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AN ATTEMPT TO CLUSTER DPI PROFILES
INTO REPLICABLE CATEGORIES

by

CATHERINE M. L. MILLER

A thesis submitted to the Department of Psychology
in conformity with the requirements for
the degree of Master of Arts

Faculty of Graduate Studies
University of Windsor
Windsor, Ontario, Canada

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ABSTRACT

Two equal samples (N=150) of a moderately heterogeneous psychiatric patient population were clustered on the basis of the similarity of their Differential Personality Inventory (Jackson & Carlson, 1969) profiles using a metric similarity index, r_p (Cattell, 1949) and a hierarchical, complete linkage clustering strategy, the Maximum Method (Johnson, 1967). Comparison of the clusters emerging from the two samples indicated five replicated "core types", ranging from normality to severe psychosis as revealed by interpretation of each cluster's DPI and MMPI mean profiles.

The results appeared to support the possibility of developing an automated taxonomy of psychopathology. Methodological improvements and directions for future research were discussed and it was concluded that the complexity of the taxonomic process will require much more detailed exploration to establish a sophisticated, reliable method of automating psychological diagnosis.

ACKNOWLEDGEMENTS

A special note of gratitude is extended to the administration, staff and patients of Windsor Western Hospital Centre for their assistance to and tolerance of the author during the process of data collection.

Thanks is also given to the University of Windsor Psychological Centre which provided the remainder of the data making this study possible.

To Martin Morf -

A small tribute to his belief in academic integrity
and empirical excellence.

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CHAPTER I

INTRODUCTION

"Classifying things is perhaps the most fundamental and characteristic activity of the human mind, and underlies all forms of science."

- R. A. Crowson (1970, p.1)

Since Kraepelin's unceasing and prolific efforts (1881-1926) to identify and systematize psychiatric diagnosis (see Kahn, 1959), psychiatry and clinical psychology have been intimately involved in the formulation of classificatory systems for psychopathology. That the results have been less than successful is witnessed by the continual criticism ranging from suggestions for refinement to recommendations of abolishment (Zigler & Phillips, 1961). While the prevailing system, that of the American Psychiatric Association, has been periodically revised, it has been variously accused of "subjective ambiguity (Cattell, 1970, p.10)", unreliability and low classification rates (Lorr, 1970), and lack of validity (Zigler & Phillips, 1961). Indeed, the latter authors suggest that the categories and their descriptions have emerged, at least in part, not through empirical documentation, but from the prevailing school of clinical thought. Thus, there may not be so much a lack of meaning in the traditional diagnostic system as a multiplicity of meaning determined by the preferred

theoretical interpretation and memory of the clinician. This is in marked contrast to a second mode of psychological diagnosis and prediction - the actuarial method, whose logical extreme is defined by Schontz (1965) as "atheoreticism" (the lack of any theoretical content whatsoever), and by Cattell (1970) as an exercise in psychological meaninglessness.

The resolution of this dilemma may be found in examining the basic methodology for establishing a taxonomic¹ system. Sneath and Sokal (1973) in analyzing this methodology define three central terms:

Classification: "the ordering of organisms into groups (or sets) on the basis of their relationships (p.3)" N.B. such groups are called taxa

Operational Taxonomic Units (O.T.U.'s): the organisms selected for classification

Characters: the items or characteristics on the basis of which the comparisons between O.T.U.'s are made, to determine their relationships

A major development in the field of taxonomy is the rapid growth of numerical treatments of taxonomic data. Sneath and Sokal (1973) define numerical taxonomy as "the grouping by numerical methods of taxonomic units (O.T.U.'s) into taxa on the basis of their character states (p.4)". As such its major characteristics are repeatability and objectivity, primary criteria for scientific endeavours. Groups are formed and evaluated on the basis of explicit mathematical rules, using data from as many characters as possible. The quantitative nature of numerical taxonomy allows ease of automation which in turn requires clearly defined assumptions

data units and procedures. Thus, it would seem that numerical taxonomy provides an ideal medium for the investigation of the classification of psychopathology by rectifying many of the problems of previous classificatory attempts.

Formal Categorical Assessment

Two major considerations form the basis of discussion of the present systems for psychopathological, or more generally, personality assessment: (i) formal versus informal methodologies; and (ii) dimensional versus categorical analyses (Morf & Krane, 1973). The former dichotomy refers to the method by which the data are collected and subsequently interpreted, formally through the use of explicit rules based on an explicit rationale, or informally on an intuitive, experiential basis. The latter dichotomy is concerned with the basic structural considerations of personality, i.e., whether personalities differ quantitatively along fixed trait dimensions (Eysenck, 1970) or whether they in fact differ in type. 'Type' refers to a unique combination of traits, i.e. personality types are qualitatively different. Morf and Krane (1973) discuss the merits and deficiencies related to the possible combinations of the above dichotomies for automating personality assessment and opt for formal, categorical systems of clinical diagnosis as a first step. Such a conclusion is consistent with these authors' arguments in favour of utilizing the currently available, sophisticated mathematical and

computer technology to update the field of personality assessment. In addition, the decision to use categorical classification is justified by the generally acknowledged need for a consistent taxonomy as the initial step in a scientific endeavour (Cattell, 1970).

Historical Overview of Psychological Assessment

Over the years, the comparison of formal versus informal assessment procedures generated a literary and empirical battle with dubious victorious distinction but with considerable heuristic value. A review of this conflict seems both to indicate some of the major problems in the area and to generate a supporting rationale for the development of a numerical taxonomic system.

Holt (1958) gives credit for the initiation of open warfare to Meehl's book Clinical Versus Statistical Prediction (1954). In this publication, Meehl lays out both sides of the debate with their respective batteries of empirical evidence. The basic issue, simply stated, is that of deciding which of two means of prediction about the psychological status and future behaviour of a patient or client is better. The mechanical combining of information for classification purposes, and the resultant probability figure which is an empirically determined relative frequency, are the characteristics that define the actuarial or statistical type of prediction. On the other hand, the clinical or case-study method of prediction proceeds on the basis of interview.

impressions, historical information, and possibly other psychometric data, e.g., personality profiles. From such information, the clinician formulates some psychological hypothesis regarding the structure and dynamics of the particular individual's personality. On the basis of this hypothesis, and expectations of future events, a prediction is made about what is going to happen. Thus the predictive process can be broken down into two major components which in turn provide two alternatives:

- (1) type of data -
 - (a) psychometric e.g. scale scores on personality inventories
 - (b) non-psychometric e.g. interview impressions
- (2) treatment of data -
 - (a) combined mechanically e.g. regression equations
 - (b) combined non-mechanically e.g. case conference hypothesis generation

Morf and Krane (1973) refer to 1(a) and 2(a) as the formal treatment of data, and 1(b) and 2(b) as informal.

Prediction of behaviour, whether statistical or clinical, relies on knowledge of past performance i.e., through past experience with various types of behaviour, a probability statement about a patient's status can be made on the basis of the given patient's similarity to classes of others who have been previously assessed. This probability may be expressed as an actual numerical value or simply a clinician's

hunch based on memory. Allport's ideographic approach to personality would define the lower limit of a continuum measuring the reliance on inference from class membership. At the other end would be Sarbin (1943) whose argument rests on the belief that whether a clinician realizes it or not, a prediction in clinical work is never a certainty but merely probable. Since probability is inherently a notion of frequency, and frequencies refer to the occurrence of events in a class, clinical prediction is in fact a non-mechanical and probably second-rate job of actuarial prediction. This value judgement about the validity of traditional clinical prediction would seem to be supported by the empirical evidence cited by Meehl (1954). He states that for "...twenty studies involving a comparison of clinical and actuarial methods, in all but one...the predictions made actuarially were either approximately equal or superior to those made by a clinician (from Mann, 1956, p.227)". Perhaps because of the emotion-charged nature of the conflict and the tendency to partisanship on one side or the other, many of these studies suffer from methodological biases, at best, and at worst are frankly irrelevant to the issue. There is nothing gained in resolving the problem by comparing "the most sophisticated actuarial approach with the least competent clinicians (Morf, 1970, p.3)". Along these lines, Holt (1958) points to the label clinical versus statistical prediction as setting up an artificial conflict which need not be the case. He outlines three types of prediction - Type I - pure

actuarial, characterized by psychometric quantitative data, mechanically combined; Type II - naive clinical, using primarily qualitative data processed entirely in an intuitive, judgemental way; and Type III - sophisticated clinical, combining both qualitative and quantitative data collected and analyzed as much as possible in an objective, scientific way, but with experienced clinical judgement contributing in a creative way to a final individually tailored prediction.

Meehl (1956) on the other hand, views the contribution of the clinician as being most valuable in the treatment rather than diagnosis of psychopathology. That an actuarial approach is possible on a practical basis was demonstrated by Halbower (1955; see Meehl, 1956). Through a five-step procedure (see Morf, 1970), Halbower (1) devised a coding system for MMPI profiles; (2) compiled case descriptions for each code; (3) grouped the profiles into four categories using rules partially derived from quantitative comparisons of profiles but with reliance on clinical experience and judgement; (4) using Q-sort technique, and within-category correlations, selected five "typical" patients as most representative of each category; and (5) took the mean of the Q-sorts for the five "core" patients as the descriptive profile for that category or personality type. As Meehl (1956) observes, Halbower (1955) had devised a small actuarial "cookbook" for clinical diagnosis. Finally, the validity of the four "recipes" was checked by correlating the recipe description of each of four patients selected to represent a

particular profile type with the criterion Q-sort descriptions provided by their therapists. These correlations were then compared with the correlations of the therapists' descriptions with the Q-sorts based on blind readings of the same patients' MMPI profiles by variously experienced clinicians. For all four categories the cookbook descriptions obtained higher criterion validity correlations than those of the clinicians.

With validity thus established the mechanical nature of the actuarial approach renders Halbower's model a prototype for computerized automation. However, while automation has come to clinical diagnosis as witnessed by the list of seven commercially available programmes for scoring and interpreting MMPI answer sheets in the latest MMPI Handbook (Dahlstrom, Welsh & Dahlstrom, 1972), none of these are automated cookbooks. The profile descriptions are based to a large degree on clinical experience and traditions rather than actuarial research. They "attempt to simulate a clinician's cognitive activity without classifying, as the cookbooks do, profiles a priori (Morf, 1970, p.5)". Morf (1970) considers the possibilities for automating the two prevailing actuarially-designed cookbooks (Marks & Seeman, 1963; Gilberstadt & Duker, 1965) and examines four critical areas - (a) validity, including stability of code types across investigators and stability of code type descriptions across samples; (b) specificity of descriptions e.g. the disproportionately frequent appearance of a few code types across

samples; (c) the inability of the cookbooks to classify a majority of a sample; and (d) the ambiguity of the decision rules. Obviously to render automation of cookbooks feasible, these issues will have to be resolved.

It should by now be clear that automation need not imply an actuarial approach. Thus, the current state of automated personality assessment presents a paradox. On the one hand, while automation has released the clinician from the time-consuming aspects of psychological assessment (one of Meehl's minor recommendations (1956)), the major emphasis on the empirically-demonstrated superiority of the actuarial approach with explicit, fixed rules and experimentally established relationships, has been neglected. Where once the criticism was made that the clinician acted as a second-rate Hollerith machine (Sarbin, 1943), it is possible to view the currently available, non-actuarial automated programmes as quick, but nevertheless second-rate clinicians. Most of the programmes involve some scale level interpretation of the MMPI (with documented low validity and reliability, e.g., Cureton, 1950; Nunnally, 1967; Bentler, Jackson & Messick, 1970). While configurational scoring of the MMPI is to be preferred (Meehl, 1950), this introduces programming problems in terms of the potential number of permutations and combinations of scale scores composing the profile, the description and meaning of the various alternatives and so on. This results in great variation in the complexity of the outputs of the various commercial programmes (for a comparison see the

assessment printouts made by several services for the same patient in Dahlstrom, Welsh and Dahlstrom, 1972). Despite over a quarter of a century of discussion, conflict and research "the current state of the science of automated psychological assessment is thus rudimentary (Morf & Krane, 1973, p.295)".

One aspect of actuarial personality assessment deserves further attention - that is, the potential of this approach for maintaining rigid, static diagnostic categories, imper-
vious to and perhaps even actively inhibiting creative theoretical growth in the assessment of psychopathology. Amazingly enough, this is one consideration shared by Meehl (1956) and Holt (1958), although the former regards this factor as minimally important, while the latter sees it as a critical feature. Specifically, Meehl (1956) suggests that the only area in which clinicians can substantially outperform the actuary is in the use of projective, non-quantifiable data, e.g., free associations. This argument is rather trivial since the actuarial approach is defined, a priori, by quantified input. Other than this, the only possibility for a clinician to contribute is in the literal invention of new theoretical relations or variables, a rare occurrence in day-to-day practice, according to Meehl. Holt, on the other hand, finds the mere possibility of theoretical growth and change sufficient to recommend the retention of the clinician's role in prediction. He cites flexibility and ease of modification as two prime attributes of clinical

methodology not shared by the actuarial approach. Obviously, these two arguments rely in part upon the faith one has in the members of the clinical profession as pioneers on the frontiers of assessment.

This leads to a consideration of a body of research stretching over some thirty years, a pioneering effort on the part of Cattell and his co-workers in the theoretical development and empirical study of personality structure and assessment. This research has culminated primarily in the use and refinement of the 16PF personality inventory and the development of means of grouping and identifying resultant profiles. For detailed descriptions of both theory and experimentation, the reader is referred to Cattell (1946; 1950), Cattell and Coulter (1966) and Cattell, Eber and Tatsuoka (1970). What is of interest to the present study is the impact such a highly-detailed, carefully constructed, yet in many ways radically creative model has had on the field of personality assessment. Cattell's claims for the system are large - unusual comprehensiveness, functional measurement, free from subjective and a priori concepts, intimately related to an organized and integrated body of practical and theoretical knowledge (Cattell, Eber & Tatsuoka, 1970), as well as the ability to measure variables underlying the dynamics of personality, not just structure. Cattell's strongly mathematical orientation lends an actuarial flavour to the predictive stance of the 16PF (e.g. use of empirically determined regression equations in clinical pre-

diction) and indeed the whole process of classifying and identifying profiles has been automated in the Taxonome Programme (Cattell & Coulter, 1966). It would not seem overly rash to suggest that herein lies an opportunity for the clinical profession to move from traditional informal and scientifically questionable personality assessment to a psychometrically and theoretically elegant system incorporating the efficiency of automation. However, one of the outstanding surface characteristics of the 16PF and its related publications is the introduction of a new system of terminology, ranging from factor labels (e.g. Factor QIII, Pathemia vs. Cortertia) through statistical terms (e.g. sten scores), to types of groups in profile classification (e.g. stats and aits). Mahrer (1970) notes the possibility that acceptance of Cattell's system in toto may, in fact, necessitate a complete reorientation of clinical teaching and practice for both psychiatry and psychology. Thus one major obstacle to widespread use of Cattell's approach may be the esoteric nature of the taxonomy which renders it inaccessible to general use. Deutsch (1966) views theories, taxonomies and models as communication codes for organizing information. One of the eight major code components is the cost (c) of setting up and operating a given system. He cites the use of esoteric codes and jargon as greatly increasing the social costs to the user. Cattell's new terminology developed and accepted among his group of colleagues, nevertheless may lack adaptability and communicability with the rest of the

field of personality, resulting in resistance to the adoption of the new coding system and thus the theory in which it is embedded.

The other code components (code is used as a generic term for theories, taxonomies and models) are defined by Deutsch (1966) as follows:

\underline{n} - large number of phenomena, to be coded into

\underline{k} - categories, comprising

\underline{S} - a set of categories connected by

\underline{r} - operating rules

\underline{S} should yield

\underline{p} - verifiable predictions with

\underline{e} - an average margin of aggregate error

\underline{f} - in the probability of leading to new observations and experiments (i.e. heuristics or fruitfulness)

\underline{x} - self-transcendence - the code will permit additional improvements on itself, leading possibly to further new codes

Given two coding systems \underline{S}_i and \underline{S}_j , \underline{S}_j will be preferable to \underline{S}_i when -

$\underline{n}_j, \underline{p}_j, \underline{f}_j$ and $\underline{x}_j > \underline{n}_i, \underline{p}_i, \underline{f}_i$ and \underline{x}_i

and $\underline{k}_j, \underline{c}_j$ and $\underline{e}_j < \underline{k}_i, \underline{c}_i$ and \underline{e}_i

The above relationships are hypothetical to the extent that it is difficult to determine what would be the numerical values e.g. for fruitfulness or self-transcendence. Nevertheless, they provide an excellent framework within which to examine the previous arguments regarding clinical and actuarial prediction and the available automated programmes

stemming from these methods. Despite claims of low error, and high potential for fruitfulness, self-transcendence and verifiable predictions, as well as being able to account for large numbers of phenomena, the limitations of Cattell's system because of a relatively high cost factor have already been noted. It would appear that the objections to the actuarial approach lie in the potential for low fruitfulness and self-transcendence. The current automated programmes, in addition to these failings, are limited by their lack of specified categories. It should also be pointed out that while a small number of categories is generally desirable, the very low classification rates of the available cookbooks are a negative feature. According to the principle of parsimony, few categories must be capable of accounting for a large number of phenomena to be considered acceptable.

The clinical approach, on the other hand, while possibly permitting fruitful and self-transcendent explorations (despite Meehl's low opinion of clinician creativity), makes the discovery of categories and operating rules difficult if they exist at all. Perhaps most importantly, the error factor, as indicated by the studies previously cited, is high relative to the actuarial approach. This is not unexpected given the human fallibility factor. Observation, recording, retention and recall errors are classic grist for the mill of empirical error. Add to this the biases of various clinical schools and the clinical prediction method suffers heavily in Deutsch's model.

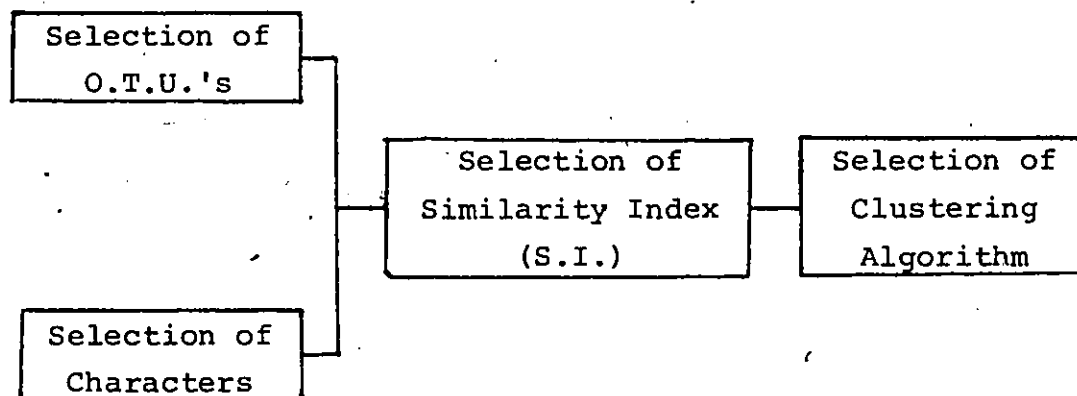
Taxonomic Procedure

There is an implied separation of classification from prediction in the preceding discussions which may be a somewhat artificial distinction. Ideally, a useful taxonomy should have as its goals both accurate and meaningful groupings of similar organisms and predictive power. The accuracy and meaningfulness of classification and prediction are intimately involved with the concepts of natural groups and error. The relationship between classification and prediction is formulated by Deutsch (1966) in his Principle of Multiple Relevance; that is, classifications should imply predictions such that any two phenomena (O.T.U.'s) classified together on the basis of one or a few characteristics will share additional characteristics. When only a small number of characters are used, the probability of error is decreased but so is the number of predictions. Such a highly restricted classification is called "artificial". For example, if a sample of human subjects were classified on the basis of only one character e.g., weight, errors in forming the groups would be unlikely but little else could be said about the groups e.g., other physical attributes such as eye colour; or psychological status; or socioeconomic position. Thus the information content implied in the classification would be low as would be its predictive value.

Nevertheless, as Gilmour (1937) points out, the purpose of a taxonomy determines to a large extent its nature. Therefore, "if the object of the system to be designed is psycho-

logical diagnosis, the domain to be sampled by the input variables is that of psychopathological tendencies (Morf & Krane, 1973, p.297)". It would be of minimal utility to include eye colour as a character for the estimation of taxonomic resemblance in this case, although such characters, sampling all aspects of human description, would render the taxonomy more "natural".

The following flow chart presents the steps involved in the determination of the taxonomic procedure. Each step will then be discussed individually.



Selection of O.T.U.'s. One of the major problems with the traditional methods of psychological classification and prediction is that the descriptive categories and behavioural inferences are determined on the basis of relatively homogeneous populations and then generalized to other institutions, agencies and geographical locations. This may account for the low classification rates of some actuarial systems when

used with populations other than those with which they were developed. The approach suggested by Morf and Krane (1973) for formulating institution-specific classifications using numerical taxonomy provides a possible solution to the problem. The easily automated nature of such a system renders this a feasible alternative such that flexible taxonomies can be devised by individual institutions and up-dated as the need arises.

The O.T.U.'s for the present study are a heterogeneous sample of cases from a university psychological clinic and from a psychiatric hospital. The former subjects range from students seeking study help, through those desiring counseling, to students actually in therapy on an out-patient basis. The latter subject sub-sample is comprised of severely disturbed inpatients, primarily classified as psychotic. It is expected that the taxa formed on the basis of these two sub-samples will be distinguished from each other in part by the differences between them, e.g., treatment facility attended.

It should be pointed out that while in some studies (particularly in the natural sciences) it may be necessary to treat groups of organisms as O.T.U.'s, in the present instance, the logical fundamental element is the individual.

Selection of characters. As has been noted, limiting the nature of the characters to a specific domain reduces the "naturalness" of the classification. To counteract this, Cattell (1970) for example, proposed the P-technique. This

attempts to formulate unique, highly natural groups through complex long term repetitive observations of patients on many physical, behavioural and psychological characteristics. The resulting mass of data is subjected to computer analysis to determine patterns of behaviour over time, underlying dynamics and so on. While such a goal is idealistically desirable, the suggested observation time, one hundred days, and the number of observations required render this technique highly impracticable.

One of the criticisms of numerical taxonomy is that despite its claims, it can never be fully objective. That is, before the statistical operations can be performed the domain to be counted and measured must be selected, which presupposes a basic intuitive classification. The characters which are the basis of a numerical taxonomy must be based on a judgement of what the relevant domain is (Crowson, 1970). The truth of this analysis lies in the obviously necessary judgement of what constitutes the domain of psychopathology and this judgement must always be relative to those values considered acceptable in a given society. Accepting that the domain of psychopathology is to a large extent socially determined and non-objective, it is nevertheless important to develop meaningful, flexible, empirically-testable classificatory systems to counter-balance, and to encourage re-evaluation of, the present concepts of mental illness.

In developing such a system, one is immediately confronted with two problems. First, most of the available

automated programmes are based on the MMPI, a psychometrically weak test whose domain was structured indirectly on the basis of existing psychiatric typologies (Bentler, Jackson & Messick, 1971). Secondly, the available cook-books provide classification categories also based on clinical judgements. That is, while the identification of new profiles as belonging to a certain type is actuarial, the initial classification procedure cannot make this claim.

To overcome the first difficulty, the present study will follow the suggestion of Morf and Krane (1973), to use a rationally constructed inventory of psychopathology, relatively free from such response biases as social desirability and true responding. The Differential Personality Inventory or DPI (Jackson & Carlson, 1969) yields scale scores on fifteen rationally derived scales each composed of twenty moderately homogeneous items, and each measuring a carefully formulated construct pertaining to psychopathology. The second problem is solved by the taxonomic grouping procedure itself, i.e., the taxa are formed mathematically without human intervention.

In determining what form the characters will take, there are a number of considerations. Characters are of three general types:

- (i) two-state
- (ii) quantitative multistate
- (iii) qualitative multistate

In selecting the DPI as the data input, two choices are pos-

sible in terms of the actual characters to be used:

- (i) each of the three hundred items can be regarded as a single two-state character i.e. the item is scored either True or False
- (ii) the scale scores can be utilized as quantitative multistate characters

Another desirable characteristic of characters is that they be relatively independent (Sneath & Sokal, 1973). Thus while there is a certain intuitive appeal in using option (i) since every piece of information collected is used, the method of DPI scale construction resulting in moderate intra-scale item correlations suggests that option (ii) is more suited to the requirements of the taxonomic process.

A further major division of taxonomies is related to certain types of characters selected. In biology, this is the separation between phylogenetic and phenetic typologies - the former refers to the historical description of O.T.U.'s, the dynamics underlying the growth and change of resemblances from the past to the present. Phenetic, on the other hand, refers to relationships evaluated purely on the basis of resemblances existing now in the material at hand - i.e. the empirically observable characteristics of the present. Although historically, biological taxonomy has been highly concerned with the discovery of phylogenetic relationships, of late this approach has been strongly criticized primarily since the selection of phylogenetic characters must rest on inference from existing organisms and may be fragmentary or

incomplete (Sneath & Sokal, 1973). The nature of the O.T.U.'s in the present study i.e. human beings, is potentially open to phylogenetic exploration and, in terms of discovering historical antecedents to types of psychopathology, this may offer a fruitful line of investigation. However, the time involved in collecting such data, the strong possibility of questionable accuracy and cells of missing information, in addition to the difficulty of adapting such diverse types of data to a consistent numerical format, mitigate against the use of such characters. Thus the present study employs quantitative, multistate, phenetic characters in the form of scale scores from the Differential Personality Inventory.

Selection of similarity index. Once values have been obtained for each O.T.U. on a series of characters, it remains to group the resulting profiles on the basis of their resemblances. To do this it is necessary to obtain some numerical estimate of how similar they are to each other, in other words to choose an appropriate similarity index. It is generally accepted that in psychological research, Pearson's correlation coefficient r is the most familiar and most widely used index of profile similarity (Howard & Diesenhau, 1967). Correlational techniques have nevertheless been strongly criticised (Cronbach & Gleser, 1953; Sawrey, Keller & Conger, 1960; Guertin, 1966; Howard & Diesenhau, 1967) primarily on the basis of the fact that such statistics ignore the contributions of profile elevation

and scatter, using only differences in shape to assess the profile similarities. Since it would seem desirable to use as much information as possible, within the given framework, in order to construct an accurate taxonomy, correlation coefficients and their related grouping methods (factor analytic techniques) are inappropriate to the task at hand.

The other large group of indices for measuring similarity are known as measures of taxonomic distance. These are the converse of correlation coefficients in the sense that they are measures of dissimilarity, i.e. the larger the value between two O.T.U.'s, the more unlike they are.

The following outline (adapted from Sneath and Sokal, 1973) is provided to help clarify how distance indices function. It is conventional to enter the initially obtained character values in an n by t matrix, where n equals the number of characters and t equals the number of O.T.U.'s. Each entry, X_{ij} , is the score of O.T.U. j for character i :

E.G. (Sneath & Sokal, 1973, p.114)

Character	O.T.U.			
	1	2	...	t
1	X_{11}	X_{12}	...	X_{1t}
2	X_{21}	X_{22}	...	X_{2t}
⋮	⋮	⋮		⋮
n	X_{n1}	X_{n2}	...	X_{nt}

The focus in the present study is on examining the associations

of the O.T.U.'s over all the characters, a practice originally called the Q-technique (Cattell, 1952). This results in the quantification of relations between organisms in order to produce classifications of the O.T.U.'s. The above data matrix can be visualized as a geometric space in n orthogonal dimensions with each O.T.U. represented by a point in that space. This space has been called A-space (attribute space) by Williams and Dale (1965) and therefore the taxonomic method of interest here is a Q-technique operating on an A-space.

Because of their geometric translatability, the distance measures have an intuitive and intellectual appeal. While distances between more than three orthogonal dimensions are difficult to visualize and impossible to represent graphically, they can be postulated and computed without violating assumptions regarding the properties of the more familiar Euclidean three-space. According to Sneath and Sokal (1973), while the A-space need not be strictly Euclidean, its topology should be determined by a metric function i.e., the measure of distance should have metric properties as follows:

Let $d(x,y)$ be the function of the distance between points x and y :

- ∴ 1. $d(x,y) \geq 0$
2. $d(x,y) = 0 \Rightarrow x = y$
3. $d(x,y) = d(y,x)$
4. $d(x,z) \leq d(x,y) + d(y,z)$

Condition 4 above is the triangle inequality; when this is strengthened, the ultrametric inequality is obtained:

$$\text{i.e. } d(x,z) \leq \max [d(x,y), d(y,z)]$$

or, in words, $d(x,z)$ is smaller than or equal to the larger of $d(x,y)$ and $d(y,z)$. The importance of employing a metric which incorporates the ultrametric inequality is simply that it provides for monotonic invariability of the data under transformations, a quality not shared by some other similarity indices, e.g. correlation coefficients (Tellegen, 1965; Howard & Diesenhuis, 1967).

A major advantage of distance measures is that they take into account all three major components of phenetic similarity, namely, elevation, scatter and shape. It is true that some distance measures may overemphasize the elevation component, being less sensitive to shape (Cronbach & Gleser, 1953). To overcome this imbalance, Guertin (1966) proposes a two-stage grouping procedure using first a correlation coefficient to identify similarly shaped profiles and then these are examined on the basis of a distance measure (the D^2 of Mahalanobis, 1936) to determine groups on the basis of elevation (level) and scatter (variance). This approach has a certain logical appeal although the technique is somewhat cumbersome. In addition, only the latter similarity index, D^2 , has metric properties.

Sneath and Sokal (1973) describe in detail many of the numerous similarity indices available. Because of the rapid growth of numerical taxonomy in many fields, similar indices

appear to have been developed almost simultaneously. Thus, part of the final choice of the index must rest "on the worker's preference in terms of conceptualization of the similarity measure (Sneath & Sokal, 1973, p.146)". The advantages of metric distance representations and their intuitive appeal appear to have generated much interest in the development and refining of such measures e.g. Generalized Distance (Mahalanobis, 1936); Coefficient of Divergence (Clark, 1952); Mean Character Distance (Cain & Harrison, 1958); and Taxonomic Distance (Sokal, 1961). Cattell, Coulter and Tsujioka (1966) on the other hand, express concern with what they regard as the "rediscovery" of these distance measures to the exclusion of r_p , a coefficient of pattern similarity developed earlier by Cattell (1949). Its formula is:

$$r_p = \frac{2k_m - \sum_{i=1}^k d_i^2}{2k_m + \sum_{i=1}^k d_i^2}$$

where k = number of profile elements (characters or scales)

d_i = difference in standard scores of two O.T.U.'s on character i

k_m = median chi-square value for k degrees of freedom

According to Cattell (Cattell, 1949; Cattell & Coulter, 1966; Cattell, Coulter & Tsujioka, 1966), r_p , while still a metric distance measure, goes beyond other such formulations and thus has distinct advantages in terms of (i) heuristics; (ii) statistical elegance; and (iii) interpretability.

Specifically, (i) r_p takes account of the number of characters and the units of measurement used such that results obtained using varied measures are still directly comparable; (ii) r_p compares the obtained inter-O.T.U. distance with the magnitude expected by chance. As well significance tables for r_p values using varying numbers of characters have been derived (Horn, 1961), thus alleviating to some extent the problem of arbitrarily deciding which r_p levels signify distinct clusters or types. Finally, (iii) r_p has values ranging from +1.00 through 0 to -1.00, providing a convenient function interpretable along the general lines of r . Thus, +1.00 represents two O.T.U.'s having the same profiles and falling on the same point in multidimensional space; 0 represents two O.T.U.'s falling as far apart as would be expected for any two points taken at random; and -1.00 indicates two points as unlike or far apart as possible. The latter is a theoretical occurrence only, in that it is difficult to imagine any two points achieving an actual absolute furthest distance apart. The r_p function approaches but never reaches -1.00.

Cattell, Coulter and Tsujioka (1966) also describe a second coefficient related to r_p , namely the Profile Nearness Coefficient, r_n . It was developed for use with highly correlated i.e. non-orthogonal, profile elements, but unfortunately has received too little attention to be used with confidence. However, the relative independence of the DPI scales supports the choice of r_p as the metric distance

measure appropriate for the present study.

Selection of clustering method. To maintain a consistency with the published literature, the methods of grouping O.T.U.'s on the basis of their similarity on a set of measured characters, will henceforth be referred to as clustering techniques. Strictly speaking, factor analysis is one such technique but it has traditionally been considered as distinct from other methods called cluster analyses. One of the most popular, traditional methods for classifying individuals has been the factor analytic Q-analysis (Cattell, 1952). According to Carlson (1970) such a use is inappropriate since factors only take into account shared variance, not individual differences and they are thus limited in their descriptive capacities. Finally, factor analysis relies almost exclusively on correlation coefficients as input data and the limitations of these have already been described.

Cluster analysis, in general, is a means of determining the constellations of O.T.U.'s in phenetic space. Further, if these sets of O.T.U.'s are to be psychologically meaningful i.e. to provide a "clear, explicit and intuitive description (Johnson, 1967, p.242)", they must be distributed in such a way as to allow the rejection of two alternative null hypotheses. While it may not be possible to statistically test the distribution, visual comparisons can be made to determine if the dispersions are uniformly regular or random in nature (Sneath & Sokal, 1973). In order to qualify as clusters, the groups of O.T.U.'s must exhibit neither uniform

regularity nor randomness. Thus cluster analysis attempts to discover "whether there is a...natural arrangement of the O.T.U.'s into homogeneous groups inherent in the data,... (Johnson, 1967, p.241)".

The most recent work of Sneath and Sokal (1973) provides detailed descriptions of the many types of analyses possible. Theoretically there are at least $2^8 = 256$ different types of methods possible, based on binary choices of eight major dichotomous aspects of clustering methods. It is conceivable that certain of these combinations would prove to be logically impossible. By far the largest body of cluster analyses is composed of those methods to which Sneath and Sokal (1973) apply the acronym SAHN, i.e. Sequential, Agglomerative, Hierarchic, Nonoverlapping. These adjectives simply mean that clusters are formed by (1) applying a recursive sequence of partitions to the data, (2) which start off as a set of t (number of O.T.U.'s) separate entities which are grouped in successively fewer sets, (3) such that each clustering is obtained by merging of clusters from the previous level, and (4) such that the taxa at any given level are mutually exclusive. Within this framework there are three alternative algorithmic strategies (i) single linkage; (ii) complete linkage; and (3) average linkage. Simply speaking, in single linkage, the similarity of an O.T.U. to an extant cluster is equal to its similarity to the closest single member of that cluster. Thus clusters are formed by single links between pairs of similar O.T.U.'s but there is a strong possibility

that the final member of a cluster may be quite dissimilar to the initial member. The result tends to be long, straggly, chain-like clusters. Complete linkage is antithetical to the above method. A potential cluster member's similarity to that cluster is equal to its similarity to the farthest member of the cluster. This has the effect of producing compact, highly structured clusters. These two methods received concurrent attention from Johnson (1967) who labelled them in terms of two ultrametric functions he developed. Single linkage is Johnson's Minimum Method using the function

$$d([x,y], z) = \min [d(x,z), d(y,z)]$$

whereas complete linkage is equivalent to his Maximum Method, for which the function is

$$d([x,y], z) = \max [d(x,z), d(y,z)]$$

Johnson (1967) using psycholinguistic data from Miller and Nicely (1955), shows that both methods yield very similar results, yet in general, recommends the Maximum Method as being more interpretable. Since the purpose of the present study is to develop a method for defining distinct psychopathological classifications with clear, meaningful interpretations, the Maximum Method is most relevant. Appendix A presents an example of this and the Minimum Method worked on the same data, provided by Morf and Krane (1973).

The third alternative, average linkage (Sokal & Michener, 1958) was developed to avoid the problems of the above two methods - in the case of single linkage, unclear

intermediate connections, and in the case of complete linkage, the tendency to leave out less easily affiliated O.T.U.'s altogether. However, average linkage raises the problem of loss of invariance under monotone transformations of the similarity indices (Johnson, 1967).

A further note should be added at this point regarding a distinction made by Lance and Williams (1967a,b). The term "cluster analysis" as used in the present study to denote all methods of grouping O.T.U.'s on the basis of their similarity, has been reserved by these authors for one of two specific subsets of systems under the more general title of "classificatory sorting strategies". The other subset is composed of "hierarchical analyses". The distinction made between clustering systems and hierarchical systems is that the latter optimize the route by which the groups or clusters are obtained. The former optimize some property of the group of O.T.U.'s in question e.g. within-group homogeneity, usually by providing for the reallocation of O.T.U.'s whose initial clustering may be sub-optimal to the final solution. Lance and Williams (1967a) note the attention which has been directed toward hierarchical analyses and these methods have attained a higher degree of elaboration than the clustering systems. This observation is borne out by the previously noted focus of discussion evidenced by Sneath and Sokal (1973). SAHN strategies, by definition, are all members of the subset of hierarchical systems. Recently, clustering systems have received increased attention e.g.

Wishart (1972), and one of the major contributions of such techniques may be in refining and optimizing results obtained from a hierarchical procedure, which may still remain as a first step.

Relevant Research

In addition to those studies which have been discussed in the development of the reasoning for the present study to this point, there are a few relevant studies which bear closer examination. The earliest of these (Sawrey, Keller & Conger, 1960) presents a criticism of Q-analysis and related statistical procedures, and proposes an objective method of grouping profiles using the square of the Taxonomic Distance Measure (Sokal, 1961) as a similarity index. Essentially, this study describes a manual cluster analysis accomplished by visual inspection of a t by t matrix of distance values and by arbitrary selection of minimum and maximum levels of these values for defining which profiles will be clustered together. Obviously the computer technology and mathematical expertise of the last fourteen years have rendered the need for such human intervention and arbitrary decision making obsolete. Nevertheless this study does provide support for the use of a distance measure to preserve all three components of phenetic similarity - elevation, scatter and shape, and points up the potential value of developing "a systematic, replicable, meaningful procedure for obtaining...clusters of individual profiles (Sawrey,

Keller & Conger, 1960, p.657)".

Lorr and Radhakrishnan (1967) proposed two methods of clustering, and went a step further than Sawrey, Keller and Conger (1960) by programming both techniques for computer analysis. Method A is similar to that described by Sawrey, Keller and Conger (1960) while Method B is a multiple group factor method. The results indicate that although both methods produce interpretable categories the classification capacity of the cluster analytic Method A was superior to the factor analytic Method B - 72% and 51%, respectively. However, one drawback of both techniques was the use of a correlational index of similarity, the limitations of which have already been discussed.

In an unpublished dissertation, Carlson (1970) discussed in detail most of the available methods of cluster analysis in preparation for devising a multivariate classification of reformatory inmates. While it appears that many of the techniques in this comprehensive review are not useful, it remains unclear why Carlson rejected Johnson's Hierarchical Clustering Scheme (1967), particularly since he emphasizes Johnson's criterion of "clear, explicit and intuitive description (p.242)" as a major criterion met by his own algorithm. Further, Carlson arbitrarily permitted a 5% error in his clustering procedure citing psychological tradition in his support, which appears to be a meagre justification. Despite these methodological difficulties, the clusters obtained by Carlson,

(1970) do point up one advantage of using a mechanical, mathematically based classification technique. Visual inspection of the mean or characteristic profiles defining some of the clusters do not indicate the significant differences which in fact do obtain between the types, as revealed by discriminant function analysis. Here again the superior sensitivity of a quantitative approach is demonstrated.

Van Atta and Ruppel (1971) clustered MMPI profiles using an automated hierarchical grouping analysis, the H-Group method (Veldman, 1967). While this study bears some resemblance to the approach proposed in the present study, a number of problems are evident. First, the similarity index is not named although multiple discriminant analysis revealed that profile elevation was the primary factor underlying the obtained groupings, suggesting some form of distance measure was employed. Secondly, the H-Group method requires the investigator to decide (somewhat arbitrarily) at what point the analysis should be terminated to yield homogeneous, mutually exclusive and meaningful clusters. Such human intervention usually places in question the reliability of the results. Finally, the obtained clusters were defined in terms of the MMPI input data, which is somewhat tautologous.

Summary

The present study proposes to examine the feasibility of deriving a taxonomic system for psychological assessment.

Examination of relevant research and the most up-to-date taxonomic methods has shown that the former is distinctly rudimentary in terms of the criteria provided by the latter. These considerations have resulted in the design of a numerical taxonomic approach using:

- (1) psychometrically rational input data - DPI scale scores (Jackson & Carlson, 1969)
- (2) a similarity index with metric properties, namely the Coefficient of Pattern Similarity - r_p (Cattell, 1949)
- (3) a clustering procedure with a distinct rationale and which maintains the assumptions underlying the similarity index, namely the Maximum Method (Johnson, 1967)

CHAPTER II

METHOD

Subjects (O.T.U.'s)

The sample consisted of 228 university students who had attended the University of Windsor psychological centre for study help, counselling or therapy, and 72 severely disturbed adult inpatients of Windsor Western Hospital Centre.

Materials

Differential Personality Inventory (DPI) (Jackson & Carlson, 1969) scale scores for each subject provided the input data for the estimation of resemblances between O.T.U.'s. In addition, scores were obtained from each subject on the Minnesota Multiphasic Personality Inventory (MMPI) (Hathaway & McKinley, 1967) to assist in the interpretation of the clusters formed using the DPI. MMPI Form R was used for the Windsor Western Hospital sample and MMPI Group Form for the psychological centre sample.

Procedure

Administration of personality inventories. The hospital inpatients were tested in groups averaging ten in number. The testing was conducted one day a week (morning and afternoon) on the wards with the DPI always being given first, }

followed by the MMPI. Most subjects completed both tests in the same session, or at least on the same day, but all irregularities in testing procedures were noted for future reference. The test results from the students had been collected between 1969 and 1972 by the psychological centre which provided the data for the present study.

Treatment of data. Item scores from the DPI answer sheets provided 15 raw scale scores for each of the 300 O.T.U.'s. This total subject sample was then halved to form two equal subsamples, Sample A and Sample B, each consisting of 36 hospitalized patients and 114 student referrals. From this point on, all data transformations and calculations were carried out twice, that is separately for each of A and B.

With the omission of two validity scales, 13 DPI raw scale scores were transformed to z -scores, such that each of the O.T.U.'s could be visualized as a point in a multi-dimensional space defined by 13 standardized characters. The metric distance measure, r_p (Cattell, 1949), was used as the similarity index on the basis of which the O.T.U.'s were clustered using the Maximum Method developed by Johnson (1967). The programme² used outputs the r_p value associated with each clustering step, indicates the clustered and remaining unclustered O.T.U.'s after each iteration, and terminates when all O.T.U.'s form a single large cluster.

Scale scores for each subject on the MMPI were obtained to provide further information, independent of the information

used to form the clusters, regarding the nature of the
obtained clusters.

CHAPTER III

RESULTS

Cluster Identification

According to the table of significant values for r_p (Horn, 1961), for 13 profile elements a cluster must have a corresponding r_p value of at least .354 to be significant at the .05 level. However, examination of the HICLUST outputs for each of Sample A and Sample B revealed that to obtain clusters composed of at least 6 O.T.U.'s, this criterion would have to be relaxed. A lower limit of 6 O.T.U.'s was chosen as an arbitrary minimum to ensure some intra-cluster stability during subsequent examination and statistical manipulation. Thus, using the criteria of $r_p \geq .20$ and a minimum of 6 O.T.U.'s, eight clusters were identified in Sample A and seven in Sample B. Table 1 presents the actual r_p values, significance levels and size of each of these 15 clusters.

Cluster Stability Within Samples

The r_p value associated with each cluster in Table 1 defines only the similarity of the final O.T.U. with the cluster to which it is joined. To give an estimate of intracluster homogeneity, the mean r_p distance between O.T.U.'s within each cluster was calculated and compared with the mean r_p for each entire subsample. Sample A and

Table 1

r_p Values, Significance Levels and Size
for Clusters in Sample A and Sample B

Sample A			Sample B		
Cluster #	r_p	N	Cluster #	r_p	N
1	.26*	7	1	.29*	7
2	.34*	6	2	.23	7
3	.32*	7	3	.28*	9
4	.20	6	4	.20	8
5	.21	6	5	.34*	6
6	.21	6	6	.34*	7
7	.34*	7	7	.29*	7
8	.37**	9			

(% of sample clustered = 36%) (% of sample clustered = 34%)

* $r_p \geq .27, p \leq .10$
 ** $r_p \geq .35, p \leq .05$ } for 13 profile elements (Horn, 1961)

Sample B means and their associated intracluster means are presented in Table 2.

While within-cluster homogeneity is important as a first step, inter-cluster distances should be large to insure that clusters are indeed distinct from each other. The nature of the \underline{r}_p function permits an examination of this aspect of the obtained clusters; to be considered as separate types they should join at low negative levels of \underline{r}_p . Tables 3a and 3b present the \underline{r}_p values and significance levels associated with the joining of each cluster pair within Sample A and Sample B, respectively.

Cluster Replicability

To establish replicability of cluster types across samples, pairwise \underline{r}_p 's between the mean profiles of the clusters in Sample A and Sample B were calculated. Since distance measures tend to emphasize elevation, Pearson \underline{r} 's were also computed to allow examination of the shape component of phenetic similarity. Table 4a presents the \underline{r}_p values for these pairwise comparisons and Table 4b presents the same comparisons using Pearson \underline{r} values.

Clusters were considered to be replicated if the highest \underline{r}_p or \underline{r} values in a given row was also the highest value in the corresponding column. For example, in row 2 of both tables (i.e. Sample A, Cluster 2), the highest values occur for Sample B, Cluster 5 and in turn these are the highest values in the B5 columns. Although the highest \underline{r}_p value

Table 2

Mean r_p 's for Samples and Clusters

Sample A (Mean $r_p = .034$)		Sample B (Mean $r_p = .034$)	
Cluster	Mean r_p	Cluster	Mean r_p
1	.45	1	.50
2	.55	2	.47
3	.53	3	.47
4	.38	4	.41
5	.39	5	.55
6	.38	6	.52
7	.49	7	.51
8	.57		

Table 3a
 Sample A r_p Values for Clustering
 of Identified Clusters

		Clusters							
		1	2	3	4	5	6	7	8
Clusters	1	1.00	-.37*	-.37	-.62	-.62	-.62	-.62	-.62
	2		1.00	-.24	-.62	-.62	-.62	-.62	-.62
	3			1.00	-.62	-.62	-.62	-.62	-.62
	4				1.00	-.48	-.48	-.48	-.48
	5					1.00	+.01	-.41	-.41
	6						1.00	-.41	-.41
	7							1.00	-.37
	8								1.00

* $r_p \leq -.29, p \leq .05$

Table 3b
 Sample B r_p Values for Clustering
 of Identified Clusters

		Clusters						
		1	2	3	4	5	6	7
Clusters	1	1.00	-.53*	-.53	-.53	-.69	-.69	-.69
	2		1.00	-.49	-.49	-.69	-.69	-.69
	3			1.00	-.01	-.69	-.69	-.69
	4				1.00	-.69	-.69	-.69
	5					1.00	-.43	-.43
	6						1.00	-.35
	7							1.00

* $r_p \leq -.29, p \leq .05$

Table 4a

Cluster Replication Using r_p

Sample B

	1	2	3	4	5	6	7
1	.35	.27	-.07	.15	.65	.47	.37
2	.07	.29	.03	.17	.91*	.57	.60
3	.19	.75	.35	.42	.58	.61	.80*
4	.24	.01	.43	.57	-.26	-.31	-.01
5	.13	.16	.35	.49	.16	.02	.37
6	.27	.38	.77	.72	.00	-.04	.37
7	.39	.54	.27	.56	.53	.32	.59
8	.05	.59	.81*	.38	.04	.07	.55

* - replicated clusters

Table 4b

Cluster Replication Using r

Sample B

	1	2	3	4	5	6	7
1	.65*	-.17	-.84	-.53	.64	.47	-.39
2	-.03	-.35	-.45	-.43	.87*	.36	-.08
3	-.37	.63	.18	-.19	.17	.58	.30
4	-.27	-.14	.49	.68*	-.73	-.56	-.04
5	-.51	-.47	.15	.29	-.10	-.28	-.02
6	-.81	-.18	.75	.44	-.59	-.24	.38
7	.17	.08	-.33	.11	.33	.04	-.16
8	-.60	.63	.85*	.08	-.25	.12	.80

* - replicated clusters

(Table 4a) for Sample A, Cluster 1 also occurs in column B5 ($r_p = .65$), this is not the highest value in that column and thus was not considered sufficient evidence of replication. Using this decision rule, three replications or Cluster Types were selected from Table 4a - Sample A, Cluster 2 and Sample B, Cluster 5 (A2B5); Sample A, Cluster 8 and Sample B, Cluster 3 (A8B3); and Sample A, Cluster 3 and Sample B, Cluster 7 (A3B7). Table 4b reveals four correlations indicating cluster shape replication, namely A1B1; A2B5; A4B4 and A8B3. Sample B, Cluster 2 appears to be equally related to A3 and A8, but since A8 is more like B3, the A3B2 relationship was considered too confounded to be accepted as a clear cluster type.

Cluster Type Descriptions

The DPI mean scale scores for each of the replicated clusters were entered on profile sheets. Unlike the DPI which has a single set of norms for both sexes, the MMPI K-corrected mean profiles had to be calculated and drawn separately for males and females within each cluster. The DPI has no accompanying manual and can be interpreted simply using the scale definitions of elevated scores (Carlson, 1970). Three atlases for MMPI interpretation were used in the present study, one clinical (Hathaway & Meehl, 1951) and two actuarial (Marks & Seeman, 1963; Gilberstadt & Duker, 1965). To determine the appropriate interpretation, each obtained MMPI profile was coded separately according to the

instructions for each atlas. These codes were then matched with the most similar code within each atlas, and the accompanying descriptions recorded. Each atlas was used independently of the others, in order to avoid having already obtained descriptions of a given cluster affect the description being sought. Only after all clusters were defined separately three times were the descriptions compared for similarities and differences.

Some problems encountered with the use of the MMPI and the interpretive atlases should be noted at the outset. The necessity of splitting each cluster by sex resulted in some "mean" profiles being calculated on two or even one subject. The reliability of any description based on such a small sample is obviously questionable. Secondly, all three atlases emphasize that interpretation based on their codes depends on extremely elevated scale scores i.e. $T > 70$, and for a number of clusters such scores did not occur. Thus only by extrapolating the peaks in the profiles to $T > 70$ would a suitable interpretation be found in the atlases. Such descriptions must, at best, be viewed with caution.

Thirdly, a visual inspection of the mean profiles frequently indicated differences in elevation and shape resulting from variability on the Mf and Si scales. Hathaway and Meehl (1952) ignore these scales altogether, while Marks and Seeman (1963) and Gilberstadt and Duker (1965) only employ the Mf scale occasionally and always secondarily in conjunction with other scale elevations. These difficulties render the cluster

descriptions derived from the MMPI tentative.

Figure 1a presents the DPI mean profiles for Cluster A2, Cluster B5, and the combined Cluster Type, A2B5. Figures 1b and 1c present the same combination for the MMPI male and MMPI female mean profiles, respectively. Figures 2abc through 5abc provide the same information for the remaining identified Cluster Types. Following each set of profiles is a cluster type description based on the profiles, and including sex, number of O.T.U.'s clustered and treatment institution attended.

—●— A2 (N=6)
 —△— B5 (N=6)
 —x— A2B5 (N=12)

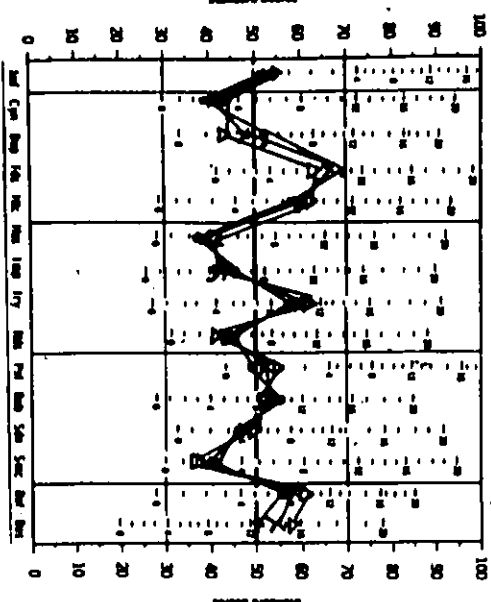


Fig. 1a: DPI Mean Profiles

—●— A2 (N=2)
 —△— B5 (N=5)
 —x— A2B5 (N=7)

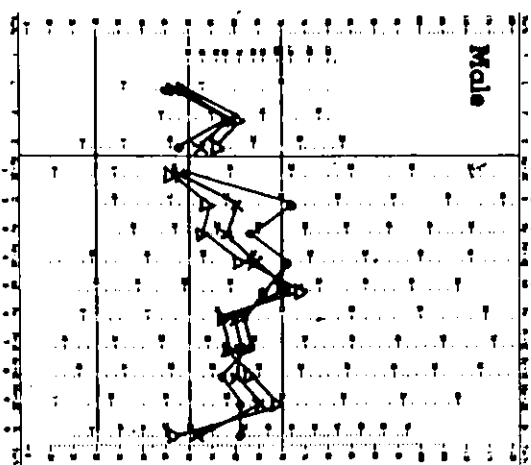


Fig. 1b: MPI Mean Profiles (Male)

—●— A2 (N=4)
 —△— B5 (N=1)
 —x— A2B5 (N=5)

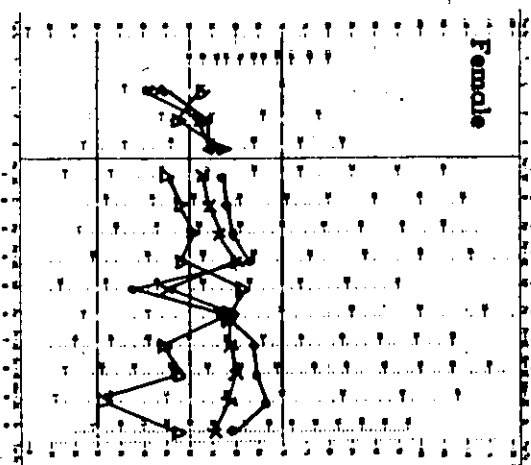


Fig. 1c: MPI Mean Profiles (Female)

Figure 1: Cluster Type A2B5

Cluster Type A2B5

DPI profiles. Figure 1a immediately reveals the strong similarity between A2 and B5 on all components of phenetic similarity - elevation, shape and scatter, verifying the high inter-cluster r_p and r values obtained. Both clusters A2 and B5, and consequently the combined cluster type, show elevations on the Familial Discord, Health Concern, Irritability and Defensiveness scales and relatively low scores on Cynicism, Hostility, Impulsivity, Neurotic Disorganization and Somatic Complaints. While none of the scores are extreme, this pattern suggests a tendency to deny overt negative physical and emotional states, and to defend against them. The nature of the Familial Discord and Irritability scale items suggest that discomfort is perceived by these individuals to be imposed on them by an external source.

MMPI profiles. Ignoring the Mf elevation, peaks occur for the male mean profile on Ma, Pd, D and Hy and all three atlases agree that such a configuration is characteristic of an emotionally unstable, antisocial, paranoid type, prone to heavy drinking. The major disparity between A2 and B5 males is the higher elevation of D for A2, but aside from the addition of reactive depression to the description, the two clusters remain substantially the same.

The female mean profile (Figure 1c) has a similar interpretation according to all the sources i.e., emotionally unstable, paranoid plus a possible psychotic reaction indicated by the higher Sc score. It is obvious that the A2 females

contribute most to the interpretation; the single B5 female has a somewhat aberrant profile, yet even here the atlas descriptions indicate paranoia associated with psychotic depression.

Other information. A2 contributed two males and four females to the cluster type, and B5 contributed five males and one female. Of these twelve cluster type members, three males and one female were psychiatric inpatients and at least one other male was in therapy at the clinic. Thus nearly one half of the cluster type were receiving some form of direct treatment intervention. Unfortunately, the status of the other seven subjects from the psychological centre was not available.

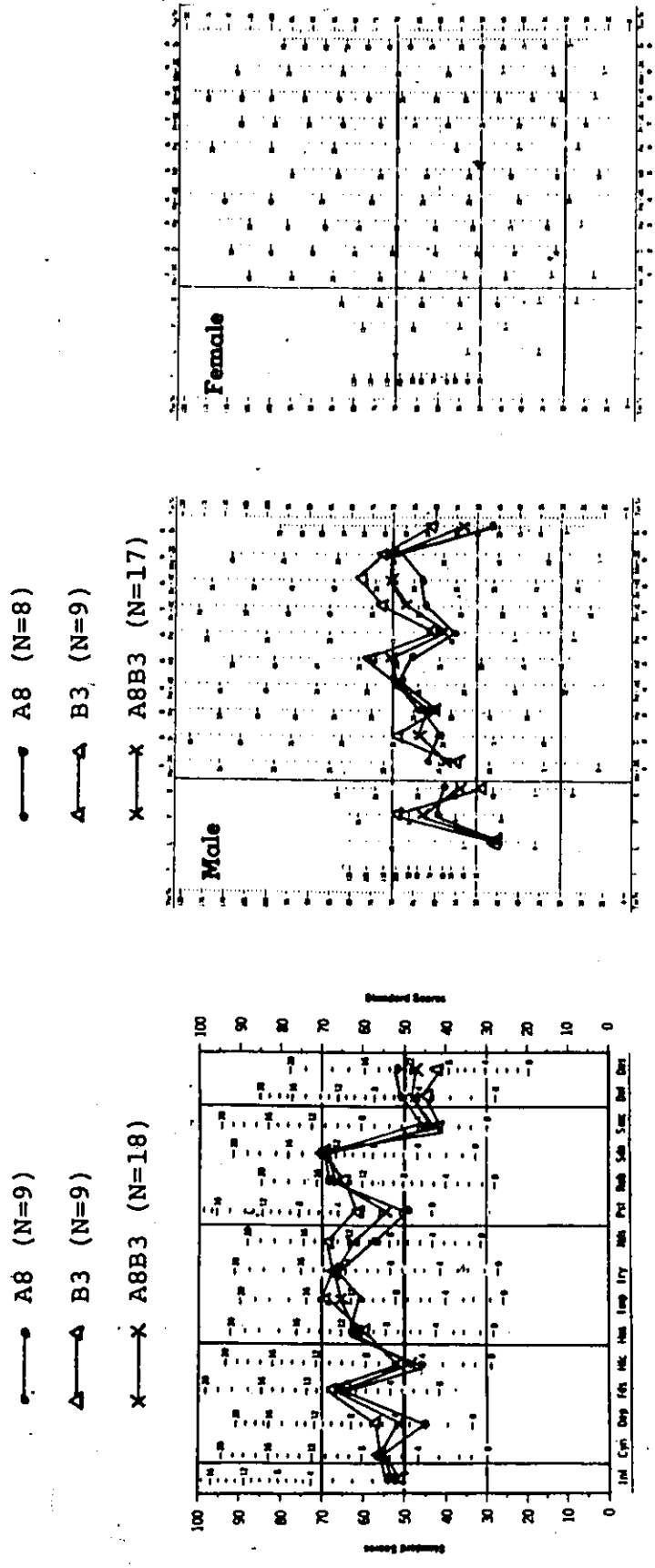


Fig. 2b: MPI Mean Profiles (Male)

Fig. 2a: DPI Mean Profiles

Figure 2: Cluster Type A8B3

Cluster Type A8B3

DPI profiles. Although cluster B3 appears to be slightly more elevated than A8. the profiles appear substantially the same with elevations on Socially Deviant Attitudes, Rebelliousness, Impulsivity, Irritability, Hostility, Familial Discord, and especially for B3, Neurotic Disorganization. Sociopathic deviancy probably associated with behavioural acting out is a simplified description but consistent with the obtained pattern.

MMPI profiles. The descriptions from the three atlases were generally consistent with each other and with the DPI results, namely sociopathy, behavioural acting out and particularly for B3 which is more elevated on D and Sc, some emotional disorganization. This latter supports the generally higher elevations for B3 on the DPI noted above.

Other information. This cluster type is composed entirely of males, nine from each cluster. Additionally, they were all university students attending the psychological centre, but again their status (i.e. in therapy or not in therapy) was not available.

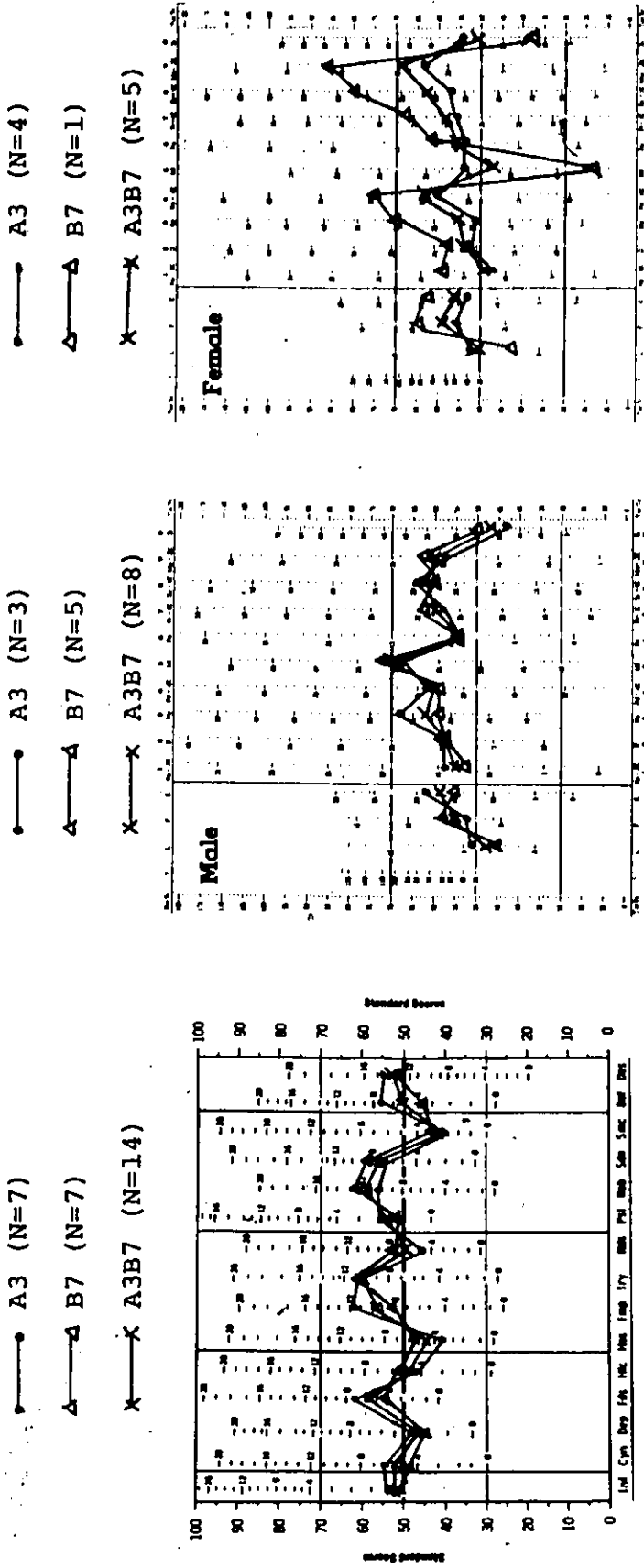


Fig. 3a: MPI Mean Profiles

Fig. 3b: MPI Mean Profiles (Male)

Fig. 3c: MPI Mean Profiles (Female)

Figure 3: Cluster Type A3B7

Cluster Type A3B7

DPI profiles. Although the r value between A3 and B7 is not sufficient to consider replication in terms of profile shape, the r_p value and Figure 3a indicate that these clusters are still remarkably similar. While there are some profile peaks, e.g. Familial Discord, Irritability, Rebelliousness, and Socially Deviant Attitudes, none of the elevations are sufficiently high to justify a detailed clinical interpretation. This cluster appears to be generally "normal"; the elevations might be expected to occur among somewhat dissatisfied university students who would tend to be more open regarding admission of socially deviant attitudes and behaviour, and rebelliousness.

MMPI profiles. With the exception of the one female in B7, none of the profiles are elevated enough to permit the use of the atlases or to warrant a definitive clinical diagnostic label. The closest approximation obtained from Hathaway and Meehl (1952) is that of a college student suffering from feelings of inferiority, simple maladjustment and emotional instability.

Inspection of Figure 3c reveals that the extreme scores of the single B7 female do in fact follow the same general pattern as those females from A3, namely peaks at Ma and Pd. Combined with the very low Mf scale, this pattern suggests that this female might be more aggressive in acting out her rebelliousness and social deviancy.

Other information. The three males and four females

from A3 and the six males and one female from B7 composing the cluster type were all university students attending the psychological centre.

6

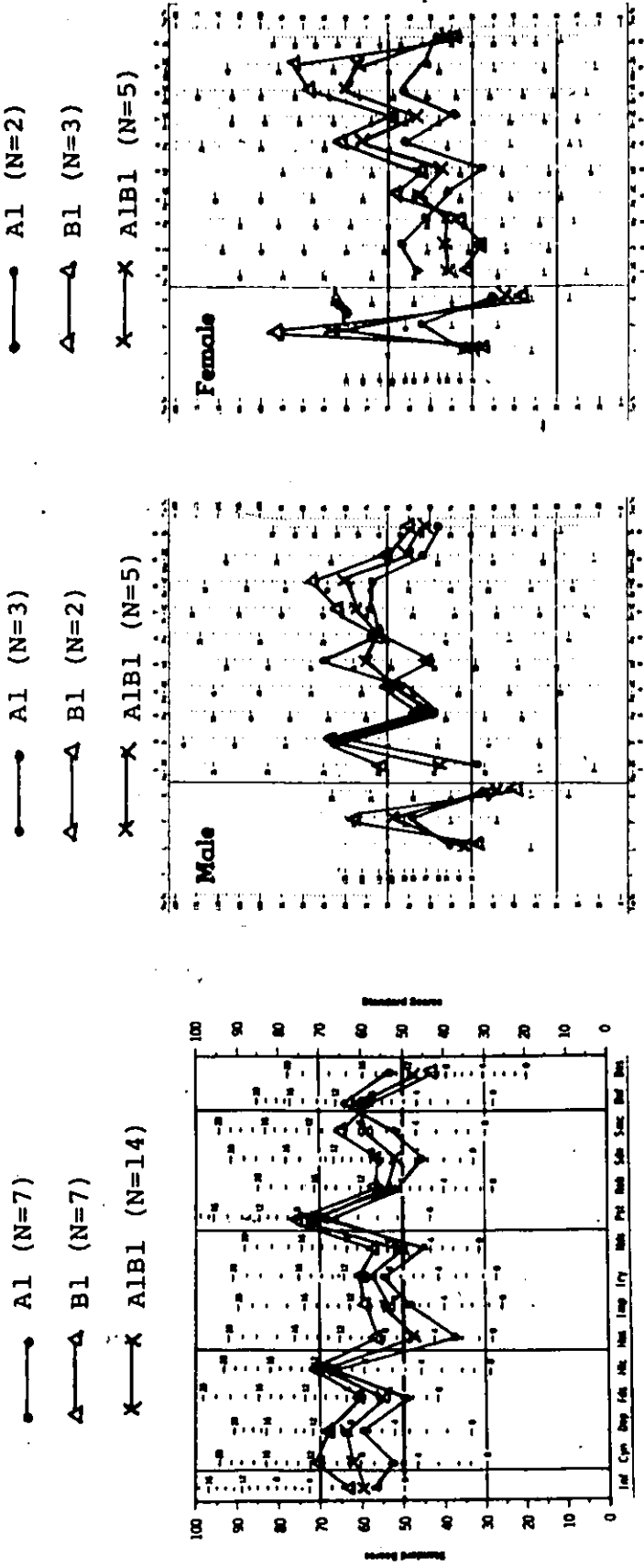


Fig. 4a: DPI Mean Profiles

Fig. 4b: MMPI Mean Profiles (Male)

Fig. 4c: MMPI Mean Profiles (Female)

Figure 4: Cluster Type A1B1

Cluster Type AlB1

, DPI profiles. It is clear from the differences in elevation yet similar shapes of the Al and B1 profiles why only the r value supports the notion of replication. Both clusters share high scores on Health Concern, Psychotic Tendencies and Defensiveness. However, in addition B1 is also elevated on the Cynicism, Somatic Complaints, Depression and Infrequency scales. The pattern suggests some form of psychosis or severe neurosis related to feelings of physical or health problems, experienced more severely by B1 subjects than Al.

MMPI profiles. Again the higher elevation of the B1 cluster is evident for both males and females, even though the patterns for both Al and B1 are similar. All three atlases provide a diagnosis of depressive reaction in a schizoid personality for both males and females of Al. However, the extremely high F scores in B1 for both sexes, which coincide with the high DPI Infrequency score for this cluster, suggest a need for caution in interpreting this cluster. However, if one takes these validity scale patterns as being indicative of severe disturbance, the appropriate diagnosis compiled from the atlases suggests schizophrenia with depressive and hypochondriacal tendencies for the B1 males and manic-depressive psychosis, manic type, for the females. Thus while there is some deviation between Al and B1 clusters, the above descriptions appear to coincide sufficiently to support the notion of a cluster type.

Other information. As would be expected from the scale elevations (i.e. severity of disturbance) three of the four males and all three females from A1, and the three males and four females from B1, were psychiatric inpatients.

●— A4 (N=2)
 ▲— B4 (N=6)
 X— A4B4 (N=8)

●— A4 (N=2)
 ▲— B4 (N=2)
 X— A4B4 (N=4)

●— A4 (N=6)
 ▲— B4 (N=8)
 X— A4B4 (N=14)

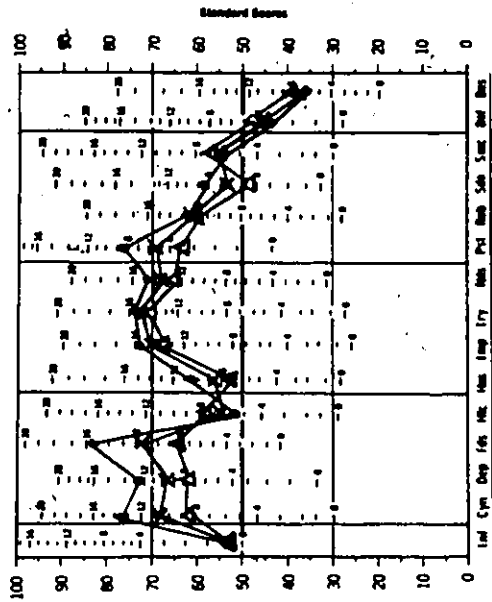
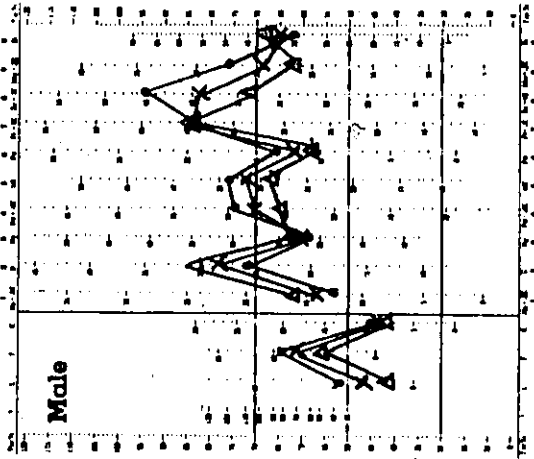
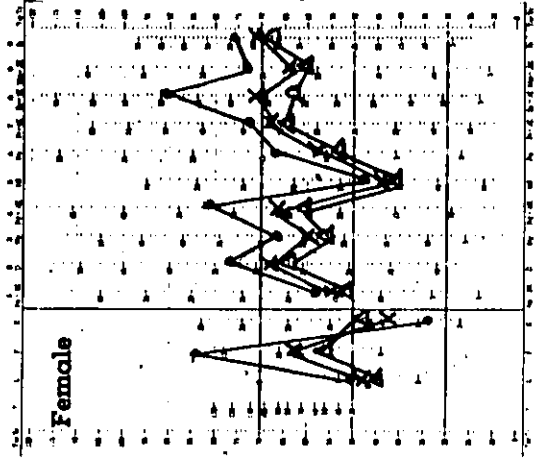


Fig. 5a: DPI Mean Profiles

Fig. 5b: MPI Mean Profiles (Male)

Fig. 5c: MPI Mean Profiles (Female)

Figure 5: Cluster Type A4B4

Cluster Type A4B4

DPI profiles. Again, disparity in elevation and similarity in shape are evident for A4 and B4 (Figure 5a). The clusters share high scores on nearly half of the scales - Cynicism, Depression, Familial Discord, Impulsivity, Irritability, Neurotic Disorganization and Psychotic Tendencies, and in addition, they are equally low on Desirability. This is certainly a cluster type characterized by severe disturbance with A4 more acutely disturbed than the B4 group

MMPI profiles. The differences in severity yet similarity in type of disturbance are supported by the profiles in figures 5b and 5c. The A4 mean profiles for both males and females are consistently higher than the corresponding B4 profiles. The atlas interpretations for the male and female profiles within the clusters are similar - A4 may be described as a borderline psychotic type characterized by obsessional thinking, B4 as a psychoneurotic type characterized by anxiety, and consistent with A4, obsessional depression.

Other information. Two of the three females in A4 were psychiatric inpatients and one of the three males was in therapy at the psychological centre. The two males and six females of B4 attended the centre but their treatment status is unknown.

CHAPTER IV

DISCUSSION

The fifteen clusters emerging from the classificatory procedure included 35% of the total subject sample (N=300), 36% of Sample A (54/150), and 34% of Sample B (51/150). The identified replicated cluster types accounted for only 24% of the entire sample (72/300). While these figures are low, the tendency for complete linkage clustering strategies (e.g. Johnson's Maximum Method, 1967) to leave less easily affiliated O.T.U.'s unclustered, accounts for these results to some extent. It would thus seem appropriate to refer to the obtained cluster types as "core types" for a taxonomy of psychopathology, and to consider the present study as an initial step in the discovery of a potentially more comprehensive system. Towards this end, a second stage would be to resubmit the two subsamples to a cluster analysis (in the sense of Lance and Williams, 1967b) using the obtained core types as the initial data partition. It would be expected that such a reallocation technique would discover the best partitioning of the data and include a much larger proportion of the O.T.U.'s (see Wishart, 1972).

However, the results of this admittedly exploratory study do support the notion that a stable i.e. replicable taxonomy of psychopathology can be approached using sophisticated mathematical techniques and a psychometrically

rational data base. In general, the hypothesis that the two initial subject samples, psychiatric inpatients and university psychological centre referrals, would be distinguished from one another is supported. The core types whose profiles were indicative of relatively severe psychiatric disturbance contained more inpatients and students in therapy than the types evidencing fewer problems. This is especially noticeable when type A3B7 is contrasted with type A1B1. The description accompanying the former type composed only of university students suggests normalcy, while the description for the latter type, composed almost entirely of hospitalized subjects, indicates schizophrenic disturbance of varying intensity. To some extent these results simply provide support for the discriminatory capacity of the Differential Personality Inventory. However, the fact that the distinctions are maintained by the statistical techniques employed, bodes well for an automated approach to taxonomy and eventually diagnosis.

One of the features of the present study was the use of an additional inventory, independent of that used in the analysis, to provide cluster descriptions. While the definitions of the core types provided by the MMPI profile interpretations are not nearly as clear cut as would be desirable for a concise taxonomy, the results are generally supportive of distinct psychopathological types. The problems encountered during the interpretive process have already been noted. One obvious partial remedy would be to replicate the

present study using a much larger subject sample. The cluster type descriptions presented in the previous chapter should not be taken as definitive or complete. The approach used was, at best, rudimentary, and the atlases employed are somewhat restrictive in their descriptive capacities i.e. flexibility within and extrapolations from the profile types they present are limited and prone to possible misinterpretations. One means of clarifying the obtained core types would be to propose and test hypotheses related to the existing descriptions e.g. behavioural indices or expected responses to treatment (e.g. Carlson, 1970).

An overly generalized summary of the five identified core types reveals one largely normal group (A3B7), one sociopathic group (A8B3), one antisocial, paranoid group (A2B5), one depressive schizoid group (A1B1) and one psychotic-psychoneurotic obsessional group (A4B4). An inspection of Tables 4a and 4b suggests that those clusters not considered to be replicated by the present study, are nevertheless related to the identified types. For example, A6 has an \underline{r}_p of .77 and an \underline{r} of .75 with B3 which was instead affiliated with A8 ($\underline{r}_p = .81$, $\underline{r} = .85$). Similarly, B2 and B6 are most similar to A3 ($\underline{r}_p = .75$, $\underline{r} = .63$ and $\underline{r}_p = .61$, $\underline{r} = .58$, respectively). A7 appears to be moderately related to a number of the B clusters in Table 4a, and somewhat correlated to B5 (see Table 4b). A tentative explanation is that these, for now, unclustered groups constitute sub-types of the identified core types, but investi-

gation of this is beyond the scope of the present study.

A number of negative correlations with high absolute values appear in Table 4b. Typically, such r values, for example, between two scales, indicate a strong negative relationship such as polar opposites on a single dimension. However, when negative relationships occur based on multi-dimensional comparisons, as in the present study, interpretation is obscured. An r value of $-.84$ (A1B3), means that where DPI scales for one cluster are elevated, the same scales are depressed for the other cluster, and vice versa. If the description of the one cluster included schizoid reactive depression (A1), it is not immediately clear what a polar opposite type would be or if in fact this is a meaningful way to interpret such a correlation. In fact, the description for B3 refers primarily to sociopathic tendencies. While this is difficult taxonomic terrain, further exploration may reveal viable theoretical advances in the area of dimensions of psychopathology beyond that traditionally recognized set of polar opposites i.e. manic-depressive psychosis.

At this point one further potential methodological modification should be mentioned. To establish cluster replicability, Carlson (1970) resubmitted the clusters emerging from his two subsamples to his clustering programme. Those clusters which joined from each subsample were considered to constitute replicated types. Such an analysis of the present data should substantiate those types identified in

Table 4a and perhaps elaborate the hypothetical subtypes previously discussed. Since correlation is inappropriate as an index of similarity in cluster analysis, it is unlikely that types identified solely on the basis of \underline{r} values (i.e. A1B1, A4B4) would be included.

It is notable that where inter-cluster relationships based on \underline{r}_p are strong (e.g. A2B5; A8B3), the correlational data substantiates the replication. In other words, all components of phenetic similarity are accounted for. However, as the similarities decrease, certain components' contributions are correspondingly diminished - in the case of A3 and B7, these two clusters are only moderately similar in shape ($\underline{r} = .30$) yet \underline{r}_p remains high (.80). Conversely, the types based on shape only (A1B1, $\underline{r} = .65$; A4B4, $\underline{r} = .68$) have moderate \underline{r}_p values, .35 and .57 respectively. Unless one is willing to limit the replication of types to strongly related clusters, which is indeed the ideal case, two stage procedures such as Guertin. (1966) and Carlson (1970) employ have merit in pinpointing the relative contributions of the phenetic components of cluster similarity.

Beyond the refinements suggested above for deriving an automated cluster analytic taxonomy of psychopathology, much research is possible and decidedly necessary. Since the objective is to establish the clearest, most meaningful and efficient system, comparisons between cluster analytic techniques and other methods e.g. factor analysis, are in order. In fact a number of permutations and combinations arising

from the selection of characters, similarity indices and grouping methods are conceivable. Further, once a taxonomy has been established, an entire second phase of clinical diagnosis remains to be explored, namely, the identification of new cases as belonging to one type or another. Morf and Krane (1973) have proposed a strategy for such research. They also consider the possibility of discovering dimensional variations within types i.e. a marriage of Cattellian and Eysenckian theories of personality structure.

It is evident that the development of viable, consistent taxonomies is a complex procedure. Single step approaches are simply inadequate. The results of the present study certainly provide an optimistic view of the possibility of sophisticated, automated systems of psychopathological diagnosis and prediction but much remains to be done.

Summary

The present study was an exploratory attempt to develop a taxonomy of psychopathology using an automated hierarchical clustering technique. A review of the literature pertaining to clinical and actuarial diagnosis of psychopathology revealed a large gap between the inadequacies of existing taxonomic systems and the sophisticated mathematical and psychometric techniques available. Using a strategy suggested by Morf and Krane (1973), but refined in the light of current research in the field of numerical taxonomy (e.g. Sneath & Sokal, 1973), two equal subsamples of moderately hetero-

geneous psychiatric population were clustered using their scores on thirteen DPI scales (Jackson & Carlson, 1969) as input characters, a metric similarity index - r_p (Cattell, 1949), and a hierarchical, complete linkage clustering algorithm (Johnson's Maximum Method, 1967). The eight clusters derived from Sample A and seven from Sample B were then compared, using intercluster r_p 's and r 's between DPI mean profiles, to assess across-sample replicability. Five "core types" were identified, two replicated on the basis of all three components of phenetic similarity - elevation, shape and scatter; one primarily on the basis of elevation and scatter, and two primarily on the basis of shape. These core types were then described using MMPI mean profiles for each cluster, independent of the data used to form the clusters. The results suggested that while the core types only accounted for a small portion of the initial sample, they did in fact constitute relatively distinct taxonomic types ranging from normality to overt psychosis. Methodological and conceptual improvements to and extensions from the present study were discussed in the light of the results and research proposed by others. It was concluded that while the present study is a positive first step, establishing a reliable taxonomy of psychopathology with clear meaning and capacity for automation is a complex process requiring further intensive exploration.

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FOOTNOTES

- 1 Taxonomy has been defined by Simpson (1961) as "the theoretical study of classification, including its bases, principles, procedures and rules (p.11)".
- 2 1973 version of Johnson's programme HICLUST developed at the Bell Telephone Laboratories, Murray Hill, New Jersey.

APPENDIX A
An Example of Hierarchical Clustering
using Johnson's Methods (1967)

JOHNSON (1967) EXAMPLE

(Note: The new "similarity function" hinges on the ultrametric inequality.)

MORF AND KRANE (1972) MATRIX (d = DC =, 1 - SC):

	2	3	4	5	6	7
1	80	70	10	38	79	57
2		80	70	23	37	90
3			41	89	71	24
4				48	51	62
5					16	50
6						91

MINIMUM METHOD

Steps of the clustering procedure

1. C_0 Minimal value of $d = \alpha_0 = 0$

Weak clustering, each O.T.U. forms a cluster.

1 2 3 4 5 6 7
.....

2. C_1 $\alpha_1 = 10$ (1,4)

1 4 2 3 5 6 7
XXX.....

3. New "similarity function" (DC,d) by:

$$d([x,y], z) = \min[d(x,z), d(y,z)]$$

(Monotone invariant transformation, unlike average of the two d's - ordinal data are assumed)

	2	3	5	6	7
(1,4)	<u>70</u>	<u>41</u>	<u>38</u>	<u>51</u>	<u>57</u>
2		80	23	37	90
3			89	71	24
5				16	50
6					91

4. $C_2 \quad \alpha_2 = 16 \quad (5,6)$

1 4 5 6 2 3 7
 XXX·XXX·.....

5. New d:

	(5,6)	2	3	7
(1,4)	<u>38</u>	70	41	57
(5,6)		<u>23</u>	<u>71</u>	<u>50</u>
2			80	90
3				24

6. $C_3 \quad \alpha_3 = 23 \quad [(5,6), 2]$

1 4 5 6 2 3 7
 XXX·XXXXX·....

7. New d:

	(5,6,2)	3	7
(1,4)	<u>38</u>	41	57
(5,6,2)		<u>71</u>	<u>50</u>
3			24

8. $C_4 \quad \alpha_4 = 24 \quad (7,3)$

1 4 5 6 2 3 7
 XXX·XXXXX·XXX

9. New d:

	(5,6,2)	(3,7)
(1,4)	38	<u>41</u>
(5,6,2)		<u>50</u>

10. $C_5 \quad \alpha_5 = 38 \quad [(1,4), (5,6,2)]$

1 4 5 6 2 3 7
 XXXXXXXXXXX·XXX

11. New d:

	(3,7)
(1,4,5,6,2)	<u>41</u>

1 4 5 6 2 3 7
 d_0
 d_1 XXX·.....
 d_2 XXX·XXX·.....
 d_3 XXX·XXXXX·....
 d_4 XXX·XXXXX·XXX
 d_5 XXXXXXXXXXX·XXX
 d_6 XXXXXXXXXXXXXXXX

MAXIMUM METHOD

Steps of the clustering procedure

- 1.
- C_0
- Minimal value of
- $d = \alpha_0 = 0$

Weak clustering, each O.T.U. forms a cluster.

1 2 3 4 5 6 7
.....

- 2.
- C_1
- $\alpha_1 = 10$
- (1,4)

1 4 2 3 5 6 7
XXX.....

3. New similarity function by:

$$d([x,y], z) = \max[d(x,z), d(y,z)]$$

	2	3	5	6	7
(1,4)	<u>80</u>	<u>70</u>	<u>48</u>	<u>79</u>	<u>62</u>
2		80	23	37	90
3			89	71	24
5				16	50
6					91

- 4.
- C_2
- $\alpha_2 = 16$
- (5,6)

1 4 2 3 5 6 7
XXX.....XXX..

5. New d:

	(5,6)	2	3	7
(1,4)	<u>79</u>	80	70	62
(5,6)		<u>37</u>	<u>89</u>	<u>91</u>
2			80	90
3				24

- 6.
- C_3
- $\alpha_3 = 24$
- (7,3)

1 4 5 6 2 7 3
XXX.XXX...XXX

7. New d:

	(5,6)	(7,3)	2
(1,4)	79	<u>70</u>	80
(5,6)		<u>91</u>	37
(7,3)			<u>90</u>

8. $C_4 \quad \alpha_4 = 37 \quad [(5,6), 2]$

1 4 5 6 2 7 3
 XXX·XXXXX·XXX

9. New d:

	(5,6,2)	(7,3)
(1,4)	<u>80</u>	70
(5,6,2)		<u>91</u>

10. $C_5 \quad \alpha_5 = 70 \quad [(1,4), (7,3)]$

1 4 7 3 5 6 2
 XXXXXXXX·XXXXX

11. New d:

	(5,6,2)
(1,4,7,3)	<u>91</u>

1 4 7 3 5 6 2
 α_0
 α_1 XXX.....
 α_2 XXX.....XXX..
 α_3 XXX·XXX·XXX..
 α_4 XXX·XXX·XXXXX
 α_5 XXXXXXXX·XXXXX
 α_6 XXXXXXXXXXXXXXXX

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3. Marker, Social Psychology Extension Course - Sept. 1970 -
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Post Graduate:

1. Researcher and Co-Author - Government of Ontario Project #17 - "Indian Education in Ontario" - July - Sept. 1971
2. Research Assistant, Social Psychology, University of Windsor - Sept. 1971 - April 1972
3. Co-Therapist, Adolescent outpatient group, Windsor Western Hospital Centre Regional Children's Centre, Windsor, Ontario - January - April 1972
4. Volunteer Counsellor and Programme Assistant, Crossroads Residential Treatment Centre for adolescent drug abusers, R.R.#2, Essex, Ontario - Sept. 1971 - August 1973
5. Coach, Vocational Preparatory Programme, Community Guidance Services, St. Clair College, Windsor, Ontario - August 1972 - August 1973
6. Vocational Rehabilitation Officer, Ministry of Community and Social Services, London, Ontario - since August 1974

THESIS:

1. B.A. - Some Aspects of Academic Success and Failure