For $p < .05$ these would be -.47 and +.50.

5.3.7.2 The Salient Variable Similarity Index

The salient variable similarity index (s) was designed by Cattell (1949) to have properties of resistance to minor pattern change in the factor loadings of a study. By this method one accepts variables above a certain arbitrary level (usually ± .10) of loading to be significantly loaded or salient variables in that factor. Two factors can then be considered similar if substantially the same group of variables is found to be loaded highly in each and if the same group of variables is found not significantly loaded in each. The formula for s is based on the cells of a cross-tabulation of the number of variables in the two factors that are positively salient, hyperplane, or negatively salient. The formula is thus:

$$s = \frac{f_{11} + f_{33} - f_{13} - f_{31}}{f_{11} + f_{33} + f_{13} + f_{31} + {}^{1}/_{2}\,(f_{12} + f_{21} + f_{23} + f_{32})}$$

where: f_{11} is the frequency of positively salient variables in both factors,

f_{33} the frequency of negatively salient variables in both factors,

f_{12} the frequency of positively salient variables in the first factor that have hyperplane loadings in the second, and so on.

Tables for the significance of s according to the percentage of variables in the hyperplane can be found in Cattell (1970 : 257-260). The salient variable similarity index thus differs from the congruence coefficient in proceeding nonparametrically.

A number of other procedures have been proposed (see Rummel, 1970; Cattell, 1978) but are too involved to warrant discussion here. Because no one method has yet been found to be significantly more superior or accurate than the others it is proposed that the results from two or more approaches be combined to give an indication of the degree of similarity between two factors.

The mathematical complexity of factor analysis, as well as the number of choices available as to the methods of extraction and rotation often make comparison difficult. Thus, without going back to the original correlations between items, the integration of results from different research efforts into a single conclusion is often well-nigh impossible. The rotation to simple structure combined with one or more factor matching procedures represents one attempt to increase the comparability of factor matrices. By far the best method, however, would be to rotate two or more matrices simultaneously to maximally similar positions. To do this, one must have access to the correlation matrices of previous studies. This is not possible in the present study, and one thus has to resort to the more hazardous simple structure criteria for factor matching.

5.4 Further Analyses

As has previously been noted, a single factor analysis of a variable set is seldom sufficient. One of the drawbacks of factor analysis is that there is no truly unique solution for a particular sample. Through the use of different methods of extraction and rotation one seeks to obtain a set of results that adequately explains the relationships between the variables or optimally approaches the hypothesised solution.

Following the results of the initial analysis, further analyses are often suggested. For instance, second-order factor analysis seeks to further reduce the data by identifying a second group of factors that account for the relationship between the initial or first-order factors. Further discussion of these more sophisticated techniques is beyond the scope of this thesis, but the reader is referred to such standard texts on factor analysis as Cattell (1978), Harman (1976) and Rummel (1970). It could also be found that other factor models are more appropriate than the ones initially employed, or even that factor analysis does not increase conceptual clarity and another method of statistical analysis is more appropriate.

In this chapter we have looked at the role of factor analysis in the construct validation of attitude scales, and examined the various decisions that have to be made at each step of the analysis. The usefulness of factor analysis in the initial stages of research should again be emphasised. The results obtained from a factor analysis suggest relationships between variables that lead to further hypotheses being developed, changes in the combination of variables, exclusion of some and inclusion of others, in a gradual progression towards a scale of increasing construct validity, and from this position moving on to the external validation of the scale.

CHAPTER SIX

MULTIVARIATE ANALYSIS 2: CLUSTER ANALYSIS

Cluster analysis (also referred to as Q-analysis, grouping, classification, numerical taxonomy, etc.. See Everitt, 1974 : 1) is a generic term for a number of techniques designed to uncover the underlying clusters into which variables on a scale could be grouped. Cluster analysis is defined simply by Tryon and Bailey (1970 : 1) as

> ... the general logic, formulated as a procedure, by which we objectively group together entities on the basis of their similarities and differences.

The various methods subsumed under cluster analysis are in general less structured than those of factor analysis. Cluster analysis is by far the simplest of the multivariate techniques used for finding the major dimensions underlying an item set. In cluster analysis, items are assigned to subsets or clusters so that the level of intercorrelation of items within a cluster is high and that between clusters is low. Specific procedures have been developed to make this task easier. Only two formal methods of cluster analysis will be discussed in this chapter.

6.1 Cluster Analysis and Factor Analysis

Cluster analysis has much in common with factor analysis. Both methodologies seek to explore the relationships between variables. However, there are a number of important differences in approach. Whereas factor analysis can be used in a hypothesis-testing role, cluster analysis is essentially an exploratory device. The value of exploratory cluster analysis lies in the tendency for new arrangements of variables to suggest relationships and principles previously unnoticed, these discoveries then leading to further (confirmatory) analyses (see Anderberg, 1973 : 19).

One must exercise caution in determining which of the two approaches is the most suitable for the variables under consideration. In some instances it is dangerous to leave the analysis to any rigidly prespecified method which rests upon specific assumptions (explicit or implicit) about the data. Everitt (1978 : 2-3) points out that what is often needed for an investigation of multivariate data are informal exploratory techniques rather than more formal confirmatory ones. Techniques of cluster analysis are well suited for this purpose since they tend to be less formal and confining, and enable the investigator to gain insight into the structure of his data without imposing restrictive constraints. Tryon (1958 : 486) notes that

> ... the formulations of cluster analysis are based directly on the psychometric principles of mental measurement and do not require the elaborate special conceptualizations and notations characteristic of factor analysis.

However, when the number of variables is large, cluster analysis might tend to become unwieldy and impractical, with factor analysis probably being more useful for the initial grouping of variables.

Cluster analysis and factor analysis should be regarded as complementary rather than mutually exclusive. Although often used in the exploratory stages of research, cluster analysis is equally applicable in a confirmatory role. The factors obtained from a factor analysis could serve as a starting point for a cluster analysis, which in turn could serve as a check on the factor analysis (see McKennell, 1977 : 202). This is the role of cluster analysis in the present study. Because of the differences between the two methods, one should expect the results to complement each other and provide greater insight when used in combination.

6.2 Clusters

A cluster is simply a grouping of variables based on specific criteria for inclusion or exclusion. Clusters are more concrete, immediately evident, and easier to understand than factors. Interpretation of a cluster is aided by the fact that a variable may only belong to one cluster at a time, whereas in factor analysis a variable might have varying significant loadings on more than one factor (see Gorsuch, 1974 : 187). However, the weakness of cluster analysis lies in the fact that the criteria for inclusion of a variable into a cluster are based on the arbitrary decisions of the researcher. Procedures have been developed to aid the process but the boundaries of a cluster remain beyond objective criteria for admission. Tryon (1958 : 482) warns:

> The ... clusters are purely surface and frequently rather arbitrary statistical groupings. To think of them as "underlying" dimensions or "basic" types would require documentation not explicit in the analyses.

To accord to clusters the same status as has oft been granted factors without confirmatory analysis is thus to misunderstand the exploratory nature of cluster analysis. Factor analysis as a technique is more firmly grounded in statistical theory, but this does not detract from the usefulness of cluster analysis as a supplementary technique.

6.3 Principles of Cluster Analysis

Anderberg (1973 : 22-23) has proposed a general set of principles for cluster analysis which aptly summarise earlier discussion. These are as follows:

1. For any given set of data there could be a number of different but meaningful classifications. Each of these alternative classifications may refer to a different aspect of the data.

2. Cluster analysis is merely a device for suggesting hypotheses, so the researcher need not feel obliged to accept any one classification.

3. A set of clusters is not itself a finished result but only a possible outline for further manipulation and interpretation.

4. Cluster analysis methods involve a mixture of imposing a structure on the data and revealing that structure which actually exists in the data.

5. The results of a cluster analysis rarely suggest a satisfactory structure for the total set of data. A logically coherent cluster is often delineated at the expense of another.

6. Caution must be exercised regarding two important possibilities that are often overlooked in cluster analysis: that there may be no clusters, and that there may be only one cluster.

The similarity between cluster analysis and factor analysis is further evidenced by the fact that the starting point for both is the matrix of correlations between the variables in the study. Cluster analysis has also been referred to as correlation analysis in that it involves examination of the correlation matrix. Cattell (1978 : 45) notes that,

> To find such syndromes (clusters) all one needs is a correlation matrix among variables and an eye to pick out the subgroups of variables within which there are substantial mutual correlations.

Cluster analysis need not be as simple as this, however. Specific techniques have been developed to aid this process. Before these are discussed, some alternative measures of association will be examined.

6.4 The Correlation Matrix

The formula for the product moment correlation coefficient has been discussed earlier, and is the most common form of input into a cluster analysis of variables. Unlike factor analysis, however, cluster analysis does not assume interval data, nor is a linear relationship between variables necessary. For this reason one is not restricted to the use of the product moment coefficient alone.

Two further measures of association for ordinal data which warrant mention are Kendall's (1948) tau (see also Siegel, 1956) and Goodman and Kruskal's (1954) gamma. Kendall's tau is based on the degree of correspondence between the rankings of individuals on two variables. Tau could thus be referred to as a coefficient of disarray (Siegel, 1956 : 215). The formula for tau is as follows:

$$\text{tau} = \frac{S}{\frac{1}{2} N (N-1)}$$

Where: N is the number of cases

S is the sum of the differences between the ranks of the two variables over all cases.

For $N \geq 8$ the sampling distribution of tau is practically indistinguishable from the normal distribution (Kendall, 1948 : 38-39). Therefore, with a large N standard scores can be used in determining significance levels for tau. Using this method, for N= 400, a tau of greater than or equal to .08 will be significant at the 1% confidence level (see Siegel, 1956 : 221 and 247). For further discussion of tau see Adler (1957), Cartwright (1957) and Schaeffer & Levitt (1956).

Goodman and Kruskal's gamma is based on the relative reduction in error between random prediction and prediction based on knowledge of one variable. This gain in the predictability of order is made possible by the association of order on the two variables and thus serves as a measure of that association (see Blalock, 1972 : 421-426; Mueller, Schuessler and Costner, 1977 : 207-219). The general formula for gamma (of which Yule's Q is a special case for 2 x 2 tables) is as follows:

$$\text{gamma} = \frac{N_s - N_d}{N_s + N_d}$$

where: N_s is the number of same-ordered pairs

N_d is the number of differently-ordered pairs

A limitation of gamma as a measure of association that can be seen from the formula above is that the magnitude of the differences for N_d are not taken into consideration. Significance of gamma is calculated as for the product moment correlation.

These two nonparametric measures of association avoid possible pitfalls inherent in using the product moment correlation with less than interval data, and are equally admissable coefficients for cluster analysis which has less assumptions about the nature of the data than does factor analysis. Tau and gamma yield similar results, but tau is a preferable measure of association as it takes into account the magnitude of difference between untied rankings. However, Blalock (1972 : 426) recommends using several different measures to see whether or not they behave similarly for the data under consideration. Whether one of these two methods or the correlation coefficient is finally selected should not greatly alter the resultant clusters. Having prepared the matrix of correlations, the variables are now ready for the delineation and identification of clusters.

6.5 Techniques of Cluster Analysis

A number of techniques are available for the cluster analysis of a correlation matrix, ranging from complex computation procedures requiring sophisticated computer programmes to simple visual inspection methods. Only two relatively straightforward cluster search methods will be discussed here, namely the ramifying linkage method (Cattell, 1952a, 170-171) and correlation profile cluster analysis (Tryon, 1939).

6.5.1 Ramifying Linkage Cluster Analysis

In the first method one adopts a minimum correlation for entry into a cluster. Any correlation above this arbitrary value is then called a linkage. All linkages in a matrix are noted (circled, underlined). One then begins with the first variable and writes down all variables that have a linkage with this variable. From this list one selects the second linked variable and notes down the rest of the variables on the list that link with it, excluding those that link only with the first variable. This process is continued for the remaining variables on this list until the first cluster is obtained. One then proceeds to do the same for the second variable in the matrix, and so on, until all possible linkages have been exhausted, and the clusters identified.

It is obvious that the level of correlation adopted as a linkage affects the variables to be included in any one cluster. It is thus advisable to repeat the above procedure using various levels of the correlation coefficient as a cut-off point, to obtain the best division of items into clusters.

6.5.2 Correlation Profile Cluster Analysis

Although similar to the above method in that both begin with the matrix of correlations and an arbitrary level of correlation for consideration in a cluster, the second method of cluster analysis, developed by Tryon (1939), aims to distinguish clusters on the basis of their correlation profiles. When the number of variables is small this can be done through trial graphs. By this method, one plots the correlations of each variable with the remaining variables, and the variables whose resultant profiles are most similar are grouped into a cluster.

When the number of variables is greater than 20, a quantitative method is adopted which utilises the coefficient of belongingness (B) developed by Holzinger (see Tryon, 1939 : 43). Calculation of the B coefficients are illustrated in Appendix C. The coefficient of belongingness is basically the ratio of cluster intercorrelations to correlations with remaining scale items. B is thus an indication of each additional item's contribution to the mean intercorrelation of a cluster. An item whose B value drops markedly from the previous entry for the cluster is discarded as not belonging to that cluster. Ideally, B should increase with each additional item until an item not congruent with a cluster is tested for membership of that cluster. However, in the case of items with only reasonable profile similarity the addition of items to a cluster will result in a decrease in the value of B, and the researcher is thus left with the decision as to when to stop adding variables to that cluster.

Once the clusters have been determined using the coefficient of belongingness, the correlation profiles for the items of each cluster are plotted on a graph. Those items whose profiles are not congruent with the remaining items in that cluster are discarded, and items with more similar profiles included. An advantage of this method is that items can be considered for membership in more than one cluster, and are eventually admitted to the cluster with which they share the most similar correlation profiles.

The clusters obtained by either of these two methods of cluster analysis might have interpretive value in themselves, or they might provide a guide for the examination of concurrent factor analysis results. Cluster analysis by itself is seldom sufficient for the analysis of an attitude scale. The initial clustering of variables should complement the results obtained through factor analysis. Cluster analysis should be seen as no more than a means of organising the overwhelming amount of information contained in a large correlation matrix into a form that aids comprehension and guides further analysis.

CHAPTER SEVEN

ALIENATION: MEANING AND MEASUREMENT

Attitude measurement and procedures for the construct validation of such measurements have been discussed in general. The focus now becomes specific: discussion of the particular concept and scale to be examined in the present study. The attitude scale used for the demonstration of construct validation methods discussed in earlier chapters is Dean's (1961) Social Alienation Scale. Before we can move on to the analysis of the scale itself it remains to discuss the nature of the concept alienation and to look at various attempts that have been made to measure the concept in question. The construct validation of an attitude measure should always be conducted within the framework of existing knowledge of the concept and attempts to measure such a concept. Thus, although the central concern of this thesis is not with alienation as such, it is appropriate to point out some of the problems associated with the meaning and measurement of alienation.

7.1 The Meanings of Alienation

A formal definition of alienation will not be proffered in this thesis for reason the primary objective is not to obtain conceptual clarity regarding alienation, but rather to discuss the particular methods by which such a conceptual clarity can eventually be attained. The discussion of the concept alienation is important in order to demonstrate how conceptual confusion and lack of precise construct definition can thwart the development of a valid measuring instrument.

Alienation is one of the most frequently used concepts in modern sociology (see Fisher, 1976 : 35), and probably one of the most abused. Pravetz (1976 : 19) writes:

> So many different meanings have been attributed to the concept of alienation, many of them vague and mystical, that the concept as it stands is virtually useless, scientifically speaking.

Alienation has been used in many disciplines and even within different theoretical frameworks within the same disciplines. Reviews of the literature on alienation have been undertaken by others (see Israel, 1971; Lutz, 1973; Pravetz, 1976) and will not be repeated here. This chapter is thus limited to a brief examination of some of the more salient studies in the empirical socio-psychological literature on alienation.

Two distinct levels of analysis with regard to the study of alienation can be identified (Josephson and Josephson, 1973). In the first, alienation is seen from the perspective of the objective societal conditions that lead to such states. This is the meaning used by Marx when he refers to capitalism as having the consequences of alienating man from his labour, from the product of his labour, and ultimately from himself (Lystad, 1972 : 91). In this approach the individual can be unaware of his alienation (Schact, 1970 : 154). The present study, however, concentrates on the second level of analysis, in which alienation is regarded as a subjective state of mind. This approach does not preclude alienating conditions in the society, but rather implies that people are aware of their alienated states, and thus that such states can be measured. A major development in this second, socio-psychological approach to alienation was the publication of Seeman's (1959) article on the various meanings of alienation. Further discussion will be centered around his classification of alienation meanings.

7.1.1 Seeman's Dimensions of Alienation

Seeman's (1959) study can be regarded as the first comprehensive analysis of the alienation concept. Seeman's aim was firstly to gain conceptual clarity regarding the meaning of alienation and secondly to

> ... make the traditional interest in alienation more amenable to sharp empirical statement.
>
> (Seeman, 1959 : 783).

After reviewing the current usages of the term he concluded that alienation was not a unitary concept, but that as many as five distinct usages of the term could be identified in the literature. The five meanings of alienation identified by Seeman are powerlessness, meaninglessness, normlessness, isolation and self-estrangement.

Seeman's five-fold classification is not the only attempt to differentiate between various meanings of alienation. Feuer (1963) identified six modes of alienation, namely the alienation of class society, of competitive society, of industrial society, of man's society, of race, and of generations (1963 : 137). This approach is far more general than Seeman's, and consequently less conducive to empirical investigation. Barakat (1969 : 3-4) proposed that alienation be seen as a developmental process consisting of three stages:

1. Sources of alienation at the level of social and normative structures;
2. alienation as a psychological property of the individual; and
3. behavioural consequences of alienation.

Seeman is concerned with the second of these stages, as is the present study. Others concentrate on the distinction made earlier between the conditions causing alienation and socio-psychological states of alienation. Most attempts to measure alienation have concentrated on the latter approach. Seeman's analysis has been of vital importance to those endeavouring to define and measure alienation, and thus his dimensions of the meanings of alienation warrant further discussion.

7.1.1.1 Powerlessness

Alienation as powerlessness is used to mean the feeling an individual has that the probability of satisfying his own needs by his own efforts is low. This is the meaning used by Hegel and Marx (see Dean, 1961 : 754) in their discussions of the worker's seperation from effective control over his economic destiny, of his helplessness in the face of exploitation. Powerlessness is defined by Seeman (1959 : 784) as:

> ... the expectancy or probability held by an individual that his behaviour cannot determine the occurence of the outcomes, or reinforcements, he seeks.

It can be seen that, although this meaning of alienation is derived from the Marxian perspective, Seeman is concerned not with the historical conditions leading to alienation but with the resultant individual experience of such a state.

7.1.1.2 Meaninglessness

A second usage of the alienation concept is summarised under the idea of meaninglessness, which refers to the individual's sense of understanding the events in which he is engaged. The individual in a state of meaninglessness cannot predict with confidence the consequences of acting on a given belief. This type of alienation is characterised by

> ... a low expectancy that satisfactory predictions about future outcomes of behaviour can be made.
>
> (Seeman, 1959 : 786)

Meaninglessness is embodied in Mannheim's notion of the result of increased "functional rationality" and decreased "substantial rationality" when an individual cannot act with insight when faced with alternative interpretations (see Seeman, 1959 : 786).

7.1.1.3 Normlessness

Alienation as normlessness is derived from Durkheim's concept of anomie (see Pravetz, 1976 : 37-38). Anomie denotes a situation in which the social norms regulating individual conduct have broken down or are not longer effective as rules for behaviour. The individual in a state of normlessness is unable to reach socially acceptable or desirable goals through societally acceptable channels, or through the social organization to which he belongs (Pravetz, 1976 : 38). Normlessness is defined as

> ... a high expectancy that socially unapproved behaviours are required to achieve given goals. (Seeman, 1959 : 788)

Dean (1961 : 754) differentiates between two distinct subtypes of normlessness: purposelessness and a conflict of norms. Purposelessness can be described as the absence of values that give purpose and direction to life (see Frankl, 1959). Normative conflict has been described by many personality theorists (see Dean, 1961 : 755).

7.1.1.4 Isolation

Seeman's fourth variant of alienation assumes that an individual has a need for affiliation or belongingness. Isolation refers to a feeling of detachment or separation from popular cultural standards rather than a lack of social adjustment. Isolation has also been taken to mean a low participation in social organisations (Dean, 1961 : 789), but this meaning has been rejected by Seeman as being "irrelevant to the root historical notion of alienation" (1959 : 789n). One must thus distinguish between Seeman's notion of <u>isolation</u> and Dean's concept of <u>social isolation.</u> Isolated individuals are defined as those who

> ... assign low reward value to goals or beliefs that are typically highly valued in the given society. (Seeman, 1959 : 789)

Dean's interpretation of social isolation, by contrast, is defined as

> ... a feeling of separation from the group or of isolation from group standards. (Dean, 1961 : 755)

7.1.1.5 Self-Estrangement

The final usage of the alienation concept is identified by Seeman as self-estrangement. This meaning can be evidenced in Fromm's writings:

> By alienation is meant a mode of experience in which the person experiences himself as an alien. He has become, one might say, estranged from himself. (Fromm, 1955 : 120)

Unlike the other four variants of alienation it is difficult to specify the structural sources of self-estrangement. Can one speak of "alienation from the self" in the same way as "alienation from popular culture"? What is apparently being postulated by Fromm and others is some ideal human condition from which the individual is estranged (Seeman, 1959 : 790). Pravetz (1976 : 38) sees self-estrangement as a condition in which the various activities of the individual are no longer a goal in themselves, but are carried on with a view to other rewards. Seeman (1959 : 790) defines self-estrangement as

> ... the degree of dependence of the given behaviour upon anticipated future rewards that lie outside the activity itself.

In the industrial environment this would embody a loss of intrinsic meaning or pride in work as such.

7.1.2 Relationship between Alienation Meanings

Seeman's typology has been criticised by Browning et al (1961) and Israel (1971) for failing to examine the relationships between the five variants of alienation within a theoretical context. Seeman acknowledges this shortcoming but notes that, although he does not present a theory of alienation, his efforts should make such a theory possible (Seeman, 1961 : 781). However, such a theory has not been forthcoming, and it is felt that Seeman's work has instead been misinterpreted as advocating a multidimensional approach to alienation. According to Seeman these various meanings of alienation are to be seen as quite distinct concepts, even based on different theoretical foundations.

Schacht (1970 : 156) notes the following regarding the writings of sociologists on alienation:

> ... the term is used in so many different connections in their writings that it cannot plausibly be viewed as designating a single (unidimensional or multidimensional) phenomenon, or even a syndrome of such phenomena. Some of the phenomena in connection with which it is used might plausibly be associated. Others, however, have nothing at all to do with each other; and some even preclude each other.

In spite of these cautions, much of the empirical research following Seeman's classification has focused on alienation as a multidimensional concept, and see Seeman's various meanings of alienation as manifestations of a single general syndrome. We now take a look at such research.

7.2 The Measurement of Alienation

Within the socio-psychological framework there are two major approaches to the measurement of subjective states of alienation. The first consists of the search for social or behavioural indicators which presumably reflect alienated states (see Fromm, 1955; Josephson and Josephson, 1973). Such indicators include suicide, alcoholism, political participation, and so on. The second approach, which forms the focus of this study, involves the measurement of those states of mind themselves and falls into the category of attitude research. This latter approach is based on the assumption that as the subject is aware of his alienated state, he is able to report such feelings. Most of the attempts to measure alienation have tended to concentrate on the attitudinal dimensions and correlates thereof.

7.2.1 Pre-1959 Research

Probably the first attempt to develop an attitude scale within the domain of alienation was Srole's (1956) five-item anomia scale. In social attitude research the distinction between anomia and alienation has become diffuse, and Srole's anomia scale is applied for the measurement of alienation interchangeably with various alienation scales themselves. Srole's scale remains the most widely applied measure of alienation to date (Robinson and Shaver, 1970 : 161). Described by some as a measure of general dissatisfaction and despair (Knapp, 1976; Ludz, 1973), the scale is based on a unidimensional concept of alienation as a psychological state.

Nettler (1957) has also developed a unidimensional scale for the measurement of alienation, consisting of 17 items scored on a two category (agree/disagree) basis. Nettler operationalised alienation as estrangement from one's society and the culture it manifests. His scale has a correlation of .309 with that of Srole for N= 345 (Nettler, 1957 : 676).

Another unidimensional scale to measure alienation within a specific context was that of Clark (1959). Published at the same time as Seeman's article, Clark gives alienation an organisational focus, and develops a 5-item Likert scale to measure the concept (conceived as powerlessness) in the work situation.

7.2.2 Post-1959 Research

Seeman's article has proved a watershed in the social-psychological approach to the measurement of alienation, significantly influencing most of the research on the subject undertaken after publication of the article. Following his article, research shifted from a unidimensional notion of alienation to a multidimensional approach. We shall examine some of the more important studies undertaken in this regard.

7.2.2.1 Dean's Social Alienation Scale

The subject of analysis in the present study, Dean's Social Alienation Scale is based on Seeman's discussion of five variants of the alienation concept. Seeking to determine the empirical relationships existing between several components of alienation, Dean chose to study powerlessness, normlessness and social isolation, following Seeman's classification. Dean conceived of powerlessness as

> ... the feeling that one understands or influences less and less the very events upon which one's life and happiness are known to depend. (See Dodder, 1969 : 252)

Normlessness is conceived as having two subtypes, namely purposelessness and a conflict of norms (Dean, 1961 : 754-755). As has been mentioned, Dean's notion of social isolation is different from Seeman's meaning of isolation, the former referring to a feeling of separation from the group or of isolation from group standards (Dean, 1961 : 755). Reasons for the exclusion of Seeman's aspects of meaninglessness and self-estrangement are not given, but can probably be attributed to the difficulty of measuring these two concepts.

From the literature 139 statements referring to the syndrome of alienation were collected. These statements were judged by seven "experts" (staff members of the Department of Sociology, Ohio State University) as to their applicability to each of the components of powerlessness, normlessness and social isolation, using a one-page description of each component as the criterion (Dean, 1961 : 756). For an item to be retained in the final list, five of the seven judges had to be in agreement, with no judge placing the items in more than one category. Apparently some form of item analysis was used for the final selection of the items, but the specific method cannot be ascertained.

The final items selected were combined to form a 24-item alienation scale, with 9 items in each of the powerlessness and social isolation subscales, and 6 in the normlessness subscale. Subjects were required to respond to each item on a 5-point Likert-type continuum ranging from strongly agree, through agree, uncertain and disagree, to strongly disagree, with scores ranging from 4 (strongly agree) to 0 (strongly disagree). Five of the items were negatively worded, for which scoring was reversed. Scores on each subscale were totalled to measure the extent of an individual's feelings of powerlessness, normlessness and social isolation, and the total scale to determine his level of alienation. Thus a score of 96 would represent the maximum alienation attainable, with 48 being the neutral point. Dean's scale is reproduced in its original form in Appendix D.

The resultant scale was administered to a sample of 384 individuals in Columbus, Ohio (Dean, 1961 : 757). The reliability coefficients (split-half technique) for the subscales are reproduced in Table 7.1, as are the inter-correlations among the alienation scale components.

Table 7.1

Reliability and Intercorrelations (r) Among Alienation Scale Components (from Dean, 1961): N = 384*

	Reliability	Intercorrelations		
		Normlessness	Social Isolation	Total Scale
Powerlessness	.78	.67	.54	.90
Normlessness	.73		.41	.80
Social Isolation	.84			.75

* For N = 384, r ⩾ .13 is significant at the 1% confidence level.

These results lead Dean to suggest that it is possible to regard the sub-components of powerlessness, normlessness and social isolation as belonging to the same general concept (alienation), yet possessing sufficient independence to warrant treating them as independent variables. He observes further that each of the subscales exhibited a normal curve of score distributions, with scores extending almost the entire possible range (Dean, 1961 : 757), supporting the combination of items into subscales and justifying the use of the product moment correlation coefficient.

Dean (1961 : 758) concludes his article with a caution:

> It may very well be that alienation is not a unitary phenomenon, but a syndrome ... In any case, certainly much more research is required before the alienation concept can be empirically validated.

In spite of Dean's misgivings regarding his scale, many researchers have accepted the scale's reliability and validity as given, and utilised one or more of the subscales in many different settings (see Bean, Bonjean and Burton, 1973; Bonjean and Grimes, 1970; Burbach and Thompson, 1973; Dubey, 1971; Muller and Brunner-Orne, 1967; Simpson, 1970; and Tolor, 1970, to name but a few). Others have put Dean's claims concerning his scale to the test, resulting in further misgivings regarding the validity of the scale. Some of these latter studies will now be discussed.

7.2.2.2 Simmons' Correlation of Dean's Subscales

Simmons administered eight measures of "personal disturbance", including Dean's three subscales, to a sample of 391 sociology and anthropology students, and presented the intercorrelations between these measures as a by-product of a larger study (Simmons, 1966 : 370). The correlations of interest to the present study are reproduced in Table 7.2 below.

Table 7.2

Intercorrelations (r) Among Alienation Scale Components (from Simmons, 1966): N = 391*

	Normlessness	Social Isolation
Powerlessness	.43	.53
Normlessness		.33

* For N = 391, r ≥ .13 is significant at the 1% level of confidence.

These correlations support those reported by Dean (1961) which point to the possibility of alienation as measured by his scale being a general syndrome consisting of interrelated but distinct components. Simmons notes on examination of the original bivariate contingency tables that most of the associations are not entirely linear (1966 : 371). Thus gamma or tau would be more appropriate measures of association than the product moment correlation which assumes linearity. Simmons concludes that factor analysis, or the intercorrelation of individual items rather than subscales would have been more useful in revealing the exact nature of the relationships between the variables.

7.2.2.3 Dodder's Factor Analysis of Dean's Scale

The first attempt to examine the underlying structure and the interrelationships between the items of Dean's Social Alienation Scale was that of Dodder (1969). He made use of factor analysis which he described as:

> A comprehensive technique which is often used to determine the presence of a general dimension underlying a set of items, as well as the independence of subscales. (Dodder, 2969 : 252-253).

Dean's scale, with a few slight changes in wording, was included in a questionnaire administered to a sample of 201 female heads of household in Kansas.

Scale items were intercorrelated and the resulting matrix was factor analysed using the method of alpha factor analysis (Kaiser and Caffrey, 1965). Correlations between subscales support the findings of both Dean (1961) and Simmons (1966) that it is feasible to consider the subscales as belonging to the same general concept, yet having a large measure of independent variation (Dodder, 1969 : 252).

The results of the factor analysis, however, presented disturbing evidence concerning Dean's scale. Where one would expect four factors (one representing the general syndrome of alienation, on which all items would load significantly, and the remaining three representing each of the three subscales) with significant loadings, eight factors with eigenvalues greater than one were extracted. The first unrotated factor accounted for 19% of the total explained variance and 46% of the variance explained by the first 8 factors (Dodder, 1969 : 253). Seventeen of the 24 scale items have a loading of greater than .30 on the first factor, suggesting the possibility of a generalised dimension underlying Dean's scale items. Using the Burt-Banks formula (see Child, 1970), which yields a significant value of .182 at the 1% level of confidence for the first factor (24 variables, N = 201), one finds that only three items do not load significantly ($p < .01$) on this first factor (items 3, 9 and 13 in Appendix D).

To obtain further evidence regarding the scale, the eight factors were rotated orthogonally and obliquely. Second-order analysis of the correlations between the obliquely rotated factors reveal one primary factor loading above .30 for all the first-order factors, suggesting a generalised dimension underlying the items but also specific sources of of variance (Dodder, 1969 : 253-254). One such source of variance could be the presence of independent subscales. Dodder (1969 : 254) writes:

> If Dean's conceptual analysis of the scale is valid, we could anticipate similarity between the oblique and orthogonal structures with the social isolation items loading heavily on one factor, the powerlessness on another, and the normlessness items comprising a third.

The orthogonal (VARIMAX) and oblique (OBLIMAX) solutions (reproduced in Appendix E) do not bear this out. Little similarity was found between the two patterns.

Dodder then proceeds to interpret the rotated factor matrix, and offers labels such as "loneliness", "fearful uncertainty", "futility", and so on for various groups of items, none of which corresponded to Dean's original divisions (Dodder, 1969 : 254-255).

Dodder concludes that, although the factor analysis of Dean's Social Alienation Scale yields evidence in favour of a generalised underlying dimension, when the specific factors are examined there is little support for the division of the scale into social isolation, normlessness and powerlessness subscales. Rather, the items are measuring

> ... unanticipated latent dimensions other than the three <u>a priori</u> dimensions defined by Dean.
>
> (Dodder, 1969 : 255)

Dodder proposes that Dean's subscales be replaced by subscales corresponding to the factors uncovered in his (Dodder's) analysis. However, one has to ask whether Dodder's divisions are any more valid or reliable than those of Dean. Are the factors underlying Dean's scale, regardless of what is being measured by them, reliable across samples?

7.2.2.4 Hensley et al's Factor Analysis of Dean's Scale

One such attempt to answer the question posed above is the study of Hensley et al (1975), which is in part a replication of Dodder's analysis. They write:

> It is an understatement to say that Dodder's work has received scant attention. Even after the appearance of this empirical evidence that Dean's scale does not fall into the hypothesised a priori categories, a number of writers continue to use the Dean scale ... without any mention of Dodder. (Hensley et al, 1975 : 556)

Through replication they hoped either to provide evidence in support of Dean, or to add weight to the reservations advanced by Dodder.

The Social Alienation Scale using Dean's original wording was administered to a sample of 240 students at Kent State University. The scale was again given to 127 of the above sample seven weeks later, and the resultant test-retest reliability for the total scale was .80, with the subscale reliabilities being .651 for social isolation, .741 for powerlessness and .644 for normlessness. Alienation is thus considered by Hensley et al (1975 : 557) to be a relatively stable personality construct, and the test-retest results indicate that, whatever the Dean scale measures, it does so with some consistency.

Concerning the factor analysis (using the alpha method), 10% of the total explained variance was accounted for by the first unrotated factor. This factor accounts for only 30% of the variance explained by the eight factors with eigenvalues greater than unity. A large proportion of the variance is thus unaccounted for, indicating that, whatever Dean's scale measures, it does so with considerable error (Hensley et al, 1975 : 558). A comparison of the orthogonal 8-factor solution (reproduced in Appendix F) with that of Dodder reveals some degree of pattern similarity. Although the factors did not emerge in the same order in each solution, it does appear that the two solutions measure, to some extent, the same structure.

Hensley et al (1975 : 561) conclude:

> Thus, our results tend to add generalizability to Dodder's conclusion that the Dean scale does not seem to measure powerlessness, normlessness, or social isolation. These results also extend Dodder's findings in that our factor structure is not isomorphic with his, implying that the Dean scale, whatever it measures among one group, measures slightly different things for another group.

The factor patterns of these two studies will be focused on later in the light of the results from the analysis of the present study.

7.2.2.5 Tolor's Comparison of Three Alienation Measures

Three instruments reflecting different conceptualisations of the alienation syndrome, namely the Gould Manifest Anxiety Measure, Rotter's Internal-External Scale, and Dean's Social Alienation Scale, were administered to 41 male and 69 female undergraduate students in a study by Tolor (1974). Results in respect of the Dean scale are summarised in Tables 7.3a and 7.3b, below:

Table 7.3a

Intercorrelations (r) Among Alienation Scale Components (from Tolor, 1974): N = 41* (males)

	Normlessness	Social Isolation	Total Scale
Powerlessness	.29	.46	.81
Normlessness		.18	.64
Social isolation			.76

* For N = 41, r ⩾ .39 is significant at the 1% confidence level, and r ⩾ .30 at the 5% level.

Table 7.3b

Intercorrelations (r) Among Alienation Scale Components (from Tolor, 1974): N = 69* (females)

	Normlessness	Social Isolation	Total Scale
Powerlessness	.45	.52	.84
Normlessness		.26	.67
Social Isolation			.82

*For N = 69, r ⩾ .31 is significant at the 1% confidence level, and r ⩾ .23 at the 5% level.

These correlations are lower than those reported by Dean (1961) and Simmons (1966), especially in the case of the male sample. This could possibly be attributed to a high error rate as a result of the small sample size. In any case the combination of the three subscales into a total alienation scale is brought into question by these results.

7.2.2.6 Knapp's Factor Analysis of Fourteen Alienation Measures

Knapp (1976 : 194) writes of the problems arising from the use of alienation as a unidimensional rather than multidimensional construct:

> Such a tendency leads to a gross over-simplification in the method of analysis, concealing many possible dimensions under one summary score. Thus, the full complexity of the variables in the population under study fails to emerge, and this leads to further confusion and contradictions when, through correlational analysis, attempts are made to relate empirically these concepts to each other as well as to important structural and socio-psychological variables.

In an attempt to develop such a multidimensional scale of the alienation syndrome, Knapp factor analysed 8 measures of alienation (a total of 97 items), including Dean's scale. The scales were administered to a sample of 436 sociology students at Clemson University (Knapp, 1976 : 197). Intercorrelations between the Dean subscales are reproduced in Table 7.4.

Table 7.4

Intercorrelations (r) Among Alienation Scale Components (from Knapp, 1976): N = 436*

	Normlessness	Social Isolation
Powerlessness	.50	.51
Normlessness		.37

* For N = 436, $r \geqslant .12$ is significant at the 1% confidence level.

These results again support the general syndrome notion of the Social Alienation Scale proposed by Dean (1961). However, the subsequent factor analysis offers little evidence for the presence of a generalised dimension underlying the concept of alienation. The first unrotated factor accounted for only 9.8% of the total variance and 31.7% of the variance explained by the first ten factors (extracted according to Cattell's scree test, eigenvalues greater than 1.45). All of the normlessness items from Dean's scale, however, loaded significantly on the second orthogonally (VARIMAX) rotated factor, as did 8 of the powerlessness items (item 13, Appendix D, being the exception), and four of the social isolation items (items 1, 3, 4 and 5), along with a number of items from other scales. This leads Knapp to label this factor "future uncertainty", and to consider it to be a core dimension of alienation (Knapp, 1976 : 208). Items 1, 7, 10, 14, 16, 18 and 22 of Dean's Social Alienation Scale load highest on this factor. These results tend to support the general syndrome notion of alienation as purportedly measured by the Dean Scale.

7.2.2.7 Pravetz's Factor Analysis of Alienation Scales

In an attempt to develop a context-specific measure of alienation, Pravetz (1976) factor analysed 35 alienation scale items, comprising the 24 Dean items, 5 items from the short form of the Srole Anomia Scale (Misruchi, 1960) and 6 items from Nettler's (1957) Alienation Scale. These items were included in the Flatland Study of the Witwatersrand University's Social Research Unit, and were administered to a sample of 482 flat-dwellers in Johannesburg (Pravetz, 1976 : 79).

The 35 items were intercorrelated and factor analysed using the principal-factor method (also called the centroid method: Cattell, 1978 : 28). The five factors extracted (to conform to Seeman's five dimensions of alienation) were orthogonally rotated using the VARIMAX criterion (an examination of the eigenvalues reveals that only two factors would have been extracted using the Kaiser-Guttman criterion). The first unrotated factor accounted for 74.6% of the variance explained by the first five factors (Pravetz, 1976 : 91). Items from Dean's scale loading highly on this rotated factor include items 1, 2, 7, 10, 11, 14 and 20. The high variance explained by the first factor again lends some support to the notion that Dean's scale measures a single general dimension, but the resultant factors do not support the scale divisions proposed by Dean (1961).

7.2.3 Other Measures of Alienation

Other approaches to the measurement of alienation include the development of unidimensional measures of general alienation (Hajda, 1961; Ghaemmag, 1973; Form, 1975; Kohn, 1976; McClosky and Schaar, 1965), measures of one or more of the subcomponents identified by Seeman (Ransford, 1968; Holian, 1972; Simpson, 1970; Fisher, 1973; Shepard and Panko, 1974; Otto, 1975; Tomeh, 1974) or context-specific measures of alienation (Thompson and Horton, 1960; Olsen, 1969; Aiken and Hage, 1966; Martin et al, 1974). Two tendencies are noted in these scales. Firstly, alienation is mostly conceptualised as multi-dimensional in nature (following Seeman's classification), and scales are developed to measure one or more of the dimensions so defined. Secondly, most researchers use Likert's summated ratings method of attitude scale construction. Most of the studies report some form of reliability coefficient, but attempts to establish construct validity are sorely lacking. In one study factor analysis was used to construct a scale (Streuning and Richardson, 1965), but in no other cases were cluster or factor analysis used to determine the structure of the multidimensional scales developed (with the exception of studies mentioned earlier in connection with Dean's measure of alienation).

Because of the diverse nature of the measures employed in the study of alienation, the comparison, replication and generalisation of results are made difficult. One has no way of determining whether the same construct is being measured in each of the studies. Thus, there is a need for valid and reliable measures of each of the components of alienation as defined by Seeman (1959). Dean's Social Alienation Scale is to date the most utilised of the multi-dimensional measures of alienation, and as such is a suitable scale for further examination of construct validity in terms of the underlying dimensions of the scale.

CHAPTER EIGHT

METHODOLOGY

As this study makes use of existing data, little control could be exercised over such methodological considerations as the construction of the questionnaire, sampling and interviewing. The data used formed part of two separate studies on general social issues conducted by final year sociology students at the University of Cape Town in 1977 and 1978 respectively. Various aspects of the research designs of the two studies relevant to the present research endeavour will be discussed in this chapter.

8.1 The Questionnaire

A modified version of Dean's Social Alienation Scale formed part of the general attitude questions included in the 1977 and 1978 studies. In each case the Dean items were scattered haphazardly among the other items on the questionnaire. One normlessness item (item 19 in Appendix D) was not included in the questionnaires, and one of the powerlessness items (17) was replaced by the following item in the two studies: Belief in a God helps me make decisions in daily life. Other minor changes in wording were made in the second survey to take into account difficulties encountered in the first study. However, the essential meaning of the questions remained unaltered.

In spite of the above alterations, and the fact that the alienation scale items appear in different orders in the two studies, it is felt that the items used resemble the original subscales sufficiently to justify both comparison of the results of the present study with those of Dodder (1969) and Hensley et al (1975), and generalisation of such results to Dean's Social Alienation Scale.

The alienation scale items as used in the present study are reproduced below, grouped into the respective subscales. The numbers preceding the items correspond to the numbering used by both Dodder and Hensley et al (see Appendix D), and will be referred to as such for ease of comparison.

8.1.1 Social Isolation Items

S1. Sometimes I feel all alone in the world.

S2. I don't get invited out by friends as often as I'd really like.

S3*. Most people today seldom feel lonely.

S4*. Real friends are as easy to find as ever.

S5*. You can always find friends if you show yourself to be friendly.

S6*. The world in which we live is basically a friendly place.

S7. There are few dependable ties between people today.

S8*. People are just naturally friendly and helpful.

S9. I don't get to visit friends as often as I'd really like.

8.1.2 Powerlessness Items

P10. I worry about the future facing today's children.

P11. Sometimes I have the feeling that other people are using me.

P12. It is frightening to be responsible for the development of a child.

P13. There is little or nothing I can do towards preventing a major "shooting" war.

P14. There are so many decisions that have to be made today that sometimes I could just "blow up".

P15. There is little chance of promotion in my job.

P16. We're so ruled today that there's not much room for choice, even in personal matters.

P17*. Belief in a God helps me make decisions in daily life.

P18. The future looks depressing.

8.1.3 <u>Normlessness Items</u>

(N19)

N20. People's ideas change so much that I wonder if we'll ever have anything to depend on.

N21. There are no definite rules to live by.

N22. I often wonder what the meaning of life really is.

N23. The only thing one can be sure of today is that one can be sure of nothing.

N24. With so many religions abroad, one doesn't really know which to believe in.

Respondents were asked to respond to each item by means of one of the following statements which, for scoring purposes were coded as follows:

strongly agree	=	4
agree	=	3
uncertain	=	2
disagree	=	1
strongly disagree	=	0

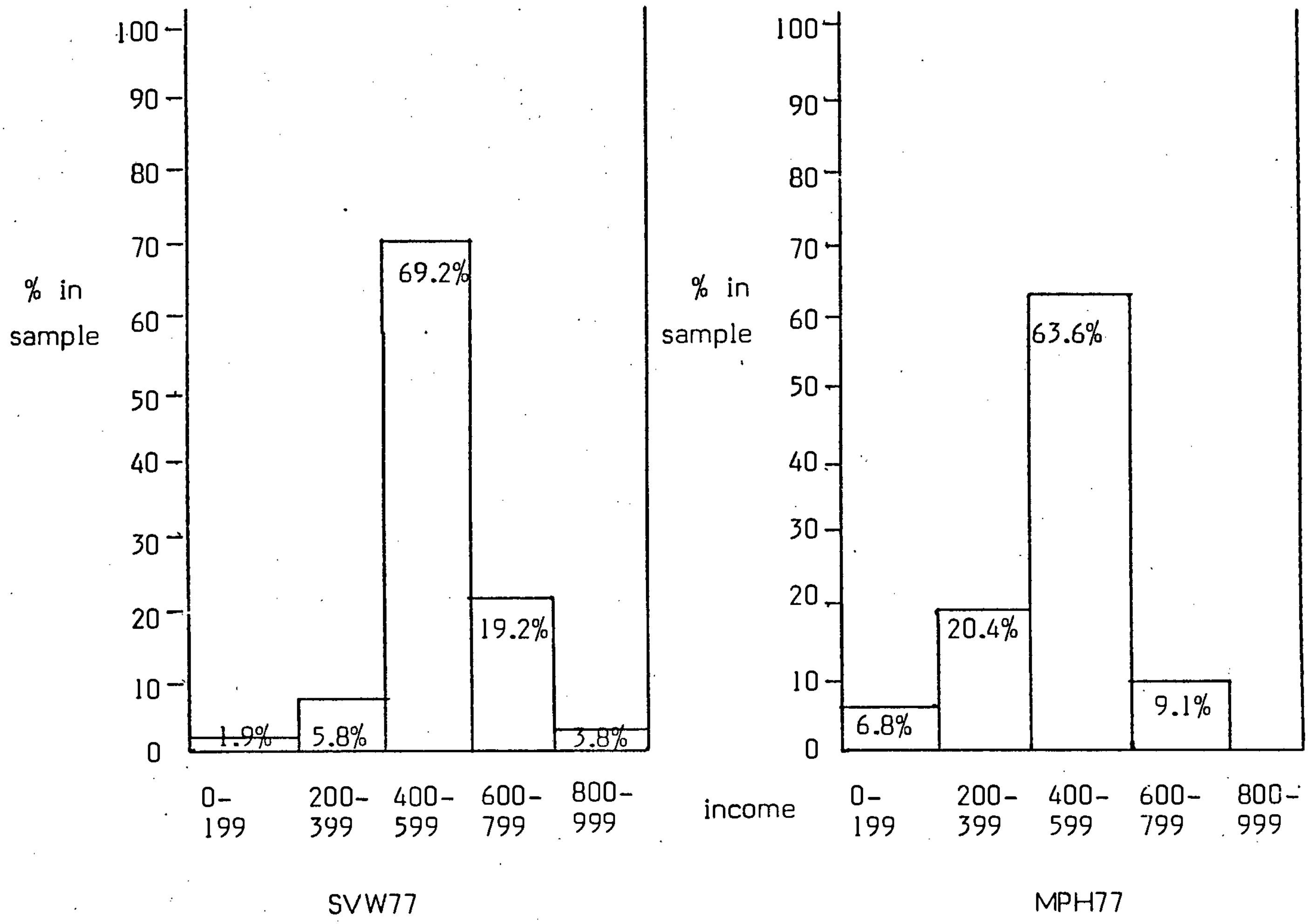
Items marked with an asterisk (items 3, 4, 5, 6, 8 and 17) are negatively worded and have the scoring reversed, with 0 representing strongly agree and 4 representing strongly disagree. Non-responses were coded as 9 in the original studies, but for the purpose of the present study were included in the uncertain category (after ensuring that the number of non-responses were negligible). Inability to respond to a particular statement is sufficiently similar to the inability to respond to one or other end of the response continuum to warrant inclusion in this category, For the total 23-item scale, individual scores could thus range from zero (no experience of alienation) to 92 (highly alienated), with a score of 46 representing a neutral position.

8.2 Sample Characteristics

The total sample consists of 404 respondents drawn from six different residential areas in the Cape Peninsula. In the 1977 study, which was intended as a comparison of the attitudes of whites and so called coloureds of similar socio-economic-status, the area sampled for each population group was Sun Valley (henceforth abbreviated as SVW77) and Mitchell's Plain (henceforth MPH77) respectively. The success of the sampling design can be examined in terms of some selected socio-demographic data tabulated below.

Table 8.1

Distribution of Incomes for the Two 1977 Samples.



It can be seen from Table 8.1 that the incomes of the two samples are similar. The Sun Valley sample has a slightly higher average family income (R534) than that of the Mitchell's Plain group (R464). An examination of other sample characteristics reveals that MPH77 is a more newly-established area than SVW77 (average length of residence in months for the former being 11.0 as compared with 55.9 for the latter). The mean number of people in the household is also higher for MPH77 (5.4) than SVW77 (4.1), whereas the mean ages of respondents is similar (35.0 for MPH77 and 35.5 for SVW77). Education levels are higher for the White group, as can be seen from Table 8.5. Thus, although not markedly dissimilar, there is a certain amount of variation between the two sampled areas of the 1977 study in terms of general socio-demographic characteristics.

Four communities were sampled in the 1978 study, which aimed at a comparison of the effects of socio-economic-status and length of residence in the community on the attitudes of Coloured respondents regarding community participation and related aspects. A 2 x 2 sample design was thus employed, with samples being drawn from the following areas: Mitchell's Plain Section One (MPL78), a newly-established low S-E-S area; Mitchell's Plain, Westridge (MPH78), a newly-established high S-E-S area; Parkwood (PL78), a well-established area of low S-E-S; and Fairways (FH78), a well-established area of high S-E-S. That the design succeeded in terms of these criteria can be seen from the tables of selected socio-demographic data below:

Table 8.2

Mean Length of Residence (in Months) in Present Home:

MPL78	:	8.2
MPH	:	4.3
PL78	:	63.6
FH78	:	52.9

Table 8.3

Mean Monthly Income of Household:

MPL78	:	R230
MPH78	:	R350
PL78	:	R178
FH78	:	R538

Table 8.5

Cumulative Percentages of Minimum Education Levels:

		Std 6	Std 8	Std 10
SVW77	:	93.9%	79.6%	28.6%
MPH77	:	74.4%	41.9%	13.9%
MPL78	:	96.2%	63.3%	11.4%
MPH78	:	96.1%	62.3%	15.6%
PL78	:	90.9%	36.4%	4.5%
FH78	:	94.2%	85.5%	47.8%

8.3 Generalisations From the Sample

Although it appears that the samples are representative of the communities from which they are drawn, in no way can they be regarded as representative of the general population, of the urban population of the Cape Peninsula, or even of the Coloured or White groups from which they are drawn. This is not considered a drawback, as this study is not concerned with generalisations from the samples to any particular population, but rather with conclusions regarding the attitude scale used. Zetterberg (1963 : 54-55) points out that the representativeness of a sample is not crucial when the research concerns relationships between variables.

What is desirable, though, is that the sample represents a certain degree of heterogeneity. The aim of attitude measurement is to distinguish between those whose attitudes are dissimilar. Thus a scale constructed using a homogeneous population in terms of general culture (such as student groups in specific faculties or classes, as are often used in attitude scale construction) might not be effective in distinguishing between extreme attitude positions. A valid attitude scale, moreover, is one that should reveal the same basic pattern of interaction between items regardless of the diversity of the populations in which it is applied. For those reasons the present samples, combined for the purpose of this study, are considered wholly adequate for the task at hand.

8.4 Sampling Procedure

The sampling procedures adopted in the 1977 and 1978 studies are similar. Maps of the erven of each area could be obtained, and it was thus decided to sample households rather than individuals. The samples (within each cluster) were thus intended to be equiprobable for households, not individuals.

Using the maps, the boundaries of each of the prescribed areas were demarcated, and all erven within these boundaries were numbered and then grouped into clusters of equal size, which were also then numbered. Four clusters from each area were selected using a table of random numbers. Within each of these clusters, 20 households were selected, again using random number tables, giving a total of 80 households sampled in each area (a total sample of 320 respondents was thus aimed for in the 1978 study). As the total population of each community was not known, and as a number of erven in each cluster were vacant lots or unoccupied premises, the procedure used could be described as a disproportionately stratified multi-stage cluster sample.

8.5 Obtaining Respondents

Interviewers were provided with maps of each sampled cluster, on which the households selected had been marked. The interviewers were instructed to interview the head of the household. Failing this his or her spouse or any other adult member of the household were to be interviewed. In the 1977 study interviews were conducted on Saturday afternoons, there being more chance of the head of household being present. In the 1978 study many of the interviews were conducted during weekday afternoons, resulting in a greater proportion of female respondents.

In the event of a suitable respondent not being found at the sampled address, or if the address proved to be an empty plot or unoccupied dwelling, interviewers were instructed to proceed to the house immediately to the left of the household sampled. If this again proved unsuccessful, the interviewer was then to try the house to the right of the originally sampled house, and then two houses to the left and so on until a suitable respondent could be obtained.

The final number of usable questionnaires obtained from each of the sampled areas is as in Table 8.6, below.

Table 8.6

Number of Respondents Obtained by Area:

SVW77	:	53
MPH77	:	45
MPL78	:	80
MPH78	:	79
FH78	:	73
PL78	:	74
		404

8.6 Interviewing Procedure

In each of the two studies the interviews were conducted by final year sociology students at the University of Cape Town, who formed the research group in each case. The interviewers were predominantly White and English-speaking, with a roughly equal mix of male and female. Although trained in the theoretical aspects of survey interviewing most interviewers had had no practical experience prior to the present studies.

Interviewers were instructed to inform respondents that they were university students conducting a comparative study of general community attitudes. Questionnaires were completed by the interviewers themselves, with interviewees responding in the indicated manner to statements or questions read to them. It should be noted that although respondents were informed that the information they gave would be confidential, anonymity could not be assured because of the nature of the interviewing procedure.

8.7 Biases Arising from the Interview Situation

A number of problems associated with the interviewing procedure could influence results. The fact that a large number of respondents were probably Afrikaans-speaking and that the interviews were conducted in English could cause misunderstandings. In a post facto attempt to control for confusion caused by language difficulties, the number of uncertain responses for each item are used as an indication of the degree of ambiguity or difficulty of that item. The translation of the questionnaire into Afrikaans would have created even more problems concerning equivalence of meaning. Almond and Verba (1970 : 351) note that in the cross-cultural context one must strive for equivalence of stimuli in the interview situation. This could not be guaranteed by translated questionnaires. It was felt that respondents would have a sufficient understanding of English to justify use of a unilingual questionnaire.

A second problem that may arise involves the response set of acquiescence (also referred to as "yeasaying": see Orenstein and Phillips, 1978 : 244-245). Ideally, an attitude scale constructed by Likert's method should consist of an equal proportion of positively and negatively worded statements to cancel the effect of acquiescence, or simple agreement with every statement made (see Carr, 1971; Likert, 1932 : 46; Heaven, 1977 : 6). This could not be done here as a pre-built scale was being used (only five of the items on Dean's scale are negatively worded). However, the pattern of responses for these negative items could be examined in an attempt to determine the level of acquiescence.

A further problem could possibly arise through the verbal responses of the interviewees. It was noted that on presentation of a statement by the interviewer, a number of interviewees responded with a simple affirmative or disagreement, without making use of the extreme response categories. To test whether this had any effect on the results, the original response scale was collapsed to a 3-point scoring system, and the results compared with those scored on the full range of responses.

8.8 Preparation of the Data Matrix

The information extracted from the 404 completed questionnaires was coded according to the scoring procedure in Section 8.1 and punched onto computer cards by the members of the research group. Both the coding and punching were independently checked, and errors eliminated.

The resultant data were stored on file at the Unviersity Computing Centre, available for further analysis. The data were analysed using the STATJOB series of programmes developed by the Madison Academic Computing Centre, performed on the Univac 1108 computer at the University of Cape Town. Specific programmes used were the DSTAT2 and CROSTAB2 series of programmes for the descriptive statistics; demographic data, calculation of gamma and tau, as well as various aspects of the item analysis. The product moment correlation coefficient and the resultant factor analyses were computed with the aid of the FACTOR3 programme series.

8.9 Analysis of the Data

Analysis of the data to be discussed in the following chapter can be subdivided under the following headings:

8.9.1 General Scale Properties

This includes the distribution of total scale and subscale scores to see whether the use of parametric strategies are applicable, an examination of subscale intercorrelations, and a look at the relationships between subscales and selected background variables. The concern of this section is disregarding the internal composition of the subscales, whether they behave as expected in terms of previous research.

8.9.2 Analysis of Internal Consistency

In this section the internal structure of the scale is examined to determine whether the combination of items in the respective subscales is justified, and, indeed, whether the items warrant inclusion in the scale. Certain items might be discardable on grounds of ambiguity (as measured by number of uncertain responses), means not in accord with the remaining scale item means, discriminative power, or too low a correlation with scale or subscale scores. However, as this study is not concerned with scale construction but rather with the analysis of a pre-built scale, these items will be retained for further analysis.

8.9.3 Multivariate Analysis

Having examined the degree of internal consistency of the scale in the previous section, attention is now focused on examination of such underlying structure as may exist in the data. Factor analysis and cluster analysis are used to determine whether the dimensions hypothesised by Dean for his Social Alienation Scale are in fact present and, if not, what alternative groupings can be found. Comparison of the results with those of other studies is done to determine the transferability or cross-cultural validity of the scale.

CHAPTER NINE

RESULTS

9.1 General Scale Properties

Before we examine the underlying structure of the Social Alienation Scale (Dean, 1961) it might be interesting to examine the results had the subscales been assumed to be reliable and valid measures of the defined constructs, and no attempt been made to determine such underlying structure as may exist. The first step would be to examine the distribution of respondents' scores on the subscales and total scale to determine whether there is a basis for treating such scores as interval measures.

Figure 9.1

Distribution of scores (N = 404) for the Total Scale:

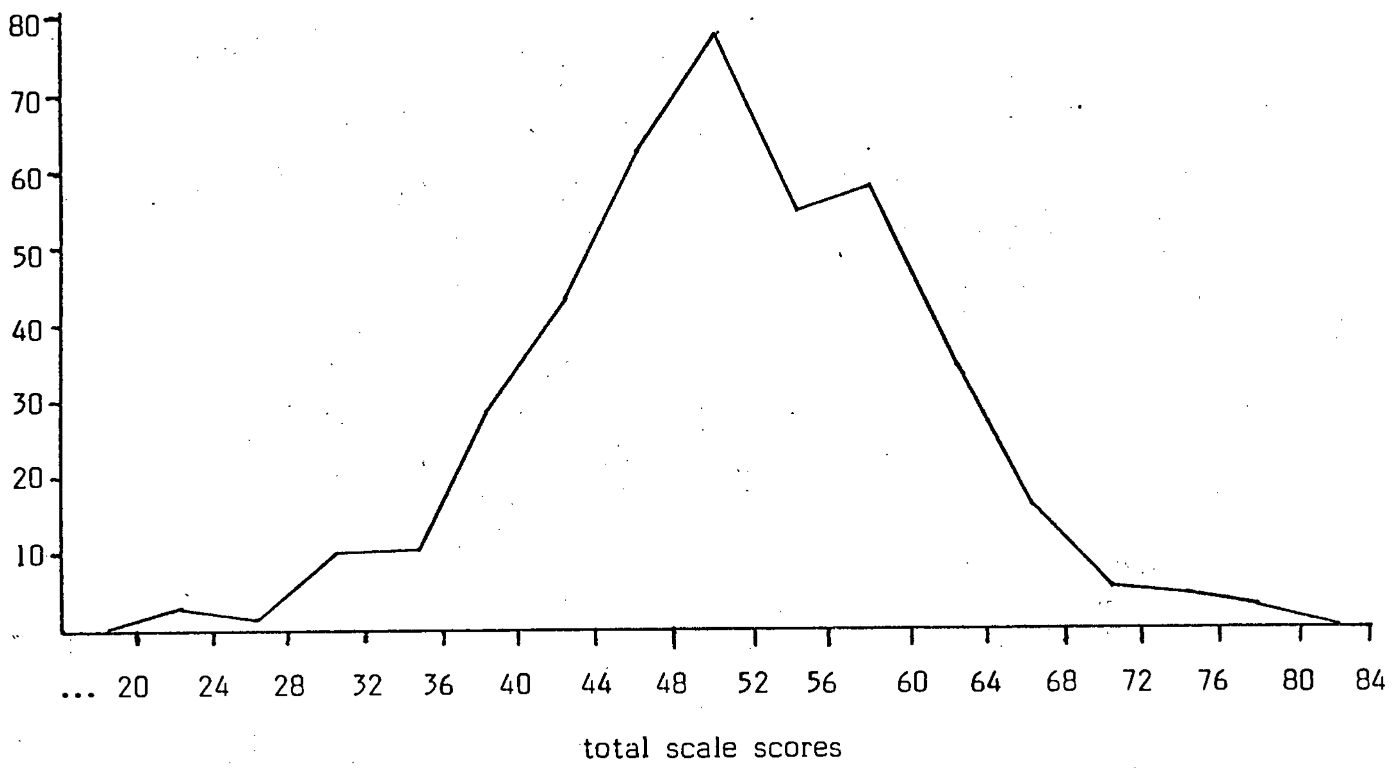


Figure 9.2

Distribution of Scores (N = 404) for the Social Isolation Subscale:

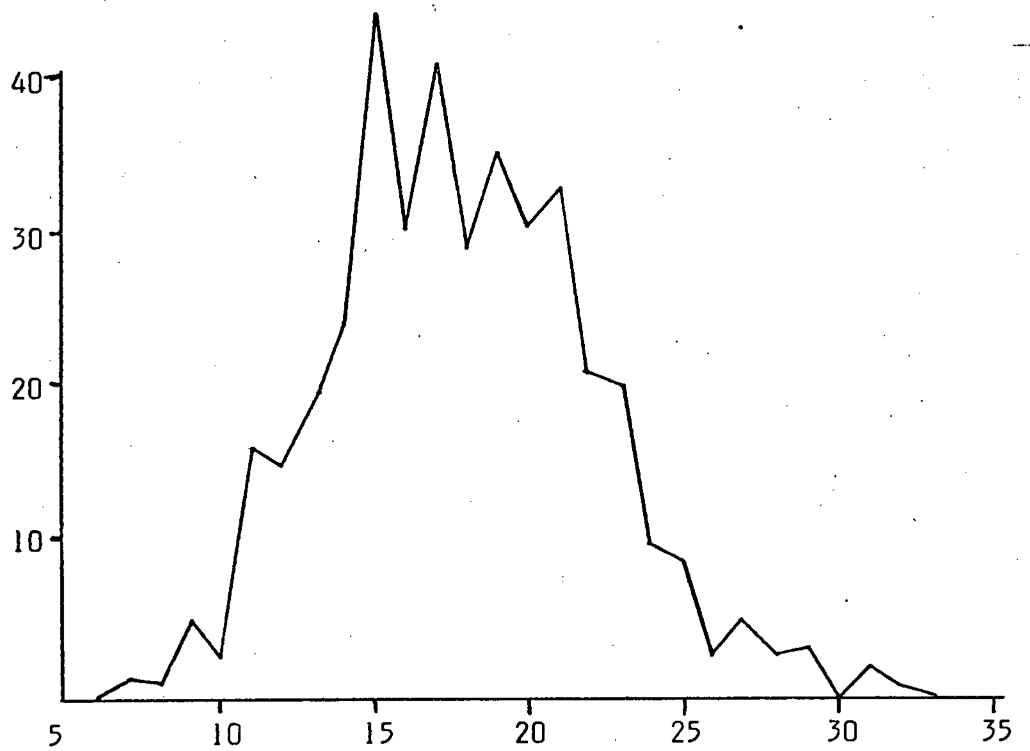


Figure 9.3

Distribution of Scores (N = 404) for the Powerlessness Subscale:

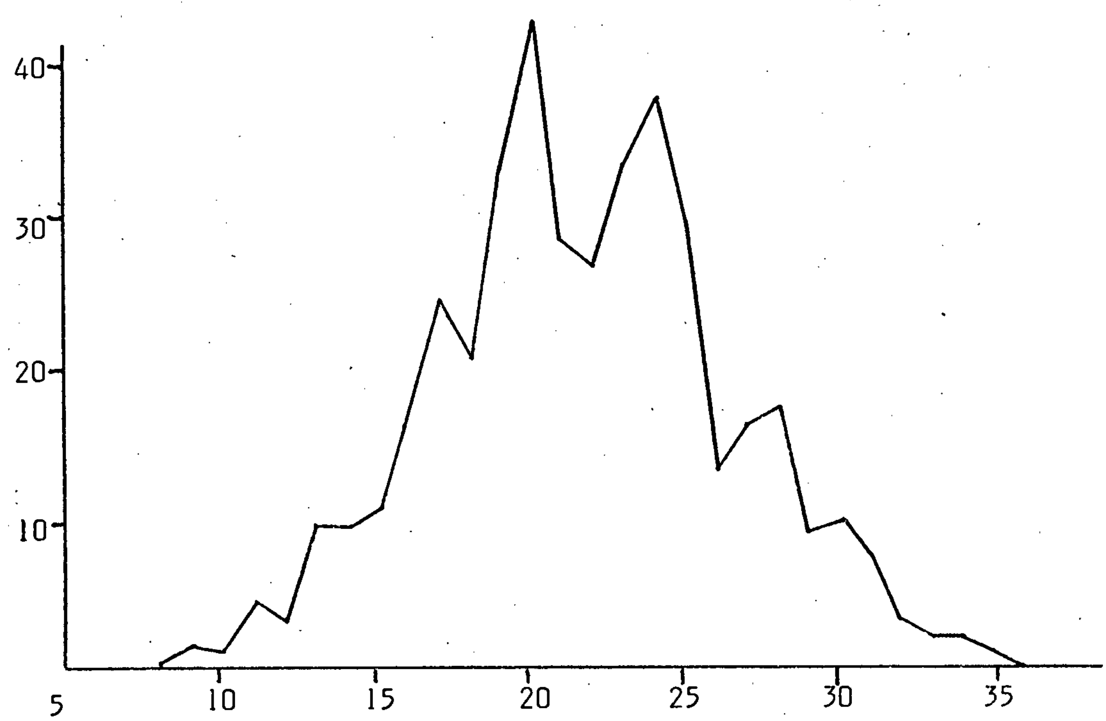
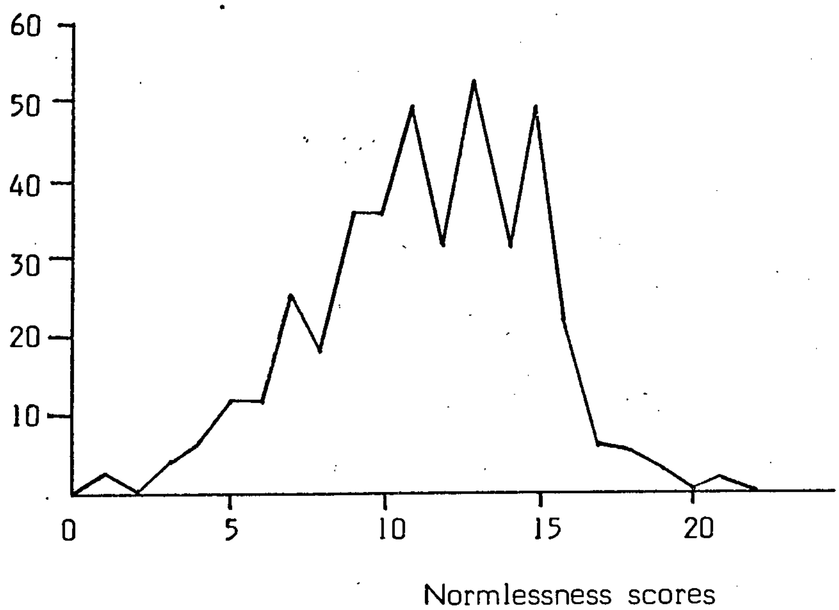


Figure 9.4

Distribution of Scores (N = 404) for the Normlessness Subscale:



It can be seen from figures 9.1 to 9.4 that the score distributions approximate normal distributions, that is, with the possible exception of the normlessness subscale, there is no marked skewness or bimodality. However, what pattern variation that is present in these distributions could possibly be due to the limited score range (especially in the case of the normlessness subscale). It could thus be argued that the summation of item scores into subscale scores and total score is justified. One could then also proceed to an examination of the correlations between the various subscales and the total scale.

9.1.1 Subscale Intercorrelations

The correlations between the various subscales, and between subscales and total scale, for the present sample are to be found in Table 9.1:

Table 9.1

Intercorrelations Among Alienation Scale Components,

Cape Town Study: N = 404*

	normlessness	social isolation	total scale
powerlessness	.44	.27	.81
normlessness		.17	.69
social isolation			.69

*For N = 404, $r \geqslant .13$ is significant at the 1% confidence level.

Although the subscale intercorrelations are all significant ($p < .01$), they are not high. The large subscale-total correlations could have resulted from the correlations of those subscale items with themselves which falsely inflates the combined correlation coefficient. Previous studies reporting such correlations (Dean, 1961; Simmons, 1966; Tolor, 1974; Knapp, 1976) have not controlled for this factor, and for comparative purposes the use of the correlation (r) without correction for item-item correlations is retained here (in the later item analysis such spurious correlations are to be accounted for). The correlations in Table 9.1 are reproduced alongside those of previous studies in Table 9.2 below for ease of comparison.

Table 9.2

Intercorrelations (r) Among Alienation Scale Components: All Studies:

corr (r)	Dean N=384	Simmons N=391	Tolor males N=41	Tolor females N=69	Knapp N=436	Present Study N=404
P - S**	.54	.53	.46	.52	.51	.27
P - N	.67	.43	.29*	.45	.50	.44
N - S	.41	.33	.18*	.26	.37	.17
P - A	.90	-	.81	.84	-	.81
N - A	.80	-	.64	.67	-	.69
S - A	.75	-	.76	.82	-	.68

* Not significant at the 5% confidence level. Remaining coefficients significant at the 1% level of confidence.

** P = powerlessness subscale; S = social isolation subscale; N = normlessness subscale; A = total social alienation scale.

It can be seen from this table that the subscale correlations of the present study are generally lower than those reported in previous studies (except for Tolor's male sample, which, as has been noted, is a small sample and makes comparison difficult), especially in the case of the correlation between the normlessness and social isolation subscales. It is also interesting to note that the powerlessness subscale correlates most highly with the total scale scores in all studies reported above. The results tabulated above indicate that there is considerable variation in the subscale (and item) intercorrelations which is not in keeping with the hypothesised dimensions of the scale, and that further analysis is warranted. One would hardly be justified in combining the subscales as aspects of the same general concept on the basis of correlations as low as those reported in the present study, although there does appear to be some degree of correspondence. The cross-cultural validity of the scale, as well as its general construct validity, are brought into question by the results of the present study as well as from other studies.

Many researchers would stop here and accept the combination of subscales into a total alienation measure as a valid instrument for the construct being measure. However, on the basis of these results one cannot with surety claim that the subscales are measuring what they were intended to measure. Further analysis is obviously necessary before such a claim could be made. Before this is done we will examine one more set of results in terms of an assumption that the combination of items into the respective subscales is justified.

9.1.2 Relationships Between Subscales and Background Variables

Dean (1961) reports a number of correlations between his subscales and selected background variables, including education, age and income, in an attempt to make predictive validity approaches more accessible. Although most of the correlations were statistically significant at the 1% level of confidence, Dean (1961 : 757) writes that

> ... the correlation coefficients are uniformly of such a low magnitude that it would not be feasible to predict the degree of Alienation from the score on any of the ... social correlates measured.

To examine whether, under different conditions, Dean's Social Alienation Scale reacts in the same way in respect of these background variables, the relevant correlations were computed for the present study and are reproduced in Table 9.3:

Table 9.3

Correlations (r) Between the Social Alienation Scale and Selected Background Variables: N = 404*

	education	income	age
social isolation	.098	.039	.074
powerlessness	.096	-.067	.080
normlessness	-.072	-.157	-.086
alienation	.069	-.076	.044

*For N = 404, $r \geq .13$ is significant at the 1% level of confidence, and $r \geq .10$ at the 5% level.

The only significant correlation ($p < .01$) is between normlessness and income. The chance of successfully predicting alienation on the basis of these background variables is thus very slim. For this reason, any form of criterion validity for the scale should be avoided. These results bring the usefulness of Dean's scale into question. What use is an attitude scale that has little or no known social correlates? Although only a few background variables are examined here, other research has confirmed that no effective criterion for alienation has yet been found.

The results of this part of the analysis have proved inconclusive, and it appears that the individual items are behaving in a manner inconsistent with their combination into the subscales proposed by Dean. However, this study does not stop here, by merely attributing such inconclusive results to problems inherent in the measuring instrument, but proceeds to examine possible causes of such results in terms of the underlying structure of the particular scale used.

9.2 Analysis of Internal Consistency

To discover the reason for the poor performance of the alienation subscales in terms of expectations aroused by Dean (1961), it is felt one needs to examine the underlying structure of the scale. In terms of its general characteristics, the Social Alienation Scale does not seem to be measuring what it is supposed to with any degree of accuracy. In this and the following sections indications of the scales construct validity will be sought.

9.2.1 Item Analysis

Although one of the most important steps in attitude scale construction, item analysis also has a part to play in the post hoc analysis of attitude scales, being an indicator of internal consistency and thus, ultimately, of construct validity. Ideally, item analysis should result in the discarding of those items that are found wanting, but as the number of scale items in the present study is already restricted, no items will be excluded in further analyses. Rather, such inconsistent items and their effect on later analyses will be noted and retained in the item set.

9.2.1.1 Detection of Ambiguous Items

One of the first steps in item analysis is to examine whether there are any items on which a disproportionately large number of respondents make use of the "uncertain" category. An acceptable level of neutral responses for an item is arbitrary, and it was decided to set this level at 20%, or one fifth of the sample, for this study. Thus, any items with more than 80 subjects (20% of the sample) responding "uncertain" should be discarded on grounds of ambiguity or misunderstanding (the distribution of item responses can be found in Appendix G).

Table 9.4

Numebr of Responses and Percentages in the Uncertain Category for Each Item:

Item	Count	Percentage
S1	24	5.94
S2	42	10.39
S3	57	14.11
S4	30	7.43
S5	14	3.47
S6	54	13.37
S7	42	10.40
S8	50	12.38
S9	13	3.22
P10	32	7.92
P11	28	6.93
P12	21	5.20
P13	93	23.02
P14	29	7.18
P15	94	23.27
P16	59	14.60

Item	Count	Percentage
P17	35	8.66
P18	54	13.37
N20	55	13.61
N21	39	9.65
N22	80	19.80
N23	61	15.10
N24	43	10.64

Table 9.4 reveals three items that have unacceptable levels of neutral or undecided response, namely items P13, P15 and N22. Item P13 reads: "There is little or nothing I can do towards preventing a major 'shooting' war". Item P15 reads, "There is little chance of promotion in my job". Item N22 is as follows: "I often wonder what the meaning of life really is". A further breakdown of these percentages into the various sampled areas to attempt an explanation for the high uncertain response rate for these three items is to be found in Table 9.5.

Table 9.5

Percentage of Uncertain Responses by Area for Three Selected Items:

Area	Item P13	Item P15	ItemN22
SVW77	18.9%	5.7%	16.9%
MPH77	28.9%	6.7%	35.5%
MPL78	17.3%	56.8%	13.6%
MPH78	26.9%	19.2%	16.6%
PL78	18.9%	19.2%	25.7%
FH78	28.8%	17.8%	16.4%

It appears that respondents from the high socio-economic-status Coloured areas (MPH77, MPH78, FH78) have more difficulty responding to item P13 than those from other areas. This could possibly be attributed to heightened political awareness and the danger of expressing opinions which might be construed as opposition to present policy. Item P15 appears to have been affected by the slightly different research designs between the 1977 and 1978 studies, with the result that a larger proportion of those interviewed in the 1978 study may have been housewives or workless, making this statement irrelevant. No explanation can be offered for the variation of uncertain responses for item N22 other than the possibility of interviewer bias or the simple inability of many interviewees to respond to such a statement.

The items mentioned above would normally have been discarded in the scale development stage of research, but for reasons mentioned earlier will be retained, but kept in mind when later analyses are attempted. A similar item selection procedure would be to examine the means of item responses to determine whether any items should have been scored in a reverse direction, or whether they are acting inconsistently with remaining items on initial inspection. This is done in Table 9.6 and Figure 9.5

Table 9.6

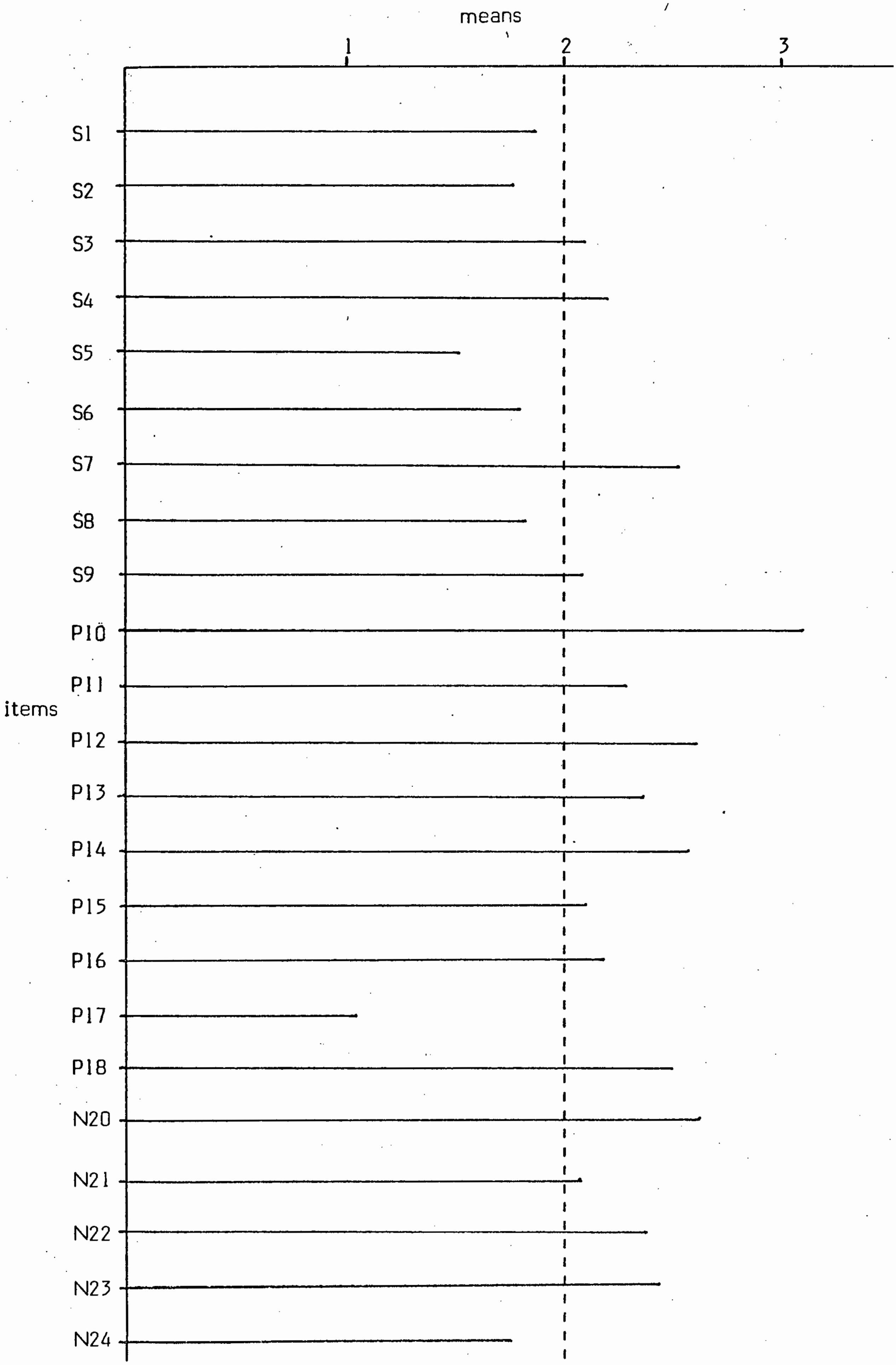
Means of Scale Items (N = 404):

Item	Mean
S1	1.88
S2	1.77
S3	2.12
S4	2.22
S5	1.54
S6	1.80
S7	2.52
S8	1.83
S9	2.07

Item	Mean
P10	3.09
P11	2.27
P12	2.61
P13	2.37
P14	2.56
P15	2.12
P16	2.21
P17	1.06
P18	2.51
N20	2.62
N21	2.06
N22	2.39
N23	2.46
N24	1.78

Figure 9.5

Graphical Representation of Table 9.6



Examination of Table 9.6 and Figure 9.5 reveals that the social isolation subscale appears to be measured with some inconsistency, with the means for items S1, S2, S5, S6 and S8 falling on the less-alienated side of the neutral point (2). This could possibly be attributed to confusion between a respondent's perception of his own isolation and of the isolation of others around him. It seems that these are two distinct ideas, with a person's sense of isolation possibly even being increased by the awareness that others around him are not experiencing such feelings. One needs to distinguish whether one is measuring the individual's isolation from his immediate community, or the community's isolation from the society at large as perceived by the individual. This distinction is not clarified by the items of the social isolation subscale.

The powerlessness and normlessness items, on the other hand, seem to act with a certain degree of consistency, with the strong exception of item P17, and possibly also of item N24. Both items involve religious beliefs, with item P17, "Belief in a God helps me make decisions in daily life", not being one of Dean's original scale items. One would like to hazard a guess as to the inconsistency of these items. In contrast to a more "intellectual alienation" experienced by students and middle-class respondents which is associated with rejection of religious values, in the working classes alienation from society is accompanied by a move toward religion. If this is the case then the cultural and even class bias of such a scale comes to the fore.

9.2.1.2 Calculation of Scale Value Difference Ratios

The above two preliminary steps in item analysis have already revealed certain inconsistencies in the data. We will now see whether these suspicions are confirmed by the more formal item analysis procedures. The first of two methods to be used here will be the Scale Value Difference (SVD) Ratio developed by Sletto (1937). The procedure was carried out for the total scale and, later, for each of the subscales.

With ten percent of the sample, or 40 respondents, being included in each of the extreme groups, the SVD ratios in terms of the total scale can be seen in Table 9.7, which is a ranking of the items in terms of their discriminative power between high and low deciles (10%) on the total scale (for the various steps in the calculation of the SVD ratio the reader is referred to Appendix B).

Table 9.7

Alienation Scale Items Ranked in Terms of Scale Value Difference Ratios:

Rank	Item	SVD Ratio
1.	P16	.57
2.	N23	.56
3.	N22	.55
4.	P18	.53
5.	P14	.52
6.	S6	.52
7.	N20	.48
8.	P12	.47
9.	N24	.46
10.	S9	.46
11.	S7	.45
12.	P11	.44
13.	N21	.43
14.	S1	.40

Rank	Item	SVD Ratio
15.	S8	.39
16.	P13	.38
17.	S2	.34
18.	S4	.29
19.	P17	.27
20.	P10	.26
21.	S3	.19
22.	P15	.17
23.	S5	.07

It can be seen that in terms of Sletto's arbitrary lower limit for the SVD ratio, only six of the items would qualify for inclusion in a single scale. Before we simply recommend discarding all remaining items on the grounds of poor discriminative powers between extreme criterion groups, we should look at another method of item analysis to see whether the above results are complemented or not.

9.2.1.3 Calculation of t-Values

The next method to be used is Edwards' (1957) t-value, based on the formula in Section 4.1.2, the results of which can be found in Table 9.8.

Table 9.8

Items Ranked in Terms of the t-Value:

Rank	Item	t-Value
1.	N23	11.32
2.	N22	9.78
3.	N20	8.07
4.	P18	7.83

Rank	Item	t-Value
5.	S6	7.61
6.	P16	7.51
7.	P14	6.84
8.	N24	6.79
9.	P11	6.63
10.	S1	6.12
11.	S9	6.07
12.	N21	5.99
13.	P13	5.97
14.	S7	5.87
15.	S8	4.95
16.	P12	4.76
17.	S2	4.76
18.	P10	4.48
19.	S4	4.28
20.	P17	2.78
21.	P15	2.32
22.	S3	2.22
23.	S5	0.79

According to the significance level of 2.70 ($p < .01$, N = 40) for the t-value, all but three of the items would qualify for inclusion in the scale. It is interesting to note that the item rankings in terms of discriminative power for the two methods is strikingly similar, the only point of contention being the cut-off point for the acceptance or rejection of items. The SVD ratio is a far more rigorous criterion of internal consistency than the t-value. One would suggest that, during scale construction, when one is paring a large collection of items, the stricter SVD criterion could be used. In the present study, however, we are more concerned with the items at the lower end of each list, that is, those with questionable consistency with other scale items. Further measures of internal consistency will thus be employed.

9.2.1.4 Item-Total Correlations

The above two item analysis procedures are concerned with the discriminative power of items in terms of extreme groups. The item-total correlations, on the other hand, are more concerned with scale homogeneity and the relationships between item and scale scores. These correlations (corrected for the correlation between an item and itself) are thus also useful measures of internal consistency. In Table 9.9 items are ranked in terms of their (corrected) correlations with the total scale.

Table 9.9

Items ranked in Terms of Item-Total correlations:

Rank	Item	$r_{i(t-i)}$
1.	N23	.395
2.	N22	.381
3.	P18	.377
4.	N20	.372
5.	S1	.348
6.	P14	.335
7.	P12	.326
8.	P11	.325
9.	P16	.287
10.	S9	.277
11.	S7	.277
12.	N21	.253

Rank	Item	$r_{i(t-i)}$
13.	S6	.235
14.	N24	.207
15.	S2	.205
16.	S8	.186
17.	P10	.107
18.	P13	.085
19.	S4	.082
20.	P17	.069
21.	P15	.023
22.	S3	-.017
23.	S5	-.145

The rankings of Table 9.9 show a large degree of correspondence with those of the previous two methods used, suggesting that the three methods (SVD ratio, t-value and item-total correlations) are equally effective in ranking scale items in terms of internal consistency. With a significance level of .13 ($p < .01$, $N = 404$) for item-total correlations, seven items would warrant exclusion from the scale. This criterion for item selection is thus less rigorous than the SVD ratio, yet more so than the t-value. It is thus suggested that for any item analysis, both an item-discriminative method and item-total correlations be used. For reasons given earlier the SVD ratio is preferred to the t-value, but it is suggested that a lower cut-off point for item acceptance be considered (such as .40).

The usefulness of item N22 was brought into doubt earlier because of the large number of uncertain responses. However, the responses of those individuals who do react positively or negatively to this item are consistent with their responses on the other items of the scale. This item would thus not be excluded from a scale using discriminative powers of items or item-total correlations as criteria for inclusion. Likewise, item N24 was questioned on grounds of its mean being inconsistent with those of other items, but proved reasonably consistent in terms of the item analysis procedures used above. The remaining items regarded as ambiguous (P13, P15 and P17) are confirmed as such by the item analysis.

What is evident from the relatively low item-total correlations, and the SVD ratios and t-values, is that a certain amount of inconsistency or heterogeneity exists among the scale items. All items do not appear to be measuring the same thing to the same degree. This supports the evidence presented by the low correlations between subscales reported earlier. However, as Dean's Social Alienation Scale is intended to be multidimensional, a certain amount of heterogeneity should be expected. One would need to examine items in terms of the subscales to which they belong in order to determine whether there is greater homogeneity within the postulated dimensions of the scale.

9.2.2 Item-Subscale Analysis

The two methods used to examine items in terms of their subscale membership are the SVD ratios and item-subscale correlations. The SVD ratios for the various subscale items are reproduced in the three tables following.

Table 9.10

Social Isolation Items Ranked in Terms of Their Scale Value Difference Ratios:

Rank	Item	SVD Ratio
1.	S8	.67
2.	S9	.64
3.	S6	.54
4.	S1	.51
5.	S4	.49
6.	S2	.48
7.	S3	.47
8.	S5	.35
9.	S7	.27

Table 9.11

Powerlessness Items Ranked in Terms of Their Scale Value Difference Ratios:

Rank	Item	SVD Ratio
1.	P18	.63
2.	P12	.62
3.	P14	.61
4.	P16	.60
5.	P13	.45
6.	P11	.37
7.	P17	.37
8.	P10	.32
9.	P15	.29

Table 9.12

Normlessness Items Ranked in Terms of Their Scale Value Difference Ratios:

Rank	Item	SVD Ratio
1.	N24	.73
2.	N21	.72
3.	N20	.67
4.	N22	.62
5.	N23	.62

Tables 9.10 to 9.12 reveal that, whereas in terms of the total scale there is a certain amount of heterogeneity, when one examines the items in terms of subscales only the picture alters. All the normlessness items act consistently with the subscale in discriminating between deciles. Both the social isolation and powerlessness subscales act with less consistency than would be expected. Thus, apart from the normlessness subscale, there appears to be little justification for the combination of the present items into their respective subscales or, in fact, into a total alienation scale. To confirm this one would need to examine the (corrected) item-subscale correlations in Tables 9.13 to 9.15.

Table 9.13

Social Isolation Items Ranked in Terms of Item-Subscale Correlations:

Rank	Item	$r_{i(s-i)}$
1.	S8	.295
2.	S6	.253
3.	S9	.222
4.	S4	.202
5.	S1	.166
6.	S2	.136

Rank	Item	$r_{i(s-i)}$
7.	S3	.086
8.	S7	.049
9.	S5	.001

Table 9.14

Powerlessness Items Ranked in Terms of Item-Subscale Correlations:

Rank	Item	$r_{i(s-i)}$
1.	P18	.286
2.	P12	.283
3.	P11	.235
4.	P16	.232
5.	P14	.227
6.	P10	.132
7.	P15	.032
8.	P17	-.024
9.	P13	-.074

Table 9.15

Normlessness Items Ranked in Terms of Item-Subscale Correlations:

Rank	Item	$r_{i(s-i)}$
1.	N23	.444
2.	N20	.389
3.	N21	.380
4.	N24	.275
5.	N22	.268

These results again complement those obtained from the SVD ratios. All the normlessness items correlate significantly with the subscale ($p < .01$, N = 404), whereas there is less consistency within the social isolation and powerlessness subscales.

9.2.3 Reliability

One more step remains in the analysis of internal consistency of the Social Alienation Scale: the determination of reliability coefficients for the various components of the scale. The measure of reliability used here is Cronbach's (1951) alpha coefficient as discussed in Section 4.2. The reliability coefficients for the alienation subscales and total scale are recorded in Table 9.16.

Table 9.16

Average Inter-Item Correlations (r) and Alpha Reliability Coefficients for Alienation Scale Components:

Component	$\bar{r}_{ij}$	Alpha
social isolation	.074	.65
powerlessness	.077	.66
normlessness	.244	.88
alienation	.071	.64

The reliabilities for the present study are somewhat lower than those reported by Dean (1961) in Table 7.1, with the notable exception of the normlessness subscale, leading one to question the cross-cultural reliability or transferability of the Social Alienation Scale. These coefficients are furthermore much lower than one would expect of an attitude scale constructed by the Likert technique (see Section 2.2.5).

The alpha coefficient can also be used as a method of item analysis, by examining the change in subscale reliabilities as a result of the addition of individual items. However, it is felt that the results of such an approach would only confirm those of other methods, and thus will not be examined here. Alpha reliabilities will again be used later, when the internal consistency of clusters are examined.

The reliability coefficients again complement the results of the item analysis, namely that the internal consistency (and transferability) of Dean's Social Alienation Scale is questionable for the present sample. This section has been concerned with the consistency of items in terms of the postulated dimensions of the scale. No attempt has been made to determine what other item groupings might be more suitable. The results so far point to a measure of multidimensionality among items that is unrelated to the postulated dimensions of the scale. Apart from the normlessness items, which are fairly consistent, this variation in the behaviour of individual items warrants the use of multivariate analysis methods to determine the presence of alternative dimensions.

9.3 Multivariate Analysis

This section has three major subdivisions: preparation of the correlation matrix; factor analysis; and cluster analysis. These will be examined in turn.

9.3.1 Preparation of the Correlation Matrix

Although the product-moment correlation matrix will be used as input for the factor analysis, it would be useful to test certain assumptions associated with the use of the coefficient. It has already been seen in Figures 9.1 to 9.4 that subscale and total scale scores approximate normal distributions. Plotting the subscale correlations for all individuals also reveals a degree of linearity. What we need to test here is whether the use of the product-moment correlations between items using Likert's simple 5-point scoring procedure is justified. To do this we will first examine the degree of correspondence between correlations obtained by this method and those using two measures of association whose assumptions are fully met by the data, namely tau and gamma. These correlations are recorded in Table 9.17.

Table 9.17

Correlations Between the Matrices Produced by Three Different Measures of Association: N = 253

	tau	product-moment
gamma	.90	.85
tau		.99

Although the correlations produced by the two ordinal measures of association seem to differ somewhat, the correlation between the product moment correlation and tau justifies the conclusion that error resulting from the use of the more powerful interval level statistic with the present data is negligible.

A further question concerns the scoring procedure used. Likert's simple scoring technique, in which each of the five categories for an item is assigned a discrete value, is based on the assumption that the intervals between these categories are regarded by respondents as equal. The sigma method of scoring (see Section 2.2.4 and Appendix A) represents an attempt to neutralise the effects of such an assumption. Furthermore, as mentioned in Section 8.7, the use of extreme (strongly agree or strongly disagree) categories in the interview situation might result in bias, and a collapsed (3-point) scale might be more effective. To test these proposals, the correspondence between the resultant inter-item correlation matrices for the sigma scoring method (see Appendix A), the collapsed scale (in which strongly agree and agree are scored 3, uncertain 2, and disagree and strongly disagree 1 for positively worded items) and the 5-point scale (scored as in Section 8.1.3) is examined. These coefficients can be found in Table 9.18.

Table 9.18

Correlations (r) Between Matrices Produced by Three Different Scoring Procedures: N = 253

	sigma	5-point
3-point	.93	.91
sigma		.97

The correlation between results of the sigma and 5-point scoring methods (.97) closely approximates that reported by Likert (1932) upon which is based his argument for the use of the simpler method, namely .99. There is a slight variation in resultant correlations between the 3-point and 5-point scoring methods which could be attributed to respondents being reluctant to make use of the extreme response categories. However, the alpha reliability of the 5-point scoring method (.673) is marginally higher than that of the 3-point method (.661). In addition, five remains the most popular number of research categories for Likert scales. Guertin and Bailey (1970 : 211) write:

> Experience has shown that the number of scale points beyond five is not particularly useful in providing more information. Less than five are too few, and seven adds only a little systematic variance to the scores.

For these reasons the 5-point scoring system will be retained in the present study.

The results of Table 9.17 and 9.18 thus justify the use of the product moment correlations between items scored according to Likert's simple scoring method for five response categories as the basic input for the factor analysis to follow. The correlation matrix for the 23 Social Alienation Scale items can be found in Table 9.19.

Table 9.19

CORRELATION MATRIX OF ALIENATION SCALE ITEMS: CAPE TOWN STUDY (N = 404)

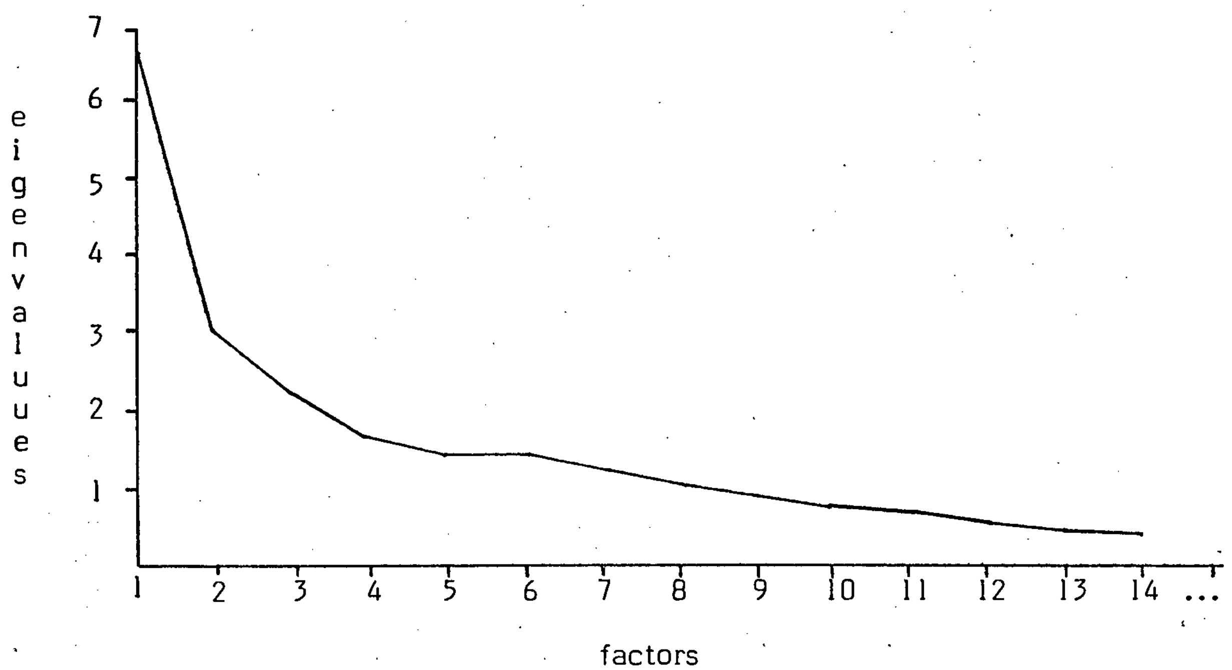
	S1	S2	S3	S4	S5	S6	S7	S8	S9	P10	P11	P12	P13	P14	P15	P16	P17	P18	N20	N21	N22	N23	N24
S1	1.000																						
S2	.210	1.000																					
S3	-.063	-.062	1.000																				
S4	.032	-.022	.157	1.000																			
S5	-.091	-.134	.124	.166	1.000																		
S6	.030	.035	.102	.216	.078	1.000																	
S7	.094	.162	-.114	-.017	-.192	.074	1.000																
S8	.101	.036	.204	.244	.069	.294	.114	1.000															
S9	.248	.327	-.040	.047	.016	.060	.084	.065	1.000														
P10	.094	.013	-.006	.055	-.091	.064	.035	.059	-.020	1.000													
P11	.250	.089	.084	.098	-.055	.135	.045	.210	.173	.104	1.000												
P12	.198	.155	.059	-.039	-.051	.068	.123	.103	.155	.098	.179	1.000											
P13	-.055	.150	.068	.088	.183	.045	.047	.092	.094	-.025	-.007	.024	1.000										
P14	.181	.081	-.101	-.011	-.126	.044	.235	-.032	.188	.109	.090	.217	.064	1.000									
P15	.021	.085	-.012	-.003	-.057	.038	-.020	.040	.099	.014	.167	.104	.066	.045	1.000								
P16	.093	.110	-.125	-.069	-.194	.133	.237	-.001	.065	.031	.115	.081	.133	.200	-.041	1.000							
P17	-.027	.035	.130	.008	.196	.052	-.025	-.009	.014	-.023	.058	.038	.004	-.080	-.148	.123	1.000						
P18	.151	.123	-.057	.020	-.152	.214	.230	.068	.262	.098	.120	.182	.082	.250	.049	.307	-.036	1.000					
N20	.190	.135	-.117	.031	-.254	.035	.303	.025	.103	.057	.170	.253	.054	.275	.049	.215	-.030	.279	1.000				
N21	.136	.063	-.177	-.008	-.055	.068	.158	-.071	.050	-.051	.075	.144	.061	.218	.077	.206	.033	.105	.329	1.000			
N22	.271	.124	-.107	.152	-.035	.097	.134	.092	.210	.135	.124	.195	.070	.431	.072	.170	.010	.175	.199	.166	1.000		
N23	.211	.091	-.126	-.021	-.213	.073	.281	.018	.097	.076	.151	.210	.142	.412	.041	.287	.011	.350	.381	.286	.318	1.000	
N24	.062	.017	-.015	-.065	.052	.047	.028	.026	.025	-.083	.071	.067	.012	.172	.006	.229	.177	.106	.157	.229	.156	.214	1.000

9.3.2 Factor Analysis

Having prepared the correlation matrix, the factor analysis can now be proceeded with in accordance with the steps listed in Section 5.3. With regard to factor models, it has already been shown that alpha factor analysis (Kaiser and Caffrey, 1965) is the most appropriate model for the present study, being concerned with variable rather than sample generalisations. For comparative purposes, the results of some of the other methods will also be mentioned to determine whether choice of factor model has an effect on the factors identified. Furthermore, communality estimates are not required in alpha factor analysis, and we can thus move directly to the next step, namely the determination of the most appropriate number of factors to be extracted. Although the eigenvalue-one criterion is an integral part of the extraction procedure in alpha factor analysis, the scree test will also be used as well for comparative and demonstration purposes.

Figure 9.6

Scree Test of Eigenvalues Versus Factor Number:



Using the Kaiser-Guttman criterion (Kaiser, 1961) eight factors with eigenvalues greater than unity are extracted for alpha factor analysis. An examination of the graph in Figure 9.5 suggests a slightly earlier alternative cut-off point, say around 3 or 4 factors. As eight is the number of factors obtained in both previous factorial studies of Dean's scale (Dodder, 1969; Hensley et al, 1975), and as the analysis of internal consistency has already indicated considerable variance and the presence of more dimensions than originally postulated for the scale, the 8-factor solution will be developed in the present study.

Because the four-factor solution also makes theoretical sense, it too will be examined. One would expect that the first factor of this solution would correspond to the general concept of alienation, upon which all items should load significantly. The remaining three factors would then be expected to correspond to the three subscales distinguished by Dean.

To determine the presence of a general syndrome underlying the items and the independence of subscales, the amount of variance explained by the first unrotated factor is examined, as are the item loadings on this factor and the communalities (determined by iteration) for the items (see Cartwright, 1965). The loadings and communalities are reproduced in Table 9.20.

Table 9.20

Unrotated Item Loadings on the First Factor and Communalities (N = 404):

Item	Factor 1	Communality
S1	.408	.325
S2	.323	.327
S3	-.142	.259
S4	.044	.287
S5	-.274	.442
S6	,216	.267
S7	.408	.251
S8	.163	.345
S9	.359	.411
P10	.149	.124
P11	.336	.306
P12	.394	.242
P13	.136	.293
P14	.543	.439
P15	.136	.202
P16	.440	.344
P17	-.002	.351
P18	.507	.304
N20	.556	.355
N21	.393	.362
N22	.508	.477
N23	.623	.471
N24	.250	.292

Using the arbitrary .30 level of significance, 13 of the 23 items attain a loading higher than this on the first factor. With the Burt-Banks formula, however, only two of the loadings fail to reach significant levels ($p < .01$). This seems to bear promise for the presence of a general dimension underlying the items. On further examination, though, it is found that this first unrotated factor accounts for only 7.8% of the total explained variance and only 24% of the variance explained by the first eight factors (factor variances and eigenvalues can be found in Appendix H). This suggests, firstly, that the lower significance level of the Burt-Banks method might be too lenient and thus less accurate than the arbitrary .30 significance level. Secondly, too little variance is explained by this factor to accept the presence of a strong generalised dimension underlying the scale items. One can only say that there does appear to be some slight degree of common variance among items. To obtain more conclusive evidence regarding the dimensions underlying the scale one needs to examine the rotated factor matrices.

Before these rotated matrices are examined, however, some further observations about the first unrotated factor can be made. It can be seen that four of the normlessness items (with the exception of N24) have loadings higher than .30 on this factor, again indicating consistency on the part of this subscale. Furthermore, the items regarded as inconsistent in terms of earlier analysis (items S3, S4, S5, P15 and P17) all have non-significant or negative loadings on this first factor. The questionability of these items and their consistency with the remaining scale items is thus confirmed by the initial factor solution.

9.3.2.1 Rotated 8-Factor Solutions

The orthogonal (VARIMAX) and oblique (OBLIMAX) solutions can be found in Tables 9.21 and 9.22 respectively.

Table 9.21

Factor Matrix of Dean's Alienation Scale Items: Varimax Rotation (N = 404)

Factors

Items	1	2	3	4	5	6	7	8
S1	.104	.285	.073	.357	.053	.167	.017	-.263
S2	.181	-.005	-.035	.525	-.025	.090	-.009	.091
S3	-.179	-.115	.256	-.089	-.165	.224	.213	.132
S4	-.110	.131	.498	.002	-.025	-.060	-.038	.061
S5	-.460	.046	.215	-.007	.133	-.116	.243	.304
S6	.157	.011	.485	.012	.029	.047	.050	.036
S7	.476	.079	.051	.106	.025	-.035	-.046	.007
S8	.053	-.031	.551	.055	-.074	.166	.021	.023
S9	.056	.132	.067	.610	.040	.081	-.010	.078
P10	.098	.201	.084	-.030	-.215	.103	-.026	-.096
P11	.080	.086	.247	.162	.064	.421	.024	-.152
P12	.182	.211	.018	.147	.002	.373	.060	.008
P13	.077	.034	.103	.113	.038	.007	-.007	.511
P14	.320	.551	-.063	.056	.100	.088	-.044	.081
P15	-.035	.005	.024	.090	.097	.310	-.280	.090
P16	.520	.058	.021	.063	.172	-.027	.183	.048
P17	-.027	-.033	.037	.028	.098	.016	.580	.017
P18	.472	.159	.138	.161	.001	.084	.001	.061
N20	.473	.200	.006	.076	.210	.184	-.074	-.049
N21	.250	.159	-.030	.030	.515	.064	-.057	-.001
N22	.129	.631	.134	.173	.112	.037	-.006	.004
N23	.517	.371	-.019	.012	.191	.143	.012	.089
N24	.137	.090	-.015	-.023	.431	.093	1263	.028

Table 9.22

Factor Matrix of Dean's Alienation Scale Items: Oblimax Rotation (N = 404)

Factors

Items	1	2	3	4	5	6	7	8
S1	.231	.071	.337	.232	.029	.146	-.276	-.023
S2	.200	-.026	.520	-.063	-.008	.064	.083	-.028
S3	-.208	.275	-.067	-.084	.232	.187	.124	-.157
S4	-.071	.493	.001	.176	-.051	-.047	.057	-.003
S5	-.393	.210	.002	.221	.258	-.054	.295	.196
S6	.162	.487	.001	-.029	.043	.003	.027	.011
S7	.469	.050	.084	-.070	-.070	-.098	.008	-.036
S8	.049	.561	.054	-.053	.024	.123	.012	-.078
S9	.143	.070	.599	.117	-.002	.084	.065	.037
P10	.119	.088	-.026	.127	-.039	.062	-.092	-.268
P11	.170	.259	.149	.031	.074	.388	-.175	-.014
P12	.285	.031	.134	.107	.100	.329	-.009	-.107
P13	.101	.109	.110	.017	.004	.019	.506	.045
P14	.498	-.071	.024	.414	-.034	.074	.075	-.045
P15	.029	.030	.081	.002	-.223	.363	.077	.082
P16	.533	.020	.034	-.093	.170	-.113	041	.082
P17	-.009	.045	.030	-.017	.583	-.058	.003	.061
P18	.504	.142	.140	-.004	-.011	.010	.056	-.086
N20	.564	.005	.038	.041	-.051	.142	-.062	.086
N21	.389	-.045	-.019	.114	-.011	.096	-.021	.430
N22	.350	.121	.142	.564	-.001	.045	-.006	-.006
N23	.647	-.022	-.028	.186	.028	.092	.078	.034
N24	.250	-.020	-.056	.072	.306	.082	.005	.346

Initial examination of Tables 9.21 and 9.22 reveals that the orthogonal and oblique solutions are not particularly similar. Since an oblique solution will be the same as the orthogonal if all factors are independent of each other, this is an indication that the oblique solution more closely resembles the data. Whichever rotation is considered, it is clear that Dean's hypothesised three subscales do not correspond to the actual dimensions underlying the scale for the present sample.

To test whether the oblique rotation maximises simple structure, we need to examine the numebr of hyperplane variables in each factor. When adjusted for communality size, only the first factor has a non-significant ($p < .05$) hyperplane variable count in terms of Sine and Kameoka's (1980) technique (see Section 5.3.6.1). This suggests that the oblique rotation still contains an initial general factor. The total percentage of variables in the hyperplane for the eight oblique factors is 76.6, confirming that the oblique solution has maximised simple structure. However, all the factors of the orthogonal solution have significant hyperplane counts, and the total hyperplane percentage (76.1) is practically the same as for the oblique solution. Thus, although the two solutions are not very similar in terms of loading patterns, they both satisfy the criterion of simple structure. For reasons mentioned earlier, the oblique solution will be examined further.

The major assumption of Dean's scale is that the items can be grouped into three independent subscales, namely social isolation, powerlessness and normlessness. We would thus expect that the factors obtained would correspond to these subscales. However, we have already seen that there is considerably more multidimensionality than should be expected, especially within the social isolation and powerlessness subscales. These subscales could possibly each consist of two or more dimensions. An examination of the oblique factors in Table 9.22 will reveal whether this is so. Items with loadings greater than .30 will be considered as belonging to a particular factor, with items loading over .20 being included where it makes theoretical sense to do so. Factors with less than three items loading significantly are ignored for the present. In addition, each item will be considered in terms of one factor only, on which it loads most highly. The items loading significantly on the first oblique factor are presented in Table 9.23, ranked according to their contribution to this factor.

Table 9.23

Factor 1 Items, Oblique Rotation:

Item	Loading
N23	.647
N20	.564
P16	.533
P18	.504
P14	.498
S7	.469
N21	.389
N22	.350
N24	.250

This first factor comprises all the normlessness items, three powerlessness items and one social isolation item. Item S5 is not included because of previously raised doubts concerning its consistency with other scale items. These items were all found to be consistent and homogeneous in terms of earlier item analysis, suggesting that a scale measuring a single general dimension could be constructed around these items. The normlessness items are the most consistent in terms of such a general dimension, and the social isolation items least consistent.

Table 9.24

Factor 2 Items, Oblique Rotation:

Item	Loading
S8	.561
S4	.493
S6	.487
S3	.275
S5	.210

Table 9.25

Factor 3 Items, Oblique Rotation:

Item	Loading
S9	.599
S2	.520
S1	.337

It can be seen from Table 9.24 and 9.25 that the remaining social isolation items are indeed split into two distinct dimensions. Dodder (1969 : 254) noted a similar split and named these two dimensions "friendliness" and "loneliness" respectively. This distinction also seems appropriate for the present study, although the particular items included in each of these dimensions do not correspond highly with those in Dodder's study. It appears that an individual's perception of his own social isolation should be distinguished from his perception of the social isolation of those around him.

Table 9.26

Factor 6 Items, Oblique Rotation:

Item	Loading
P11	.388
P15	.363
P12	.329

The three powerlessness items loading above .30 on the sixth factor seem to have little in common, and do not correspond to any groupings delineated by either Dodder (1969) or Hensley et al (1975). The remaining items (P10, P13 and P17) are scattered over the rest of the factors and seem to have very little in common with the remaining scale items.

9.3.2.2 Four-Factor Solution

Compressing the number of factors extracted to correspond to the (artificial) dimensions proposed by Dean (1961) adds little to the observations already made regarding the scale. Two approaches are possible here: to extract only four factors and then rotate them, or to extract eight factors and rotate only the first four. The first approach is adopted here. The oblique four-factor solution is reproduced in Table 9.26.

Table 9.26

Factor Matrix of Dean's Alienation Scale Items (Oblimax Rotation): Four-Factor Solution (N = 404)

	Factors			
Items	1	2	3	4
S1	.192	.477	-.085	-.042
S2	.197	.320	-.002	.017
S3	-.242	.103	.337	.184
S4	-.108	.033	.391	.031
S5	-.359	-.106	.213	.468
S6	.100	-.009	.482	-.075
S7	.462	-.057	.025	-.208
S8	.031	.128	.617	-.083
S9	.141	.409	-.006	.028
P10	.087	.143	.100	-.165
P11	.065	.471	.194	-.025
P12	.287	.346	.027	.082
P13	.123	-.022	.294	.198
P14	.549	.248	-.066	.021

Items	1	2	3	4
P15	-.052	.333	.058	-.196
P16	.536	-.084	.055	.042
P17	.009	-.023	.021	.477
P18	.489	.107	.125	-.137
N20	.523	.141	-.067	-.066
N21	.445	.097	-.098	.110
N22	.406	.289	.118	.129
N23	.673	.098	.024	.024
N24	.335	.047	-.010	.334

The first four rotated factors accounts for 25.3% of the total variance of the scale, which is less than the 32.5% accounted for by the eight-factor solution. Thus a certain amount of information is being lost as one forces unrelated items into artificial groupings.

Items loading above .30 on the first of the factors in Table 9.26 are exactly the same as those for the 8-factor solution. The second factor, however, consists of the following items: S1, S2, S9, P11, P12 and P15. In the 8-factor solution the three social isolation items formed one factor (factor 3) and the three powerlessness items another (factor 6), which makes more sense than their combination into a single factor. The third factor in Table 9.26 comprises the following social isolation items: S3, S4, S6 and S8, with S5 loading above .20 on this factor. This third factor is identical to factor 2 of the 8-factor solution in terms of salient variables, and merely confirms the previous observation that these items do not measure what is measured by the remainder of the social isolation subscale items, or indeed by the total scale.

9.3.2.3 Other Factor Analytic Models

The use of other factor models yields results complementary to those of the alpha method discussed above. Image analysis, for example, yields twelve factors with eigenvalues greater than unity, but only on the first three orthogonally rotated factors are there items with loadings greater than .30. These three factors comprise the following items:

factor 1: P14, P16, P18, N20, N21, N22, N23

factor 2: S1, S2, S9

factor 3: S4, S6, S8

Similar patterns emerge using the common factor method and principle components analysis. No further clarity would be gained by detailed analysis of the results of these alternative factor analysis procedures.

9.3.2.4 Conclusions Regarding the Factor Analyses

One could continue applying various factor models and different rotation procedures to the data until every possible avenue of investigation is exhausted. Because of the difference in procedure one would expect slight differences to emerge in the results. However, such an approach is both time-consuming and pointless. The most appropriate method (alpha factor analysis) has been used, with confirmation from alternative procedures, and the results are as fair a reflection of the data as will be attained using factor analysis methods.

The aim of the factor analysis has been achieved. The earlier analysis of internal consistency revealed a measure of multidimensionality among the alienation scale items, and factor analysis has confirmed this. Furthermore, certain dimensions have been disclosed which are unrelated to those originally postulated by the author of the scale. Tentative propositions have been made concerning the constitution of these alternative dimensions. There appear to be four major groupings, ignoring extraneous items. The first has a core comprising items P14, P16, P18, N20, N21, N22 and N23, with the possible inclusion of items S7 and N24. The second grouping consists of items S4, S6 and S8, with S3 and S5 being potential members. The third group is composed of three social isolation items: S1, S2 and S9. Items P11, P12 and P15 form a possible fourth group.

These tentative groupings elicited from the factor analysis require further examination. The first task in this connection is an investigation of whether there is any stability to these alternative dimensions. This will be done by examining the degree of correspondence between the factors of the present study and those of two previous studies concerning Dean's (1961) Social Alienation Scale.

9.3.2.5 Factor Matching

As all three matrices are rotated to simple structure using the same method of factor analysis and the same rotation procedure, it is felt that the obliquely rotated factor matrix of the present study can be compared to those reported by Dodder (1969) and Hensley et al (1975). However, as factors may have been extracted in different orders in the three studies, one must guard against expecting that, say, the fourth factor in one study be most similar to the fourth in another.

Three methods of factor matching (as discussed in Section 5.3.7) are used here, namely the correlation coefficient, the congruence coefficient and the salient variable similarity index. The results of these three procedures are tabulated below (Tables 9.27 to 9.29). The numbers refer to the factors as numbered in the three studies, thus D3 is the third factor as reported in Dodder (1969), and H4 the fourth factor in Hensley et al (1975), with F1 to F8 referring to the oblique factors of the present study. The factor matrices of the other two studies are reproduced in Appendices E and F). The levels of significance for the three factor matching procedures are approximations based on the suggestions of the respective authors.

Table 9.27

Correlation Coefficients for Oblique Factors of Three Studies:

	F1	F2	F3	F4	F5	F6	F7	F8
D1	.175	.178	.317	.281	.359	.002	.110	.616
D2	-.200	.518	-.127	-.261	-.163	-.105	.123	-.191
D3	-.014	.043	-.069	-.039	.138	.147	-.403	-.311
D4	.202	-.265	.130	.379	-.288	.096	.005	-.360
D5	.253	.034	-.058	.262	-.215	-.082	-.455	.128
D6	.040	.291	-.089	.251	-.105	.164	-.227	.001
D7	-.112	.159	.724	.175	-.227	.061	.368	.076
D8	-.239	.443	-.163	.016	.019	-.044	.067	-.013
H1	.609	.382	-.249	-.160	.083	-.205	-.086	.312
H2	-.332	.232	-.136	-.157	.529	-.266	.236	-.185
H3	.346	.117	-.060	.237	-.394	-.067	-.216	.035
H4	.099	.564	-.234	-.189	-.093	-.217	-.128	.000
H5	.134	-.073	-.373	-.290	.345	.193	-.332	.232
H6	-.410	.135	.053	-.661	-196	.394	.393	.195
H7	.260	-.221	-.081	.017	.085	.139	-.084	-.088
H8	-.418	.262	-.030	.000	-.142	.140	.164	-.677

For N = 23, r $\geqslant \pm$ .500 is significant at the 1% confidence level.

Table 9.28

Congruence Coefficients for Oblique Factors of Three Studies:

	F1	F2	F3	F4	F5	F6	F7	F8
D1	.278	.007	-.151	-.127	.407	.118	.162	.621
D2	.192	.655	.155	.045	.038	.175	.230	-.113
D3	.111	.143	.035	.058	.192	.219	-.335	-.284
D4	.445	.089	.339	.524	-.074	.316	.126	-.265
D5	.123	-.034	.002	.176	-.237	-.123	-.464	.116
D6	-.017	.193	-.114	.183	-.123	.103	-.238	-.007
D7	.041	-.016	.710	-.057	-.144	.148	.398	.094
D8	.149	.593	.113	.243	.178	.207	.177	.038
H1	.798	.253	.252	.288	.315	.281	.144	.279
H2	-.678	-.365	-.478	-.477	.010	-.548	-.075	-.193
H3	.703	.570	.435	.531	.156	.439	.144	.110
H4	.504	.734	.200	.217	.173	.216	.086	.073
H5	-.191	-.390	-.551	-.485	.072	-.152	-.409	.130
H6	-.714	-.419	-.389	-.730	-.179	-.228	.005	.023
H7	.618	.314	.328	.373	.286	.459	.136	.020
H8	-.603	-.111	-.277	-.247	-.288	-.153	.008	-.635

For N = 23, $r \geq \pm .600$ is significant at the 1% confidence level.

Table 9.29

Salient Variable Similarity Indices for Oblique Factors of Three Studies:

	F1	F2	F3	F4	F5	F6	F7	F8
D1	.069	.000	.250	-.222	.267	.000	.154	.429
D2	.194	.476	.200	.182	-.105	.273	.235	-.111
D3	.071	.111	.000	-.105	.125	.105	-.286	.000
D4	.370	.235	.375	.667	.133	.111	.154	-.267
D5	-.069	.105	.000	.100	-.235	.100	-.133	.125
D6	.074	.000	-.125	.222	.000	.111	.000	.000
D7	.074	.235	.500	-.111	.267	.111	.154	.143
D8	.222	.211	.125	.333	.133	.111	-.154	-.143
H1	.811	.296	.462	.429	.160	.214	-.087	.167
H2	-.769	-.483	-.571	-.533	-.222	-.400	.000	.154
H3	.750	.533	.483	.645	.286	.323	.000	.190
H4	.529	.500	.261	.480	.273	.160	.000	.095
H5	-.364	-.522	-.636	-.583	-.077	-.250	-.105	.100
H6	-.750	-.467	-.483	-.581	-.286	-.387	.077	.074
H7	.541	.519	.462	.429	.320	-.111	.087	.000
H8	-.600	-.300	-.421	-.571	-.333	-.095	.000	-.353

For N = 23, $r \geqslant \pm .500$ is significant at the 1% confidence level.

Because of the differences between the results of the three methods of factor matching tabulated above, it was decided to examine only those factors which showed significant similarity on more than one method. The following combinations present themselves:

F1 - H1

F1 - H3

F2 - H4

F4 - H6

F2 - D2

F3 - D7

F4 - D4

F8 - D1

In examining each of these combinations in turn, it was decided that items with loadings of greater than .30 in absolute value on one factor and non-zero (greater than ± .10) loadings on the other be admitted as items common to the two factors being compared.

The first group, F1 - H1, thus has the following items in common: S7, P14, P16, P18, N20, N21, N22, N23 and N24, with all but N21 and N22 having significant loadings on both factors. This seems to be a relatively stable item cluster, emerging in various analyses in this study. To determine whether the same group may be present in the third study, the Dodder factor with the highest similarity to this first factor (D4) was examined. However, only three items are common to these two factors: P14, P18 and N23, and these at a low level of loading for factor D4.

Factor H3 has the same items in common with F1 as has H1, but has in addition a number of social isolation items loading significantly which do not have significant loadings on F1, suggesting that H1 is the best match for F1.

Examination of factors F2 and H4 reveal a group with the following common items: S4, S6 and S8. These correspond to the first three items of the second factor of the oblique solution discussed earlier. Including factor D2 in the comparison we see that items S6 and S8 (as well as S5) load highly on this factor, with S4 having a zero loading. Again, the presence of a relatively stable item cluster is indicated.

The following comparison is between factors F4 and H6. Five common items are identified: S1, P10, P14, N22 and N23. This does not correspond to any previously discovered grouping, and the inclusion of factor D4 in the comparison yields only three items common to all three factors: P10, P14 and N23.

The fourth group, F3 - D7, has items S2, S9 and P13 in common. Items S1, S2, S9 and P13 are common to F3 and H2, suggesting a cluster centering around items S2 and S9, with the possible inclusion of S1 and P13. The final group, F8 - D1, although significantly similar in terms of two of the factor matching procedures, have no salient variables in common.

The results of the factor comparisons between these three studies lead to the conclusion that not only do the dimensions delineated in the present study not correspond to those proposed by Dean, but also the reliability across samples (cross-cultural stability, transferability) of these alternative dimensions is in most cases questionable. However, what has emerged is a small number of alternative groupings with some similarity across studies which warrant further attention.

9.3.3 Cluster Analysis

Although cluster analysis should logically precede factor analysis, as both methods are being used for the same purpose and cluster analysis is seen as complementary to factor analysis, it is examined here. The factor analyses discussed above have confirmed that there is a large amount of dimensionality among the alienation scale items that cannot be accounted for in terms of the components originally proposed for the scale. In this way the scale has been shown to lack construct validity: the scale does not seem to measure what it purports to. The logical next question is, "What is the scale measuring?" Following the factor analyses tentative proposals have been made regarding alternative conceptualisations of item groupings. These will be examined further here.

Cluster analysis, although essentially an exploratory approach, is used here as an adjunct to the factor analyses. The results of the cluster analysis will be used to confirm or disprove the presence of groupings identified through factor analysis, as well as to aid interpretation of the alternative dimensions. Factor analysis can be confusing in that a variable may load significantly on more than one factor. In addition, the level of significance chosen in factor analysis, as well as decisions made regarding factor extraction and rotation, can lead to different conclusions concerning the data. Cluster analysis, being a statistically less complicated method, and thus involving fewer assumptions and decisions by the investigator, is used as a complementary technique to factor analysis.

Two methods of cluster analysis are employed here, namely ramifying linkage cluster analysis and correlation profile cluster analysis. Both methods will be applied to the matrix of correlations reproduced in Table 9.19, as the coefficients produced by this method sufficiently resemble those produced by ordinal measures of association to justify their use.

9.3.3.1 Ramifying Linkage Cluster Analysis

Cattell (1952a) recommends adopting a minimum correlation that permits about half of the variables in the matrix to be in one or other cluster. Any correlations above this minimum are called linkages. However, for the present study, a minimum correlation of .30 which would achieve this, results in only one cluster of more than two variables. Thus, this minimum correlation for admission to a cluster is set at .20 to allow greater cluster size. Using this cut-off point, the linkages between items are listed in Table 9.30.

Table 9.30

Linkages ($r \geq .20$) for Alienation Scale Items:

Item	Linkages
S1	S2, S9, P11, N22, N23
S2	S1, S9
S3	S8
S4	S6, S8
S5	
S6	S4, S8, P18
S7	P14, P16, P18, N20, N23
S8	S3, S4, S6, P11
S9	S1, S2, P18, N22
P10	

Item	Linkages
P11	S1, S8
P12	P14, N20, N23
P13	
P14	S7, P12, P16, P18, N20, N21, N22, N23
P15	
P16	S7, P14, P18, N20, N21, N23, N24
P17	
P18	S6, S7, S9, P14, P16, N20, N23
N20	S7, P12, P14, P16, P18, N21, N23
N21	P14, P16, N20, N23, N24
N22	S1, S9, P14, N23
N23	S1, S7, P12, P14, P16, P18, N20, N21, N22, N24
N24	P16, N21, N23

Using Table 9.30 one proceeds to select clusters in terms of common linkages. To demonstrate the procedure we will begin with item S7, for which the following linkages are found: P14, P16, P18, N20, N23. We then move to the second item in this cluster (P14) and find linkages with the remaining items in this cluster, so it is included. The same applies to the remaining items in the cluster, and we thus emerge with the first cluster consisting of items S7, P14, P16, P18, N20 and N23. Three other possible clusters are identified using this method:

cluster 2: S1, S2, S9

cluster 3: S4, S6, S8

cluster 4: P12, P14, N20, N23

It can be seen that, with the exception of the fourth cluster, all the clusters correspond in large part to previously identified factor groupings. With regard to the first factor in Table 9.23, it is suggested that items N21, N22 and N24 be possibly excluded from this factor. This is also true for items S3 and S5 in factor 2 (Table 9.24).

9.3.3.2 Correlation Profile Cluster Analysis

The end-point of this method as has been discussed earlier is the production of a graph of the correlation profiles of the items in a cluster, with the scale items forming the abscissa and the correlation magnitude the ordinate. Those items whose correlation profiles (patterns of correlations) are most similar are considered to belong to a cluster. Before proceeding with this method, it would be interesting to plot graphs for the subscales as originally delineated to confirm visually what has previously been noted.

Figure 9.6

CORRELATION PROFILES OF SOCIAL ISOLATION ITEMS

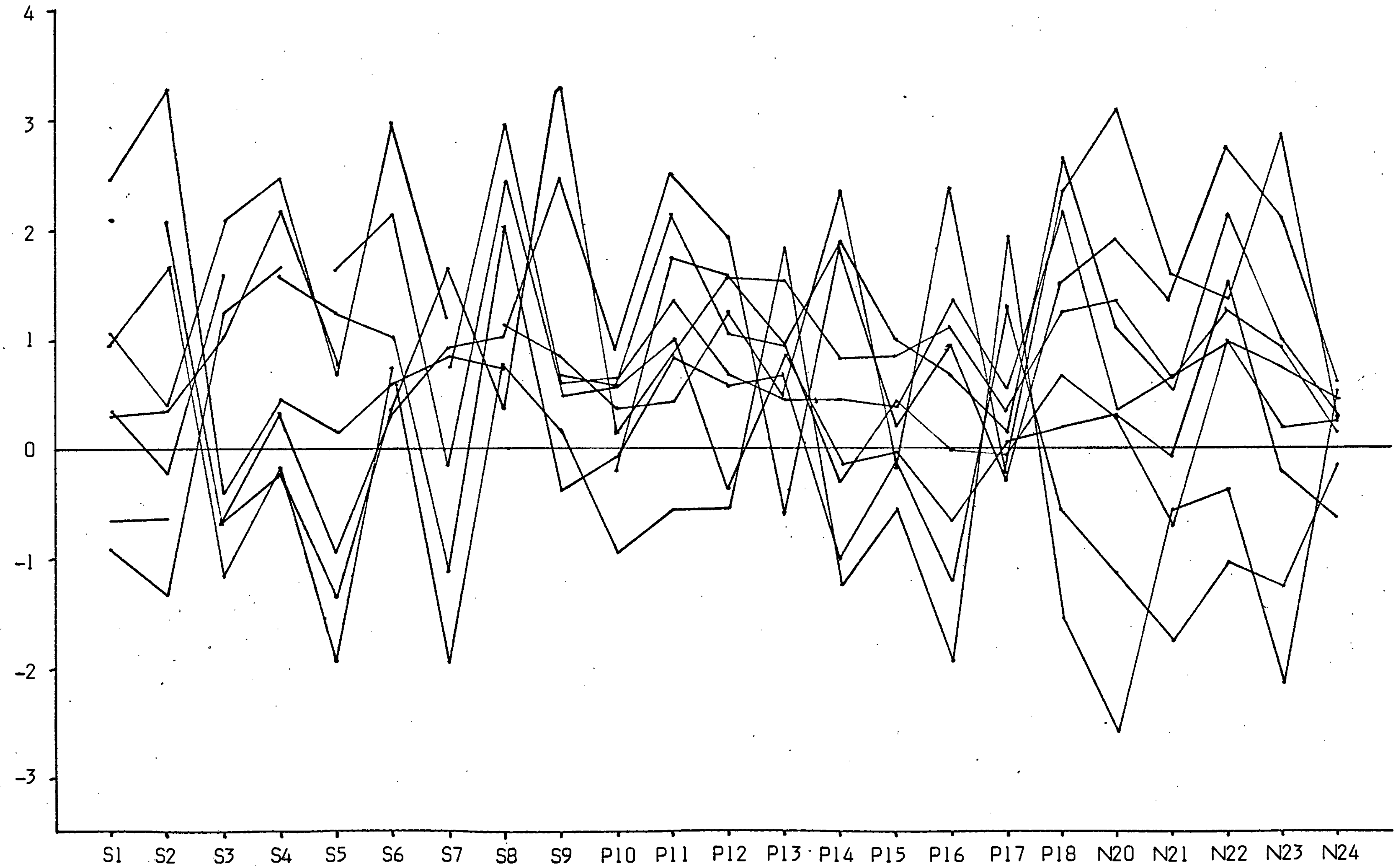


Figure 9.7

CORRELATION PROFILES OF POWERLESSNESS ITEMS

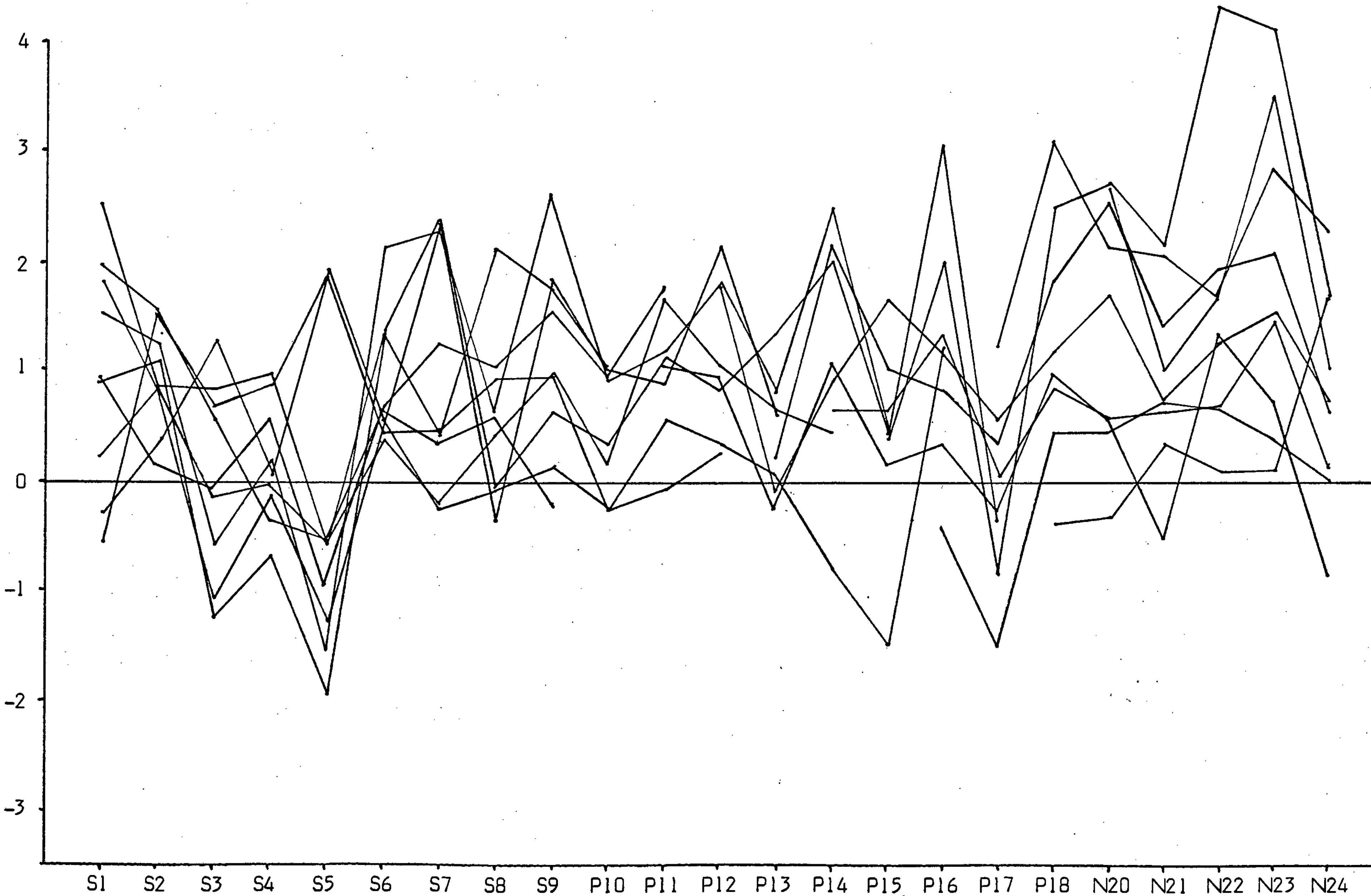
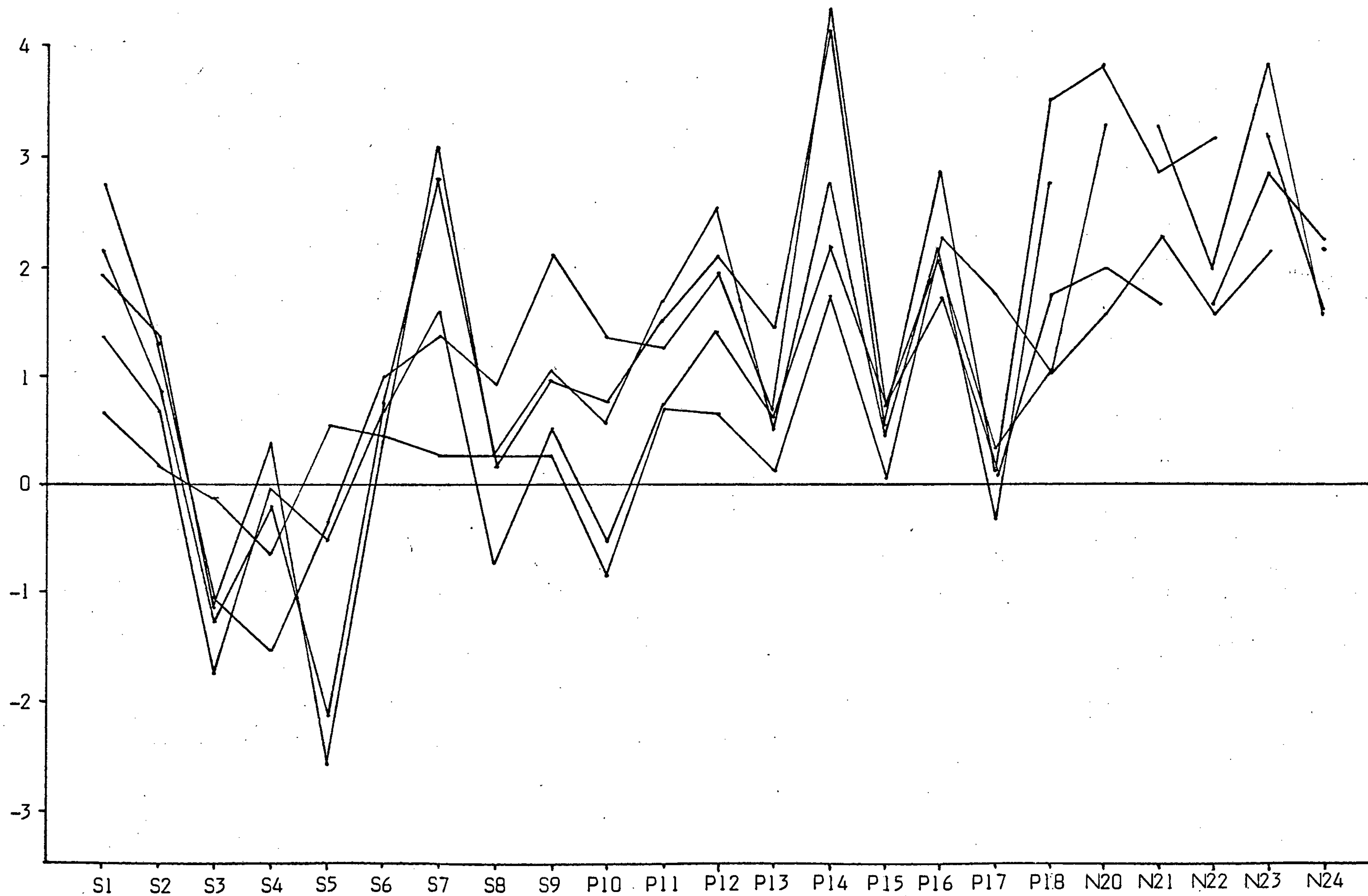


Figure 9.8

CORRELATION PROFILES OF NORMLESSNESS ITEMS



An inspection of Figures 9.6 to 9.8 confirm the results of earlier analysis. The correlation profiles for the social isolation and powerlessness subscales have no discernible pattern whatsoever. The normlessness items reveal a certain similarity of pattern, though with considerable variation between items. If the items were measuring the same construct one would expect a definite pattern in the correlation profiles for the items of each subscale. We have seen that the scale items do not conform to the hypothesised pattern. We will now see whether there is an alternative pattern that fits the data. The ensuing method of cluster analysis aims to unscramble this confusion of item profiles, and group those items with similar profiles into clusters.

Although both methods have similar starting points, unlike the ramifying linkage method, in which all items above a certain predetermined magnitude of correlation are eligible for entry into a cluster, in the method of correlation profiles (discussed in Section 6.5.2) the magnitude of the correlation determines the order of items considered for a cluster. Table 9.30 is thus altered to indicate such magnitude, and the new form can be found in Table 9.31.

Table 9.31

DISTRIBUTION OF CORRELATIONS FOR EACH ITEM:

	.200 - .249	.250 - .299	.300 - .349	.350 - .399	.400 - .449
S1	S2, S9, N23	P11, N22			
S2	S1		S9		
S3	S8				
S4	S6, S8				
S5					
S6	S4, P18	S8			
S7	P14, P16, P18	N23	N20		
S8	S3, S4, P11	S6			
S9	S1, N22	P18	S2		
P10					
P11	S8	S1			
P12	P14, N23	N20			

Table 9.31 (Contd.)

	.200 - .249	.250 - .299	.300 - .349	.350 - .399	.400 - 449
P13					
P14	S7, P12, P16, N21	P18, N20			N22, N23
P15					
P16	S7,P14,N20,N21,N24	N23	P18		
P17					
P18	S6, S7	S9, P14, N20	P16	N23	
N20	P16	P12, P14, P18	S7, N21	N23	
N21	P14, P16, N24	N23	N20		
N22	S9	S1	N23		P14
N23	S1, P12	S7, P16, N21	N22	P18, N20	P14
N24	P16, N21, N23				

Following the procedure discussed in Section 6.5.2 and further illustrated in Appendix C, three major clusters were identified, in terms of coefficients of belongingness. Item P10 was excluded from the analysis at the outset for failing to meet the criterion of having any items with correlations significantly different from zero (higher than $\pm$ .15). The signs for items S3 and S5 were reflected for the analysis.

The first cluster identified comprises items P14, N23, N20, P18, P16, S7, N21, P12 and N24, in order of acceptance into the cluster. This 9-item cluster has a mean inter-item correlation of .220 and an alpha reliability coefficient of .72. The second cluster is composed of items S6, S8, S4 and S3, with an average correlation of .203 and alpha of .50. Items in the third cluster are S2, S9, S1, P11 and N22, with a mean correlation of .203 and alpha of .56. Item N22 was first considered for membership in the second cluster but was found to result in a coefficient of belongingness too low for admittance. Items S5, P13, P15 and P17 were considered for membership in each cluster in turn, but failed to meet the criterion for membership. These items also did not form any worthwhile clusters themselves. Before the three clusters identified using the coefficient of belongingness are examined in detail, the correlation profiles for the items of each cluster will be illustrated graphically (see Figures 9.9 to 9.11) to determine whether certain items of these clusters should be discarded because of correlation profiles that are not congruent with the profiles of the remaining cluster items.

Figure 9.9

CORRELATION PROFILES OF ITEMS P14, N23, N20, P18, P16, S7 (N21, P12, N24)

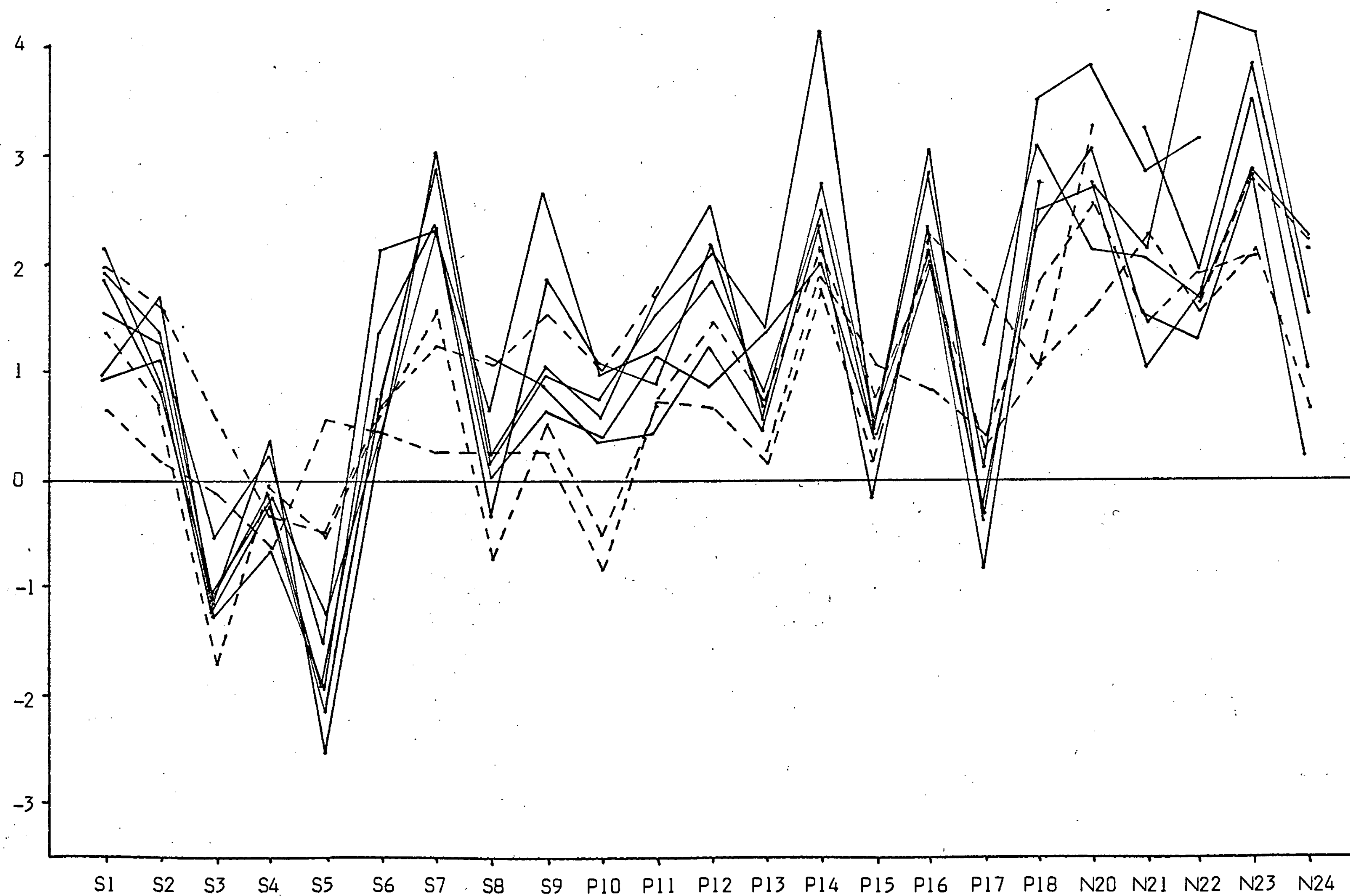


Figure 9.10

CORRELATION PROFILES OF ITEMS S6, S8, S4, S3

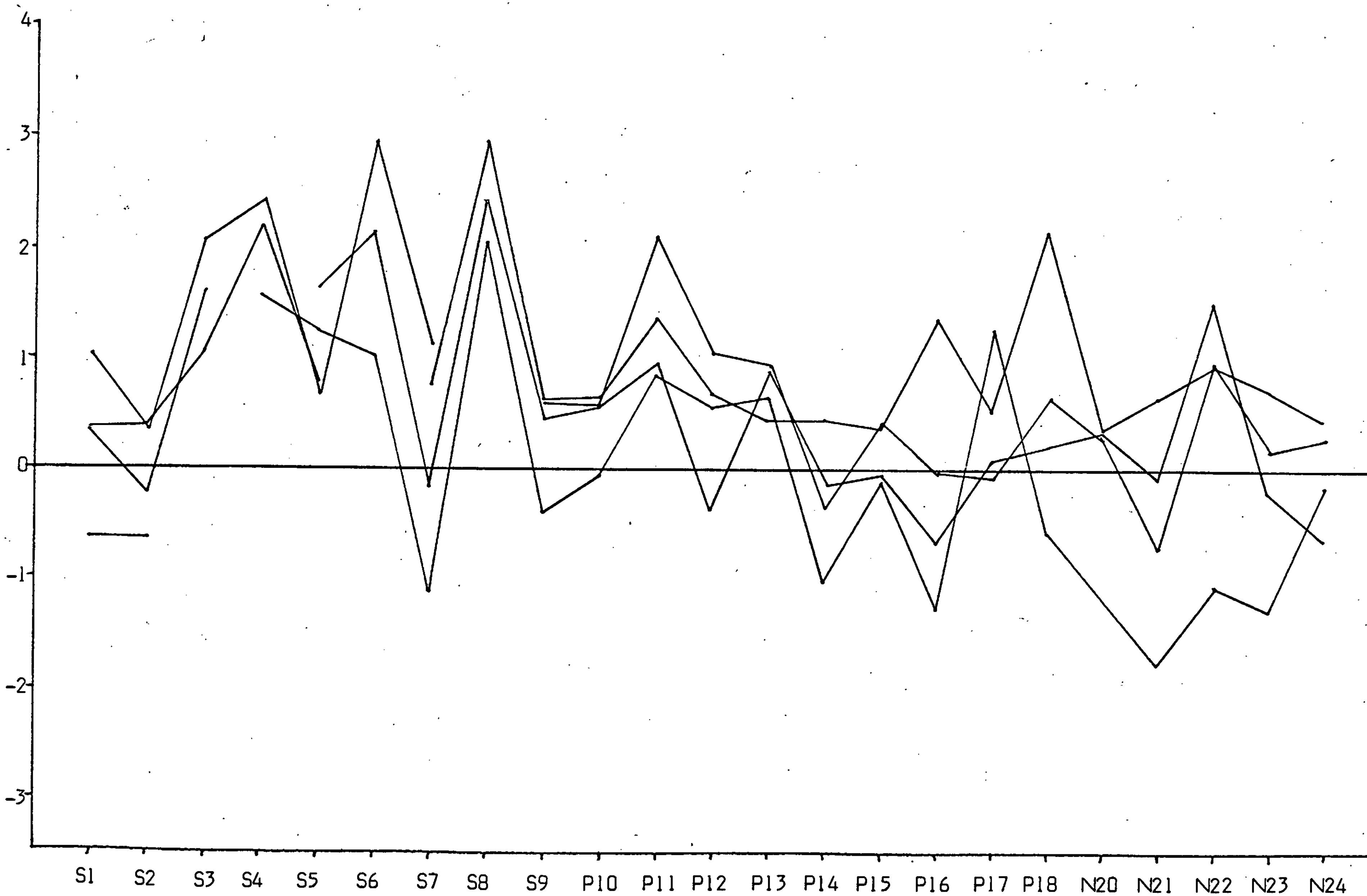
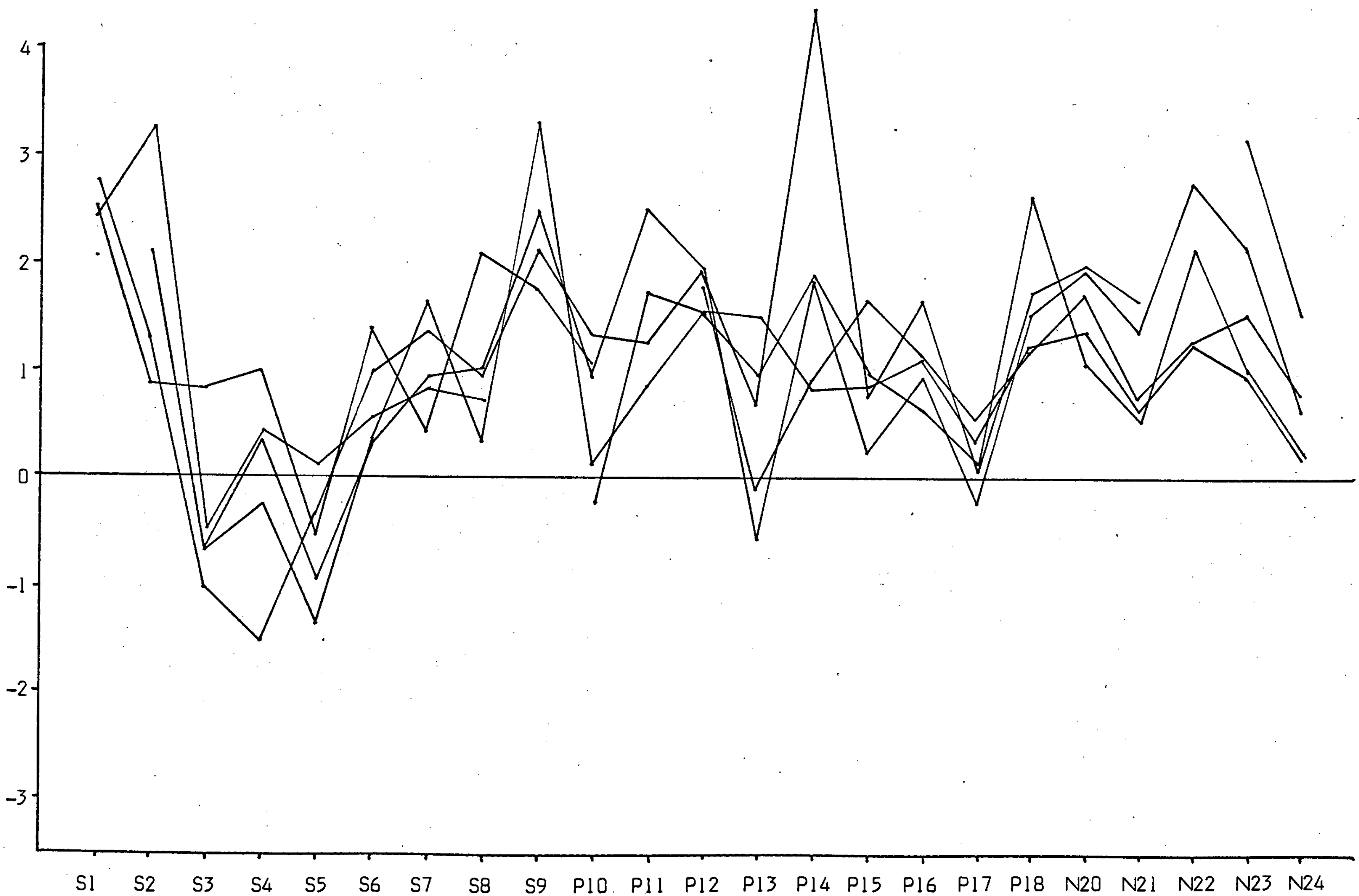


Figure 9.11

CORRELATION PROFILES OF ITEMS S2, S9, S1, P11, N22



Inspection of the correlation profiles of the first cluster (Figure 9.9) suggests that items N21, P12 and N24 (broken lines) be dropped from the cluster on grounds of profiles inconsistent with the remaining items. Whether the 6-item (with average inter-item correlations of .281 and alpha of .701) or 9-item cluster is accepted, the reliabilities are only slightly higher than those reported for Dean's subdivisions of the alienation scale (Table 9.16), and far lower than those theoretically attainable using the Likert method of scale construction. The same applies for the second and third clusters. Although the correlation profiles for the clusters identified here yield greater pattern similarity than those for the original components (Figures 9.6 to 9.8), there remains a notable degree of variation between item profiles within each cluster.

9.3.4 Interpretation of Identified Groupings

We have now come to the end of a number of analyses that have yielded similar results. In whatever way the data are manipulated, one is still left with a large amount of unaccountable variation between scale items. Dean's subdivision of the Social Alienation Scale into three components is found to be invalid in terms of the analyses discussed in this chapter. What remains is a number of alternative item groupings that have a certain amount of stability but dubious internal consistency reliability. Dean's original components were based on theoretical proposals regarding the concept under consideration, and appeared to be conceptually coherent. One now has to determine whether any theoretical sense can be made of the alternative groupings proposed.

The core items of the first group as identified by both factor and cluster analysis are as follows:

P14: There are so many decisions that have to be made today that sometimes I could just "blow up".

N23: The only thing one can be sure of today is that one can be sure of nothing.

N20: People's ideas change so much that I wonder if we'll ever have anything to depend on.

P18: The future looks depressing.

P16: We're so ruled today that there's not much room for choice, even in personal matters.

S7: There are few dependable ties between people today.

Some of these items seem to correspond to the notion of alienation as meaninglessness as described by Seeman (1959), rather than powerlessness or normlessness. Dodder's notion of a "futility" dimension also seems appropriate. "Future uncertainty" could also be accounted for by item P18, and item S7 could refer either to social isolation or normlessness. The notion of alienation as purposelessness could also make sense. Almost all of the variants of the concept alienation could be represented by the items of this cluster, leading one to think in terms of a "general dimension" of alienation. This proposal will be returned to in the following chapter.

The items of the second cluster are as follows:

S6: The world in which we live is basically a friendly place.

S8: People are just naturally friendly and helpful.

S4: Real friends are as easy to find as ever.

S3: Most people today seldom feel lonely.

All these items are negatively scored, with strong agreement indicating low alienation. These items conform to Dean's notion of social isolation (but not to Seeman's isolation variant), and are also well-described by Dodder's notion of a "friendliness" dimension.

This second grouping could, however, also have emerged as a result of a general response set of acquiescence, as all the items are negatively scored. These being practically the only negative items in Dean's scale (items S5 and P17 having been shown to be inconsistent and unreliable), one is unable to confirm the proposition regarding response set in this study. The inclusion of further items with reversed scoring would have served as a counterbalance to the possibility of such bias.

The third group as identified in the various analyses comprises the following items:

S2: I don't get invited out by friends as often as I'd really like.

S9: I don't get to visit friends as often as I'd really like.

S1: Sometimes I feel all alone in the world.

The items are all from the same subscale and seem to measure social isolation as loneliness. Adding items P11 and N22 to this group only confuses the issue. It thus seems clear that the social isolation subscale consists of two separate dimensions: an individual's experience of his own social isolation (loneliness) and his experience of the social isolation of others (friendliness).

Although the normlessness items behave more consistently than the other subscale items in terms of total scale and subscale scores and internal consistency, they do not form a single distinct cluster on further analysis. Accepting a further dual-dimensionality, the social isolation items (with the exception of S5 and S7) appear to be most valid in terms of subscale definition. The remaining groupings identified bear little resemblance to the dimensions expected in terms of construct definition during scale construction. It can thuse be concluded that Dean's (1961) Social Alienation Scale lacks validity in terms of the constructs it purports to measure.

CHAPTER TEN

DISCUSSION

What conclusions can be drawn from the various analyses performed above? It is felt that discussion should be centered around the two major stated aims of this study, namely an examination of various methods of construct validity as applied to attitude scales, and an evaluation of the construct validity of a particular attitude measure, Dean's (1961) Social Alienation Scale. These will be discussed in reverse order.

10.1 Conclusions Regarding Dean's Social Alienation Scale

Dean's scale has been shown to lack construct validity. The reliability of the scale is also questioned in terms of a lack of internal consistency, stability and transferability. Both the factor and cluster analyses lead to the conclusion that the scale does not measure a single general dimension. In addition, the subscales do not behave in the manner expected in terms of the author's definitions of the constructs and the methods employed for the construction of the scale. A number of alternative dimensions have been identified by Dodder (1969) and Hensley et al (1975), as well in the present study, but there is not enough similarity between these dimensions to claim cross-cultural stability for the scale.

The use of Dean's scale qua scale for the measurement of alienation is thus strongly discouraged. Some of the items (especially from the social isolation subscale) could well be used as core items for an alternative scale measuring well-defined aspects of alienation.

Part of the problem with the scale could lie in Dean's assumption that the general concept of alienation consists of only three components. Multivariate analysis has revealed the presence of more dimensions than originally conceptualised by Dean (1961). The classification of items into only three subscales is an artificial one, and more would have been gained by allowing for further variants of alienation such as meaninglessness and estrangement.

Another source of error might lie in Dean's misunderstanding of Seeman's (1959) conceptualisation of the alienation concept. Seeman argued that alienation has been used to mean at least five distinctly different things. Dean assumes that not only are these conceptualisations not mutually exclusive but that they can in fact be combined as subcomponents of a single general concept. No attempt to develop a valid measure of the general syndrome of alienation (viewed as a conglomerate of the various meanings identified by Seeman) has yet been successful, and Dean's scale is no exception. However, context-specific measures of well-defined alienation variants have proved more successful. This leads to two important conclusions.

10.1.1 Construct Definition

The first conclusion to be drawn from the failure of Dean's subscales to meet with criteria of construct validity lies in construct definition. The need for precise construct definition in the early stages of scale construction have already been emphasised. The meanings in operational terms of Dean's subscales are imprecise and unspecified. The present writer finds it very difficult to assign some of Dean's items to their "correct" subscale on the basis of Dean's reference to Seeman's classification of alienation meanings. It is thus felt that Dean's scale fails at the level of assigning items to subscales. It is suggested that some form of multivariate analysis in the scale construction process would have added to the effectiveness of the method of arbitrary assignment of items to subscales on the basis of judges' ratings.

10.1.2 Context-Specific Approach

The second conclusion that can be drawn from the failure of Dean's Social Alienation Scale when compared to other approaches to the measurement of the concept concerns the gneeral nature of Dean's scale. Attemtping to develop a comprehensive measure of general alienation for all contexts, the results of Dean's efforts are of little practical value. If the scale did prove to be reliable and valid, and we could show that one particular individual or group was more or less alienated than another, what would this mean? Alienated from what? Dean's scale fails in trying to be too general and comprehensive a measure of what is actually a number of related but independent concepts. The success of context-specific measures of alienation (see Burbach, 1972; Wegner, 1975) points to the position that alienation should not be conceived of as a general orientation to the social order, but rather as a set of context-specific attitudes. Alienation should not be equated with human unhappiness in general.

When viewed in terms of particular contexts, the various aspects of alienation can in fact be mutually exclusive. Seeman (1967), for example, has found that work alienation was unrelated to a person's general attitudes towards society. Similarly, social isolation is not always a basis for alienation. Wegner (1972) reports that college students with the least social activity were among the most committed to the institution. An individual's economic powerlessness and his powerlessness (or normlessness, for that matter) in the religious sphere might be totally unrelated. It seems clear that the determination of alienation should involve not a single measure of discontent, but rather an attempt to capture the dynamics of a particular situation and the relationships between social structure and processes and attitudes such as alienation.

This could well be the reason for the social isolation items failing in terms of consistency with total scale scores but proving reliable when considered as separate groups. The items of the subscale are measuring specific orientations of the individual in the context of his community or social network. It is the specificity of these items that makes them most useful. In contrast, the powerlessness items have no context-specificity. The subscale could be measuring economic powerlessness, political powerlessness or religious powerlessness, to name but a few possibilities. Similarly, the normlessness items involve alienation in terms of religious norms, cultural norms, etc.. In conclusion, it is recommended that when one sets out to develop a measure of alienation, one must first be able to answer the question: "Alienation from what?".

10.2 Conclusions Regarding Construct Validation Techniques

Because alienation as purportedly measured by Dean's scale is a concept lacking in operationally defined empirical referents, construct validity is a more appropriate measure of scale performance than the more traditional criterion approaches to validity. The methods of construct validation demonstrated in this study were chosen not only for their appropriateness to the scale under question, but also for their ease of calculation, whether by hand or using one of many pre-programmed statistical packages available at computer centres in this country (STATJOB, BMDP, SPSS, etc.).

The task of this study has not been to establish specific procedures for determining the superiority of one method of internal consistency or multivariate analysis over another. Rather, an eclectic approach has been adopted in that the use of more than one technique is felt to add to our understanding of the data under consideration. The various techniques are based on differing sets of assumptions, yet have the same basic aims, and can thus be regarded as complementary.

The methods of item analysis discussed here are found to be most useful in ranking items in terms of their consistency with total scale scores or subscale scores. However, these methods proceed from the assumption of a reasonable amount of homogeneity among scale items. The techniques cannot reveal if more than one construct is being measured by the items, or even whether these dimensions correspond to the postulated subscales. Thus the determination of internal consistency or lack thereof is never enough. Techniques of multivariate analysis are necessary to determine the underlying structure of the data.

Although the item rankings of the various internal consistency measures are remarkably similar, enough variation exists to warrant the use of more than one method. In scale construction, which is essentially exploratory in nature, one must guard against the rejection of an item that is actually consistent with the remaining items (alpha error). With significance levels that are quite arbitrary this is a distinct possibility. It is thus recommended that at least two item analysis techniques be used in conjunction when selecting items for inclusion in a scale, and that items be chosen on grounds of their consistency for each method used.

As has been noted, the analysis of internal consistency alone is insufficient evidence for construct validity. Multivariate analysis is necessary to determine whether all the items are measuring the same construct, or to determine what the alternative structures are. Factor analysis provides a good indication of the presence of alternative dimensions, but interpretation is made difficult by the large number of item-factor loadings. Cluster analysis is a useful adjunct to factor analysis, being used to provide a clearer picture as to the membership of groupings identified by factor analysis.

For our study the parametric and non-parametric measures of association, as well as the various scoring procedures, approximated each other closely enough to justify the use of interval level statistics. Together with previous research mentioned in Section 5.3.1, this supports the notion that interval-level statistical procedures can be used with a 5-point Likert scale scored using the simple assignment of numbers to response categories. The more powerful statistical procedures based on the product moment correlation, such as factor and cluster analysis, can thus be advocated for this type of scale without the risk of unacceptable error levels.

It is felt that the minimum information concerning construct validity should include at least one method of item analysis, reliability coefficients, factor analysis (the alpha method being the most appropriate for this type of study) and/or cluster analysis. These should be regarded as vital initial steps in the construction of valid attitude scales. This applies not only to the scale development process, but also to the use of attitude scales in populations other than that in which the scale was constructed and validated. One should exercise extreme caution in assuming that a scale developed in, say, the United States, and having "established" construct validity, is equally applicable to a South African sample. The transferability or cross-cultural validity of Likert-type attitude scales is questionable, and it is recommended that some indication of reliability and validity be obtained for every population in which a particular scale is applied.

A final recommendation concerning the methods used here, is that as far as possible in research of this type, the matrix of correlations between the items be published or, at least, be available to other researchers. The correlation matrix being the basic input for both factor and cluster analysis, this would not only facilitate further analysis of results by other researchers but would also make comparison between various research efforts a far less hazardous affair. In many cases the information published does not allow for further research on the construct validity of an attitude scale without having to resort to further data collection that is both costly and time-consuming.

10.3 Implications for Attitude Research in South Africa

The use of pre-built attitude scales in populations other than that on which they were validated is questioned in this thesis. However, this is not to say that such scales are useless, and all such research should be discontinued. The advantages of such scales for comparative research have already been discussed. What is advocated is that researchers take precautions to ensure that such pre-built attitude scales are reliable and valid measures of the constructs they desire to measure before the results of the instruments concerned are used to make generalisations to the population under consideration. The analysis of Dean's Social Alienation Scale has demonstrated the danger of believing that the popular use of an attitude scale is a guarantee of its validity.

For scales that have few objective criteria against which they can be evaluated, construct validity proves the most useful approach. The methods of analysis discussed in this thesis are most effective in determining the underlying structure of such scales, a vital aspect of internal reliability and validity approaches. These procedures provide the minimum information required concerning the utility of an attitude scale for each population under consideration. Having determined that a scale has reasonable construct validity, and is thus worth further investigation, one should move on to examine the external validity of the scale, using the more traditional criterion-related validity procedures.

The use of pre-built scales in South Africa should not be viewed as a short-cut to measuring a particular attitude structure for, in the long run, such an approach will prove wasteful in time, money and effort. Unfortunately, there are no short-cuts if one's aim is to develop and use accurate measuring instruments to further our understanding of the society in which we live.

The methods demonstrated in this thesis, although applied to a pre-built attitude scale, are equally applicable to self-constructed attitude scales. Those researchers who feel that scales be constructed for each population under consideration to avoid the problem of equivalence and transferability could do well to take note of the cautions voiced in this study. The question of validity will arise sooner or later, and it is better to ensure validity through strict scale construction procedures than be faced with an invalid measuring instrument after many years of use. Validation is a systematic procedure that forms an essential part of any research endeavour, and cannot be ignored or considered half-heartedly.

This thesis was undertaken in response to an observed lack in attitude research in South Africa of concern regarding the qualities of the measuring instruments used. An unreliable and invalid research tool will always give questionable results. It is hoped that the demonstration of the more simple and accessible construct validation procedures in this thesis will encourage social scientists in South Africa to strive for greater accuracy in the measurement of attitudes, whether developing their own scales or using those developed by others.

APPENDIX A

CALCULATION OF SIGMA WEIGHTS FOR ALIENATION SCALE ITEMS

The steps involved in the calculation of sigma or normal deviate weights for the response categories of an item (following Edwards, 1957 : 149-152) are demonstrated using the first item of Dean's scale. These are set out in Table A.1.

Table A.1

Sigma Weights for Response Categories Based on Proportion of Individuals (N = 404) Falling in Each Category:

	SD	D	U	A	SA
(1) p	.121	.384	.059	.361	.074
(2) cp	.121	.505	.564	.925	1.000
(3) midpoint cp	.061	.313	.535	.745	.962
(4) z	-1.546	-.487	.088	.659	1.787
(5) z + 1.546	0.000	1.059	1.634	2.205	3.333

The various steps in the above table are calculated as follows: The proportions (p) of individuals in each response category (SD etc.) for that item is obtained directly from the data. From these proportions the cumulative proportions (cp) are calculated as in row (2). The midpoint cp in row (3) is the proportions below a given category plus half the proportion within that category. From a table of areas under the normal curve (as in Mueller, Schuessler and Costner, 1977 : 503) the norma deviates corresponding to the proportions of row (3) are obtained. The normal deviates are shown in row (4). To make the weights all positive, one adds the absolute value of the largest negative value to all entries in the row, thus obtaining the values in row (5), which are used as such for weighting response categories, or rounded to the nearest integer for such weighting.

The sigma weights for the scale items are given in Table A.2 below.

Table A.2

Sigma Weights for Alienation Scale Items:

	Response Category				
Item	SD	D	U	A	SA
S1	0.000	1.059	1.634	2.205	3.333
S2	0.000	1.179	1.875	2.489	3.689
S3	0.000	1.181	1.849	2.543	3.677
S4	0.000	1.044	1.587	2.231	3.362
S5	0.000	1.282	2.041	2.453	3.360
S6	0.000	1.400	2.209	2.765	3.678
S7	0.000	1.251	1.829	2.773	4.269
S8	0.000	1.552	2.356	3.007	4.264
S9	0.000	1.372	2.355	2.590	3.821
P10	0.000	1.083	1.617	2.513	3.675
P11	0.000	1.109	1.653	2.361	3.608
P12	0.000	0.879	1.301	2.019	3.165
P13	0.000	0.750	1.370	2.195	3.280
P14	0.000	1.192	1.725	2.500	3.709
P15	0.000	1.094	1.843	2.596	3.628
P16	0.000	1.071	1.699	2.457	3.678
P17	0.000	2.011	2.147	2.559	3.152
P18	0.000	1.017	1.598	2.363	3.482
N20	0.000	1.170	1.786	2.695	3.963
N21	0.000	0.977	1.557	2.239	3.464
N22	0.000	1.080	1.776	2.634	3.862
N23	0.000	0.920	1.507	2.356	3.590
N24	0.000	0.980	1.566	2.171	3.278

APPENDIX B

CALCULATION OF SCALE VALUE DIFFERENCE RATIOS

The formula for the SVD ratio (Sletto, 1937) is as follows:

$$SVD = \frac{\bar{X}t_H - \bar{X}t_L}{\bar{X}i_H - \bar{X}i_L}$$

Where $\bar{X}t_H - \bar{X}t_L$ is the item scale value difference, calculated using total scale scores, and $\bar{X}i_H - \bar{X}i_L$ is the maximum potential difference value, calculated on the basis of item scores alone.

The calculation of the SVD ratio is demonstrated using the first item of the alienation scale used in this thesis, item S1. It was decided to include 10% of individuals in each of the high and low criterion groups, thus, with N = 404, the number in each group is 40. First the item scale value difference is calculated using the frequency (f) of each item response weighting (x) for the highest and lowest total scale scores. This is shown in Table B.1 below.

Table B.1

Mean Responses for High and Low Criterion Groups Selected in Terms of Total Scale Scores:

		Frequency (f)		Fx	
Response	Weighting (x)	High	Low	High	Low
SD	0	2	13	0	0
D	1	6	17	6	17
U	2	2	1	4	2
A	3	24	9	72	27
SA	4	6	0	24	0
		40	40	106	46

The means for the high and low groups are then calculated:

$$\bar{X}t_H = \frac{106}{40} = 2.65$$

$$\bar{X}t_L = \frac{46}{40} = 1.15$$

with the item scale value difference becoming 2.65 - 1.15 = 1.5.

The distribution of responses to each item alone is used to calculate the maximum potential difference value:

Table B.2

Distribution of Responses for Item S1 (N = 404):

Response	Frequency	Weight
SD	49	0
D	155	1
U	24	2
A	146	3
SA	30	4

The 40 individuals in the low group have a mean ($\bar{X}i_L$) of $\frac{0}{40}$ = 0 for this item. For the high group the mean is:

$\frac{30 \times 4 + 10 \times 3}{40} = \frac{150}{40} = 3.75.$ The maximum potential difference value becomes 3.75 - 0.0 = 3.75. The SVD ratio for item S1 is 1.5 divided 3.75 which equals .40.

APPENDIX C

CALCULATION OF COEFFICIENTS OF BELONGINGNESS

The coefficient of belongingness (B), developed by Holzinger (see Tryon, 1939), is based on the ratio of an item's mean intercorrelation with other items in a cluster over the mean intercorrelation of that item with the remaining items in the scale, and is a measure of each successive item's contribution to a cluster. However, calculation of B coefficients is not as simple as this, and Tryon has developed a table to make such calculation easier. Following Tryon's (1939) method, the procedure for calculating B coefficients is demonstrated in Table C.1, and below.

From the distribution of intercorrelations in Table 9.31, one selects the two items with the highest correlation (P14 and N23). These are written in column (1). In column (2) the sum of correlations ($\sum$ r) for each item with all other items in the scale is entered. The correlation (r) between these two items is entered in columns (3) and (4). Add the two bracketed values in column (2), from this total subtract twice the value in column (3), and enter the difference in column (5). Thus: (3.203 + 3.892) − 2(.412) = 6.271. In column (6) enter k, the number of variables in the cluster, which at this stage is two. Column (7) is the number of intercorrelations in the cluster and is calculated as shown. Column (8) is the number of correlations remaining between these two items and the rest of the scale items (remembering that item P10 was excluded because of a lack of significant loadings, thus n = 22). Columns (9) to (11) are calculated as shown, with the value in column (11) being the B coefficient of P14 and N23, namely 2.629.

Using Table 9.31 one then selects the next item having the highest correlations with both P14 and N23, namely N20. This new item is represented by i in the table below. In column (2) the sum of correlations for this new item are entered, and in column (3) the sum of r's between item i and the other members of the cluster, thus .275 + .381 = .656. Add the value in column (3) to that of the preceding row, column (4), and enter the total in column (4) (.656 + .412 = 1.068). From the value in column (2) subtract twice the value in column (3), and add this difference to the value in the preceding row, column (5), entering the result in column (5) (3.524 - 2(.656) + 6.271 = 8.483). The remaining columns are completed as indicated, with the B coefficient entered in column (11). Although this value represents a drop over the previous value, this item is accepted as a member of this cluster.

One then continues to add items to the cluster until the drop in the value of the B coefficient is large enough to warrant discarding an item. Having obtained the members of the first cluster, one proceeds to repeat this procedure with the two items having the next highest correlation, and so on, until all items have been tried in at least one cluster. On the basis of the clusters so identified one plots the correlation profiles to determine whether these cluster groupings are justified.

Table C.1

CALCULATION OF B COEFFICIENTS

Preceding Group + i	i with n variables	i with Group	(3) + preceding (4) = between variables in Group	(2) - 2 x (3) + preceding (5) = between variables not in Group	K = number of variables in Group	K (K-1) / 2 = number of inter-r's	K (n-k) = number of remaining r's	(4)/(7) = mean inter-r	(5)/(8) = mean remaining r	(9) / (10) = B
B (P14,N23)	3.203) 3.892)	.412	.412	6.271	2	1	40	.412	.157	2.629
B(P14,N23,N20)	3.524	.656	1.068	8.483	3	3	57	.356	.149	2.389
B(P14,N23,N20, P18)	3.192	.879	1.947	9.917	4	6	72	.325	.138	2.355
Etc..										

APPENDIX D

DEAN'S (1961) SOCIAL ALIENATION SCALE

(The numbers preceding each item correspond to the numbering used in the studies by Dodder and Hensley et al, as well as in the present studies. The original order of Dean's is identified by the numbers in brackets following each item).

Social Isolation

1. Sometimes I feel all alone in the world (1).

2. I don't get invited out by friends as often as I'd really like (3).

3. Most people today seldom feel lonely (5).

4. Real friends are as easy to find as ever (8).

5. One can always find friends if he shows himself friendly (11).

6. The world in which we live is basically a friendly place (14).

7. There are few dependable ties between people any more (17).

8. People are just naturally friendly and helpful (22).

9. I don't get to visit friends as often as I'd really like (24).

Powerlessness

10. I worry about the future facing today's children (2).

11. Sometimes I have the feeling that other people are using me (6).

12. It is frightening to be responsible for the development of a little child (9).

13. There is little or nothing I can do towards preventing a major "shooting" war (13).

14. There are so many decisions that have to be made today that sometimes I could just "blow up" (15).

15. There is little chance for promotion on the job unless a man gets a break (18).

16. We're so regimented today that there's not much room for choice even in personal matters (20).

17. We are just so many cogs in the machinery of life (17).

18. The future looks very dismal (23).

Normlessness

19. The end often justifies the means (4).

20. People's ideas change so much that I wonder if we'll ever have anything to depend on (7).

21. Everything is relative, and there just aren't any definite rules to live by (10).

22. I often wonder what the meaning of life really is (12).

23. The only thing one can be sure of today is that he can be sure of nothing (16).

24. With so many religions abroad, one doesn't really know which to believe (19).

APPENDIX E

FACTOR MATRICES FOR DEAN'S SOCIAL ALIENATION SCALE ITEMS: DODDER (1959 : 254)

Table E.1

VARIMAX ROTATION

FACTORS

ITEMS	1	2	3	4	5	6	7	8
S1	.03	-.01	.60	.13	.05	.15	.11	.03
S2	.15	.14	.21	.07	-.10	.10	-.62	.12
S3	-.16	.29	.45	-.15	-.18	-.28	-.29	.17
S4	.03	.17	.04	.17	.02	.04	.01	.75
S5	.05	.52	-.08	.17	.07	.01	.12	.20
S6	.06	.64	.09	-.03	.01	.01	-.01	.08
S7	.27	.28	.19	.12	.03	.33	.12	.20
S8	-.04	.38	.05	-.06	.06	.14	.02	.44
S9	-.03	-.10	-.15	.33	-.22	.08	.28	-.05
P10	.07	.07	.14	.47	.03	.15	-.01	.14
P11	.12	.09	.35	.01	.09	.00	.16	.40
P12	.41	.08	.05	.44	.08	-.01	.17	-.01
P13	.08	-.05	-.02	-.01	-.55	.12	.06	-.07
P14	.38	-.04	.39	.39	-.01	.16	.13	.13
P15	.50	.15	-.03	.16	-.14	.27	.04	-.06
P16	.73	.11	.13	.16	-.05	.17	-.04	-.02
P17	.39	-.09	.05	.03	-.14	.47	.08	.12
P18	.36	.24	.15	.29	-.14	.31	.23	-.01
N19	.07	-.03	.04	.06	-.23	.45	.04	.01
N20	.23	.21	.05	.13	.04	.46	.24	.12
N21	.38	.03	-.02	.11	.04	.18	.18	.09
N22	.24	.00	.08	.11	.13	.28	.17	-.05
N23	.45	.20	.04	.40	-.09	.43	-.03	.08
N24	.63	-.07	-.02	-.09	-.03	.03	.07	.05

(N = 201)

Table E.2

OBLIMAX ROTATION

FACTORS

ITEMS	1	2	3	4	5	6	7	8
S1	-.18	.05	.49	.05	-.02	-.11	.00	-.01
S2	.05	.14	.03	.00	.04	-.02	.50	.07
S3	-.01	.23	.43	-.02	-.39	-.10	-.03	.05
S4	-.02	.00	-.01	.03	.00	.09	-.04	.67
S5	-.04	.44	-.26	.17	.10	.30	.03	.05
S6	.04	.57	-.04	.04	.01	.18	-.02	-.11
S7	.02	.24	.09	.03	.12	.01	-.04	.10
S8	.02	.29	.02	-.09	.14	.05	-.05	.29
S9	-.19	-.06	-.25	.29	-.07	-.05	.29	.02
P10	-.25	.05	-.01	.41	.00	.11	-.12	.12
P11	.08	.01	.27	-.07	.00	.04	.06	.32
P12	.06	.03	-.16	.33	-.03	.30	.01	-.01
P13	.05	-.04	.01	-.02	-.37	-.43	.32	-.01
P14	-.02	-.08	.23	.26	-.11	.01	-.01	.13
P15	.20	.10	-.10	.06	-.06	-.04	-.01	-.07
P16	.39	.01	.05	.00	-.14	.04	-.12	-.03
P17	.14	-.12	.12	-.12	-.02	-.30	-.13	.16
P18	.00	.23	-.03	.20	-.02	-.03	.12	-.06
N19	-.12	.02	.08	.01	.03	-.35	.04	.03
N20	-.04	.21	-.04	.04	.25	-.04	.03	.06
N21	.18	-.02	-.08	-.02	.08	.06	.03	.09
N22	.02	.02	.02	.03	.20	.03	-.05	-.05
N23	-.01	.15	-.08	.26	.01	-.01	-.16	.05
N24	.53	-.18	.00	-.03	-.10	.00	.02	.09

(N = 201)

APPENDIX F

FACTOR MATRICES FOR DEAN'S SOCIAL ALIENATION SCALE ITEMS: HENSLEY ET AL (1975 : 559)

Table F.1

VARIMAX ROTATION

FACTORS

ITEMS	1	2	3	4	5	6	7	8
S 1	.10	-.42	.18	-.05	-.19	.18	-.20	-.07
S 2	.07	-.03	-.16	-.02	-.05	.41	-.25	.04
S 3	-.19	-.33	-.05	-.08	.04	.11	-.15	.01
S 4	.03	-.15	.40	-.11	.01	.04	.04	.09
S 5	-.02	.05	.38	-.09	-.02	-.00	-.09	-.15
S 6	.13	-.13	.16	-.65	-.01	-.02	-.03	-.03
S 7	.41	-.12	.27	-.24	-.31	.09	-.24	-.01
S 8	.18	-.08	.14	-.68	-.03	.08	.09	.07
S 9	-.00	-.07	.15	-.01	.14	.44	.08	-.16
P 10	.03	-.22	-.03	-.14	.05	.37	-.00	-.03
P 11	.08	-.06	.19	.05	.02	.30	-.14	.09
P 12	.07	-.10	.04	.04	.09	.06	-.47	-.08
P 13	.16	.03	.11	.09	.22	.12	-.20	-.03
P 14	.37	-.46	.12	.06	.16	.14	-.01	.07
P 15	.54	-.04	.12	-.09	.10	.09	-.07	.00
P 16	.70	-.09	-.02	.03	-.07	.05	.01	-.15
P 17	.56	-.03	-.04	-.13	.00	-.00	-.14	.01
P 18	.50	.02	-.01	-.35	.06	.22	-.09	-.07
N 19	-.01	.04	.00	.04	-.31	-.06	.03	-.03
N 20	.34	-.11	.34	-.14	.40	.10	.14	.00
N 21	.17	-.12	.05	.03	-.03	.08	-.13	-.48
N 22	.20	-.64	.08	-.14	.03	.06	.02	-.17
N 23	.46	-.27	.19	-.18	-.05	-.05	-.27	-.08
N 24	.45	-.04	-.04	-.03	-.06	-.08	.10	-.34

(N = 240)

Table F2

OBLIMAX ROTATION

FACTORS

ITEMS	1	2	3	4	5	6	7	8
S 1	.19	-.38	.52	.14	.00	-.58	.37	-.12
S 2	.12	-.56	.09	.02	-.11	-.12	.20	.03
S 3	-.16	-.27	.05	.07	-.04	-.38	.21	.05
S 4	.04	-.07	.55	.20	-.23	-.22	.05	.02
S 5	.01	.02	.44	.15	-.14	-.01	.13	-.20
S 6	.27	-.11	.41	.79	-.01	-.28	.19	-.06
S 7	.55	-.25	.70	.41	.11	-.32	.43	-.13
S 8	.30	-.19	.43	.81	-.05	-.23	.04	.01
S 9	.01	-.47	.34	.04	-.43	-.18	-.13	-.23
P 10	.08	-.52	.23	.18	-.23	-.34	.00	-.06
P 11	.09	-.39	.42	-.01	-.30	-.15	.13	.03
P 12	.14	-.23	.20	-.02	-.14	-.19	.51	-.07
P 13	.18	-.18	.23	-.05	-.37	-.04	.17	-.07
P 14	.42	-.33	-48	.08	-.36	-.64	.15	.02
P 15	.63	-.19	.45	.24	-.28	-.21	.14	-.09
P 16	.82	-.14	.35	.13	-.05	-.28	.10	-.25
P 17	.67	-.13	.27	.27	-.05	-.18	.25	-.04
P 18	.64	-.36	.38	.50	-.21	-.18	.15	-.15
N 19	-.01	.09	-.01	-.04	.34	.06	.01	-.04
N 20	.42	-.13	.68	.29	.14	-.26	.02	-.14
N 21	.26	-.14	.22	.03	-.04	-.25	.18	-.51
N 22	.31	-.29	.43	.27	-.12	-.84	.19	-.19
N 23	.61	-.61	.58	.35	-.06	-.48	.49	-.15
N 24	.55	.07	.13	.13	.07	-.16	-.02	-.40

(N = 240)

APPENDIX G

DISTRIBUTION OF ITEM RESPONSES: N = 404

Item	SD	D	U	A	SA
S1	49	155	24	146	30
S2	40	176	42	129	17
S3	20	136	57	156	35
S4	29	124	30	173	48
S5	52	223	14	88	27
S6	22	198	54	98	32
S7	6	80	42	248	28
S8	13	198	50	129	14
S9	17	171	13	173	30
P10	3	33	32	103	143
P11	21	121	28	195	39
P12	23	76	21	199	85
P13	31	61	93	166	53
P14	9	92	29	211	63
P15	21	118	94	134	37
P16	22	114	59	177	32
P17	110	217	35	26	16
P18	15	83	54	185	67
N20	6	68	55	222	53
N21	39	126	39	171	29
N22	11	85	80	189	39
N23	18	75	61	204	46
N24	64	141	43	131	25

APPENDIX H

FACTOR VARIANCES AND EIGENVALUES

The factor variances as percentages of the total factor variance and total variance respectively for the unrotated eight-factor solution can be found in the table below, along with the eigenvalues for each factor.

Table H.1

Proportion of Variance by Factor and Eigenvalues for Unrotated Matrix:

Factor	Percent of Total Factor Variance	Percent of Total Variance	Eigenvalue
1.	24.0%	7.8%	8.61
2.	15.7%	5.1%	3.98
3.	13.9%	4.5%	2.68
4.	12.6%	4.1%	2.05
5.	9.5%	3.1%	1.72
6.	8.7%	2.8%	1.53
7.	8.6%	2.8%	1.41
8.	7.0%	2.3%	1.02
	100.0%	32.5%	

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