SELECTION, TRAINING and CAREER DEVELOPMENT of NAVAL OFFICERS

A LONG-TERM FOLLOW-UP USING MULTIVARIATE TECHNIQUES

by

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VOLUME 2

FURTHER STUDIES

SELECTION, TRAINING and CAREER DEVELOPMENT of NAVAL OFFICERS

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PART 6

INTRODUCTION TO FURTHER RESEARCH

CHAPTER 22

SCOPE OF FURTHER RESEARCH

Introduction

1. In Volume 1 of this thesis a detailed account was given of a long-term follow-up of 520 candidates for Special Entry officer cadetships in the Royal Navy who appeared before the first six "new-type" Admiralty Interview Boards between 1947 and 1949.

2. Choice of sample was dictated by the requirement that all officers remaining in the service should have passed through the zone of promotion to Commander, since this promotion was used as the primary criterion of success.

3. A possible criticism of conclusions drawn from this research is that they relate to a selection procedure of twenty five years ago - an inevitable consequence of the choice of criterion. In order to assess the relevance of the findings in more recent samples two additional groups have been studied, one consisting of 252 candidates who appeared before Boards 7 to 10 in 1950/51 and the other consisting of 227 candidates interviewed in the year 1969/70.

4. The results of comparative analyses of the three groups are reported in this second volume, together with an exploration of methodology for co-relating the basic structures of data for the different samples for predictive purposes.

5. An account has also been included of some further research on interests, biographical and annual report data for the original sample.

Structure of Volume 2

6. Volume 2 is divided into three parts which together comprise an account of further research forming a logical development of the work reported in Volume 1. The parts, chapters and appendices of Volume 2 are consequently numbered in continuation from Volume 1.

7. Part 6 provides an introduction to the further research, an outline of the analyses reported, a description of the new data and an account of the methodology.

8. The investigations are described in Part 7. The first two chapters contain reports of further analyses of the primary group and may be regarded as explorations in greater depth of biographical, interests and annual report data. In each of these

areas the report in Volume 1 was curtailed in the interests of clarity of the long-term follow-up. Chapter 28 contains a description of the univariate analyses of the two new groups and is followed by a report of comparative studies of the primary and the two later groups. In Chapter 30 the condensation of selection data for all three groups using a three dimensional model is described. Examples of the use of these three dimensional scores for predictive purposes are given in Chapter 31.

9. The final Part contains two chapters, the first summarising the conclusions drawn from the further investigations and the second outlining general conclusions drawn from the entire research.

<u>Summary of Objective</u>

10. The aims of the research, already defined in Volume 1, were:-

a. To identify the abilities associated with training and career success (of naval officers).

b. To assess the effectiveness of the "new-type" selection procedure for determination of these abilities.

c. To determine the usefulness of various classes of data for predictive purposes.

d. To draw conclusions about the relevance of the findings to the current problems of selection and training.

11. Volume 1 is concerned with the first three of these aims, and Volume 2 chiefly with the last two. In this second volume the usefulness of biographical, interests and annual report data for predictive purposes is further examined and the relationship of recent selection data structure to that of the primary group is studied in depth.

OUTLINE OF FURTHER ANALYSES

1. The research described in this second volume falls into two main categories, the first being further studies of the primary group and the second being studies of the two later groups and their relationship to the primary group.

Further Analyses of the Primary Group

2. In Volume 1 it was suggested that the two dimensional structure of annual report data might be identified with the three dimensional structure of selection data by locating the "intelligence" axis in the cognitive plane and by identifying "social skills" with "personality" (see Vol. 1, p. 146, para. 29). This hypothesis was based on subjective reasoning and has been tested by principal component analysis to locate the composite S206 factor scores in the selection data structure. The results indicate that the hypothesis was incorrect and a further analysis has been undertaken to examine whether any meaningful "track" could be identified which would demonstrate the nature of time dependance of report markings when viewed in an ability structure. It was also hypothesised (Vol. 1, p. 157, para. 11) that for Engineer officers there is a substantial change of role in mid-career. The locations of composite S206 factor scores vectors relative to training and long-term success vectors support this hypothesis.

3. The possibility that Cluster Analysis of Interests data might yield useful results, although Principal Component Analysis had failed, was mentioned in Volume 1 (p. 108, para. 12). The results of a Cluster Analysis are reported in Chapter 27 and whilst they are strikingly similar to those of the Principal Component Analysis they confirm the unsuitability of the data for predictive purposes.

4. The relationship between Cluster Analysis and Principal Component Analysis models has also been investigated for the Biographical data and again there is a close similarity but because of low inter-correlations between Biographical variables the clustering does not yield meaningful groups.

Analyses of Later Groups and their Relationship to the Primary Group

5. The univariate analyses of the two later groups (ie candidates of selection boards 7 to 10 and 1969/70) provide a convenient means

of setting the scene for the subsequent research, by defining the sample characteristics, and are reported in Chapter 28.

6. Comparisons of the three groups have been made by means of both univariate statistics and the results of Principal Component Analyses. The latter indicated a high degree of consistency between groups and the likelihood that three dimensional Factor models of the groups could be derived and co-related to provide, for each individual, a score on three basic variables representative of his ability as measured at selection.

7. In Chapter 30 the Factor-Analytic procedure adopted for condensation of the selection data to three dimensions is described, together with the subsequent rotations to align the models for the three groups. The factor scores derived for each individual are used as data for the predictive studies described in Chapter 31. Examples are given of both Regression and Discriminatory predictions using the condensed data and of the refinement of the predictors by inclusion of biographical data and results of early training. This work, which may be seen as a logical development of an aspect of the primary research which was curtailed for the reasons given in Volume 1, p. 143, para. 15, illustrates the power of combinations of descriptive and predictive techniques and provides further evidence in support of the hypothesis that use of a common selection criterion for all branches is inefficient.

CHAPTER 24

ADDITIONAL DATA

1. The three groups on which further research has been completed, together with associated variables, are defined below.

Group A

2. The group studied in the primary investigations reported in Volume 1 is defined as Group A for reference purposes in further investigations. This group, which embraces samples X, E, S and F, consists of 520 candidates of the first six "new-type" selection boards held between 1947 and 1949. Use of this group enabled career performance to be followed up over a period of about 20 years and promotion to Commander (the first selective promotion) to be used as part of the criterion of long-term success.

3. Further studies of this primary group are reported in Volume 2 and some new variables have been introduced. These are defined as follows:-

STATUS = (7 - F.OCC), a measure of paternal socio-economic status varying from 0 for unskilled manual to 6 for professional and high administrative.

S.TRG = (14 - T.LCDR), a measure of overall success in training defined by the award of seniority gained.

Clustered Biographical Variables:-

BA = PREF + GAMES + CORPS

BB = SOCS + PR.ATT + ON.CH.

BC = PAR.DD + FAT.RN

BD = F.ARMY + HMC.SC + B.PREF

Clustered Interest Variables:-

EAA = MUSIC + THEATRES + READING + POLITICS

EAB = TRAVEL + PEOPLE + ORGANISING + CHILDREN

EBA = LISTENING + CINEMA + ANIMALS + DANCING + PARTIES

EBB = SPORTS + SCIENCE

IAA = ART GALLERIES + DRAWING + MUSEUMS + WRITING + RELIGION

IAB = COUNTRY + GARDENING + DOMESTIC

IBA = COLLECTING + PHOTOGRAPHY + SAILING

Condensed Selection Variables:-

P   a composite measure of "personality"

M   a composite measure of "mechanical ability"

V   a composite measure of "verbal ability"

4. The clustered biographical and interests variables and the condensed selection variables are derived from analyses which are described in detail in Part 7.

Group B

5. Group B consists of 252 candidates who appeared before selection boards 7 to 10 in 1950 and 1951. Of these 90 were accepted and 162 rejected.

6. Not all members of the group have yet passed through the promotion zone and consequently only the selection data has been analysed. The variables used are identical to those used for Group A with the exception that B.MARK was assessed out of 400 instead of 300. This change of scaling is not important from an analytical viewpoint since all data is standardised before processing. The change may well have had an effect on the ranking of candidates however. This is investigated in Chapter 30.

Group C

7. To enable the characteristics of the selection process used for Groups A and B (ie when the "new-type" board was introduced) to be compared with current characteristics (ie 25 years later) a third group, defined as Group C, has been studied.

8. This group consists of 227 candidates who appeared before the selection board in 1969/70, of whom 89 were accepted.

9. The variables used for this group are defined as follows:-

GT35 and SP21	as before
SP70/23	Matrices test of general intelligence
SP R(E)	Arithmetic and Algebra speed and accuracy test
VMD	Vincent's Mechanical Diagrams - a simplified version of SP160
B.MARK	Aggregate Board Mark out of 1000
AGE	Age at selection in months over 17 years

10. The age range of candidates in this group is considerably greater than in the two earlier groups since it includes candidates for Direct Entry, University Cadet Entry and Graduate Entry.

11. The selection procedure applicable to this group differs from that for Groups A and B to the extent that the competitive Civil Service Commission examination has been replaced by a minimum "A level" requirement. Consequently the sole contribution to selection ranking in Group C is the judgmental board mark.

CHAPTER 25

METHODOLOGY

1. An outline of the further studies has been given in Chapter 23. The techniques used in these studies are to a large extent similar to those described in Volume 1, namely Principal Component Analysis, Factor Analysis, Multiple Regression Analysis and Discriminatory Analysis.

2. An additional technique, used in the further study of biographical and interests data, is Cluster Analysis. Many clustering routines are available. The computer programmes used in this case were developed by R. Newport who has described the routine as follows:-

Description of "Profile Clustering"

The clustering system is a divisive one which splits the items considered into two groups on each occasion. It is applied to a matrix of correlations between items by forming the correlation between rows (or columns) of the matrix. This modified powering is continued until there is a fixed pattern of signs. If continued to the limit it leads to a correlation matrix with elements ± 1 of rank 1. The items are divided into two groups so that items in the same group have positive correlations in the limit matrix.

The limit has not been proved algebraically but observed in several instances. There are some other limiting possibilities as when the initial matrix is a diagonal one.

The plausibility of the limit rests on the analogy to powering of the matrix which also leads to a limiting matrix of rank 1. The only correlation matrices of rank 1 are patterned ones with elements ± 1.

The plausibility that it will produce reasonable clusters is based on the idea that if two items are similar to one another they should have similar patterns of similarities with the other objects. The actual levels, however, are subject to masking by noise elements. Correlation is then a reasonable measure for filtering out the effect of the noise and measuring the similarity between rows of the matrix.

3. The methodology used in Chapters 30 and 31 is of particular interest since it relies on a combination of descriptive and predictive techniques (Factor Analysis and both Multiple Regression and Discriminatory Analysis) to provide co-relation of samples for predictive purposes. The procedure consists essentially of the following stages:-

a. Derivation of three dimensional models of the selection variables for each of the three groups using Factor Analysis.

b. Alignment of the three models by rotation onto common axes labelled P, M, V (composite measures of "personality", "mechanical ability" and "verbal ability").

c. Derivation of P, M, V scores for all candidates.

d. Calculation of Regression and Discriminatory functions for Group A using P, M, V scores.

e. Application of predictor functions to Groups B and C.

4. The rotation of factor models used in the above and also in the analysis of S206 data (Chapter 26) relies on the transformation:-

$$Y_t = T^{-1} (A'A)^{-1} A'Z$$

Where A and Z have the same meaning as in Volume 1, p. 68, para. 11, T is the matrix of direction cosines of old versus new axes, and Y_t is the matrix of factor scores relative to the rotated axes. The derivation of appropriate rotations is described in the chapters concerned.

PART 7

R E P O R T   O F   F U R T H E R   I N V E S T I G A T I O N S

CHAPTER 26

FURTHER STUDIES OF THE PRIMARY GROUP - ANNUAL REPORT DATA

1. The nature of annual report data for Group A and the results of its analysis have been described in Volume 1, Chapters 10 and 17 respectively.

2. The analysis showed that the data available in the form of S206 markings could be adequately represented on a two dimensional factor-analytic model, ie that the marks recorded on each report on the five or ten personal qualities (pre '60 or post '60) could be condensed into pairs of factor scores in each case.

3. For sample E, the engineer officers of Group A, the two-factor scores for each of four pre-'60 reports were condensed by means of a further factor analysis into one pair of factor scores defined as F1 and F2. Similarly the two-factor scores for each of four post-'60 reports were condensed into a pair of factor scores defined as F1A and F2A. Thus, for any individual, the F1, F2 score represents a condensation of all the marks on four pre-'60 reports, and the F1A, F2A scores represent a condensation of all the marks on four post-'60 reports.

4. These scores were used as predictors in discriminatory and multiple regression analyses reported in Volume 1, Chapters 18 and 19 but no attempt was made in the primary investigations to locate the F1, F2, F1A, F2A vectors in the structure of selection and training variables. A report of a Principal Component Analysis for this purpose is given below.

Location of Condensed Annual Report Vectors for Sample E in Selection and Training Data Structure

5. In Volume 1, Chapter 15 a series of Principal Component Analyses was reported with the object of providing a set of success/ability models to illustrate the inter-relationships of the various types of data and to provide a conceptual basis for the predictive studies.

6. The results of analysis of the E sample were reported on page 93 and illustrated in Figure 15.5. These showed that, in this sample, the vectors representing both training success and long-term

success, when plotted in the three-space of the first three principal components, all lay in a discoid cluster close to the cognitive plane containing the vectors of V:ED and K:M, and that the B.MARK vector was orthogonal to this plane.

7. A further Principal Component Analysis of this sample has been completed with the condensed Annual Report scores F1, F2, F1A, F2A included among the variables. The sample size was reduced to 78 to avoid observations with missing values in the annual report data. Thus all officers who left the service before achieving four years service as Lieutenant Commander were eliminated.

8. The results of the analysis are tabulated in Appendix 15 and are illustrated in Figure 26.1. As before the diagram is confined to projections of the first three principal components.

9. Comparison of Figures 26.1 and 15.5 reveals that, in spite of the further truncation of the sample, the structure of selection, training and success vectors is almost identical. Again the cognitive discoid and the orthogonal B.MARK are clearly apparent.

10. The vectors of F1, F2, F1A and F2A all lie in the cognitive discoid as is clearly shown in the three dimensional model illustrated in Figure 26.2. The locations of the vectors confirm the hypothesis in Volume 1, p. 157, para. 11 that there is a substantial change of role in mid-career. The F1, F2 vectors are more closely related to training results and the F1A, F2A vectors to S.INDB.

11. The high cognitive loadings of F1, F2, F1A, F2A suggest that the hypothesis in Volume 1, p. 113, para. 25, ie that "social skills" may be identified with "personality" as measured by B.MARK, is incorrect. It is unlikely that the time-condensed variables, F1, F2, F1A and F2A, would all lie so close to the cognitive plane if the variables from which they were derived, ie F1T1 to F2T8, could be considered as vectors in a plane spanning between B.MARK and the cognitive plane.

12. The location of the four annual report variables relatively close together in the cognitive discoid suggests that there is a pronounced halo effect in reporting, all marks being influenced to a considerable extent by the individuals' intelligence. A fuller investigation of this is reported below.

13. In Volume 1, Chapter 17 a series of principal component analyses on the annual report data for samples X, E and L showed that in each case a two dimensional model should give a good account of the inter-relationships between markings of the individuals' qualities.

14. In the case of sample E the adequacy of two dimensional representation was confirmed for both pre-'60 and post-'60 reports by means of Factor Analysis (see Volume 1, Figure 17.2).

15. In order to confirm the adequacy of two dimensional models for X and L samples, to assess whether the models for different samples were similar, and to investigate whether time-dependancy of markings could be detected in any of the samples (E, X or L), a set of six factor analyses was completed, one for pre-'60 data, and one for post-'60 data, for each of the samples.

16. For these analyses the variables TIMREP and REP.SD were included with the personal qualities. Definitions of these variables are given in Volume 1, p. 51, para. 5. The former is a measure of the timing of the report relative to the time of promotion of the individual concerned to Lieutenant Commander. The latter is a measure of the degree to which markings of individual qualities depart from the mean, ie the spread of marking.

17. The results of these six analyses are tabulated in Appendix 16 and illustrated in Figures 26.3 to 26.8. In each case the "residuals" follow a pattern similar to that found for the E sample and reported in Volume 1, p. 111 and it is therefore deduced that the two dimensional models give a satisfactory account of the inter-relationships between variables.

18. The communalities of the variables representing reported qualities are relatively high but the communality of TIMREP is, in each case, substantially lower. This implies that only a small proportion of the variance of the variable representing "time of report" is common to the two-space of the reported qualities, ie that models giving a fuller account of the time element would require at least one additional dimension, uncorrelated with the domain of the reported qualities. Nevertheless the common variance is substantial, the coefficients of correlation of TIMREP with each of the reported qualities being "very highly significant" in all three samples.

19. The structures of the models for samples E and L, the two technical groups, are strikingly similar. In the pre-'60 models TIMREP is closely associated with M.QUAL, showing a tendency for markings of "Intelligence" to develop with time to a greater extent than "Social Skills". In the post-'60 models there is substantially more tendency for "Social Skills" to be time dependant.

20. In the X samples this change does not occur; "Intelligence" markings being more time dependant in both pre-'60 and post-'60 models.

21. The location of vector REP.SD relative to vectors of reported qualities shows the degree of inter-dependance of level of marking and range of marking. In all cases the correlation is low and for the "Social Skills" vectors is negative, ie the higher the "Social Skills" marking the less the range of marks.

22. The relative locations of REP.SD and TIMREP vectors show that there is a small but consistent tendency for range of marking to increase with time in the pre-'60 reports (ie during Lieutenancy). There is, however, a marked tendency for spread of marks to decrease with time in post-'60 reports (ie during pre-zone service as Lieutenant Commander). This indicates an increasing halo effect as officers approach the promotion zone.

23. The clear evidence of time dependancy of report marking, coupled with the low communality of TIMREP prompted a deeper investigation to examine the relationship of the "time-track" of markings in the ability structure. This analysis is described below.

Investigation of Time-Track of Report Markings in Ability Structure for Sample E

24. In Volume 1, p. 112 the derivation for sample E of sixteen variables, which were labelled F1T1 to F2T8, was described. The scores on these variables are two dimensional condensations of the raw report scores for eight reporting occasions for each individual.

25. The scores were derived by means of the transformation:-

$$Y = A'Z$$

Where Z is the matrix of normalised observations, A is the factor loading matrix and Y is the matrix of "factor scores". (See also Volume 1, p. 68, para. 11.)

26. It is more meaningful to apply the transformation:-

$$Y = (A'A)^{-1} A'Z$$

the scores so obtained being the estimate which best accounts for the original observations on a regression model.

27. It is also helpful, from the point of view of facilitating interpretation of results, to rotate the factor axes to definable directions. In this case an obvious choice is the pair of vectors at the extremes of the two dimensional model, namely "intelligence" and "Social Skills" (see Volume 1, p. 110, para. 7).

28. The transformation required for oblique rotation of axes is:-

$$Y_t = T^{-1}Y$$

where Y_t is the matrix of factor scores on the rotated axes and T is the matrix of direction cosines of old versus new axes.

Thus the total transformation becomes:-

$$Y_t = T^{-1} (A'A)^{-1} A'Z$$

This transformation was calculated for both pre-'60 and post-'60 Sample E models using the values for A given in Volume 1, Table App. 11.2 and the following values for T:-

Pre-'60		Post-'60	
.94	.92	.82	.97
-.34	.38	-.57	.24

(Note: This is an oblique rotation to axes defined as "Intelligence" and Social Skills".)

29. To simplify the task of locating the time-track in the ability structure a total of six reporting occasions for each individual was selected, three occasions pre-'60 and three post-'60. This was done by eliminating the first pre-'60 and first post-'60 from the

eight previously used in the primary investigations. The 12 variables thus obtained were labelled:-

FAT2, FBT2, FAT3, FBT3, FAT4, FBT4
FAT6, FBT6, FAT7, FBT7, FAT8, FBT8

where FAT2 to FBT4 represent three pairs of pre-'60 scores, each pair being a condensed and rotated version of the data in one report. Similarly FAT6 to FBT8 represent three pairs of rotated post-'60 scores. In each case the A score is the co-ordinate on a "Social Skills" axis and the B score on an "Intelligence" axis. The notation T2 to T4 denotes increasing seniority as a Lieutenant and T6 to T8 as a Lieutenant Commander.

30. The location of these 12 variables in the ability structure was determined by means of a principal component analysis using the scores on the 12 variables and the selection data for the 78 individuals for whom reports were available. The results are tabulated in Appendix 17 and illustrated in Figure 26.9.

31. Inspection of the component loadings in Table App. 17.1 reveals that the first principal component is almost coincident with B.MARK and that all other variables have negligible loading on this component. Thus the B.MARK vector is near-orthogonal to the hyperspace containing all other variables. In the projections shown in Figure 26.9 the C_1 axis has been ignored and the two plots show the locations of vectors of variables other than B.MARK in the C_2, C_3, C_4 hyperspace. Thus the C_1 axis (or B.MARK) is orthogonal to this 3-space.

32. The vectors of SP tests form a cluster close to the C_3C_4 plane, which may therefore be regarded as the cognitive plane found in earlier investigations (Volume 1, Chapter 15).

33. The three pairs of vectors representing pre-'60 annual reports (FAT2 to FBT4), ie the reports during Lieutenancy, all lie in a plane which is close to the cognitive plane. The vectors of FAT2, FAT3 and FAT4, representing the "Social Skills" axis of reported qualities, form one tightly grouped cluster. The vectors of FBT2, FBT3 and FBT4, representing the "Intelligence" axis, form another. The centroid vectors for these two clusters are shown on Figure 26.9.

34. There is no definable "time-track", ie pattern of movement through the $C_2C_3C_4$ structure, corresponding to passage of time as indicated by the T2, T3, T4 notation. This implies no tendency for marking to follow a progressive pattern in terms of cognitive ranking during Lieutenancy.

35. The near coincidence of the pre-'60 report plane and the cognitive plane suggests that although the reported qualities are variously named (ranging from Mental Qualities to Personal Qualities) the attributes which are actually assessed are various interpretations of cognitive ability. It seems probable that the reporting officers form a judgment of the appropriate mean level of marking, determined to a large extent by the individual's intelligence, and that the marks on particular qualities are then ranged around this. This "spread" of marking is shown by the positions of pairs of boundary vectors, eg FAT2 and FBT2. The mean level would lie on a vector approximately bisecting the arc between each pair. Inspection of the C_3C_4 projection in Figure 26.5 shows that the "mean vectors" would lie in the region bounded by SP117 and GT35, ie measures representing mechanical and verbal ability, a result which is strikingly consistent with that of the analysis of time condensed data shown in Figure 26.1.

36. The three pairs of post-'60 vectors, FAT6 to FBT8, form a pattern similar to that for the pre-'60 vectors. Again the "mean vectors" would lie close to the cognitive plane, and in similar positions in the plane. The "spread" of marking spans an arc orthogonal to that for the pre-'60 case, suggesting that this ranging of the marking is influenced by some other factor at this later stage (the officers were then Lieutenant Commanders). This factor, whatever it is, is measured by the second principal component.

37. The orthogonality of B.MARK to the C_2, C_3, C_4 3-space shows that there is little or no connection between B.MARK and the annual report assessments (or the measures of cognitive ability).

Conclusions

38. These investigations provide evidence of a pronounced tendency to halo-effect in the marking of annual reports. There are indications

that the mean level of marking is closely identifiable with the "intelligence" of the individual concerned. The spread of marking on Lieutenants is associated with a range of cognitive abilities, showing the dependance of early career success on these abilities. The spread of marking on Lieutenant Commanders is uncorrelated with that of Lieutenants, showing the change of role and of requirements for success from early to mid-career. These results confirm and strengthen those obtained in the primary investigations by locating training and long-term success vectors in the ability structure.

39. In the case of Engineer officers the locations of condensed annual report vectors relative to those of training and long-term success show that there is a substantial change of role in mid-career. Success in training is relevant to performance in early technical appointments as measured by annual report assessments during Lieutenancy. Performance as a Lieutenant Commander, as measured by annual report markings, is more relevant to long-term success.

40. Analysis of time-dependancies shows that, although the overall correlations of markings with time-of-report are very highly significant, there is no recognisable "time-track" of marking in an ability structure. There is, however, clear evidence of tendency for halo effect to increase as officers approach the promotion zone.

FIG 26.1 PROJECTIONS OF FIRST THREE PRINCIPAL COMPONENTS OF PRE-ENTRY, TRAINING AND S.206 VARIABLES: TRUNCATED SAMPLE E

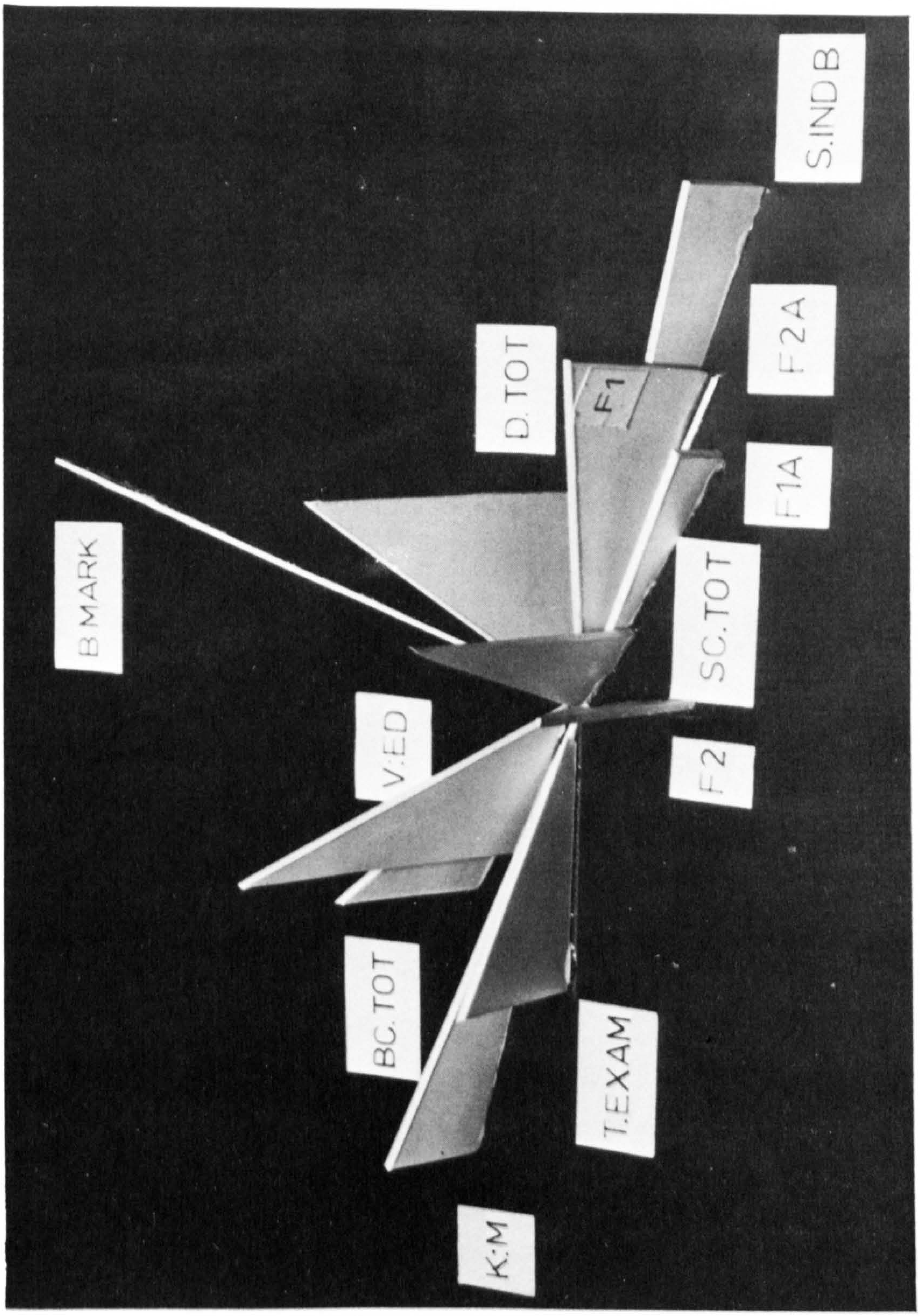


FIG 26.2 PART-SAMPLE E P.C.A. MODEL

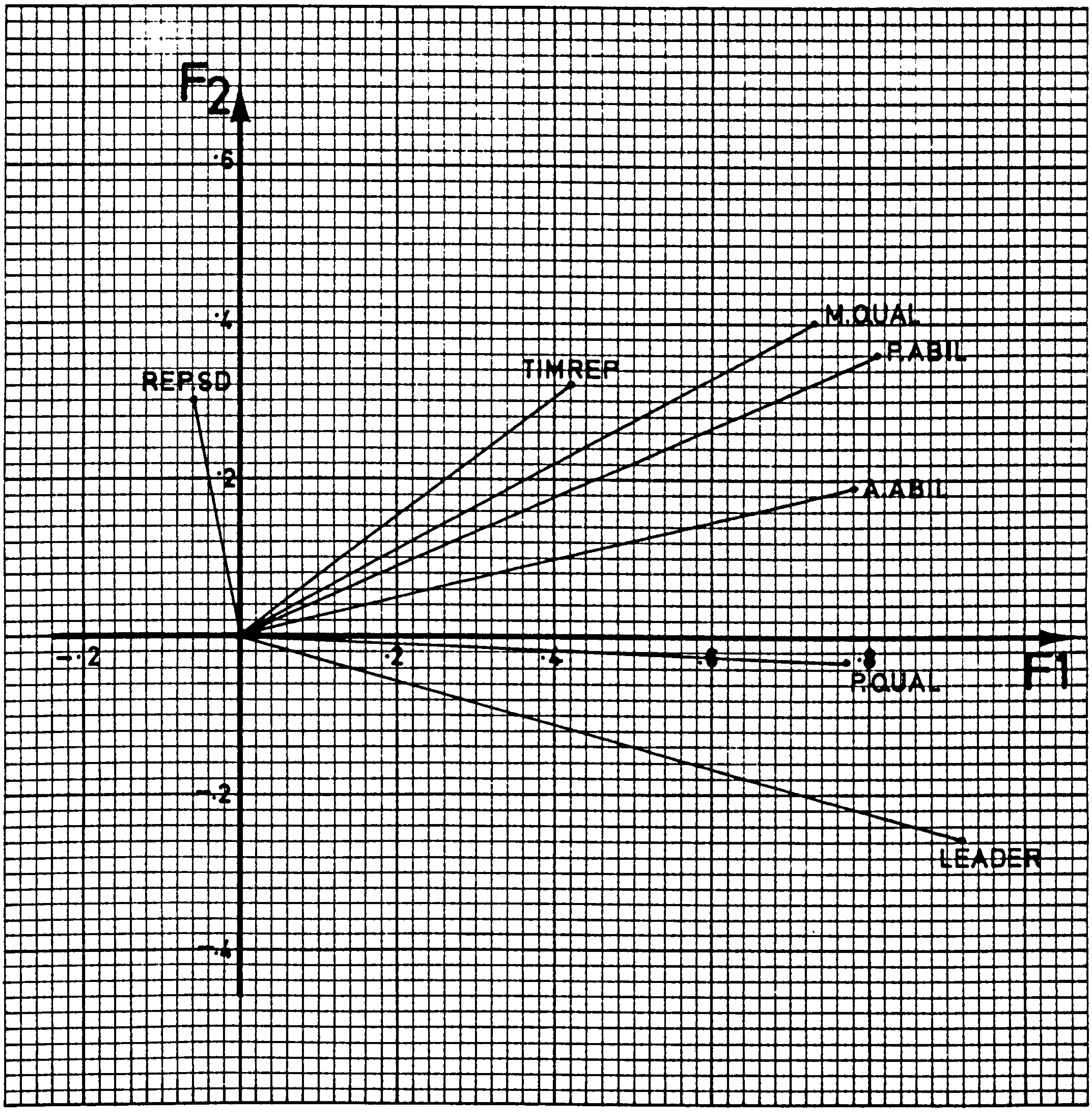


FIG 26.3 PRE '60 ANNUAL REPORTS - SAMPLE E
TWO-FACTOR MODEL SHOWING TIME-DEPENDENCE

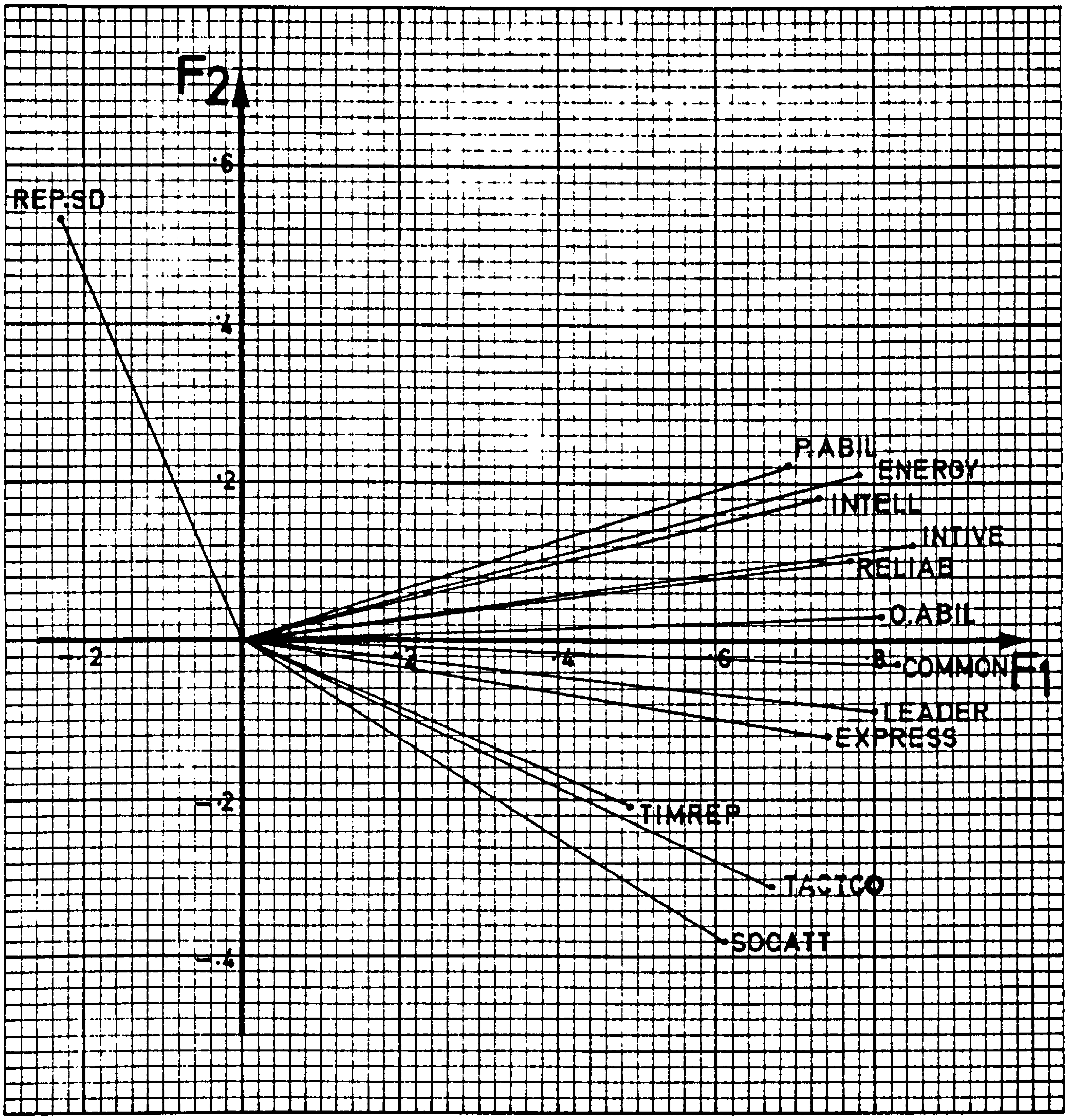


FIG 26.4. POST '60 ANNUAL REPORTS - SAMPLE E
TWO-FACTOR MODEL SHOWING TIME-DEPENDANCE

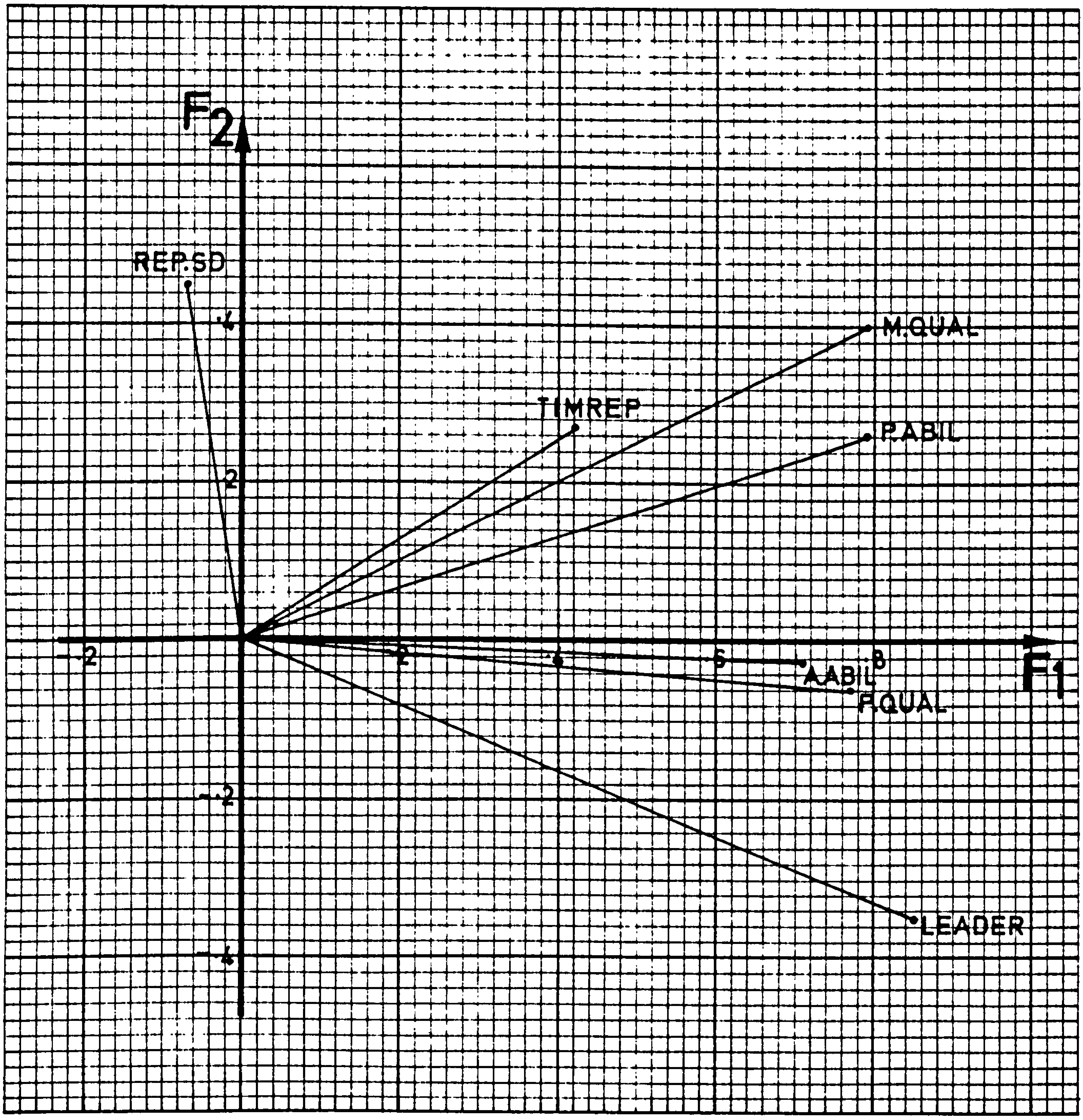


FIG 26.5. PRE'60 ANNUAL REPORTS - SAMPLE L
TWO-FACTOR MODEL WITH TIMREP

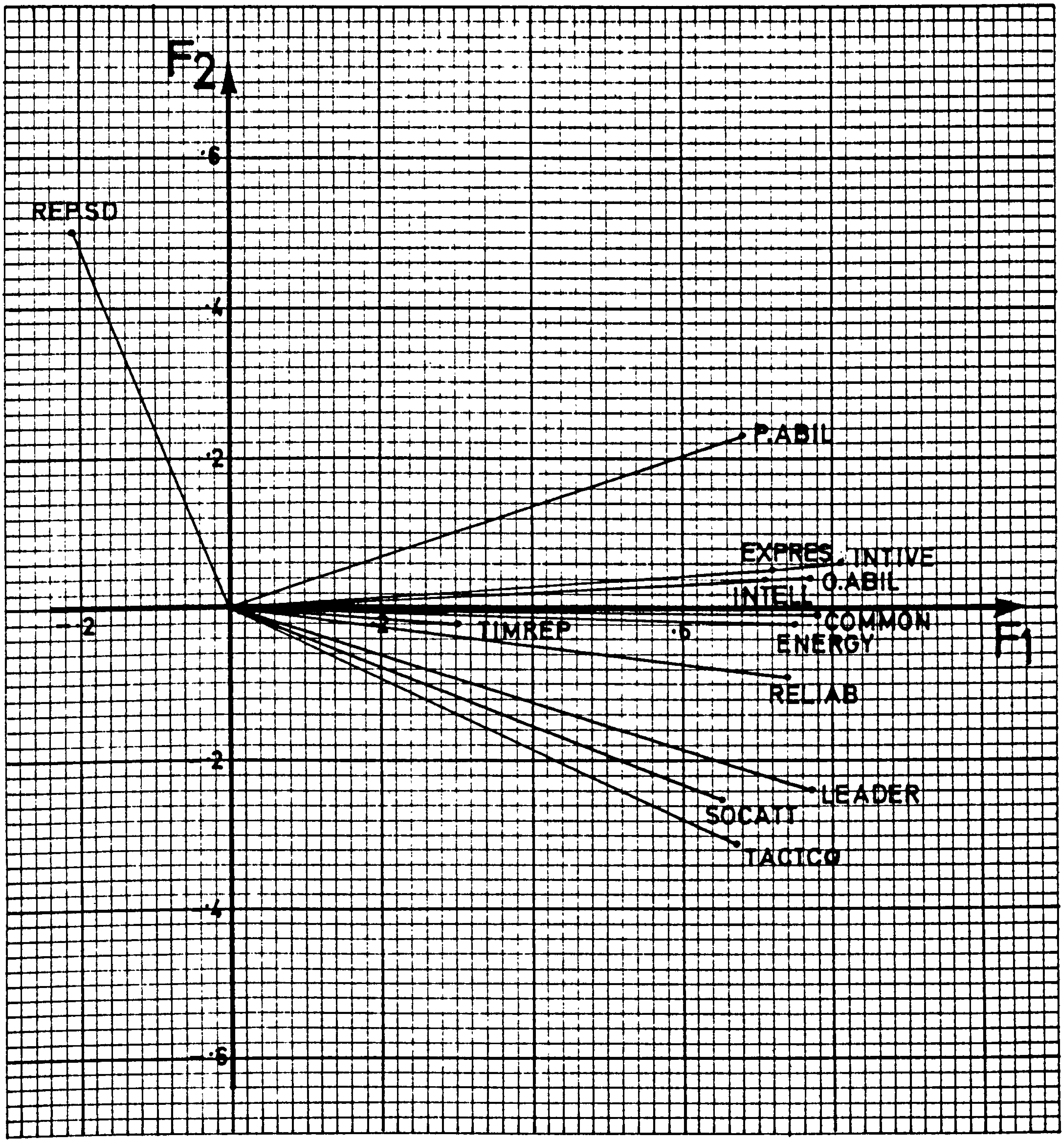


FIG 26.6. POST '60 ANNUAL REPORTS - SAMPLE L
TWO-FACTOR MODEL WITH TIMREP

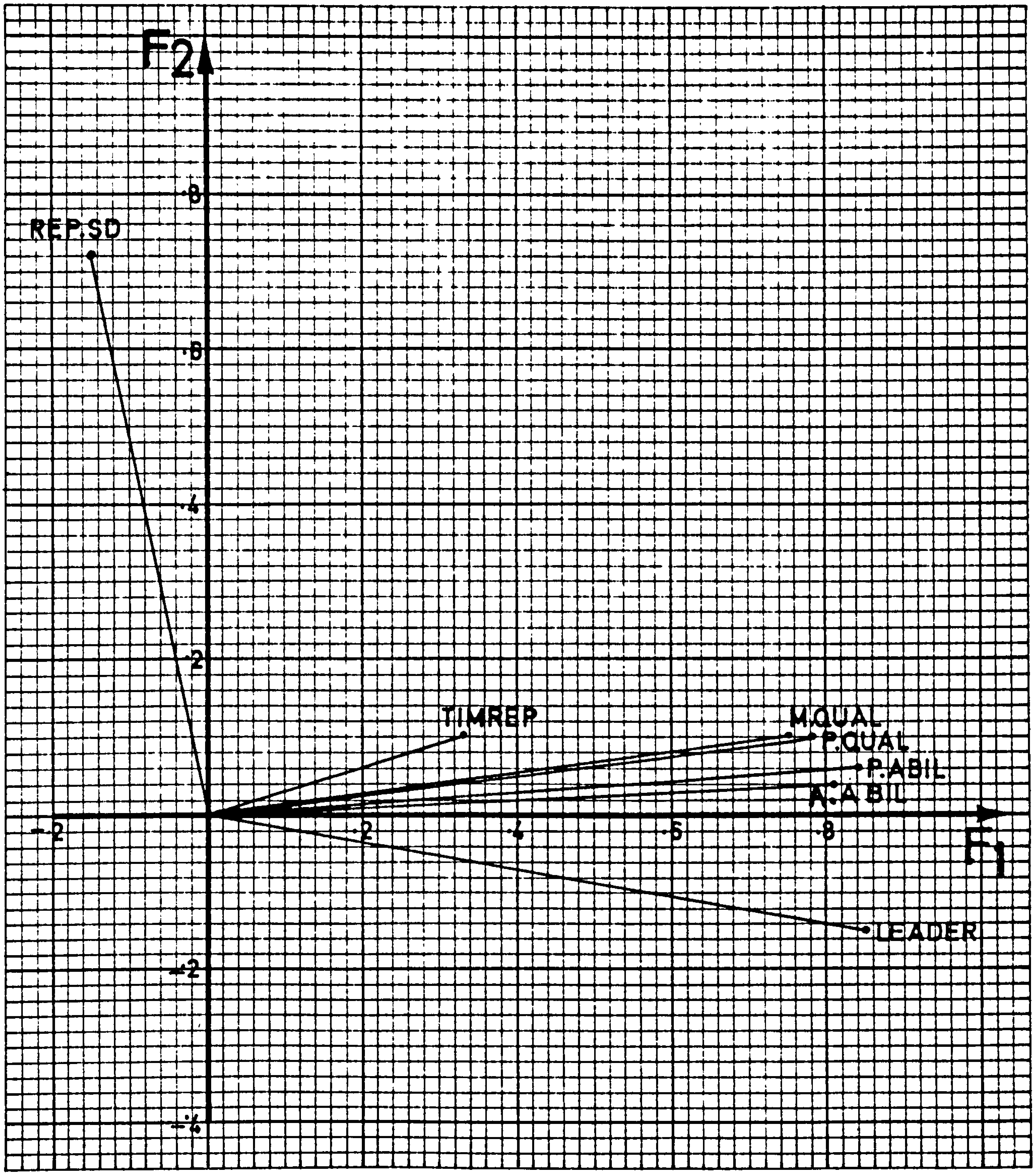


FIG 26.7. PRE '60 ANNUAL REPORTS - SAMPLE X
TWO-FACTOR MODEL WITH TIMREP

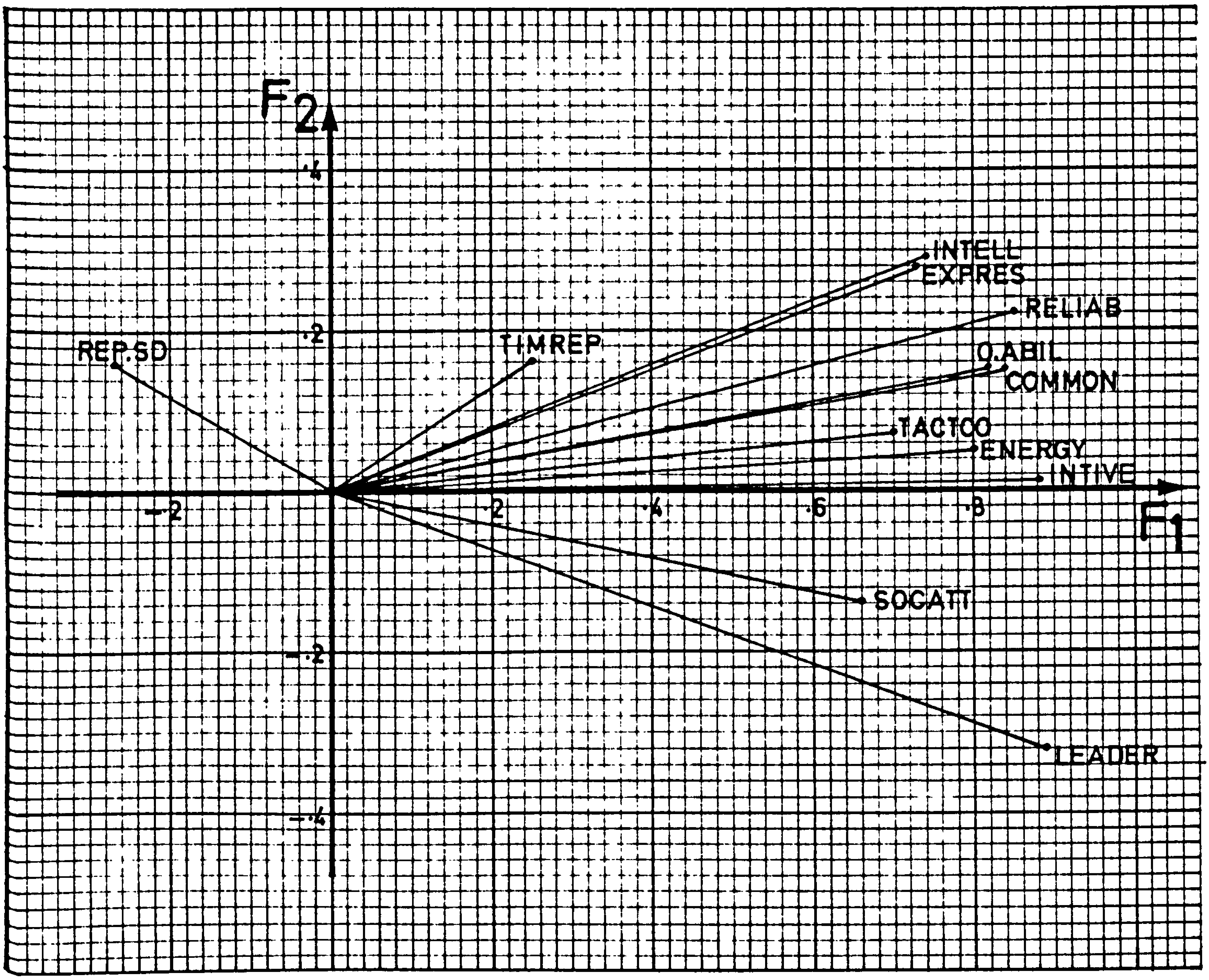


FIG 26.8. POST '60 ANNUAL REPORTS - SAMPLE X
TWO-FACTOR MODEL WITH TIMREP

FIG 26.0. LOCATION OF CONDENSED ANNUAL REPORT VECTORS IN ABILITY STRUCTURE

CHAPTER 27

FURTHER STUDIES OF THE PRIMARY GROUP - BIOGRAPHICAL AND INTERESTS DATA

1. Biographical and Interests data for Group A were derived from the SP Form Q78 completed by each candidate at the Admiralty Interview Board. The Form is reproduced in Volume 1, Appendix 1 and the nature of the data is defined in Chapter 8.

2. Most of the variables used to quantify this data are essentially binary and the use of such variables in the predictive studies may be criticised on grounds of non-normality.

3. Various techniques are available for combining such data so as to achieve more satisfactory distributions and to improve the predictive value. These range from purely intuitive grouping to purely analytical methods designed to extract maximum correlation or maximum variance combinations.

4. Two analytical techniques have been used in the research described below. The first, Principal Component Analysis, identifies uncorrelated linear combinations with maximum variance. The second, Cluster Analysis, identifies clusters of variables with maximum inter-correlations between variables within each cluster.

5. Both techniques have been used on both Biographical and Interests data (the Principal Component Analysis of Interests data is described in Volume 1, Chapter 16). The results are compared and the predictive value of clustered data is assessed.

Analysis of Biographical Data

6. The results of a Principal Component Analysis of Biographical data for 258 individuals in Group A (sample XES), are given in Table App. 18.1. Projections of the first two principal components are shown in Figure 27.1.

7. Inspection of the loadings on Component No. 1 reveals that the variables are polarised into two groups, those with positive loadings representing "attainments" (with the exception of ON.CH.) and those with negative loadings being "environmental".

8. The table of accumulated value of variance shows, however, that there is little prospect of a meaningful result from condensation of these variables since a total of 7 out of the 11 components is required to account for 75% of the variance.

9. The correlation matrix used for the Principal Component Analysis was also subjected to a Cluster Analysis routine developed by R Newport (see Chapter 25, para. 2). The result, shown in Figure 27.2, is readily identifiable with that shown in Figure 27.1, as has been shown on the latter by the dotted lines enclosing variables in each cluster.

10. The figures inserted on each branch of Figure 27.2 show the number of powerings required for correlations to exceed an arbitrary limit of $r = \pm 0.99$. These figures are therefore an indication of the ease of identification of clusters.

11. The wide dispersion of vectors in Figure 27.1 and the difficulty of clustering apparent from Figure 27.2 confirm that grouping of Biographical variables is unlikely to yield improved predictions. This stems essentially from the more or less uniformly low inter-correlations of Biographical variables.

Analysis of Interests Data

12. Principal Component Analysis of the Interests data for sample XES has been reported in Volume 1, Chapter 16 and the results tabulated in Appendix 10. It was concluded that there was no evidence of meaningful groupings of Interests variables but it was observed that Cluster Analysis might yield better results though it seemed unlikely.

13. Further examination of the component loadings in Table App. 10.2 reveals that the loadings on component No. 1 are a measure of the contribution of each variable to "aggregate interest". The loadings on component No. 2 may be seen as polarising the variables into two groups (with positive and negative loadings), and it is noticeable that the positive loadings relate broadly to interests which may be considered extrovert and the negative to interests which may be considered introvert. Similarly, positive loadings on Component No. 3

appear to be associated with passive or aesthetic interests, and negative loadings with active or technical interests.

14. A plot of the C_2C_3 hyperspace is shown in Figure 27.3. The wide dispersion of variables confirms the earlier conclusion that meaningful grouping is unlikely to be achieved since, although the relationships described in para. 13 above are apparent, a careful examination of the variables in the extrovert/introvert categories, or in the active/passive or aesthetic/technical categories, shows that many of the one-word definitions are capable of a range of interpretation.

15. Since Cluster Analysis appeared particularly relevant to this type of problem an analysis was undertaken using the same routine as for the Biographical data. The results are shown in Figure 27.4. As before, dotted lines have been used to identify the clusters on the principal component model, Figure 27.3.

16. Examination of the clusters reveals that there is a close similarity between the results of the Principal Component and Cluster Analyses. The first level clustering yields a grouping (labelled E and I on Figure 27.4), which is almost identical with the polarisation of component No. 2. The second level clustering yields sub-groups of E and I (labelled EA, EB, IA, IB), which correspond approximately to the polarisation of component No. 3. Third level clustering yields the 8 sub-sub-groups which have been labelled EAA to IBB, and it is these which are shown on Figure 27.3.

17. Although superficially there is some resemblance between variables in most of the clusters, there is no obvious and simple means of naming them which would result in a coherent structure for their inter-relationships.

18. In order to test the usefulness of the clusters for predictive purposes a series of analyses has been completed for the individual samples X, E and S to determine the correlations of EAA to IBB with S.TRG and S.INDB. The opportunity was also taken of examining the correlations with B.MARK, in order to assess whether the selection board had been influenced by any recognisable Interests characteristics. The results are given in Table App. 18.2. The definitions of the

cluster designations used in the table are as shown in Figure 27.4.

19. Correlations which are significant at the 5% level are marked with an asterisk. None of the correlations is significant at the 1% level. Of the correlations with B.MARK, EBB (ie sports and science) is negatively significant for sample X, and EBA (listening-in, cinema, animals, dancing and parties) is negatively significant for sample E. For sample S there is a significant positive correlation between B.MARK and EAA (music, theatres, reading and politics) and negative with IBA (collecting, photography and sailing).

20. In both sample X and sample E the correlations between S.TRG and EBA are significant and negative, showing the tendency for those with active interests in what might be termed "the gay life" to fare badly in training. Curiously, S.INDB correlates negatively with EAB in sample X and positively with EBB in sample S.

21. Although these correlations reach the "significant" level, they are all small and there is no consistent pattern. It is therefore deduced that the predictive value of the clusters is small.

22. This finding confirms the conclusion reached in the primary investigation that the interests data has little value for predictive purposes, probably because one-word definitions are not sufficiently precise to ensure reliable data.

Associations of Component Scores of Biographical and Interests Data

23. In the above reports of analyses of biographical and interests data it has been postulated that condensation for predictive purposes is unlikely to be worthwhile. In order to test this hypothesis a further set of exploratory analyses has been completed.

24. In both cases the component scores on the first three principal components for all individuals in the XES sample have been derived. Contingency tables have then been constructed to show the relationship between above/below zero component score and promotion/no promotion in each of the samples X, E and S.

25. The contingency tables and corresponding values of χ^2 are shown in Tables App. 18.3 and 18.4. Where the value of χ^2 exceeds the 5% probability level the value of α, the probability of the observed χ^2 occurring by chance, is given.

26. In the case of the biographical data, significant associations are observed on component number 2 for sample X and component number 1 for sample E, the latter reaching the highly significant level. This shows that, for Engineer officers, promotion tends to be associated with positive C_1 score, ie with individuals having high childhood "attainment", as opposed to "environmental" scores.

27. In the case of the interests data there are no significant associations between component scores and promotion.

28. For both interests and biographical data a further contingency table has been constructed for the purpose of testing whether there is any recognisable pattern of distribution of above/below zero component scores in the three samples, X, E and S. The results, given in Tables App. 18.3 and 18.4, show significant associations on component number 3 of the interests data and component number 2 of the biographical data.

29. These two results have been brought together in Table App. 18.5 which shows the proportions of each sample in the above/below zero categories in each case. The tables show a tendency for Supply and Secretariat officers to have positive biographical C_2 score and positive interests C_3 score, the former being primarily a measure of enforced independence as a child and the latter a measure of aesthetic/passive early interests. Engineer officers tend to have the opposite loadings in each case, but Seaman officers tend to have negative biographical C_2 score and positive interests C_3 score.

30. The results given in Tables App. 18.3 and 18.4 again confirm that there is little prospect of useful condensation of interests data, though further research to find optimum groupings of biographicals might be worthwhile.

Conclusions

31. The results of cluster analyses of the Biographical and Interests data confirm the findings from principal component analyses that no

worthwhile condensation of either of these for descriptive purposes is possible. The low inter-correlations between the variables in both cases prevent any meaningful clustering.

32. Since the correlations of success with individual and grouped Interest variables are also low it is concluded that this data has little predictive value probably because of "noise" in the data resulting from ambiguity of interpretation of one-word definitions.

33. Individual Biographical variables were shown to be useful predictors in the primary investigations and it is concluded that to attempt to improve the distribution of Biographical data would probably involve weakening its predictive value because of loss of information in the process of condensation.

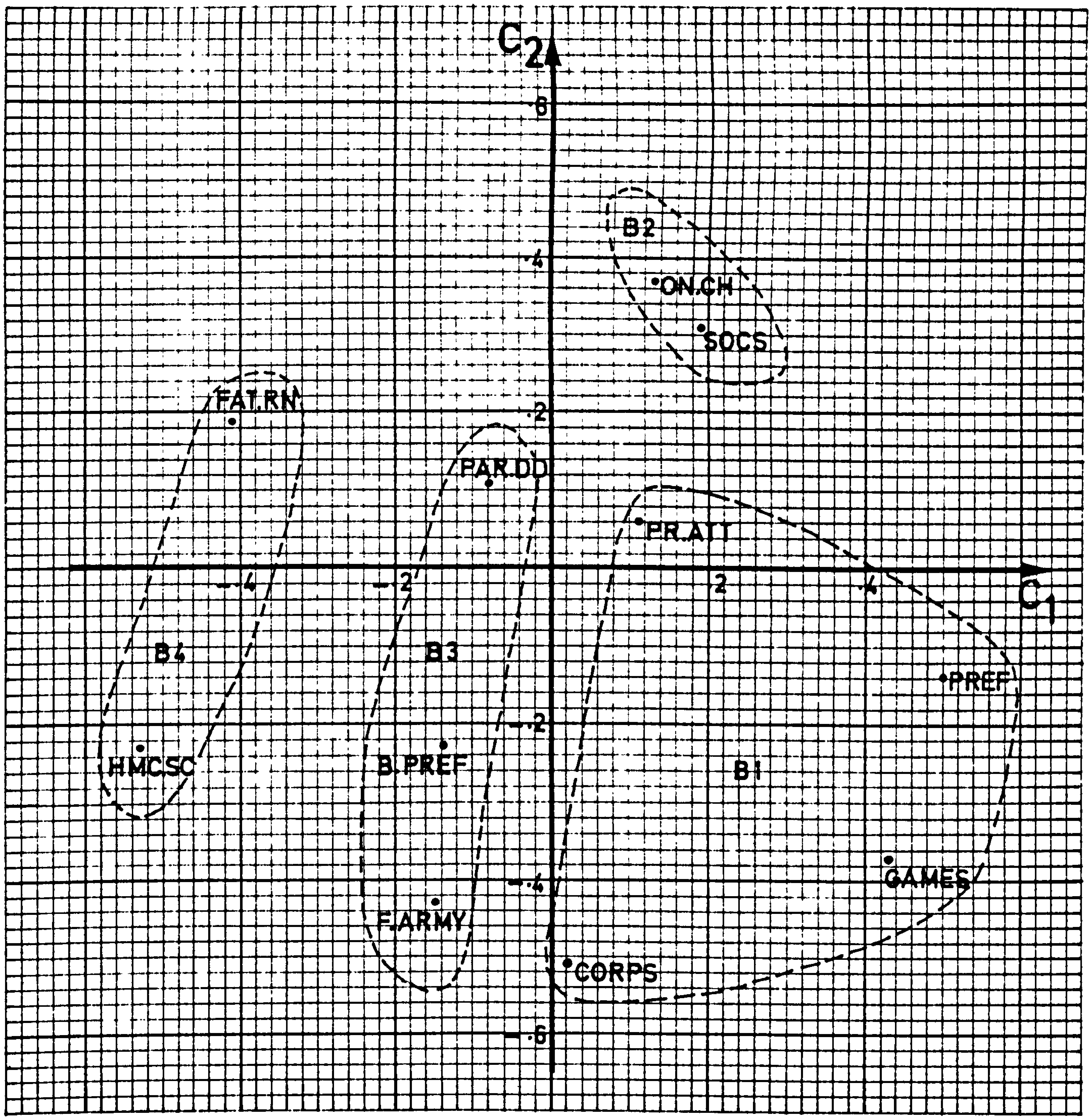
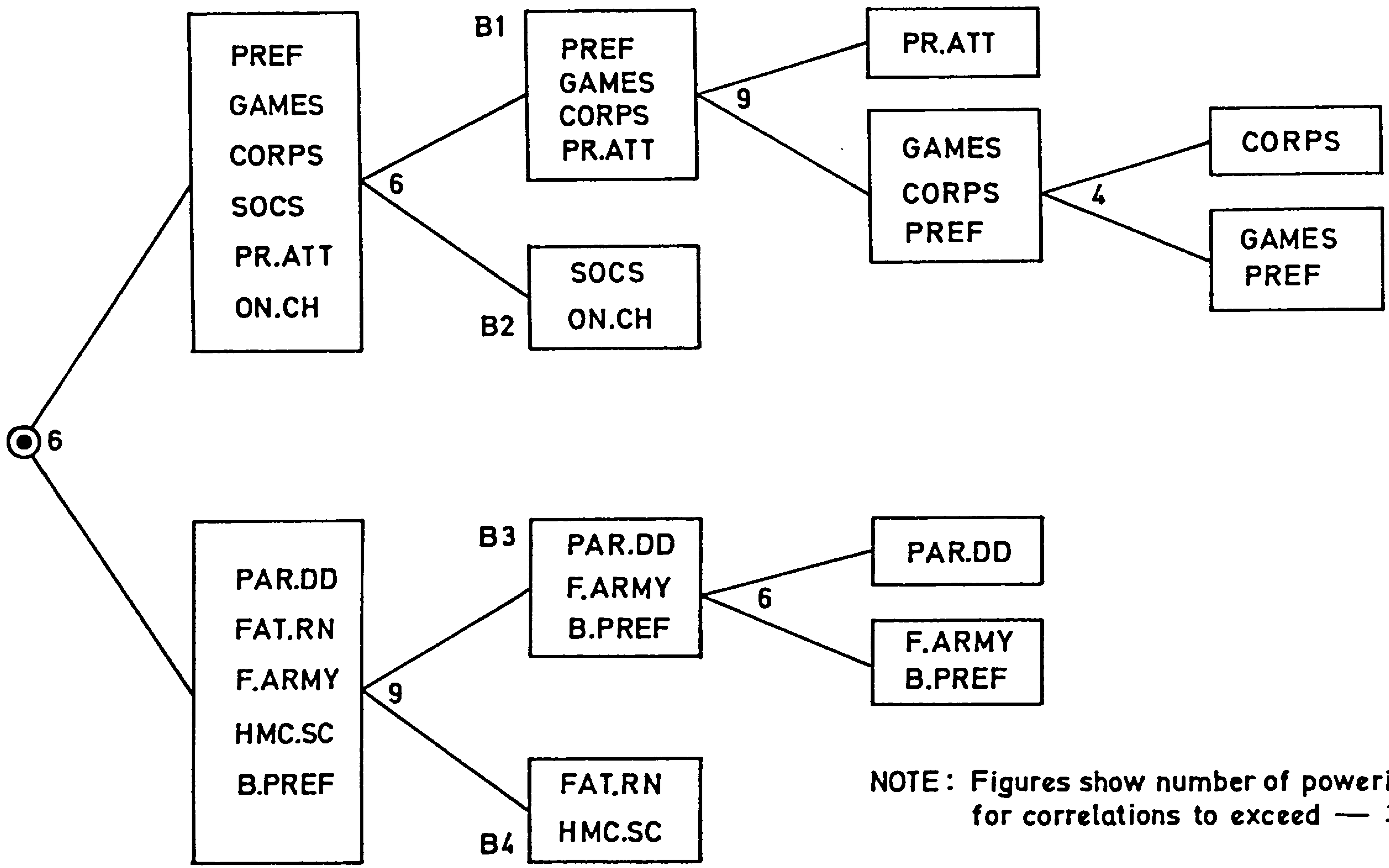


FIG 27.1. PROJECTIONS OF FIRST TWO PRINCIPAL COMPONENTS OF BIOGRAPHICAL DATA - SAMPLE XES



NOTE: Figures show number of powerings required for correlations to exceed — ± 0·99

FIG 27.2. CLUSTER ANALYSIS OF BIOGRAPHICAL DATA – SAMPLE XES

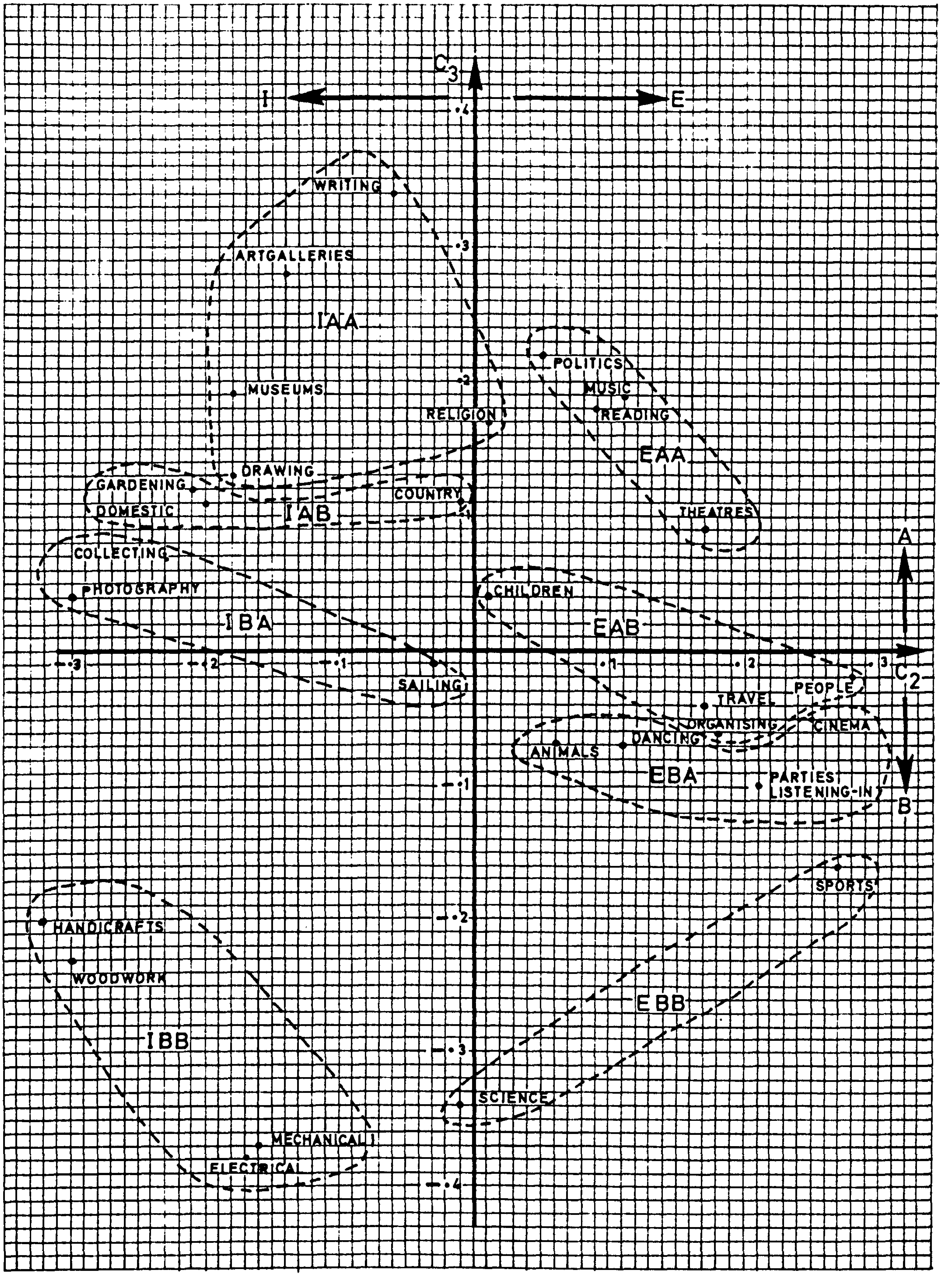


FIG 27.3. PROJECTION OF C_2C_3 HYPERSPACE OF INTERESTS DATA - SAMPLE XES

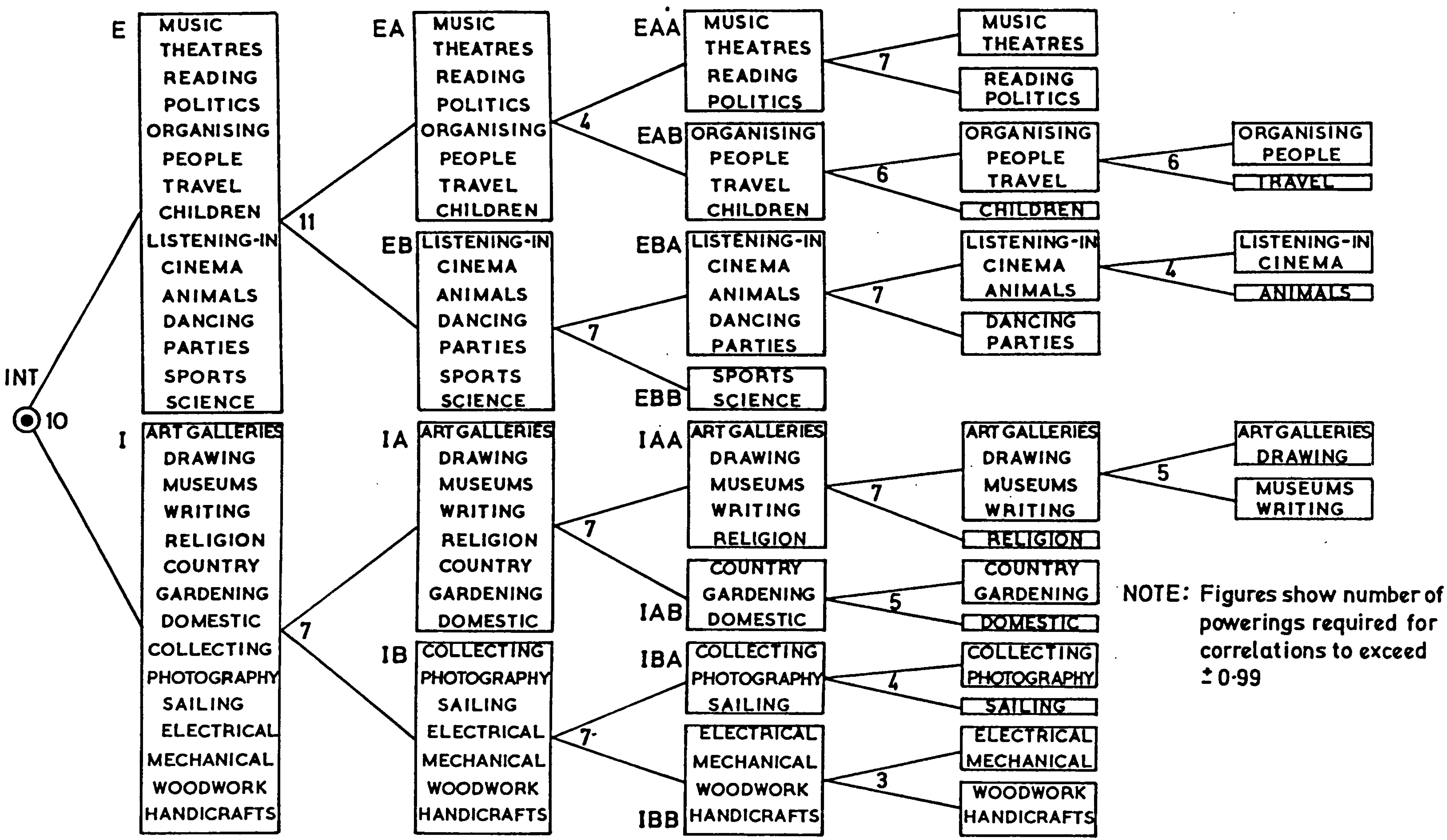


FIG 27.4. CLUSTER ANALYSIS OF INTERESTS DATA – SAMPLE XES

CHAPTER 28

UNIVARIATE ANALYSES OF GROUPS A, B AND C

1. The means and standard deviations of all variables used in the primary studies of Group A, the candidates of AIBs 1 to 6, have already been tabulated in Volume 1, Appendix 4 and discussed in Chapter 13.

2. In order to provide a background to the multivariate studies reported in Chapters 29 to 32, and to provide a simple basis for comparison of the three Groups, the means and standard deviations of all variables used in the studies of the later Groups (B and C), have also been calculated. (Group B consists of candidates of AIBs 7 to 10 and Group C of candidates of AIBs 1969/70.)

3. The values of these univariate statistics for Groups B and C are tabulated in Figures 28.1 and 28.2 and for ease of comparison the corresponding statistics (of relevant variables) of Group A are included in Figure 28.1.

4. Examination of Figure 28.1 shows that the statistics for the verbal type tests (GT35, SP96 and SP21) are almost identical in Groups A and B. There is a small but consistent tendency for means of mechanical type tests (SP117 and SP160) to be lower in Group B, but the differences are not significant.

5. The change in means of B.MARK reflects the introduction of a new maximum mark of 400 in board No. 7, replacing the earlier maximum of 300. The mean of 146 for all candidates (accepted and rejected) in Group A is raised to 196 for all candidates in Group B, a change which is almost exactly in the ratio 4/3. The change in means of accepted candidates is, however, from 185 to 268, whereas 185 x 4/3 = 247. Similarly the change for rejected candidates is from 105 to 157 whereas 105 x 4/3 = 140. This shows that the introduction of the increased maximum mark was accompanied by a corresponding increase in range of marking, which was the main objective of the change. The difference of means of accepted and rejected candidates was, in fact, increased from 80 in Group A to 111 in Group B, which is slightly greater than the value of 107 which results from increasing 80 in the ratio 4/3.

6. The change of mean and range of marking does not affect the multivariate analyses reported later in this volume, since all variables are standardised to a mean of zero and standard deviation of unity before further processing.

7. Only two of the variables for Group C can be directly compared with those for Groups A and B, viz GT35 and SP21, and in both cases the means are significantly higher in Group C. Indeed the means for rejected candidates in Group C are similar to those for accepted candidates in Groups A and B.

8. On all the SP tests in Group C the pattern is similar to that in the earlier Groups, ie the means for rejected candidates are significantly lower than for accepted candidates.

9. The maximum score on B.MARK in Group C and the mean value of 457 for all candidates correspond closely with the corresponding mean (expressed in fractional terms) in earlier Groups. The differences of means of accepted and rejected candidates (609 - 359 = 250) is rather less than the value of 267 which results from increasing 80 in the ratio 10/3. This implies that the range of actual marking has not been increased proportionately with the available scale. A similar deduction results from expressing the standard deviation for all candidates as a fraction of maximum marks. For Group B the fraction is 72.5/400. The expected fraction for Group C is 181/1000, but the actual standard deviation in Group C is only 150. (Note that the numbers in these two samples are comparable.)

10. The major difference between Group C and Groups A and B is that the age range is much greater. Candidates for the earlier boards fell into a narrow age band around 17.8 years (see Volume 1, p. 33), but in Group C the ages ranged from just under 17 to 25 years. The AGE variable has been included to enable the effects of this increased range to be investigated.

11. Univariate statistics of derived data (eg condensed selection variables P, M and V) are discussed in relevant Chapters.

VARIABLE	GROUP A (AIB 1-6)						GROUP B (AIB 7-10)					
	ALL (Sample XESF)		ACCEPTED (Sample XES)		REJECTED (Sample F)		ALL		ACCEPTED		REJECTED	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
GT35	145	16.7	149	15.5	141	16.9	145	17.6	152	17.4	141	16.5
SP96	23.3	3.55	24.1	3.11	22.4	3.76	23.3	3.46	24.4	3.36	22.7	3.37
SP21	121	19.2	123	18.1	118	20.0	121	18.0	126	16.9	119	17.1
SP117E	17.6	3.96	18.5	3.50	16.6	4.13	17.1	3.89	18.2	3.26	16.5	4.08
SP117M	16.6	4.74	17.5	4.56	15.7	4.78	16.2	4.84	17.0	4.41	15.8	5.02
SP160	32.6	8.28	34.2	7.73	30.7	8.43	31.1	7.73	33.3	7.70	29.8	7.45
B.MARK	146	70.1	185	50.5	105	64.6	196	72.5	268	45.8	157	51.1

FIG. 28.1 UNIVARIATE STATISTICS of GROUPS A and B

VARIABLE	GROUP C (AIB 1969/70)					
	ALL		ACCEPTED		REJECTED	
	Mean	SD	Mean	SD	Mean	SD
GT35	154	15.7	160	12.5	150	16.2
SP70/23	37.2	6.33	39.7	5.24	35.6	6.48
SP21	132	16.3	135	14.7	129	16.9
VMD	75.4	29.7	87.7	26.8	67.4	28.9
SP R(E)	29.6	6.60	31.1	6.39	28.6	6.56
B.MARK	457	150	609	82.9	359	88.8
AGE	27.3	22.7	28.2	22.3	26.8	23.0

FIG. 28.2 UNIVARIATE STATISTICS of GROUP C

CHAPTER 29

COMPARATIVE STUDIES OF PRIMARY AND LATER GROUPS

1. Since the sample used in the primary investigations was the most recent in which all officers had equal opportunity of promotion, there is no way of cross-validating the results of long-term predictive analyses in terms of more recent samples.

2. In order to assess the relevance of results obtained in the primary investigations to the current selection situation it is therefore necessary to compare selection data for recent candidates with that for the original sample.

3. Since some of the variables on which data is currently recorded are the same as in the original sample, and some are different, the most powerful method of comparison is by analysis of data structure.

4. A convenient method for a preliminary comparison is principal component analysis which provides:-

   a. an insight into the structural relationships;
   b. an estimate of the dimensionality required for a Factor Analytic model if this proves worthwhile.

5. In order to assess the stability of the data structure found in the original sample, Group A, and to assess its relationship with the current situation, a series of three principal component analyses has been completed. The first two provide a comparison of Groups A and B (ie AIBs 1 to 6 and 7 to 10), for which identical variables are available (except that the contribution of B.MARK to selection aggregate was greater in Group B). The third shows the structure for Group C, the current situation (AIBs 1969/70).

6. The results of these analyses are tabulated in Appendix 19 and illustrated in Figures 29.1, 29.2 and 29.3.

7. Comparison of Figures 29.1 and 29.2 reveals that, in the hyperspace of the first three principal components, the structures for Groups A and B are almost identical. As before the vectors of the SP tests are dispersed close to a "cognitive plane" and the B.MARK vector is orthogonal to this plane.

8. Figure 29.3 shows that, for Group C, with the exception of SP R(E) the vectors of SP tests again fall close to a plane. The B.MARK vector is a little less than orthogonal to this plane, indicating that the board may now be taking slightly more account of SP test results than hitherto. The AGE vector is almost orthogonal to B.MARK, showing that the board is highly successful in eliminating age bias from their markings.

9. In all three analyses the first three principal components account for about 70% of the total variance and it is deduced that, in each case, a three-factor model should give a good account of the relationships among variables.

10. In view of this, and of the basic similarity of the structures for the three groups, it was decided to undertake the necessary Factor Analyses with a view to subsequent rotation of the models for the purpose of inter-relating them. These analyses are described in Chapter 30.

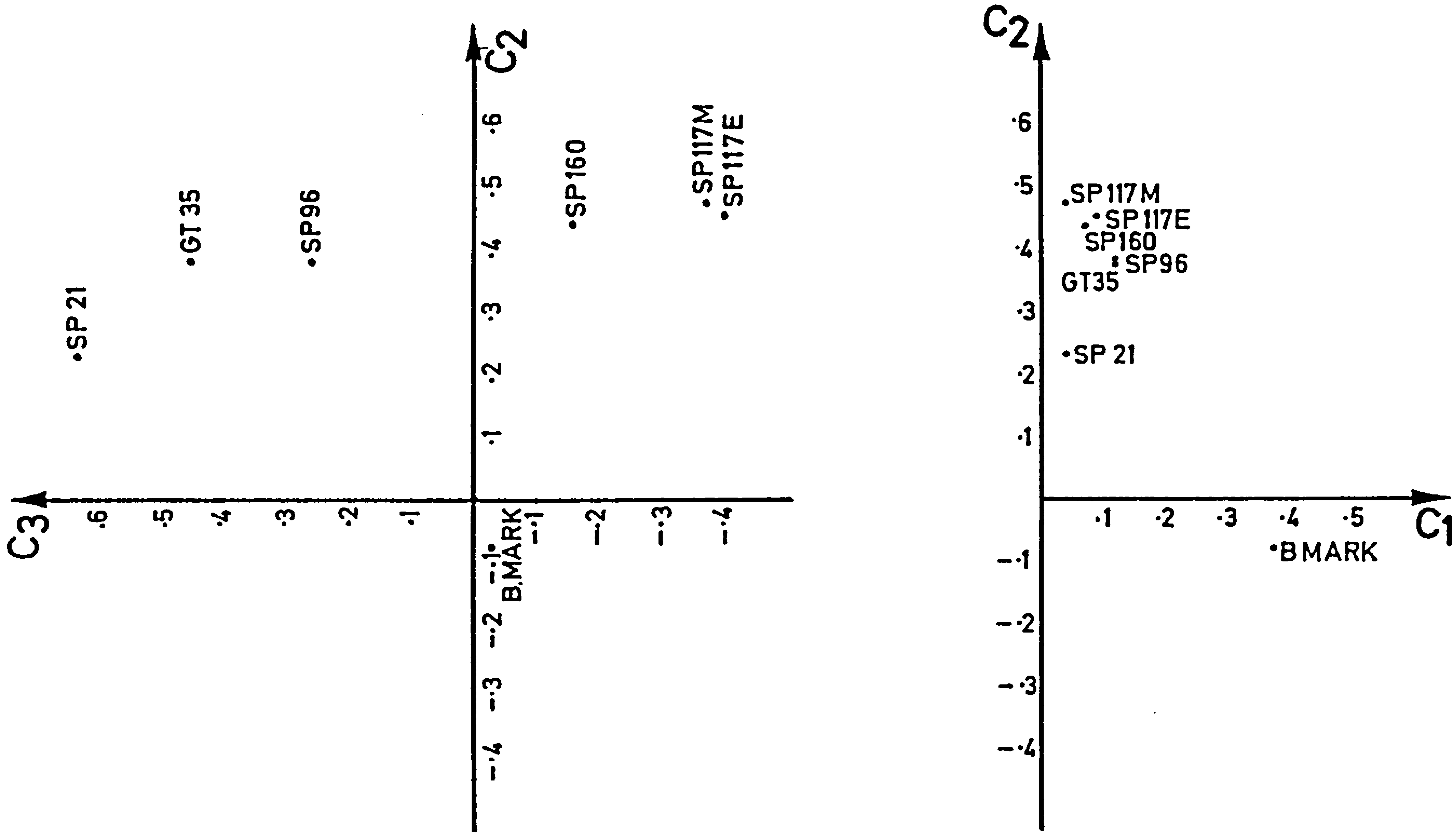


FIG 29.1. PROJECTIONS OF FIRST 3 PRINCIPAL COMPONENTS OF GROUP A SELECTION DATA

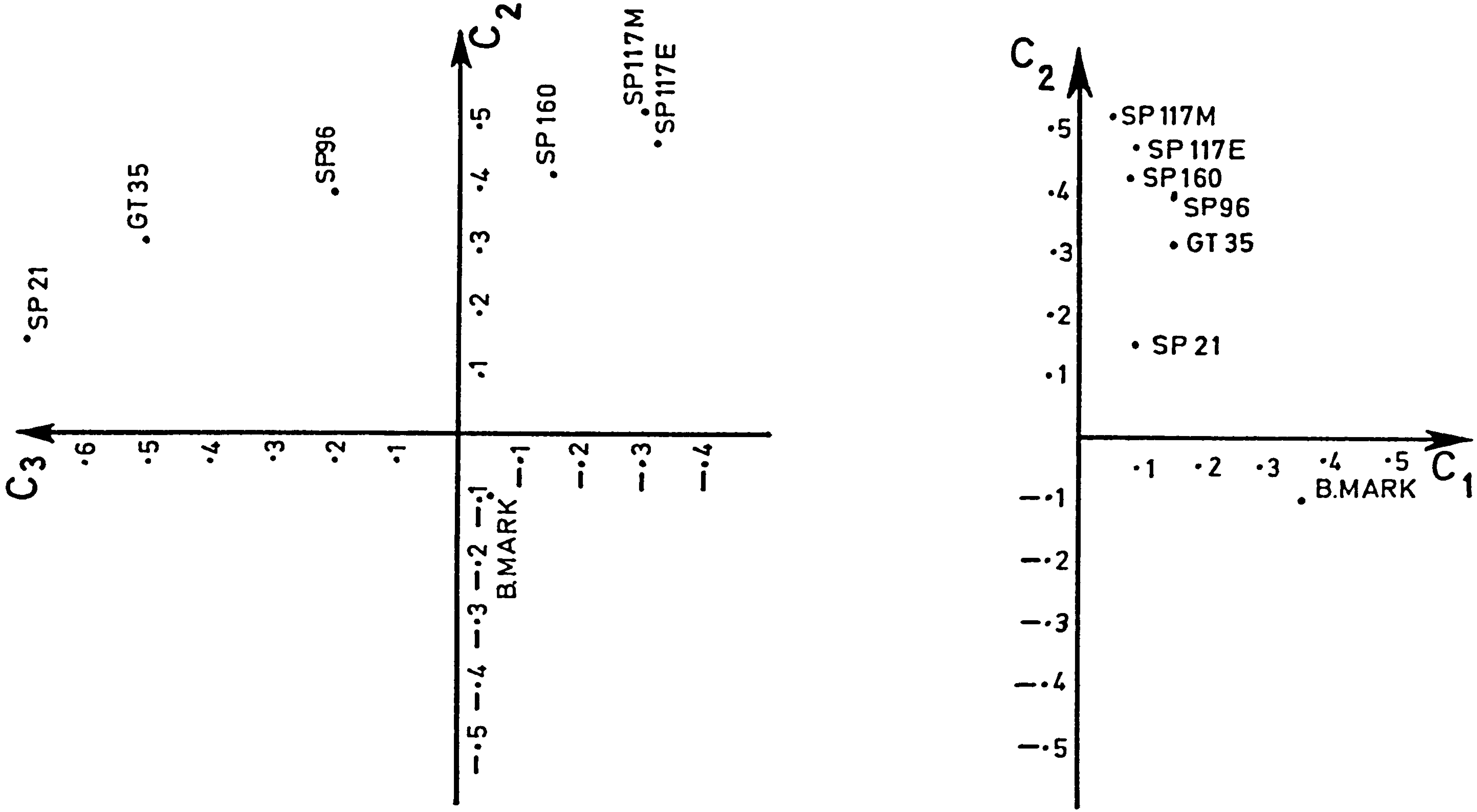


FIG 29.2. PROJECTIONS OF FIRST 3 PRINCIPAL COMPONENTS OF GROUP B SELECTION DATA

FIG 29.3. PROJECTIONS OF FIRST 3 PRINCIPAL COMPONENTS OF GROUP C SELECTION DATA

CHAPTER 30

CONDENSATION OF SELECTION DATA FOR PRIMARY AND LATER GROUPS

1. The results of the Principal Component Analyses reported in Chapter 29 showed that the structure of the selection data in each of the three groups was essentially similar, and that, in each case, a three dimensional model was likely to give a good account of the data.

2. To enable comparable three dimensional models to be derived a factor analysis has been completed on the selection data for each group. The results of the three analyses are given in Tables App. 20.1, 20.2 and 20.3 and are illustrated in Figures 30.1, 30.2 and 30.3.

3. The Factor models are essentially similar to their Principal Component counterparts shown in Figures 29.1, 29.2 and 29.3 and are also essentially similar to each other. The feasibility of co-relating the models, which was hypothesized in Chapter 29, is therefore confirmed.

4. The adequacy of the three factor solutions has been tested by the method proposed by Lawley (see Volume 1, p. 111, para. 14).

Group	U
A	3.2
B	5.5
C	0.6

In each case there are 3 degrees of freedom and the critical value of χ^2 at the P .05 level is 7.8. The residuals are not significant and the models are therefore assumed statistically adequate.

5. To confirm the stability of the models the value of a residual function at the end of every 10 iterations has been plotted in Figures 30.4, 30.5 and 30.6. These show that convergence was satisfactory in each case.

Co-relation of Models

6. The three dimensional factor models of the three groups have been rotated onto common axes using the following techniques:-

a. For each of the three models individually the angles between vectors and the angles between vectors and factor axes were calculated from the factor loading matrices A. The cosine of the angle between the vectors of variables i and j is given by $\hat{R}_{ij} / \sqrt{\hat{R}_{ii} \cdot \hat{R}_{jj}}$ where $\hat{R} = AA'$. Similarly the cosine of the angle between the vectors of variable i and factor j is given by $A_{ij} / \sqrt{\hat{R}_{ii}}$. These transformations are summarised in Figure 30.7 and the derived angles are listed in Tables App. 20.4, 20.5 and 20.6.

b. Three orthogonal factor axes, labelled F1A, F2A and F3A, were plotted on the surface of a sphere and the vectors for the variables of Group A were plotted in relation to these factor axes. The result is shown in Figure 30.8a. Corresponding models for Groups B and C are shown in Figures 30.8b and 30.8c. It should be noted that, in each case, vectors would terminate at the surface of the sphere only if their communalities were unity. Actual communalities are listed in Table App. 20.6a.

c. Since the variable GT35 was common to the data of all three groups, and it had relatively high communality in each of the models, the GT35 vector was used as a pivot for plotting the vectors of all three groups on a common model as shown in Figure 30.8d.

d. To provide the second datum necessary for relating the models the centroid of the vectors of the mechanical test variables of Group A was found. The corresponding centroids for Groups B and C were then located in the plane through GT35 and the Group A mechanical test centroid (ie the "cognitive plane"). The three mechanical test centroids were found to be almost coincident, as is shown in Figure 30.8d.

e. The remaining vectors, both of variables and of Factor axes, for all three groups were then plotted in relation to the established positions of the verbal and mechanical test vectors. The Factor axes for Groups A, B and C are labelled F1A, F2A, F3A, F1B, F2B, F3B and F1C, F2C, F3C respectively in Figure 30.8d.

f. The "M" and "V" axes ("mechanical ability" and "verbal ability") were then defined by positioning them at right angles to each other in the cognitive plane so that the angles between GT35 and V and between M and the centroid of mechanical tests were equal. In this way the M V arc embraced most of the tests.

g. The "P" axis ("personality") was then located so as to be orthogonal to the M and V axes.

7. As a result of these rotations the factor models for Groups A, B and C were brought into alignment onto common axes labelled P, M and V, as shown in Figure 30.8d.

8. It is interesting to note, at this stage, some of the features of the co-related model.

a. The models for Groups A and B are almost identical.

b. There is clear evidence in the model for Group C that some account is now taken of the cognitive test results, or of the abilities they measure, in the assessment of B.MARK. The model is, however, essentially similar to those for Groups A and B.

c. The segment bounded by the P M V planes contains almost all vectors of interest.

d. The majority of test vectors lie close to the "cognitive plane", defined as in 6d above.

9. The three models having been aligned, it was necessary to derive the scores of each observation in all three groups on the new P M V axes. The process used is described below.

<u>Derivation of P M V scores</u>

10. The procedure for the derivation of P M V scores is summarised in Figure 30.9. The steps are:-

a. For each group derive the transformation $(A'A)^{-1}A'$ where A is the factor loading matrix. When the normalised observations Z are pre-multiplied by $(A'A)^{-1}A'$ the result is the scores which best account for the original observations expressed in terms of the factors.

b. For each group measure the angles between the factor axes for that group and the P M V axes. Then, if T is the matrix of direction cosines of F versus P M V axes, the rotated factor loading matrix is AT, and the transformation for obtaining P M V scores from Z is

$$Y_t = T^{-1} (A'A)^{-1} A'Z$$

The T matrices for Groups A, B and C are given in Table App. 20.7. The factor loadings on the P M V axes, ie AT, are given in Tables App. 20.1, 20.2 and 20.3.

11. It would have been possible to have chosen oblique axes V' and M', coinciding with GT35 and the centroid of mechanical tests vectors. The necessary additional steps to rotate the P M V scores to P M' V' scores are summarised on Figure 30.9. Essentially, if T_o is the matrix of direction cosines of P M' V' axes versus P M V axes, the factor loadings become ATT_o and the observation scores become

$$Y_{to} = T_o^{-1} T^{-1} (A'A)^{-1} A'Z$$

The matrix T_o is given in Table App. 20.7 and the loadings ATT_o are listed in Tables App. 20.1, 20.2 and 20.3.

12. The orthogonal axes P M V have been used for the further investigations in preference to the oblique axes P M' V' since:-

a. the choice is an arbitrary one;

b. the interpretation of results is facilitated by the use of orthogonal axes.

13. The transformations:-

$$Y_t = T^{-1} (A'A)^{-1} A'Z$$

were consequently applied to the observations of all three groups to give scores for all individuals on the P M V axes.

<u>Distribution of P M V scores</u>

14. Univariate statistics for the resulting P M V scores for each group are given in Table App. 20.8. The table shows the means, ranges and standard deviations of P M V for:-

a. all candidates

b. accepted candidates

c. rejected candidates

in each group.

15. To enable the distribution of P M V scores of these three categories of each group to be shown graphically the 95% and 99% probability boundaries for each variable, category and group were calculated. The values are listed in Table App. 20.9.

16. The ideallised distributions of the P M V scores are illustrated in Figures 30.10 to 30.15. The locations of the means and the 95% and 99% limits for accepted and rejected candidates have been shown in each case.

17. It is at once apparent that there has been a progressive tendency for the P score to become more dominant in the selection process. The mean P score of accepted candidates was considerably higher in Group B than in Group A, presumably as a result of increasing the weighting of B.MARK from 300 to 400. The effect is greater still in Group C where the difference of mean P scores of accepted and rejected candidates is almost twice the difference in Group A. This reflects the complete removal of the C.S.C. examinations score from the selection ranking and entire reliance on B.MARK.

18. Univariate statistics have also been calculated for the individual samples X, E and S of Group A. Values of means and standard deviations are listed in Table App. 20.10 and the interrelationship of means is shown in Figure 30.16. The plot illustrates the tendency for Seaman officers to have high P scores, for Engineer officers to have high M scores and for Supply and Secretariat officers to have high V scores.

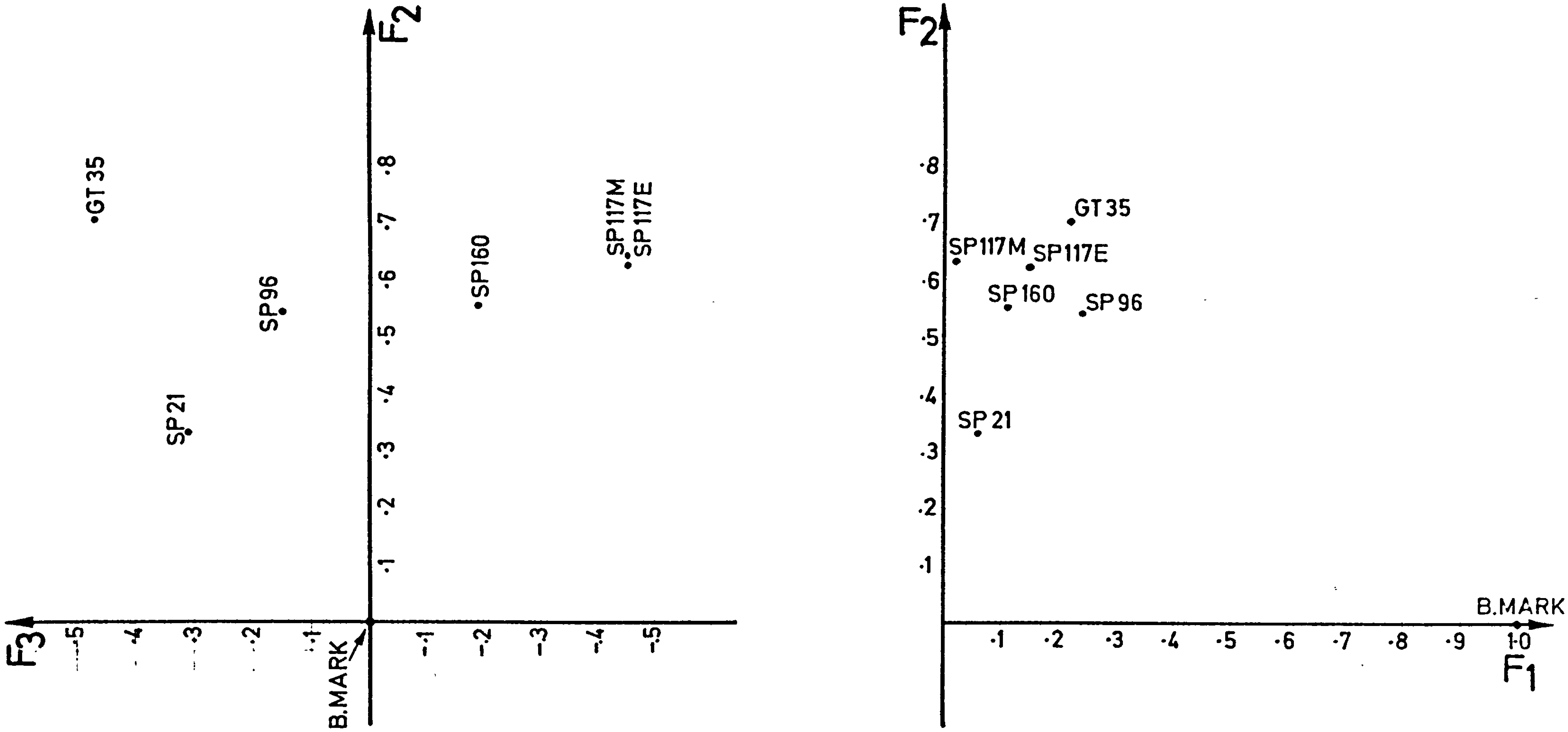
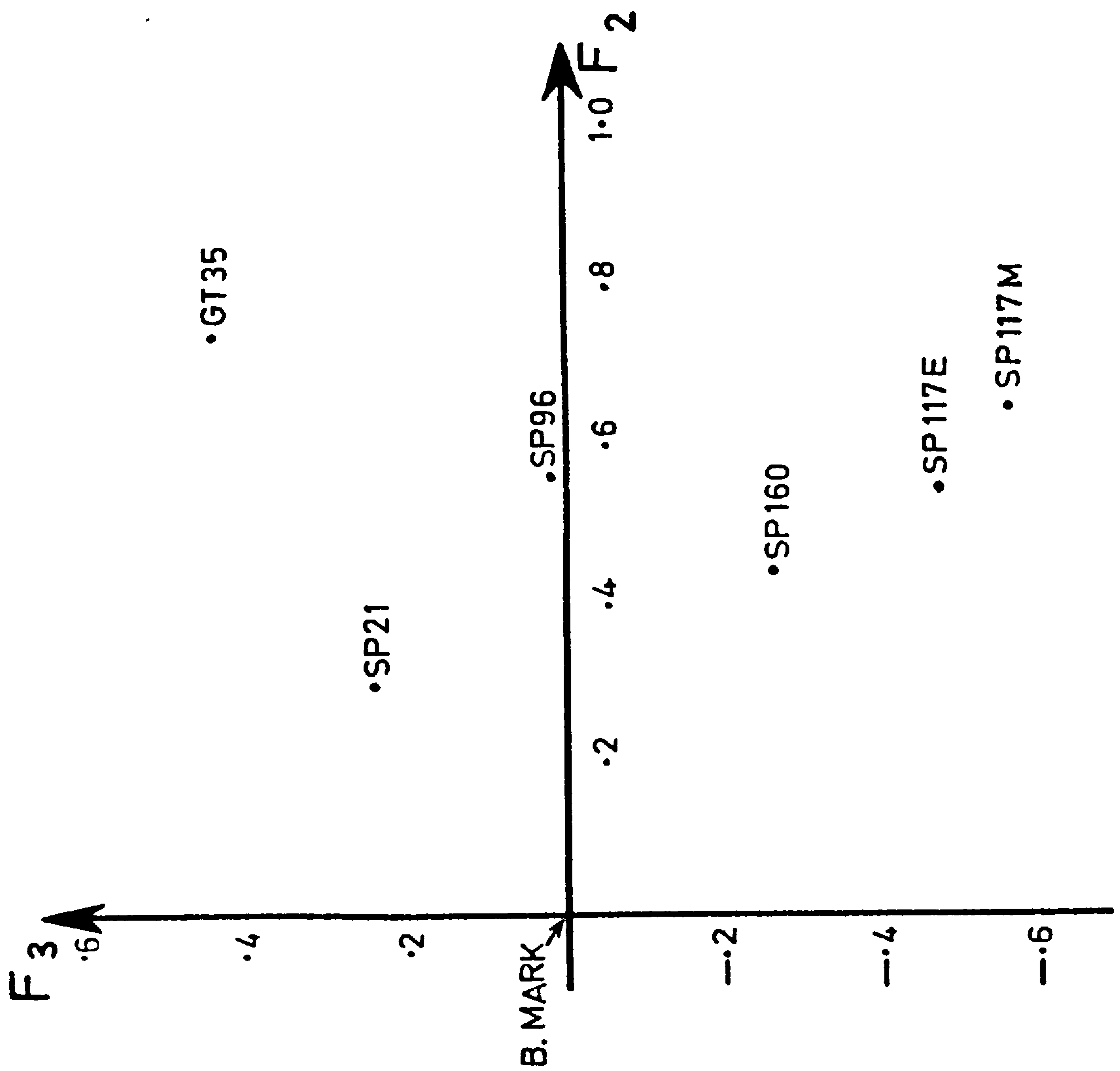


FIG 30.1. THREE-FACTOR MODEL OF GROUP A SELECTION DATA



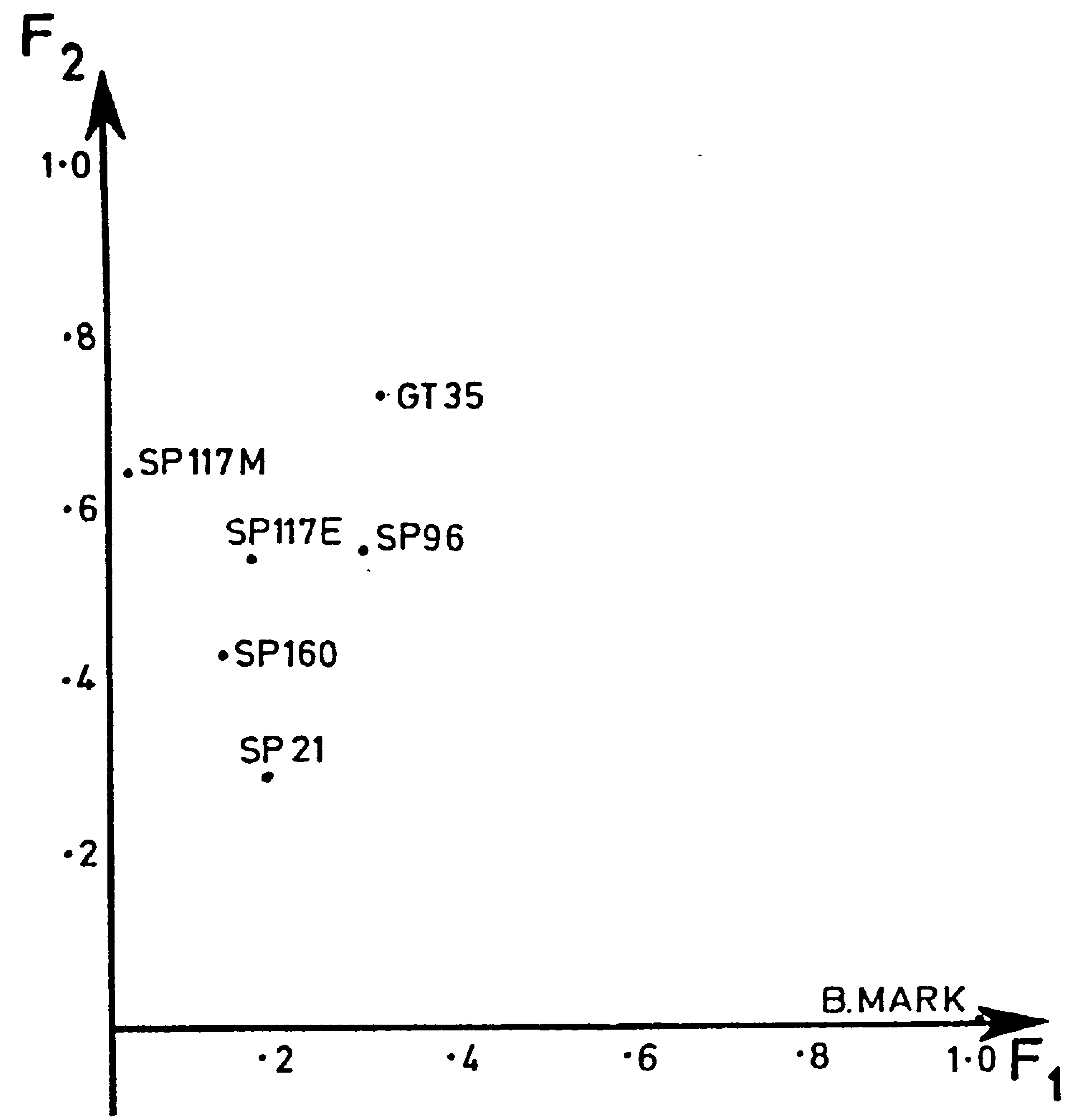
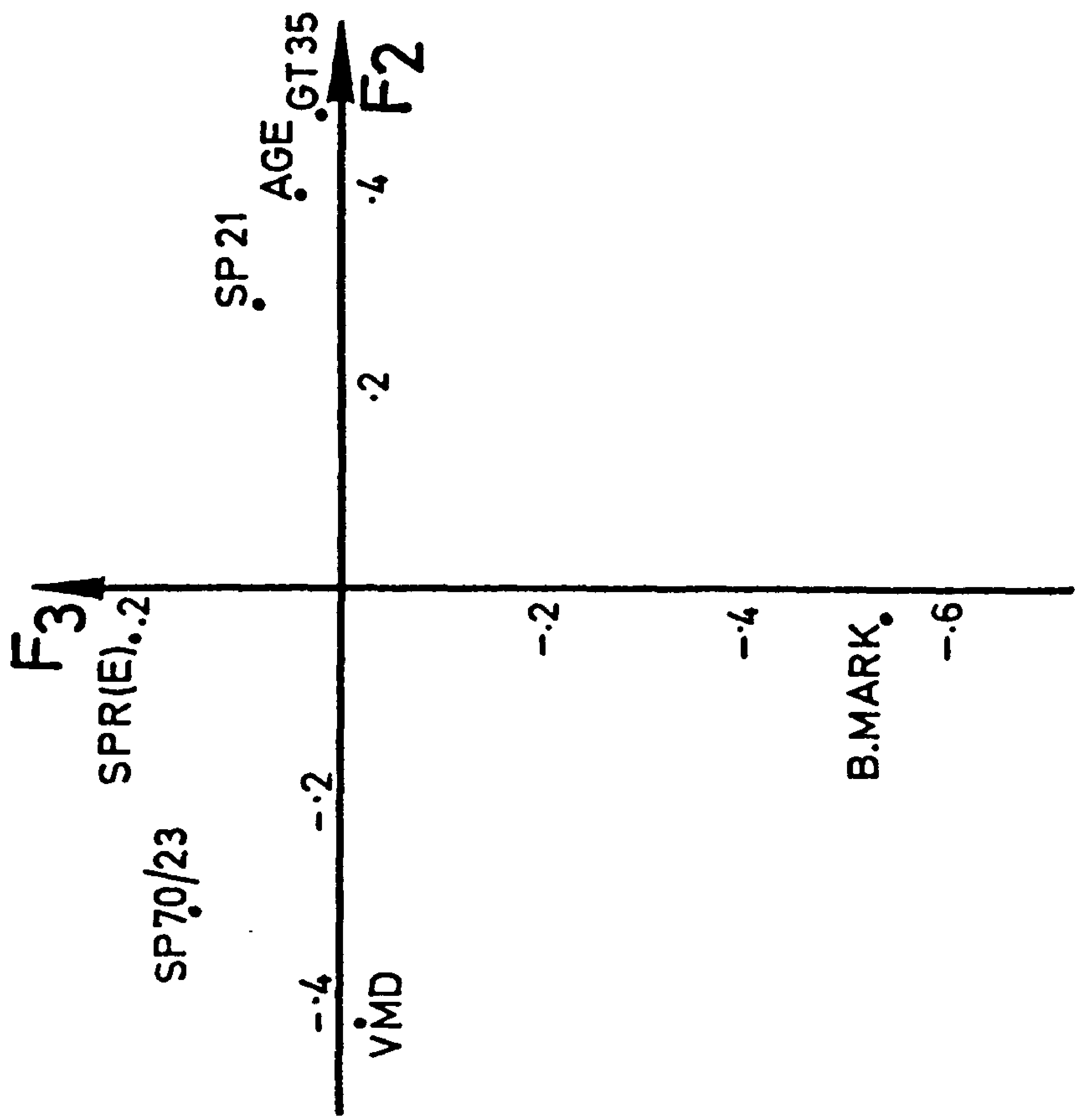


FIG 30.2. THREE–FACTOR MODEL OF GROUP B SELECTION DATA



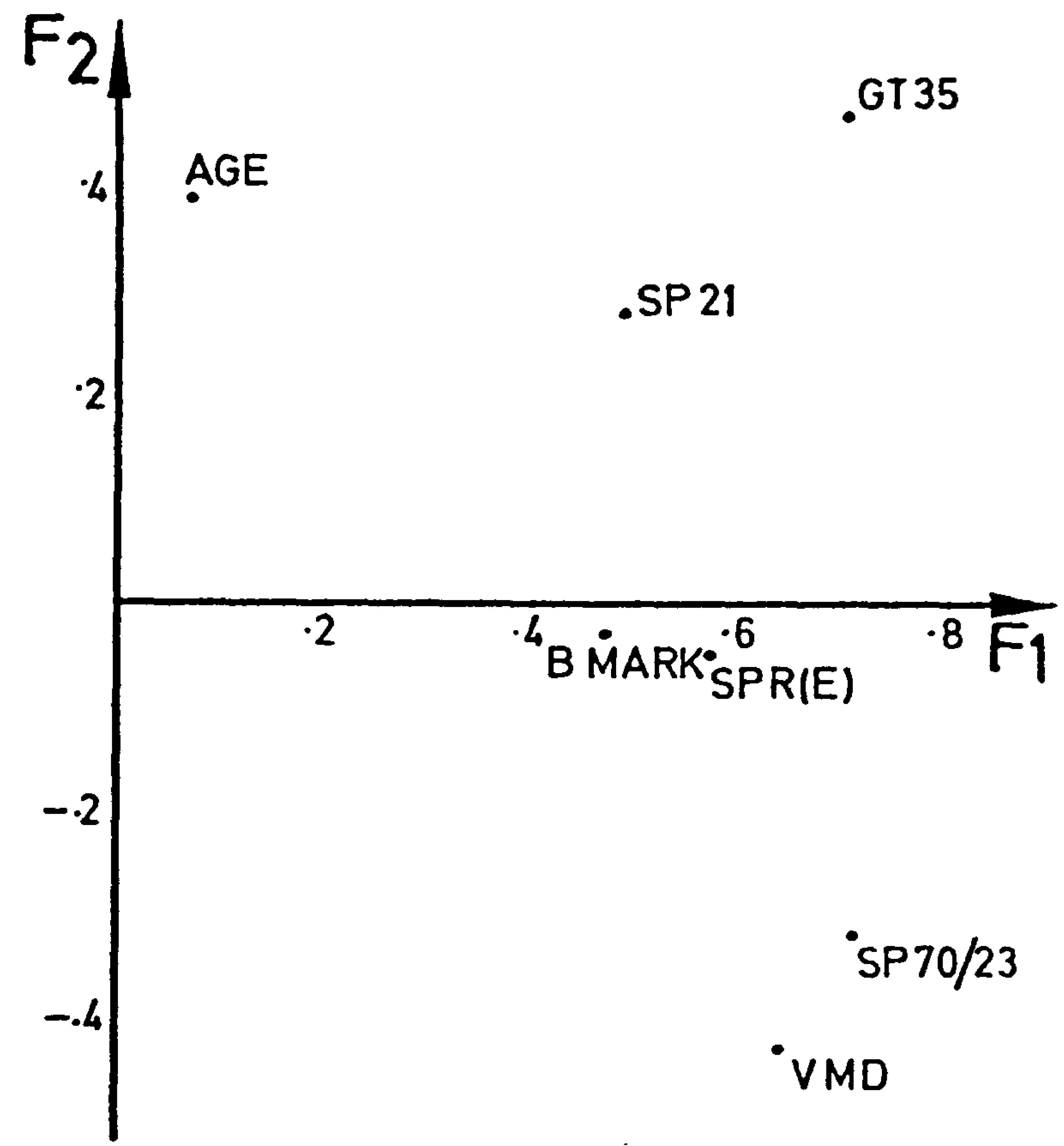


FIG 30.3. THREE-FACTOR MODEL OF GROUP C SELECTION DATA

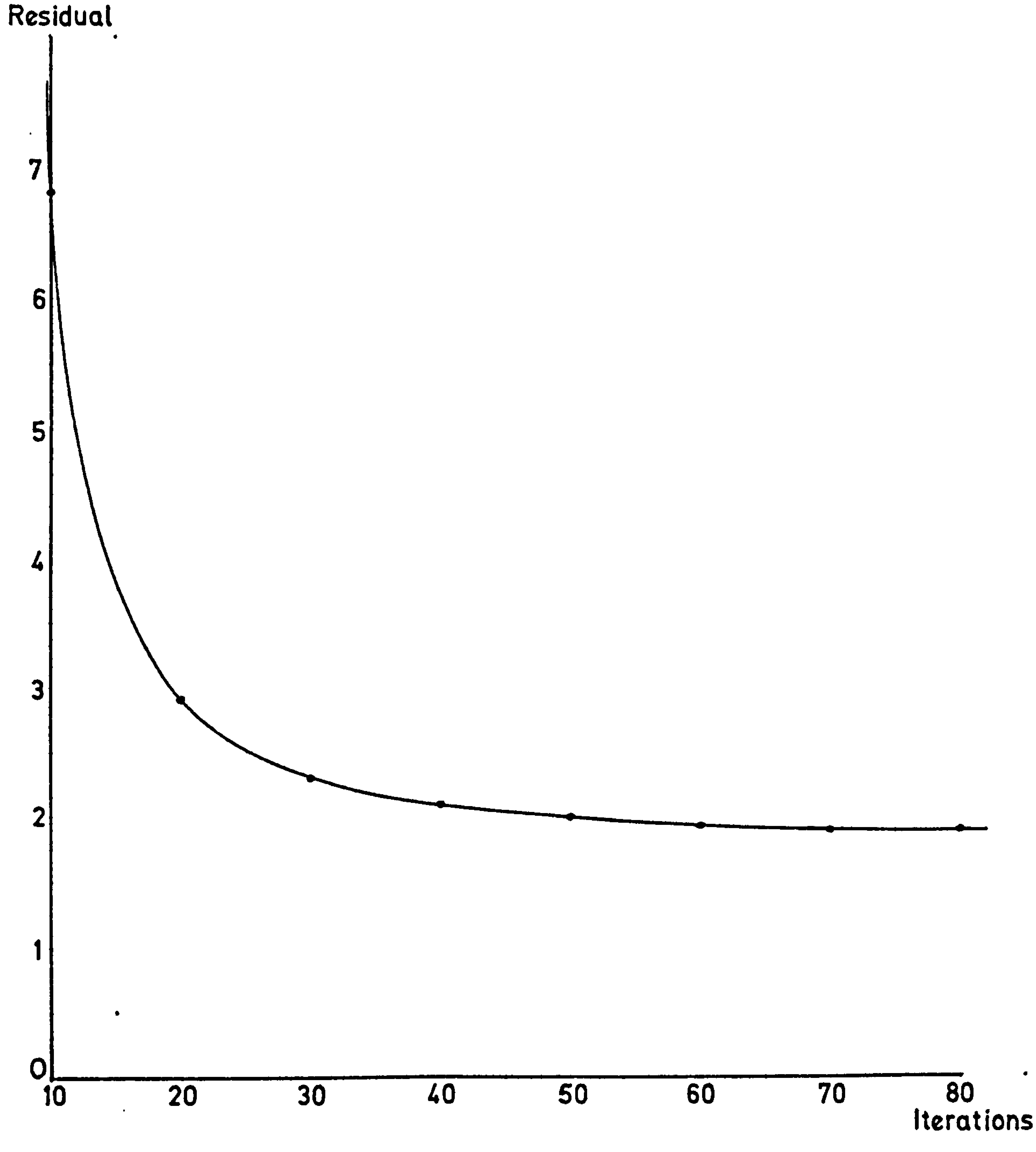


FIG 30.4. CONVERGENCE OF FACTOR SOLUTION – GROUP A

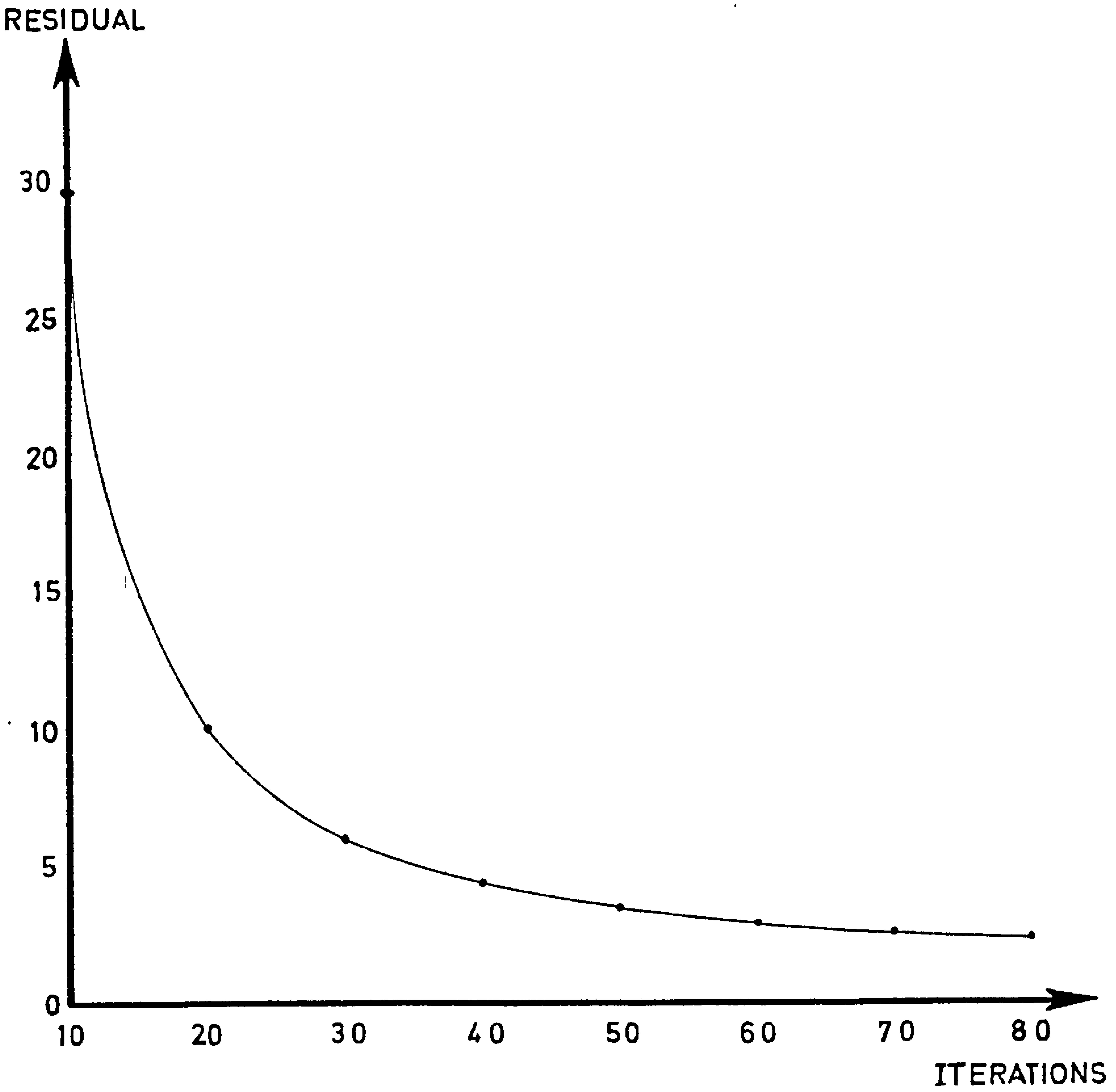


FIG 30.5. CONVERGENCE OF FACTOR SOLUTION - GROUP B

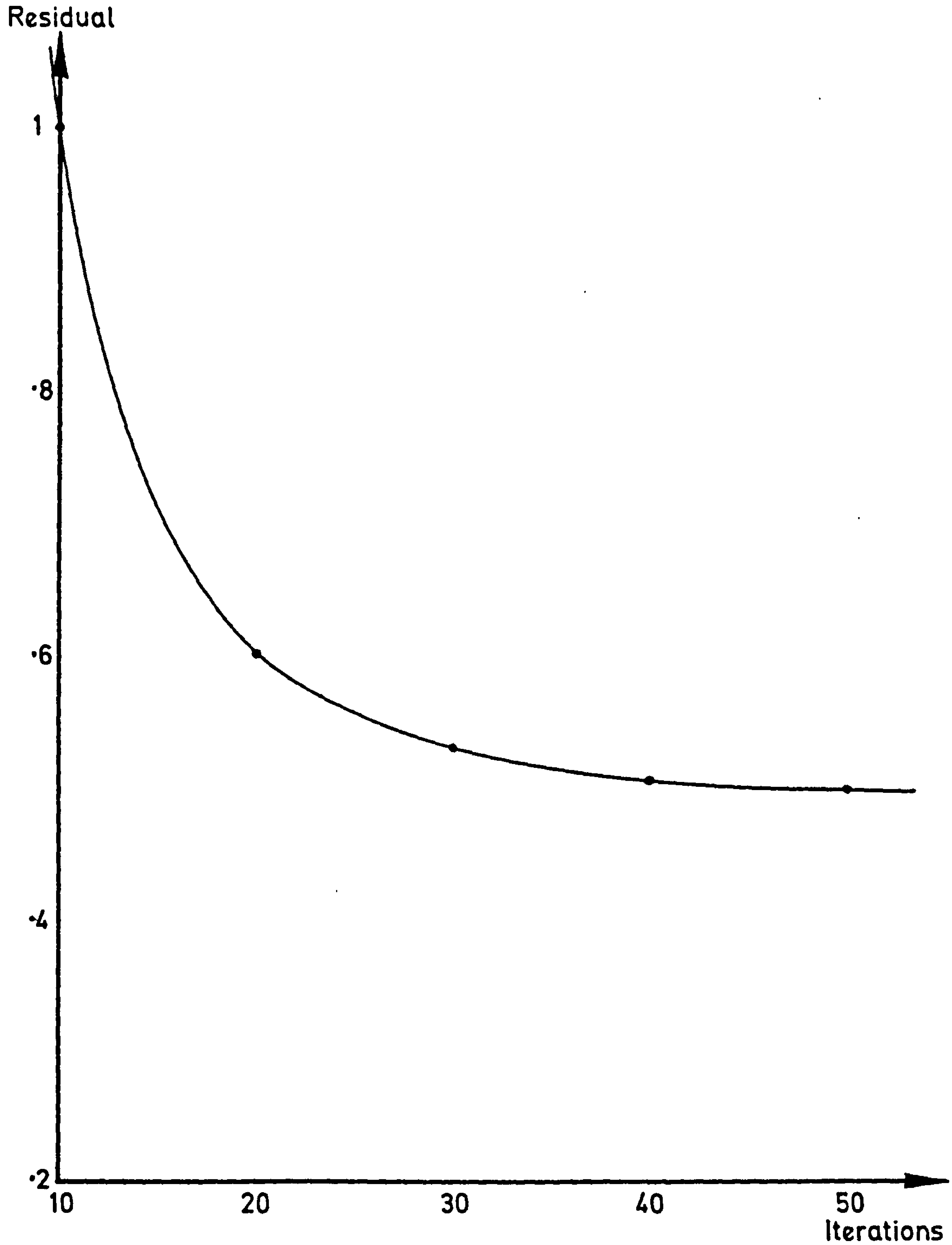


FIG 30.6. CONVERGENCE OF FACTOR SOLUTION - GROUP C

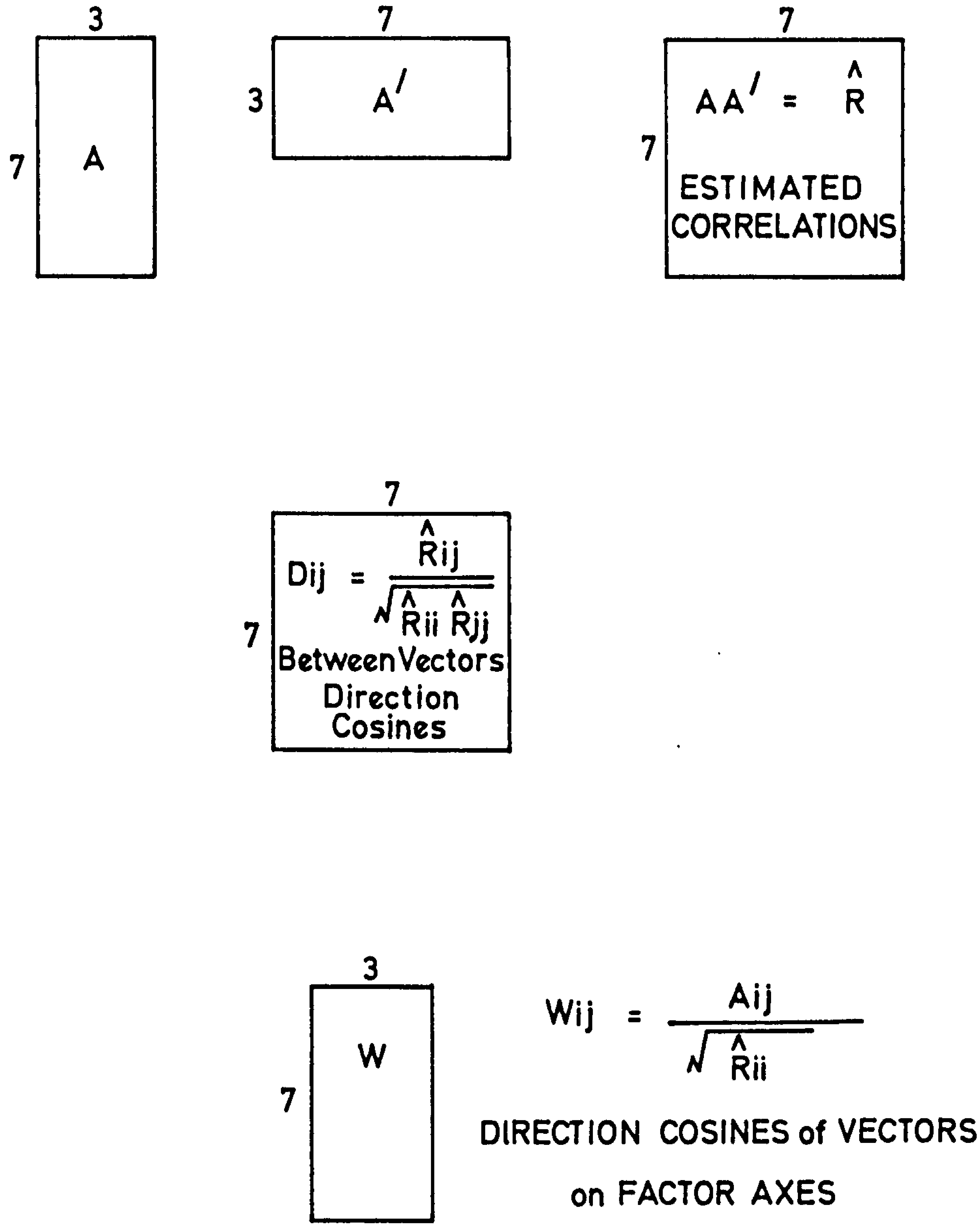


FIG 30.7. DERIVATION OF ANGLES BETWEEN VECTORS AND BETWEEN VECTORS AND FACTOR AXES

FACTOR MODELS of SELECTION DATA

FIGURE 30.8a	GROUP A on F1, F2, F3 AXES
FIGURE 30.8b	GROUP B on F1, F2, F3 AXES
FIGURE 30.8c	GROUP C on F1, F2, F3 AXES
FIGURE 30.8d	GROUPS A, B and C on P M V AXES

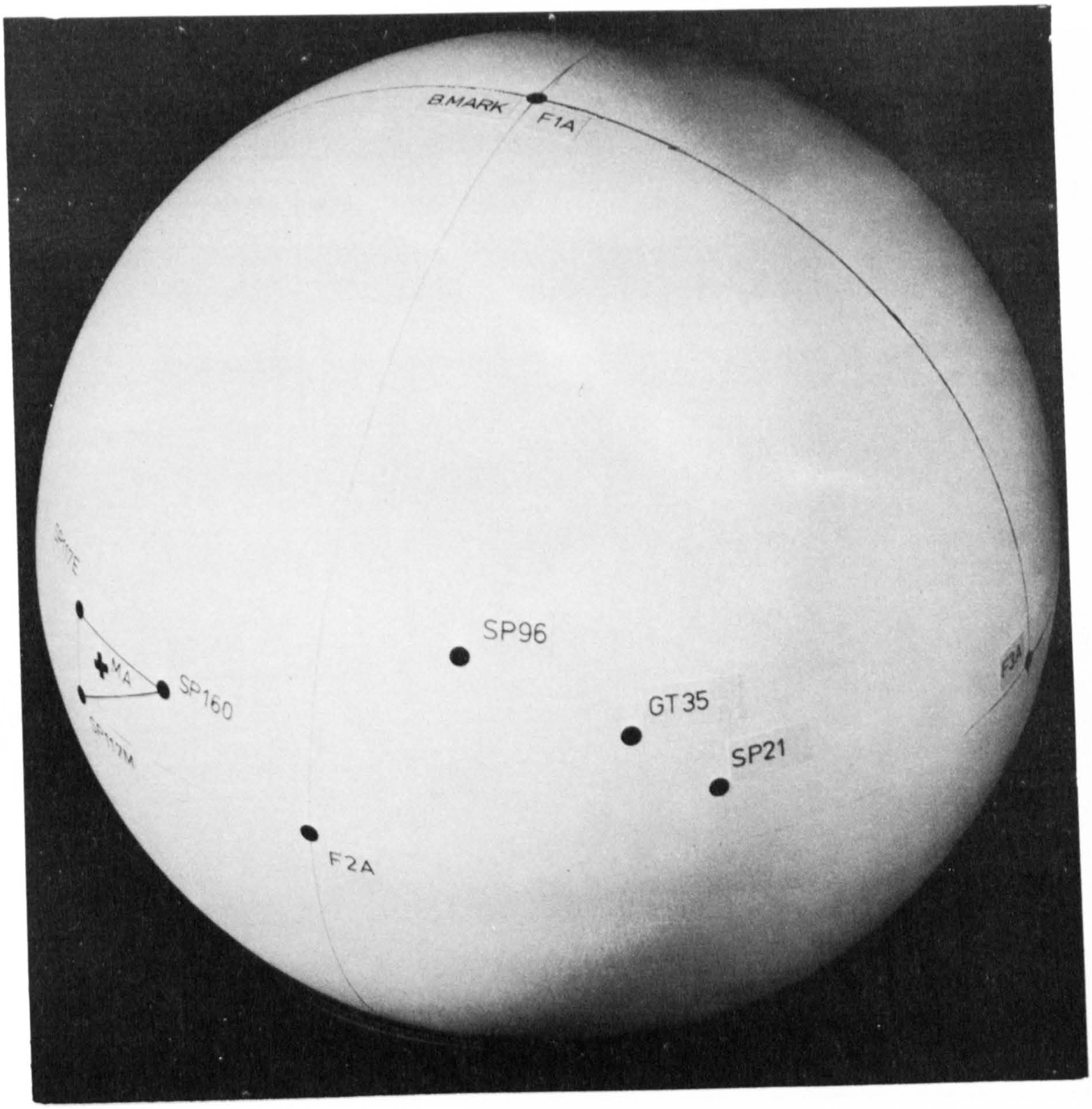


FIG 30.8a GROUP A FACTOR MODEL

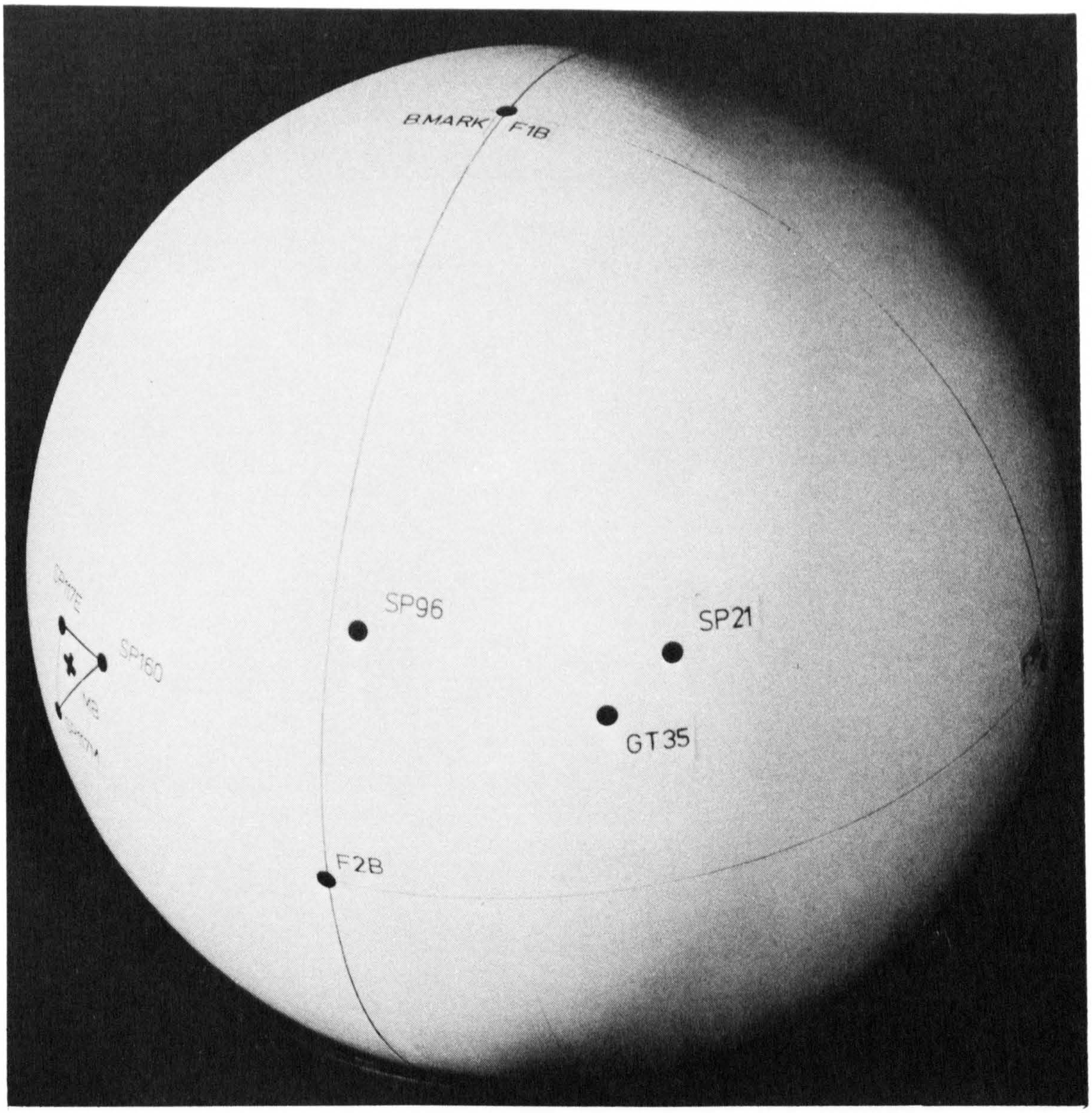


FIG 30.8b GROUP B FACTOR MODEL

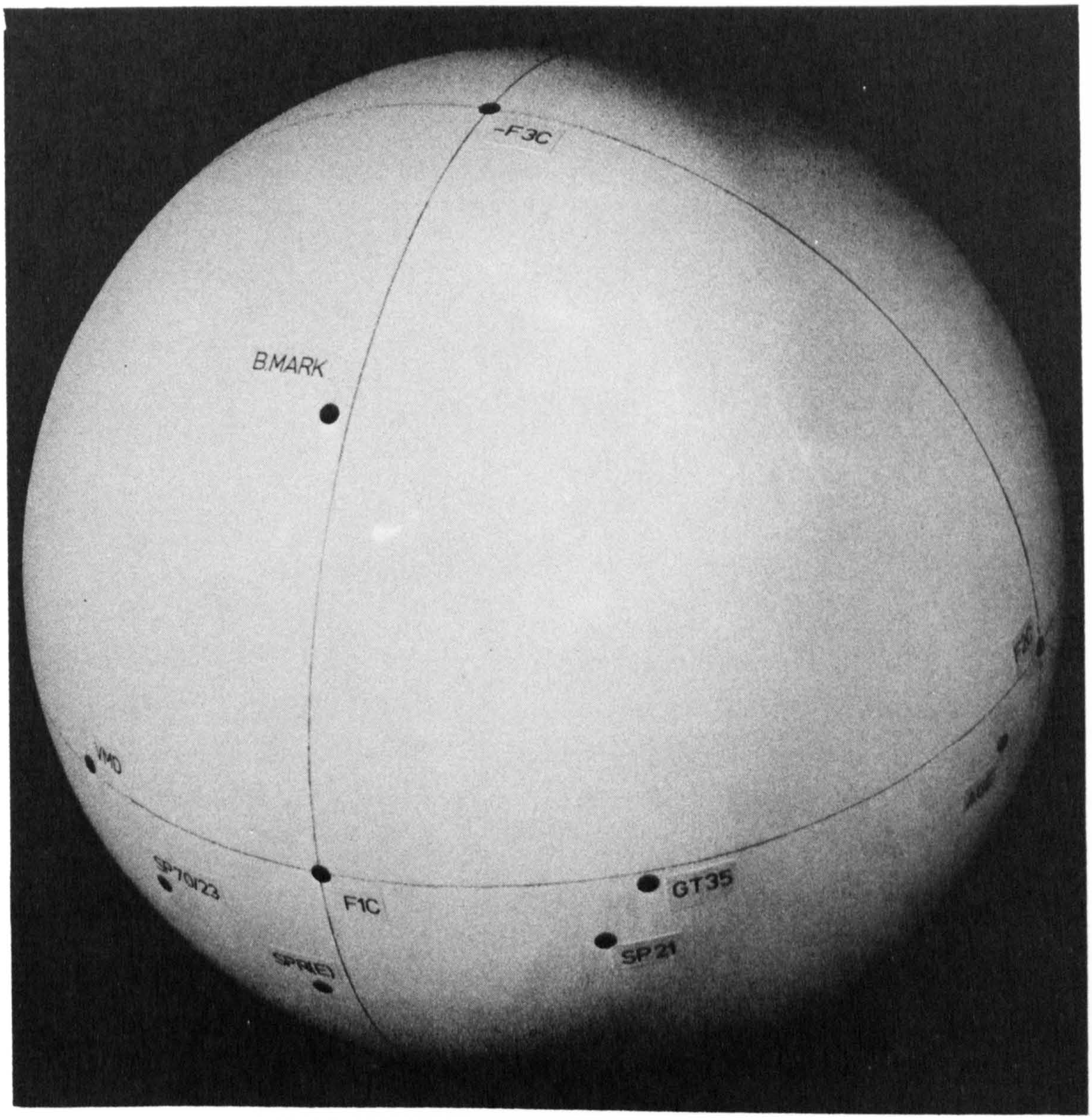


FIG 30.8c GROUP C FACTOR MODEL

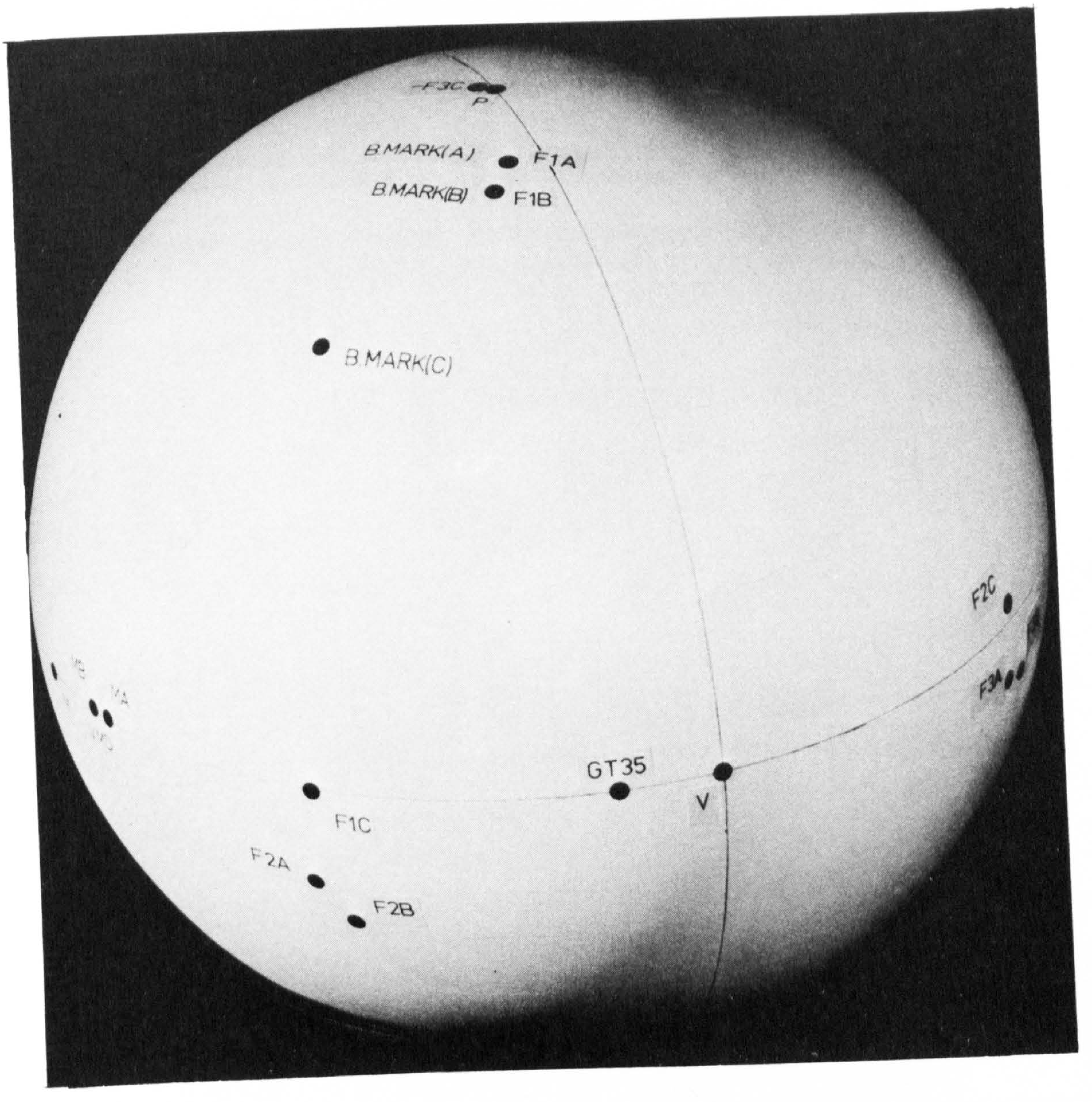


FIG 30.8d GROUPS A, B AND C FACTOR MODEL

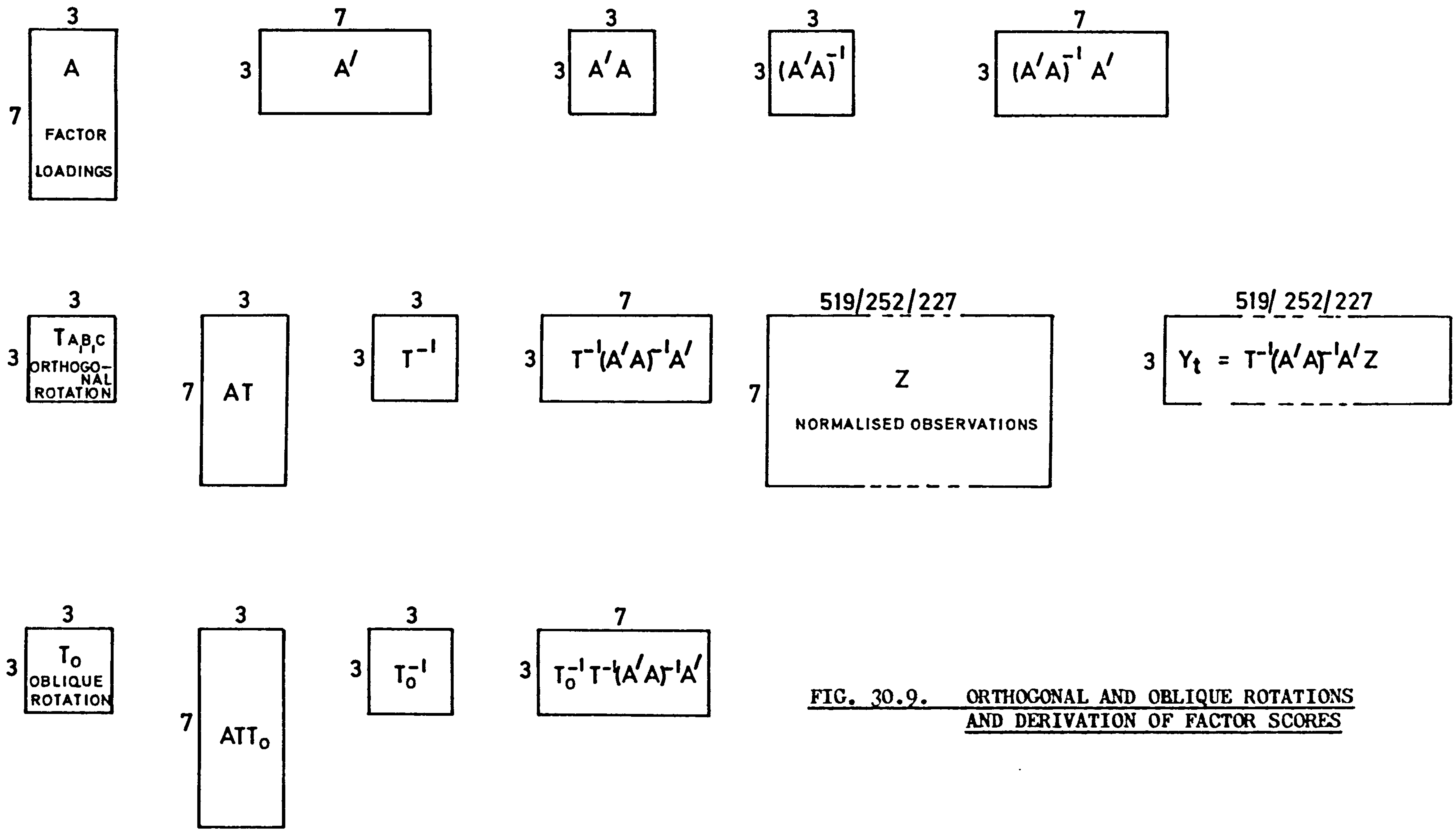
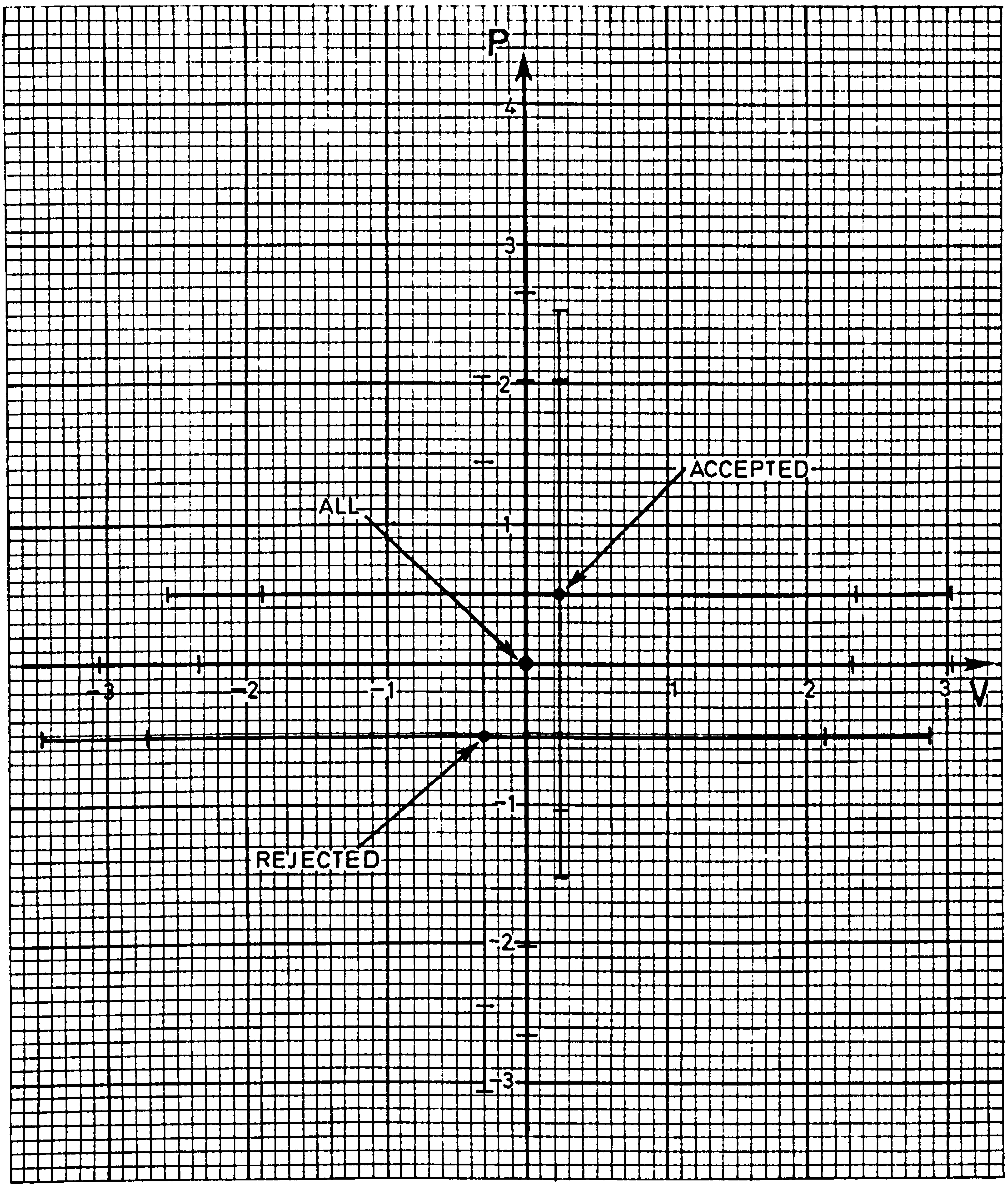


FIG. 30.9. ORTHOGONAL AND OBLIQUE ROTATIONS AND DERIVATION OF FACTOR SCORES



Inner and outer marks denote 95% and 99% contours in each case

FIG 30.10. GROUP A - DISTRIBUTION OF PV SCORES

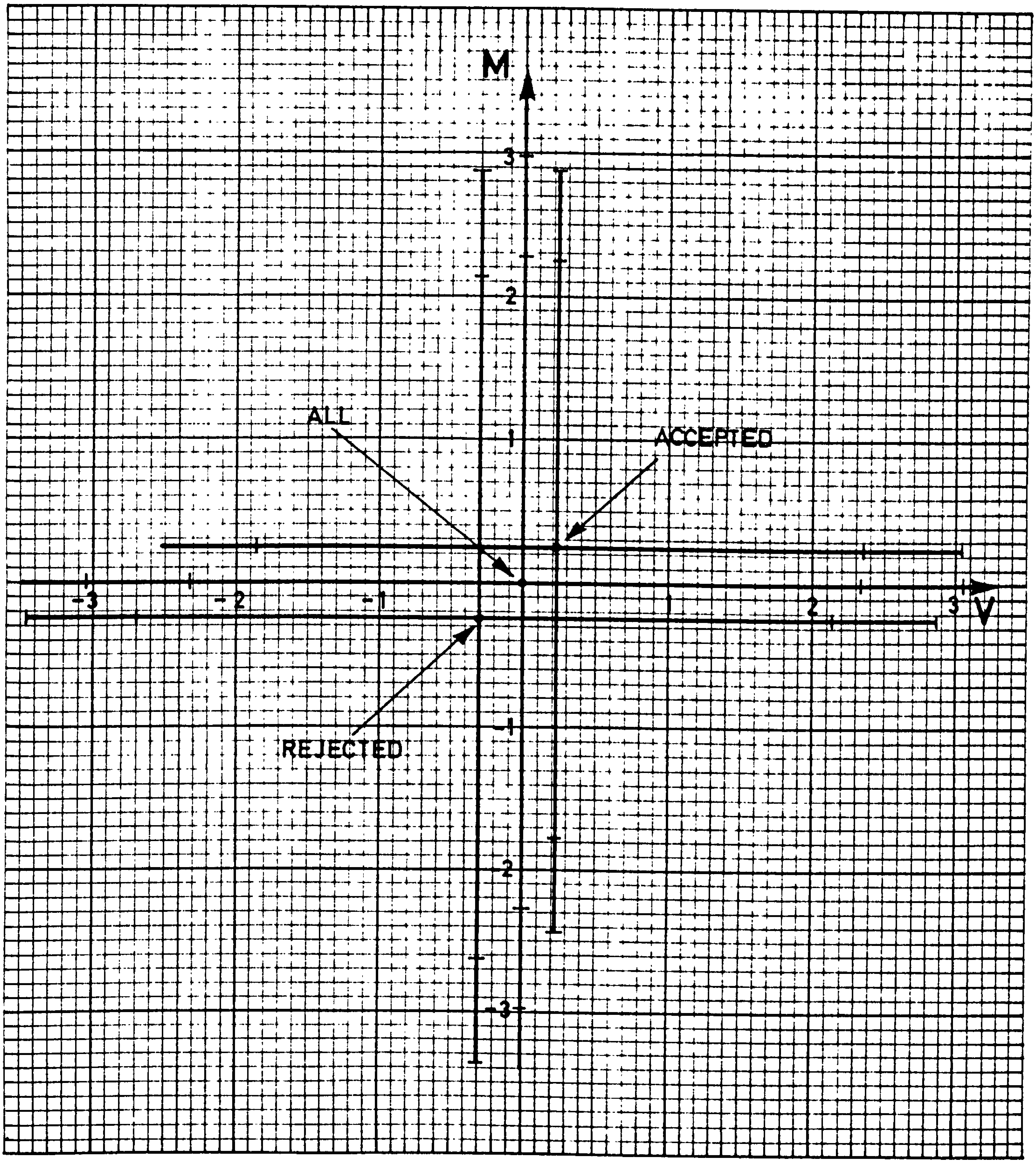


FIG 30.11. GROUP A – DISTRIBUTION OF MV SCORES

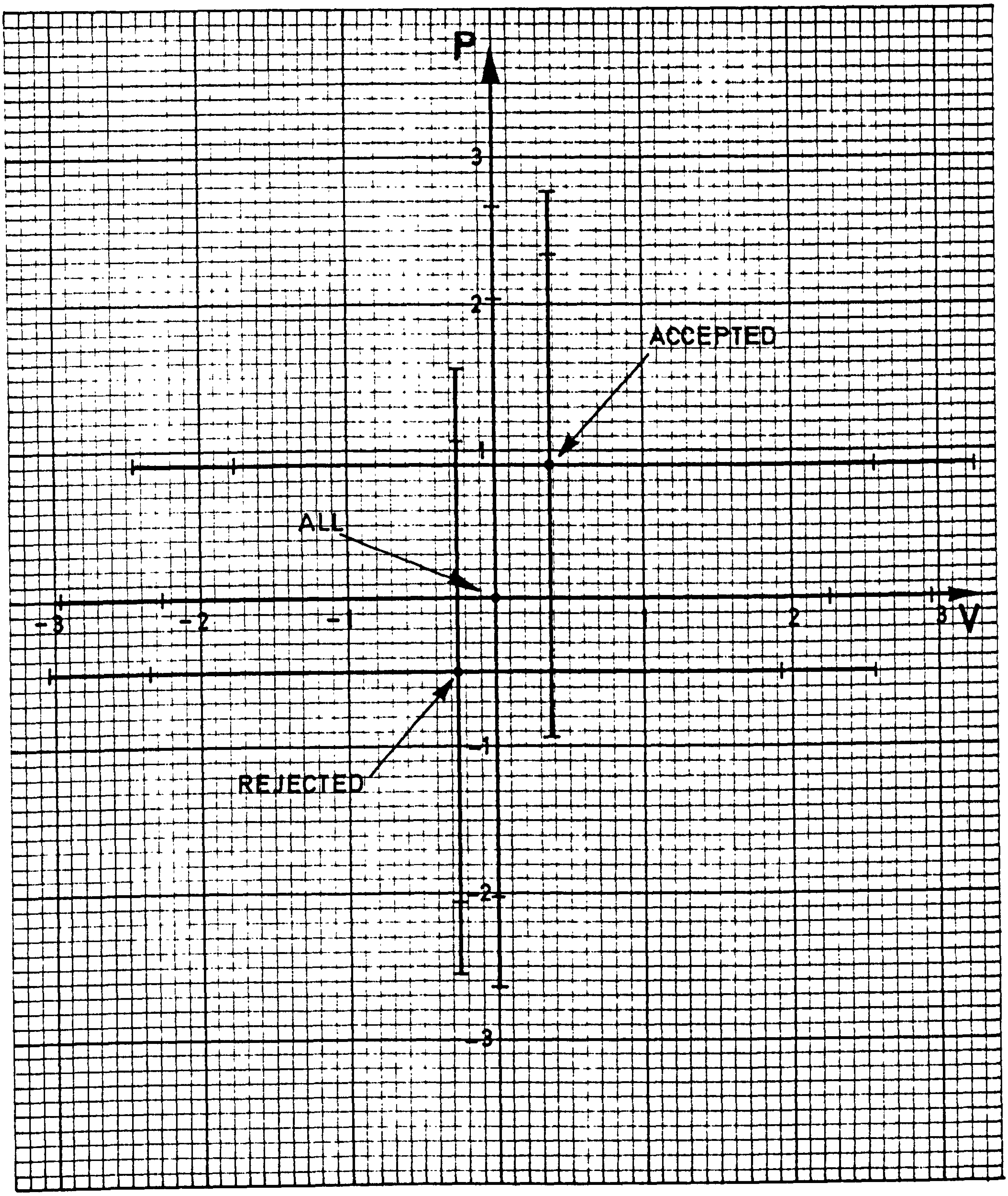


FIG 30.12. GROUP B - DISTRIBUTION OF PV SCORES

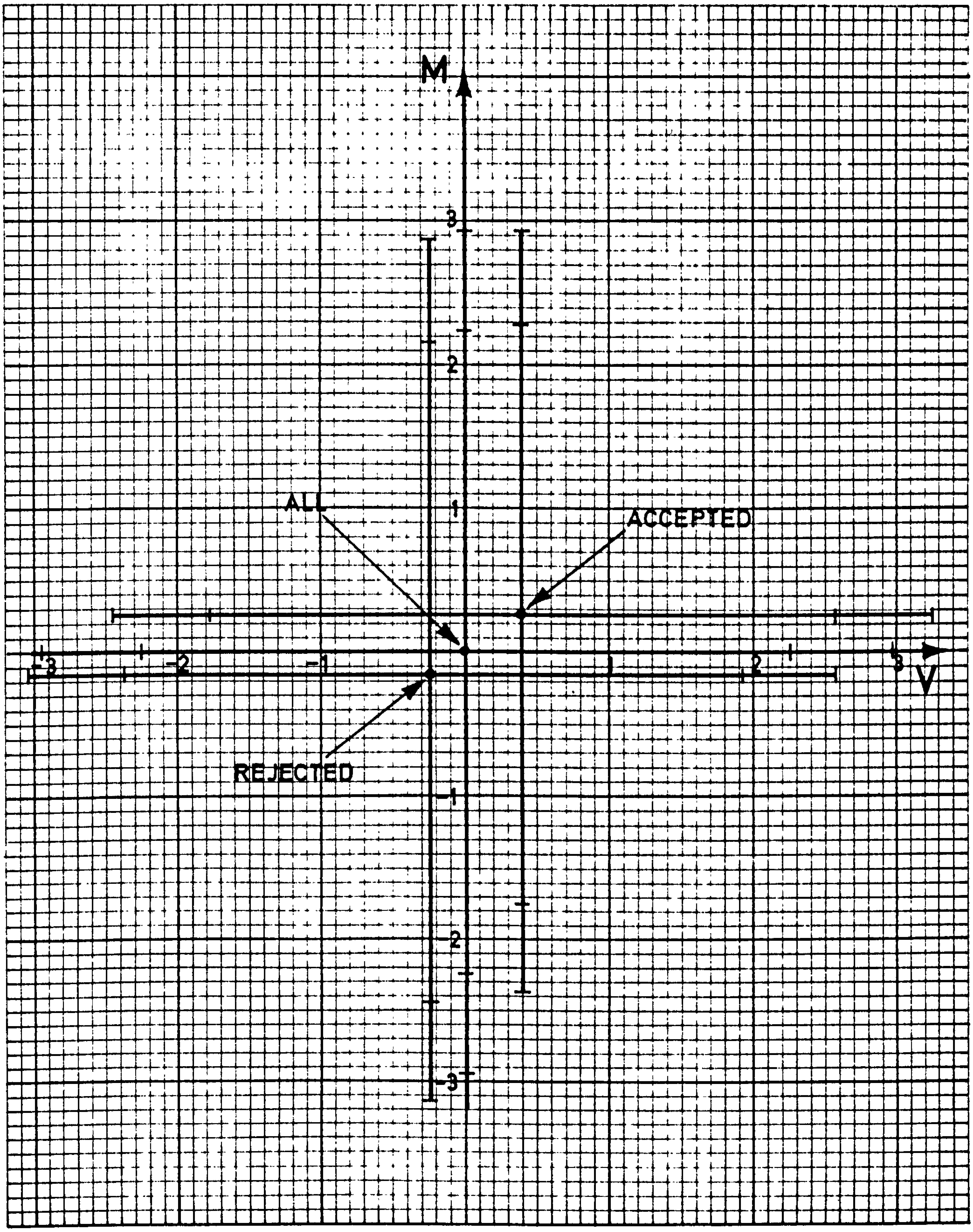


FIG 30.13. GROUP B - DISTRIBUTION OF MV SCORES

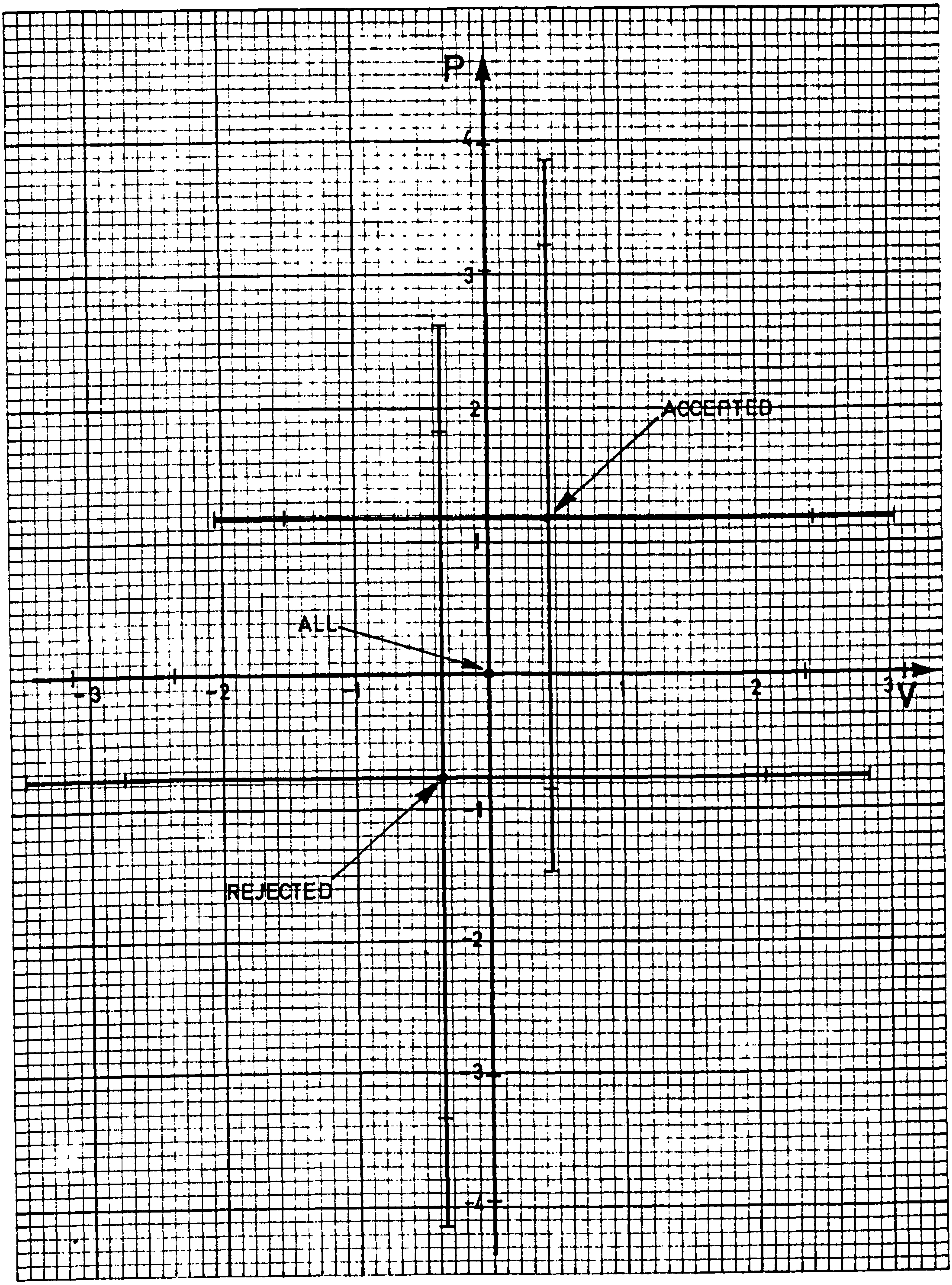


FIG 30.14. GROUP C - DISTRIBUTION OF PV SCORES

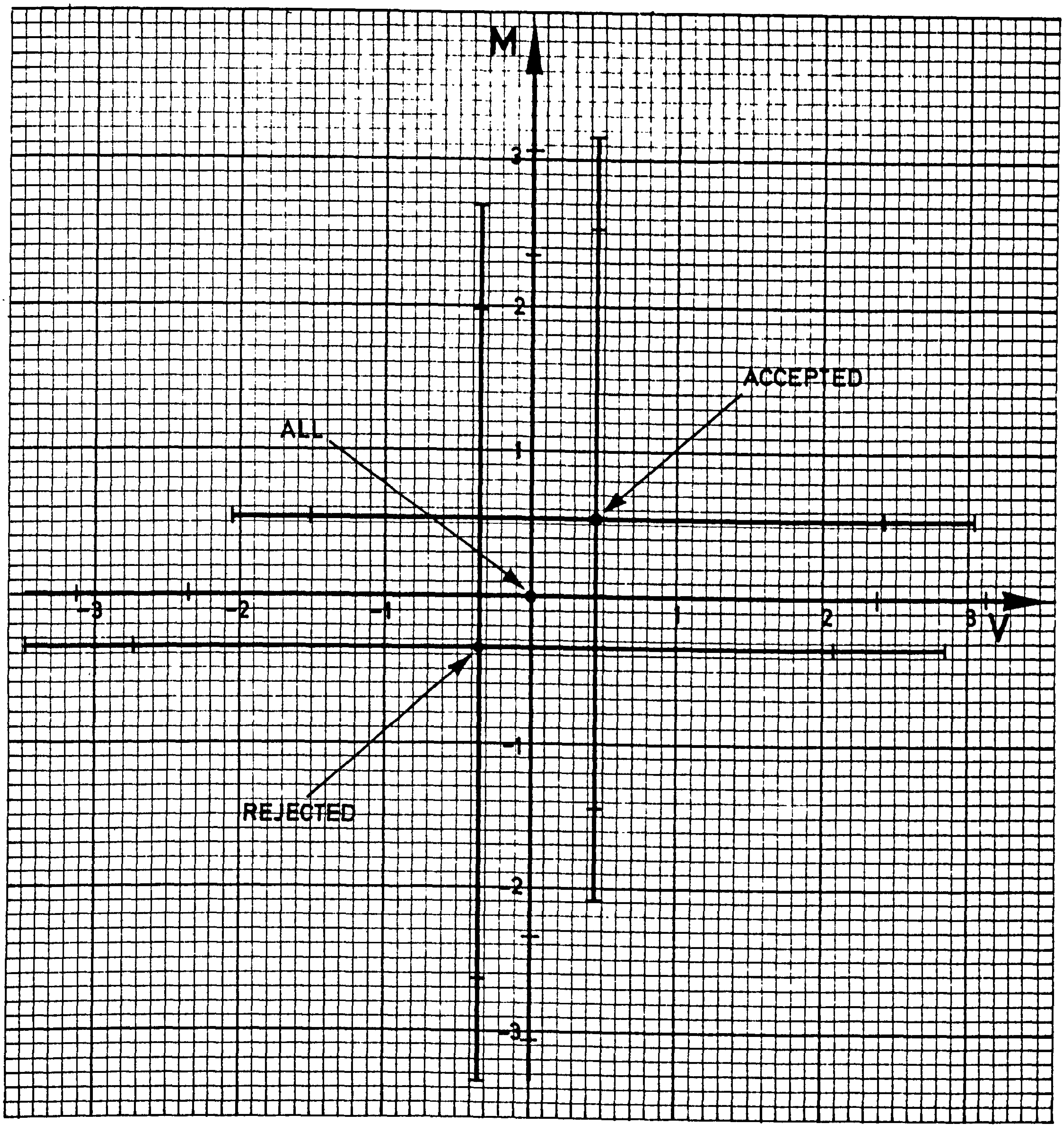


FIG 30.15. GROUP C - DISTRIBUTION OF MV SCORES

FIG. 30.16 <u>RELATIONSHIP of MEANS of P M V SCORES of SAMPLES X, E and S</u>

CHAPTER 31

DERIVATION OF PREDICTORS USING THE CONDENSED DATA

1. The derivation of P, M and V scores for each candidate of the three groups has been described in Chapter 30. The use of these scores for predictive purposes is now considered.

2. Experience with the primary investigations showed that relatively good predictions of training results are obtainable from the selection test scores from which P, M and V are derived, but that forecasts of long-term success are substantially improved by the use of biographical predictors.

3. Since biographical data is not available for Groups B and C, the predictor methodology has been developed using P M V scores only, but examples are given of the refinement which may be achieved by use of biographical data and early training results. As in the primary investigations the use of both regression analysis and discriminatory analysis has been explored.

Regression of D.TOT on P M V

4. In order to demonstrate the use of P M V scores as a means of inter-relating samples for predictive purposes a multiple regression analysis of sample X of Group A has been completed, using D.TOT as criterion and P, M and V as predictors.

5. The variable P proved to be non-significant and the equation derived was:-

$$D.TOT = 34.2M + 27.4V + 953$$

The t statistics for M and V were 3.55 and 2.79 respectively, with 86 degrees of freedom. The former is significant at the P .0005 level and the latter at P .005. The multiple correlation R = 0.40.

6. This equation demonstrates particularly well the importance of cognitive scores, and the relative insignificance of P, for prediction of early training success.

7. The equation has been applied to all observations in Group C and to sample F of Group A and the results are summarised in Figure 31.1. The table shows that, in Group A, 36% of the rejected

candidates are forecast as above mean D.TOT, ie as likely to be better than average in first year naval training. For Group C, the 1969/70 sample, 35% of rejected candidates and 81% of accepted candidates are forecast as above mean D.TOT.

8. It is particularly interesting to observe the different ratios for rejected Direct Entry, University Cadet Entry and Graduate Entry candidates. Almost half the rejected University Cadet Entry candidates are forecast as potentially above average in first year training compared with only a quarter of Direct Entry and a third of Graduate Entry. Thus it appears that considerably more stringent standards are being applied to candidates for University Cadetships.

9. Whilst it is unlikely that any major change has occurred there is no certainty that the function D.TOT is truly representative of current conditions and if the predictor were to be used in the selection process it would be essential to investigate this. For such a short-term criterion it would be more appropriate to use a recently qualified sample for the purpose of deriving a predictor function. The example given above is provided only as a means of demonstrating the use of the synthetic P M V scores for predictive purposes since, in order to demonstrate predictions of long-term success, it is desirable to introduce biographical variables which are not currently recorded.

Regressions of S.INDB on Selection and Early Training Data

10. A series of regression analyses has been completed with the object of exploring the use of combinations of P M V scores, biographical data and early training results for predictions of long-term success. The sample used was again the Seaman officers of Group A. It is not possible to apply the predictors to later samples because biographical data is not available for them.

11. Using P M V scores alone the multiple correlation of S.INDB is 0.2, but introduction of the variable STATUS raises this to 0.26. A further improvement, to 0.35, is obtained by inclusion of the clustered biographicals BA and BB (see Chapter 24), the regression equation (using significant variables only) being:-

$$S.INDB = .26V + .36BA - .44BB + .32\ STATUS + 3.3$$

This equation confirms the findings of the primary investigations, namely:-

a. the dependance of long-term success on verbal ability;

b. the importance of "STATUS" as a long-term predictor;

c. the usefulness of biographical predictors.

12. Inclusion of D.TOT, representing performance in first year training, among the predictors gives a further improvement of R to 0.43, with the following equation:-

$$S.INDB = .29\ STATUS + .008\ D.TOT - 3.6$$

both predictors being very highly significant. This equation demonstrates the value of early training results for long-term prediction and underlines the conclusion drawn from the primary investigation that there is considerable merit in the concept of probationary service.

Discriminatory Predictions using P M V

13. Use of the synthetic P M V scores for discriminatory predictions has also been explored. Using sample X of Group A a pair of discriminatory functions has been derived for prediction of membership of three categories:-

Prom	Promoted to Commander
NPSS	Not promoted, still serving at zone-top
NPLP	Not promoted, left service prematurely (ie before reaching zone-top)

14. The discriminant functions are:-

$$D_1 = -.17P - .05M - .11V$$

$$D_2 = -.03P + .11M + .02V$$

and the group centroids are:-

	Prom	NPSS	NPLP
D_1	- .250	- .183	- .204
D_2	- .003	.005	- .021

15. The relationship of the group centroids of the three prediction categories in terms of D_1 and D_2 scores, and the inter-relationship of D scores and P M V scores, are shown on Figure 31.2. The location of the discriminant plane relative to P, M, V axes is indicated on Figure 31.2a.

16. In broad terms Promotion is associated with high P and V scores and average M scores. Premature leaving is associated with low M scores and long service without promotion with low P and V and high M scores.

17. The predictors have been applied to the parent observations in order to test prediction accuracy. With three categories a random forecast would result in a 33% hit rate. In the present case the hit rate was 55%. Thus, although the absence of biographical variables undoubtedly weakens the predictions, a useful forecast is possible on P M V scores alone. Scrutiny of the forecasts shows that accuracy is highest for the "Prom" category and lowest for "NPSS".

18. The discriminant functions have been cross-validated by applying them to the P M V scores of seaman officers in Group B (AIB 7-10). In this case a hit rate of 53% was achieved, suggesting that the result may be considered stable.

19. The functions have also been applied to the P M V scores of all candidates of Group C (AIB 1969/70). The results, which are summarised in Figure 31.3, appear to provide striking evidence of the success of current selection when measured in terms of forecast prospects of promotion in the Seaman branch. Of the accepted candidates, 49% are forecast as probable promotions (to Commander), 33% as likely to continue to serve to zone-top unpromoted, and 18% as likely to leave prematurely. Of the rejected candidates only 1 is forecast as a probable promotion, 65% as likely to serve to zone-top unpromoted, and 34% as likely to leave prematurely.

20. It must be remembered that no provision has been made in these particular discriminant functions for estimating likely failure. It is reasonable to suppose that potential failure might correspond to high D_1 and low D_2 scores. Examination of the forecasts reveals that a substantial proportion of those predicted as NPSS might well belong to such a category. If the method were to be used for

selection it would be necessary to identify the parameters of the failure category by including it in the discriminatory analysis. A convenient class might be "withdrawn from training".

21. A similar analysis has been completed using the P M V scores of sample S of Group A (ie the Supply and Secretariat officers). Discriminatory functions for prediction of membership of the same three categories (Prom, NPSS, NPLP) were found to be:-

$$D_1 = .11P - .10M + .05V$$

$$D_2 = - .24P - .09M - .09V$$

with the following group centroids:-

	Prom	NPSS	NPLP
D_1	.158	.056	.072
D_2	- .117	- .073	- .159

22. The inter-relationships of the group centroids of the three prediction categories and of P M V scores with D_1 and D_2 scores are shown on Figure 31.4. Both promotion and premature leaving are associated with high P and V scores, the former being related to low M and the latter to high M. The location of the discriminant plane relative to P, M, V axes is also shown on Figure 31.4a.

23. The predictors have been applied to the parent observations, on which the hit rate was 52%. They have also been cross-validated by applying them to the P M V scores of "S" officers in Group B. The resulting hit rate of 57% again suggests stability of predictor functions.

24. The results of applying the functions to the P M V scores of Group C (AIB 1969/70), which are summarised in Figure 31.5, provide striking confirmation of the hypothesis that the present use of common criteria for all branches at the AIB leads to inefficient selections. In terms of potential success as an "S" officer a rejected direct entry candidate in 1969/70 was 6 times as likely to achieve promotion as an accepted direct entry candidate.

Conclusions

25. The examples described have illustrated the feasibility of deriving regression and discriminant functions in terms of the synthetic P M V scores, and of using these functions for predictive purposes in other samples.

26. There are two fundamental assumptions implicit in this procedure; first that the predictive relationship is unaffected by passage of time; second that the co-related P M V scores for different samples are comparable.

27. There is at present no means of verifying the long-term stability of long-term predictions but the short-term stability has been confirmed by comparing discriminatory predictions for Groups A and B.

28. The comparability of P M V scores in different samples can only be assessed in terms of the process by which they were derived. The essential similarity of selection data structure and the statistical adequacy of the three-factor models suggest that the procedure is sound.

29. The value of biographical variables and early training results for long-term predictions is again underlined and it seems likely that further research along these lines might be fruitful.

30. The use of condensed selection test data (P M V scores) in predictor functions has the merit of identifying the predictive value of the data in terms of three readily recognisable dimensions rather than a variety of individual tests. Use of condensed biographical data is perhaps more questionable since meaningful clusters are not so readily discernible. The condensation does, however, produce variables with a more satisfactory distribution.

31. Forecasts of long-term success of recent candidates have been obtained by deriving discriminant functions in terms of P M V scores for samples X and S of Group A and applying these functions to Group C. The results suggest that the selection procedure is successfully ranking candidates in terms of long-term prospects in the Seaman specialisation but is highly inefficient in ranking candidates for the Supply and Secretariat specialisation. Results of the primary investigations suggest that a similar result would be obtained for the Engineering specialisation.

SAMPLE			FORECAST ABOVE MEAN D.TOT	FORECAST BELOW MEAN D.TOT
GROUP A REJECTED CANDIDATES			36	64
GROUP C	ACCEPTED	DIRECT ENTRY	76	24
		UNIVERSITY CADET ENTRY	91	9
		GRADUATE ENTRY	74	26
		TOTAL	81	19
	REJECTED	DIRECT ENTRY	26	74
		UNIVERSITY CADET ENTRY	49	51
		GRADUATE ENTRY	33	67
		TOTAL	35	65

Note: All figures are %s.

FIG. 31.1 FORECASTS of D.TOT for GROUPS A and C

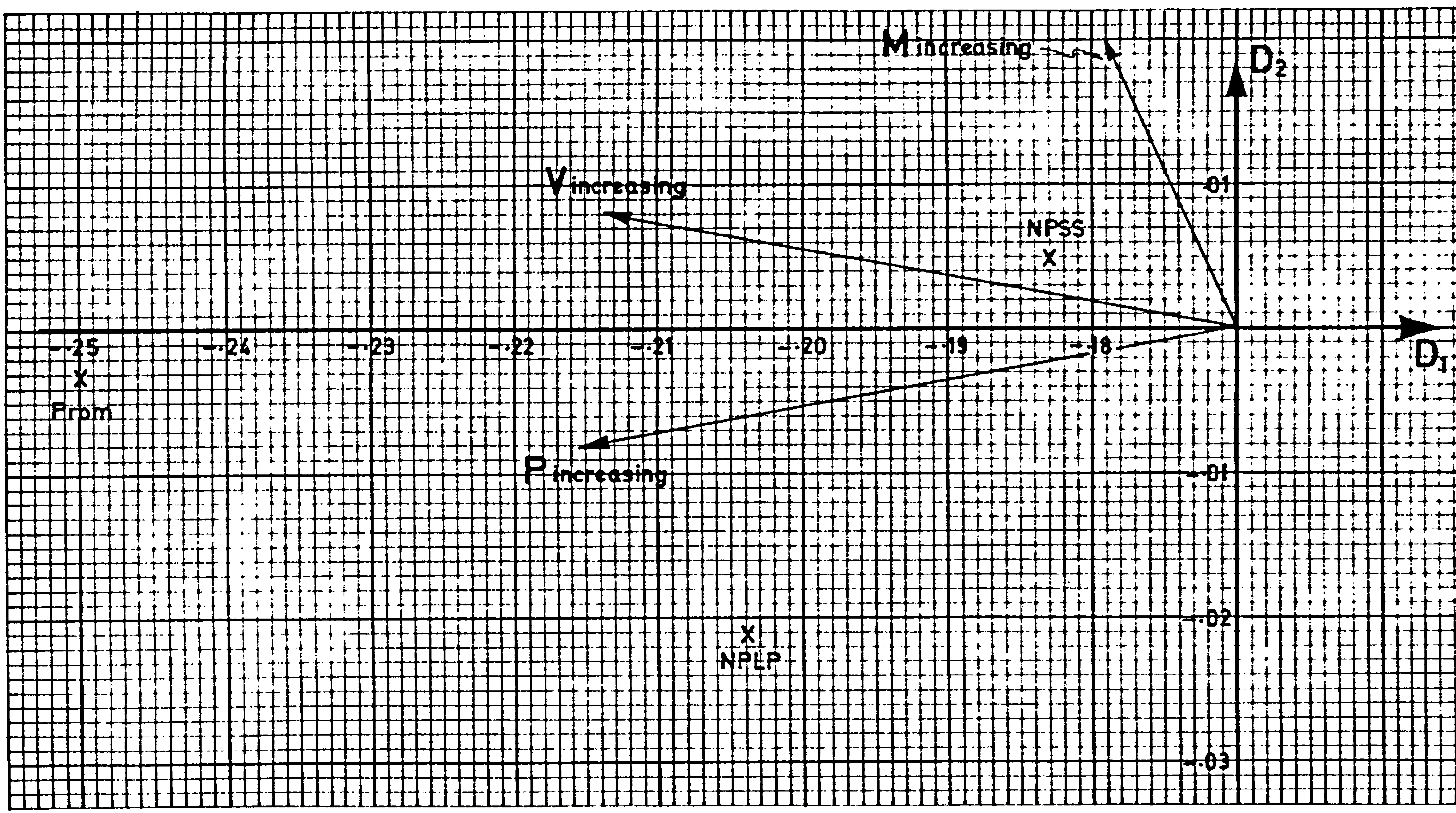


FIG 31.2. DISCRIMATORY ANALYSIS OF SAMPLE X USING PMV SCORES

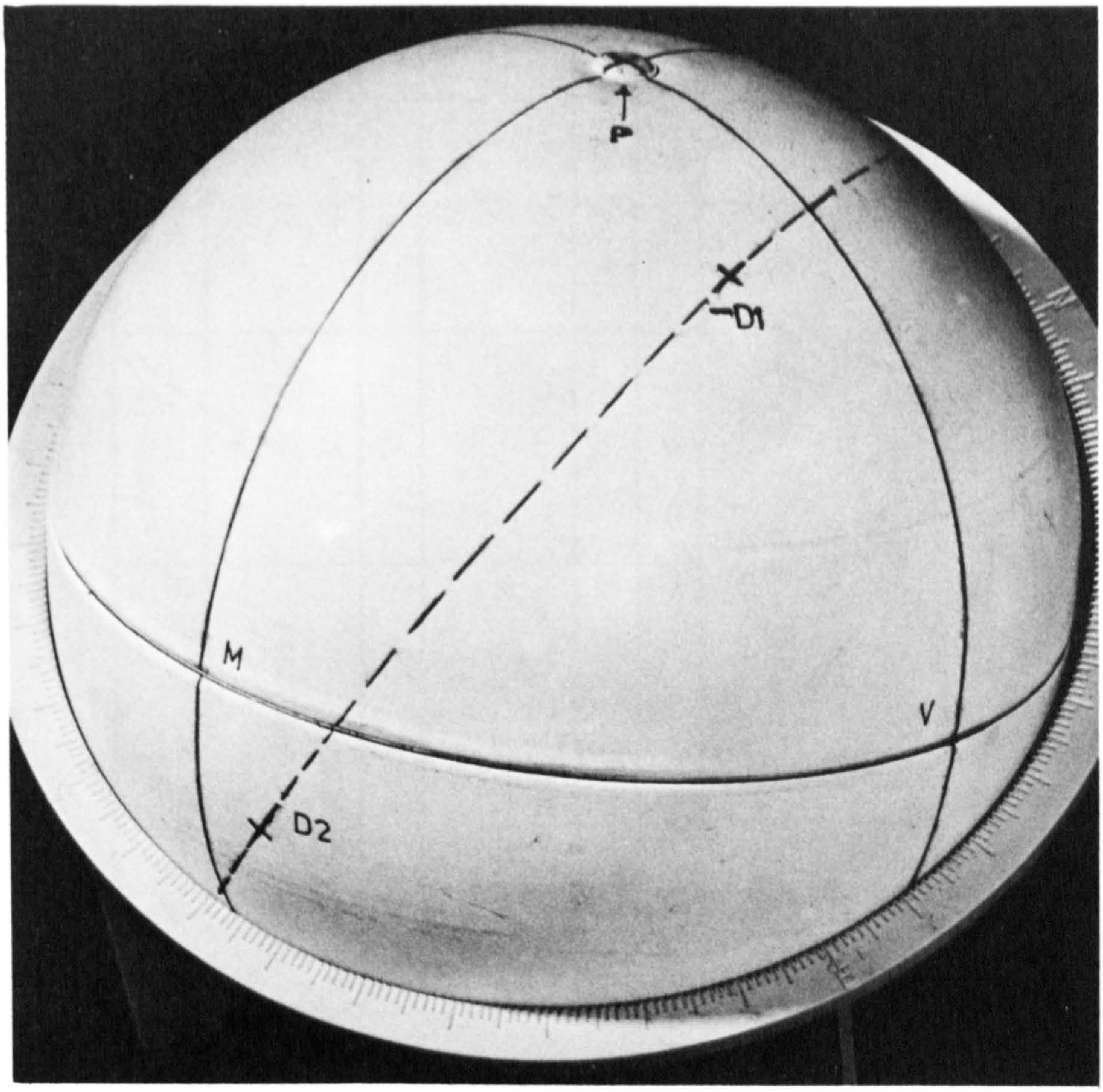


FIG 31.2a SAMPLE X DISCRIMINANT PLANE LOCATION

SAMPLE		FORECAST PROM	FORECAST NPSS	FORECAST NPLP
ACCEPTED	DIRECT ENTRY	54	35	11
	UNIVERSITY CADET ENTRY	52	21	27
	GRADUATE ENTRY	37	47	16
	TOTAL	49	33	18
REJECTED	DIRECT ENTRY	1	64	35
	UNIVERSITY CADET ENTRY	0	73	27
	GRADUATE ENTRY	0	54	46
	TOTAL	1	65	34
TOTAL		20	52	28

Note: All figures are %s.

FIG. 31.3 FORECASTS of LONG-TERM SUCCESS using SAMPLE X DISCRIMINANT FUNCTIONS on P M V SCORES of GROUP C (1969/70)

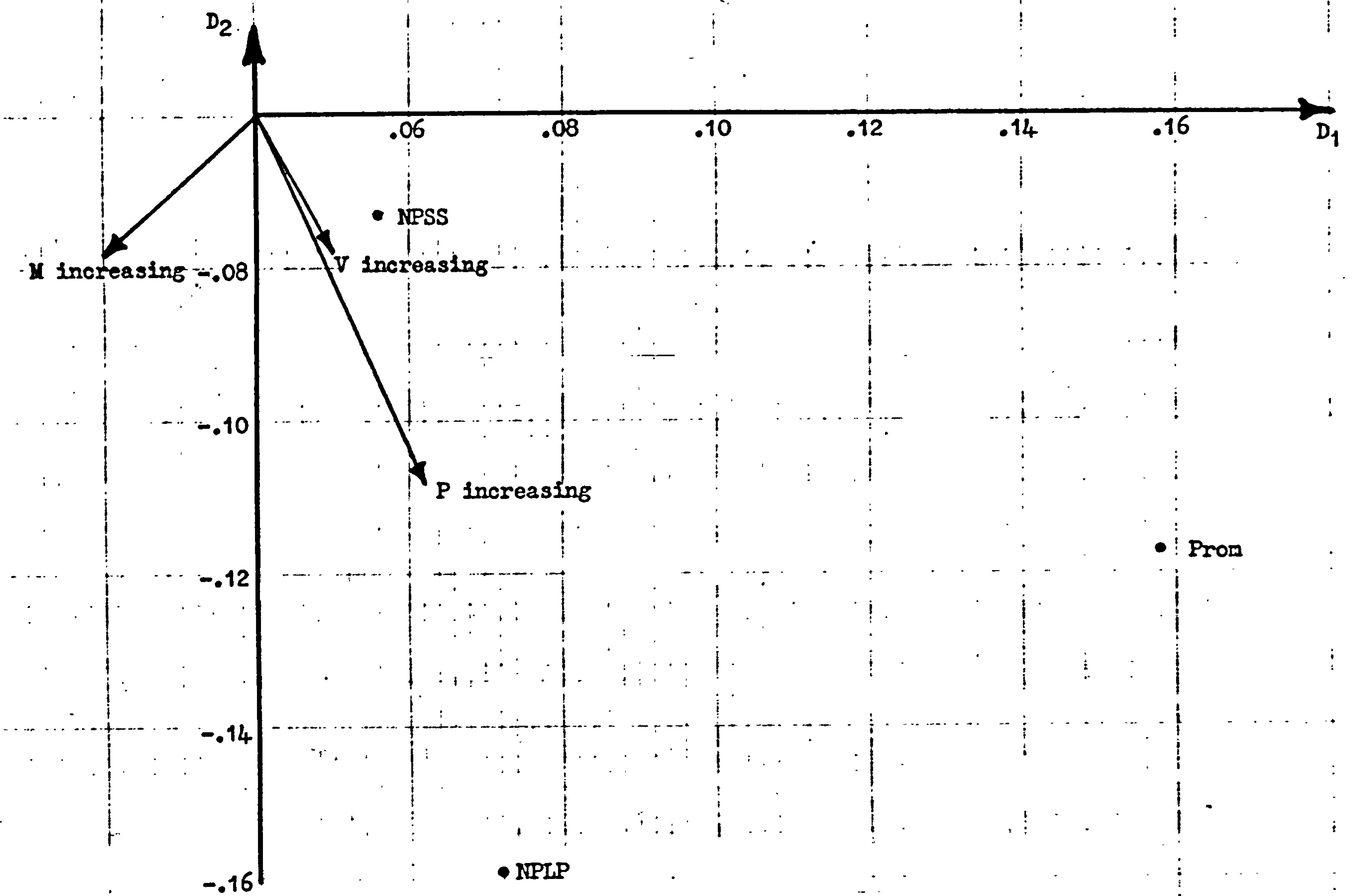


FIG. 31.4 DISCRIMINATORY ANALYSIS of P M V SCORES of SAMPLE S

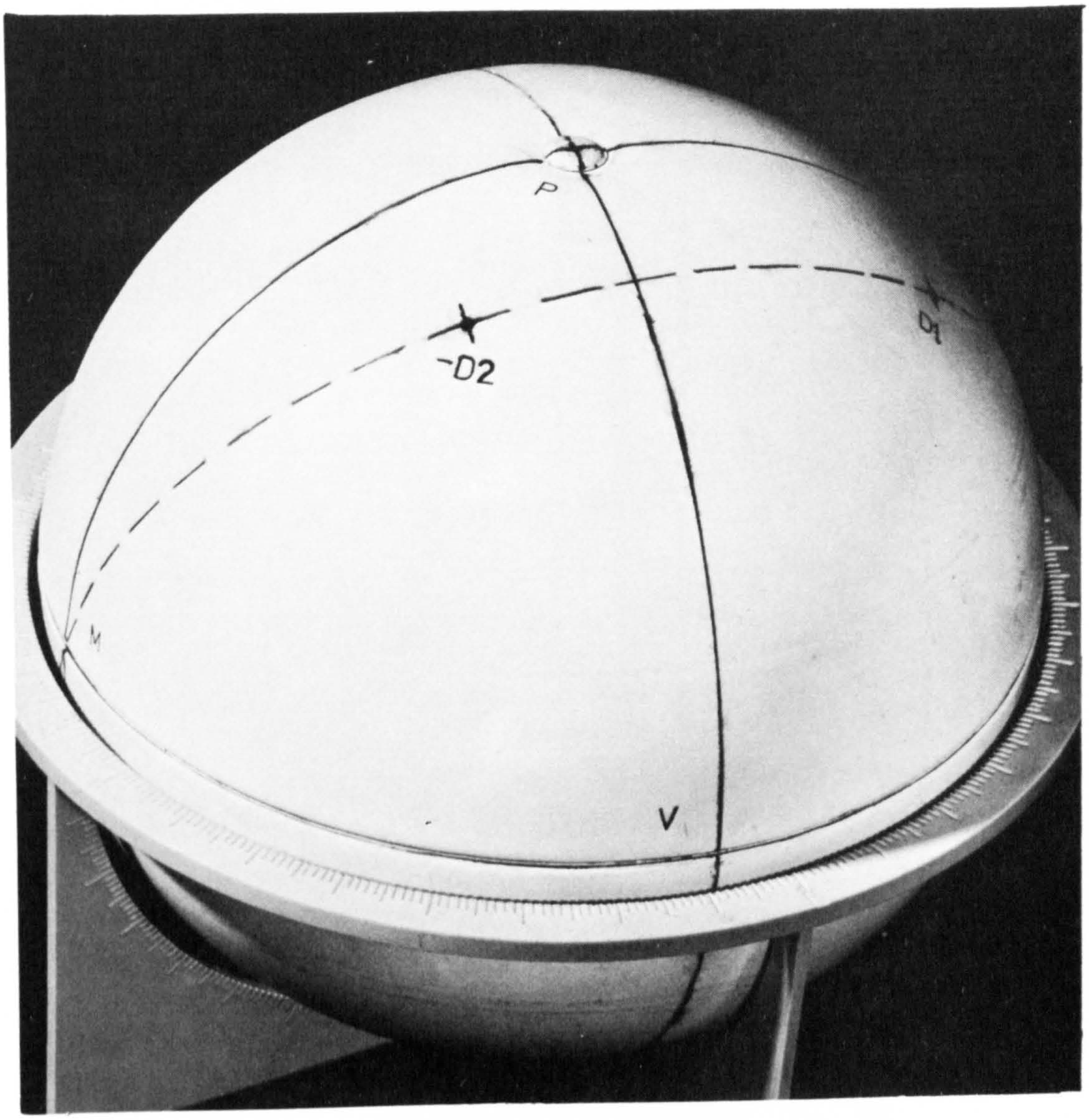


FIG 31.4a SAMPLE S DISCRIMINANT PLANE LOCATION

SAMPLE		FORECAST PROM	FORECAST NPSS	FORECAST NPLP
ACCEPTED	DIRECT ENTRY	3	3	94
	UNIVERSITY CADET ENTRY	9	12	79
	GRADUATE ENTRY	37	11	52
	TOTAL	12	8	80
REJECTED	DIRECT ENTRY	18	12	70
	UNIVERSITY CADET ENTRY	22	9	69
	GRADUATE ENTRY	30	7	63
	TOTAL	22	10	68
TOTAL		18	9	73

Note: All figures are %s.

FIG. 31.5 FORECASTS of LONG-TERM SUCCESS using SAMPLE S DISCRIMINANT FUNCTIONS on P M V SCORES of GROUP C

PART 8

SUMMARY OF CONCLUSIONS

CHAPTER 32

CONCLUSIONS FROM THE FURTHER INVESTIGATIONS

1. The research reported in this second volume falls into two parts:-

   a. Further studies of the primary group, viz candidates of boards 1 to 6 held between 1947 and 1949.

   b. Comparative studies of two more recent groups, the first being candidates of boards 7 to 10, held during 1949 and 1950, and the second being candidates of the 1969/70 boards. These studies include the development of a methodology for predictions using co-related factor scores of selection data.

Further Studies of the Primary Group

2. In the work described in Volume 1 two important areas were left unexplored (in the interests of clarity of reporting) and it was suggested that further investigation of these areas might throw more light on both the data structure and the methodology.

3. The first topic, discussed in detail in Chapter 26, is the analysis of S206 Annual Report data. In the primary investigations it was found that the markings on annual reports could be adequately represented on a two dimensional model with axes defined provisionally as "Intelligence" and "Social Skills". The axes were named by reference to the qualities on which officers were assessed in the reports. It was hypothesized that the two dimensional plane of the annual report model might be located in the three dimensional ability structure by aligning "Social Skills" in the former with "Personality" in the latter and by relating "Intelligence" in the former with a vector representing general intelligence in the cognitive plane of the latter.

4. This hypothesis has been tested by using principal component analysis to locate the vectors of time-condensed factor scores of sample E S206 data in the success-ability structure and by plotting the time-tracks of factor scores in the ability structure. The results show that the hypothesis was incorrect and provide evidence

of pronounced halo-effect in the marking of annual reports. The mean level of marking is closely identifiable with general intelligence of the individual. The spread of marking on Lieutenants is associated with a range of cognitive abilities, showing the dependance of early career success on these abilities. The spread of marking on Lieutenant Commanders is uncorrelated with that on Lieutenants, showing the change of role, and of requirements for success, from early to mid-career. There is also evidence that the halo-effect increases as officers approach the promotion zone.

5. These results accord with those of the primary investigations, in which training and long-term success vectors were found to be near-orthogonal in an ability structure. It appears that, for these Engineer officers, training success is closely related to early career success and that an important change of role, and of relevant abilities, occurs in mid-career. This hypothesis is supported by the occurrence of relatively high correlations between time-condensed S206 scores on Lieutenants and training results on the one hand, and between those on Lieutenant Commanders and promotion success on the other.

6. The second topic, discussed in Chapter 27, is the structural analysis of biographical and interests data. The primary investigations showed that certain biographical variables were valuable predictors but that the "raw" interests data was unsuitable for predictive purposes. A principal component analysis of the interests data also showed that there was little prospect of meaningful condensation, but it was observed that Cluster Analysis might yield better results.

7. The results of Cluster Analysis and Principal Component Analysis of both biographical and interests data have now been compared. In both cases it was found that the results from the two procedures were similar but in neither case was the clustering found to be meaningful, except in very broad terms. This is attributable to the low inter-correlations between variables.

8. It is concluded in both cases that meaningful condensation for descriptive purposes is not possible and that condensation for

predictive purposes is not worthwhile, since reduction of dimensionality involves substantial loss of information. It is arguable, in the case of the biographical data, that the improved distributions of composite variables may justify some degree of merging of compatible variables.

Comparative Studies of Primary and Later Groups

9. The main objective of the primary investigations was to identify the abilities associated with long-term success (of naval officers). The principal criterion of success adopted was the first selective promotion (to Commander), since data was available on an adequate sample of officers selected after introduction of the "new-type" AIB procedure in 1947.

10. An obvious criticism of the results is that they are no longer relevant. Since the sample used was the most recent in which all officers had equal opportunity of promotion to Commander there is no way of cross-validating the results in terms of more recent entries. Further, any attempt to forecast changes in the "requirements" for promotion, ie the qualities associated with suitability for higher rank, can only be conjectural.

11. It is possible, however, to compare the structure of selection data for the original sample and a current sample, to ascertain whether any important change in the selection process has occurred which might affect the validity of results.

12. Such a comparison has been made. By means of Factor Analysis, three dimensional models of the selection data structure have been constructed for three groups - candidates of boards 1 to 6, candidates of boards 7 to 10 and candidates of 1969/70.

13. The first two models were found to be almost identical, with three near-orthogonal axes identified as board mark, verbal ability and mechanical ability. The model for the most recent sample, although containing some new variables, proved strikingly similar.

14. There is evidence that board marks are now influenced to a greater extent by candidates' intelligence, and this undoubtedly tends to offset to some extent the loss of the C.S.C. examination component in selection ranking, as also does the introduction of a

minimum cut-off level on the national "A" level examination though the latter provides relatively crude measures of ability. There is also clear evidence that, although the age range of candidates is now much greater, the board successfully avoids any age bias.

15. In view of the successful derivation of three dimensional models for each group, and of the basic similarity of these models, it was decided to attempt to co-relate them by aligning the cognitive planes and the GT35 vectors.

16. After rotation it was found possible to identify three orthogonal axes which have been labelled "personality" P, "verbal ability" V, and "mechanical ability" M. P M V scores were then derived for all candidates in all three groups.

17. The distributions of these scores show clearly the changes which have occurred in the outcome of the selection process. There is a progressive tendency for the P score to become more dominant in the ranking of candidates. This trend is particularly interesting when viewed in the light of the findings of the primary investigations, viz that for Engineer officers training success is dependent on a combination of M and V and long-term success primarily on V. For Seaman officers training success is rather more dependent on V but long-term success has a substantial P loading.

18. The P M V scores derived from the descriptive models have been used in a series of prediction studies and the feasibility of using them in both regression and discriminant functions has been demonstrated. The results of the studies provide further evidence in support of the contention that use of a common selection criterion for all branches is inefficient.

<u>Summary</u>

19. This further research has served to throw more light on the nature and usefulness of biographical, interests and annual report data for the primary samples.

20. A study of the selection data for a recent sample has shown its structure to be essentially similar to that for the primary samples. The feasibility of constructing a single three dimensional descriptive model and of using the scores on this model for predictive purposes has been demonstrated.

21. The further studies have again underlined the value of discriminatory techniques for prediction of career outcome. The combination of the predictive discriminatory model with the descriptive factor model appears particularly powerful.

22. The hypothesis that use of a common selection criterion for all branches is inefficient is supported by the results of predictive investigations using condensed data.

CHAPTER 33

GENERAL CONCLUSIONS AND RECOMMENDATION

1. The primary aim of this research was to identify the abilities associated with success of naval officers up to age forty and to assess the effectiveness of the selection procedure for determination of these abilities. The usefulness of various classes of data for predictive purposes has also been considered and a methodology has been evolved for assessing the relevance of the findings to the current selection situation.

Data

2. Three groups of officer candidates have been studied. The first group includes all 520 candidates of the first six Admiralty Interview Boards after the introduction of the "new-type" selection procedure in 1947. The second group comprises the 252 candidates of boards 7 to 10 and the third group the 227 candidates interviewed during 1969/70. Each of the groups includes candidates for Seaman, Supply and Secretariat, and Engineer specialisations. The age range of candidates in the first two groups was 17 to 18½ but in the third group extends up to 25 as a result of the introduction of a Graduate Entry scheme.

3. The most comprehensive data is available on the first group, and variables used in the analyses include biographicals, selection scores (examinations, psychological tests and interview board marks), training course results and career reports, as well as criteria of career success. For the second and third groups the selection scores have been used as a basis for comparison of the groups.

Evolution of Selection Procedure

4. When the "new-type" selection procedure was introduced in 1947 as a result of the Noble Committee recommendations it consisted essentially of two stages. All candidates were required to sit the Civil Service Commission examinations. Those who passed were then interviewed by the Admiralty Interview Board which awarded a board mark which was an aggregate judgmental interpretation of the candidates' behaviour in group and individual tasks and interviews.

The board mark (out of 300) and examination mark (out of 800) were totalled for the purpose of ranking the candidates.

5. In 1949, for boards 7 onwards, the weighting of board mark was increased to 400, but in recent years the C.S.C. examinations have been replaced by a minimum requirement of two "A" levels. Thus the board mark (now out of 1000) constitutes the sole criterion for ranking of candidates in the 1969/70 group.

6. A battery of psychological tests has been included in the selection procedure since 1946, minor changes having occurred in its composition from time to time. The scores on these tests have never been used in the ranking of candidates, although they have been available to the board for consideration along with school reports, etc.

Outline of Research

7. The report of the investigations is divided into two parts. The first, in Volume 1, is concerned with the long-term follow-up of the first group, ie candidates of boards 1 to 6. A conceptual framework for the identification of abilities associated with success has been provided by the construction of three dimensional statistical models depicting the loadings of training and career success on intelligence (verbal and mechanical abilities) and personality. Predictive studies using both regression and discriminatory analyses have enabled the effectiveness of the selection procedure and the usefulness of various classes of data to be assessed.

8. The conclusions reached from these primary investigations may be summarised as follows:-

a. Training success is almost wholly associated with intelligence. Relative loadings of verbal and mechanical abilities vary from one training course to another and tend to have the highest mechanical loading in the specialist courses for Engineer officers and lowest in those for Seaman officers, as well as in early general naval training.

b. Long-term success for Engineer and Supply and Secretariat specialisations is also associated almost wholly with intelligence, predominantly of the verbal type. Indeed, high mechanical ability appears to be a handicap to long-term success. Further investigations of annual report data, described in Volume 2, confirm the hypothesis that there is a substantial change of role for Engineer officers in mid-career. Training and early career success is dependent on technical performance, which, in turn, is partly associated with mechanical ability. In later careers verbal ability becomes progressively more important.

c. Long-term success of Seaman officers has a substantial personality as well as verbal loading.

d. In view of these differences between branches, and between short-term and long-term, a selection procedure which attempts to rank candidates on a single scale of suitability for all forms of employment must inevitably be an inefficient compromise but, assuming it to be necessary, the overal validity of the ranking system which was used in 1947 could have been improved by reducing the proportion of AIB mark.

e. Considerably better forecasts could have been produced by using separate predictors for short-term and long-term prospects and for each branch, particularly if advantage were taken of the predictive value of biographical and psychological test data.

f. The best predictions of long-term success are provided by results of first year naval training. The concept of probationary service or protracted selection is thus particularly attractive.

g. The technique of discriminatory analysis is particularly suitable for providing the classificatory predictions envisaged in e. above.

h. Multivariate analysis provides a powerful means of monitoring career development, using the data available from selection tests training course results and annual report assessments.

j. There is evidence of pronounced halo effect in annual report assessments, markings being determined to a large extent by intelligence.

9. The second phase of the investigations, reported in Volume 2, is chiefly concerned with assessing the relevance of the findings recorded above to the current selection problem.

10. In order to assess whether any substantial change in the results of the selection process has occurred which might affect the validity of the findings the selection data structure for the three groups has been analysed. By means of Factor Analysis a three dimensional descriptive model of this data has been constructed for each group.

11. The models for the first two groups were found to be almost identical and for the third and most recent group essentially similar although some new variables were included. There is evidence that board marks are now influenced to a greater extent by candidates' intelligence.

12. The similarity of the three models has enabled a methodology to be developed for co-relating them by rotation onto common axes which have been labelled "Personality" P, "Mechanical Ability M, and "Verbal Ability" V.

13. Analysis of the P M V scores shows that there has been a progressive tendency for the P score (which is measured primarily by board mark) to become more dominant in the selection ranking. In view of the findings of the primary investigations this change appears to be retrogressive.

14. The P M V scores have also been used for predictive studies which demonstrate the value of a combination of descriptive and predictive modelling. The combination of Factor Analysis and Discriminatory Analysis appears particularly powerful and well-suited to this problem. The results of these studies support the conclusion that use of a common selection criterion for all branches is inefficient.

Recommendations

15. With the demand for high-ability manpower ever increasing we cannot afford to run unnecessary risks of misuse of those who wish to serve. Guidance of candidates to the type of employment for which their abilities suit them best, and in which they are therefore most likely to succeed, must surely be regarded as an essential feature of the selection process. This research demonstrates the power of multivariate techniques generally, and of discriminatory predictions in particular, to enhance such guidance.

16. It is recommended that the present judgmental methods of selection should be replaced by a placement procedure using discriminatory techniques. A necessary corollary of the use of such techniques is greater dependance on objective measures of ability, a change which would seem timely when viewed against current trends in the Civil Service (vide Recommendation 28 of the "Fulton Report", Cmnd. 3638 and the findings of the "Davies Committee", Cmnd. 4156).

17. It is further recommended that terms of entry and career structures should be modified to take full advantage of the predictive value of early training results. This could best be achieved by the introduction of a period of probationary service as a means of confirming initial placement allocations.

18. The existence of a marked change of role of Engineer officers in mid-career indicates the potential value of education designed to develop the verbal abilities associated with managerial success, as distinct from the technical abilities which are relevant in early appointments. To be most effective such education should be arranged to coincide with the change of role, ie around the time of promotion to Lieutenant Commander.

19. It is also recommended that systematic review of career development of all officers should be introduced, using predictor functions embracing selection and training scores and annual report markings. This would be assisted by modification to the annual report form to remove redundancy and by improvement of objectivity of marking (by definition of interpretation of markings) to reduce halo-effect.

20. This research has shown how the methodology of operational research and the techniques of mathematical modelling may be used in the study of selection, training and career development. It is proposed that the necessary further study to enable the above recommendations to be developed in detail should be undertaken at the earliest opportunity.

APPENDIX 15

PRINCIPAL COMPONENT ANALYSIS

of

SAMPLE E

SELECTION, TRAINING and ANNUAL REPORT DATA

COMPONENT LOADINGS

VARIABLE	COMPONENT NO. 1	2	3	VARIABLE	COMPONENT NO. 1	2	3	VARIABLE	COMPONENT NO. 1	2	3
GT35	.10	.05	.11	T.EXAM	.10	.01	.15	ELEC	.15	-.02	-.05
SP96	.08	.05	.06	PR.ATT	-.03	.07	.10	GUNY	.11	-.01	.02
SP21	.03	-.03	.06	CORPS	-.03	.02	-.17	TAS	.12	.02	-.06
SP117E	.04	.02	.12	SOCS	.04	.03	.02	NAVN	.16	-.02	-.05
SP117M	.05	.01	.13	GAMES	-.03	-.01	-.11	COMM	.16	-.05	-.09
SP97	.02	-.05	.11	PREF	.03	.02	-.11	ENGG	.15	-.01	-.04
SP160	.05	.12	.20	ON.CH.	.02	-.01	-.05	SEAM	.13	.05	-.08
V.ED	.11	.06	.10	PAR.DD	.03	.03	-.05	OLQ	.04	.06	-.14
K.M	.07	.06	.24	FAT.RN	.04	-.02	.03	D.TOT	.21	.01	-.11
PRES	0	.26	-.12	F.ARMY	-.02	-.06	-.04	ECON	.12	.06	.05
DP	-.03	.30	-.11	HMC.SC	0	.08	-.08	MATHS	.16	-.03	.02
CS	0	.31	-.13	B.PREF	.02	.02	.02	MECH	.19	.05	.11
EO	0	.31	-.06	S.INDA	.09	-.09	-.26	ENG.SC	.19	.04	.07
SO	-.01	.31	-.10	A.ENT	-.02	.08	.09	CHEM	.13	.05	.02
PSYCHO	.03	.28	-.06	F.OCC	-.05	-.10	.08	ELECT	.19	.05	.03
TO	-.03	.29	-.09	S.INDB	.06	-.10	-.26	PRAC	.17	0	.08
B.MARK	0	.34	-.11	T.HSC	.03	-.01	.06	BC.TOT	.23	.04	.08
ENGL	.02	-.02	.02	A.AIB	-.02	.07	.12	SC.TOT	.19	-.03	-.04
GENL	.03	-.04	-.13	T.LCDR	-.22	-.03	-.02	N	.15	-.05	-.02
MATH	.11	-.06	.10	B.AGG	.09	.25	.04	X	.10	-.09	-.04
PHYS	.11	-.01	.11	B.SD	-.05	-.02	-.02	E	.14	.09	.04
F1	.11	-.07	-.17	F1A	.04	-.08	-.13	L	.11	.03	.06
F2	.14	-.07	-.01	F2A	0	-.08	-.17	M	.12	.01	.12
				T.DART	.21	-.02	.02	S	.11	-.09	-.03

TABLE APP. 15.1 PRINCIPAL COMPONENT ANALYSIS of SAMPLE E SELECTION, TRAINING and ANNUAL REPORT DATA

VARIANCES

COMPONENT NO.	COMPONENT VARIANCE	ACCUMULATED VALUE AS % OF TOTAL VARIANCE
1	15.3	17.8
2	7.1	26.1
3	6.4	33.5
4	4.5	38.7
5	4.2	43.6
6	3.3	47.4

TABLE APP. 15.2 PRINCIPAL COMPONENT ANALYSIS of SAMPLE E SELECTION, TRAINING and ANNUAL REPORT DATA

APPENDIX 16

FACTOR ANALYSES

of

SAMPLES E, X AND L ANNUAL REPORT DATA

PRE-'60 REPORTS

VARIABLE	COMMUNALITY	SPECIFIC VARIANCE	FACTOR 1 LOADING	FACTOR 2 LOADING
P.ABIL	.78	.22	.81	.36
M.QUAL	.69	.31	.73	.40
LEADER	.91	.09	.92	-.26
A.ABIL	.65	.35	.78	.19
P.QUAL	.60	.40	.77	-.03
REP.SD	.07	.93	-.06	.25
TIMREP	.28	.72	.42	.32

SAMPLE SIZE 712

POST-'60 REPORTS

VARIABLE	COMMUNALITY	SPECIFIC VARIANCE	FACTOR 1 LOADING	FACTOR 2 LOADING
P.ABIL	.52	.48	.69	.22
ENERGY	.66	.34	.78	.21
RELIAB	.60	.40	.77	.10
COMMON	.68	.32	.83	-.03
INTELL	.56	.44	.73	.18
INTIVE	.73	.27	.85	.12
LEADER	.64	.36	.80	-.09
EXPRES	.56	.44	.74	-.12
O.ABIL	.65	.35	.81	.03
TACTCO	.55	.45	.67	-.31
SOCATT	.51	.49	.61	-.38
REP.SD	.34	.66	-.23	.53
TIMREP	.28	.72	.49	-.21

SAMPLE SIZE 919

TABLE APP. 16.1 FACTOR ANALYSES of SAMPLE E ANNUAL REPORT DATA

PRE-'60 REPORTS

VARIABLE	COMMUNALITY	SPECIFIC VARIANCE	FACTOR 1 LOADING	FACTOR 2 LOADING
P.ABIL	.69	.31	.79	.26
M.QUAL	.77	.23	.79	.40
LEADER	.85	.15	.85	-.35
A.ABIL	.51	.49	.71	-.03
P.QUAL	.59	.41	.77	-.06
REP.SD	.20	.80	-.07	.45
TIMREP	.25	.75	.42	.27

SAMPLE SIZE 305

POST-'60 REPORTS

VARIABLE	COMMUNALITY	SPECIFIC VARIANCE	FACTOR 1 LOADING	FACTOR 2 LOADING
P.ABIL	.52	.48	.68	.23
ENERGY	.57	.43	.75	-.02
RELIAB	.55	.45	.74	-.09
COMMON	.61	.39	.78	-.01
INTELL	.70	.30	.71	.45
INTIVE	.66	.34	.81	.06
LEADER	.65	.35	.77	-.24
EXPRES	.52	.48	.72	.05
O.ABIL	.60	.40	.77	.04
TACTCO	.55	.45	.67	-.31
SOCATT	.48	.52	.65	-.25
REP.SD	.29	.71	-.21	.50
TIMREP	.09	.91	.30	-.02

SAMPLE SIZE 465

TABLE APP. 16.2 FACTOR ANALYSIS of SAMPLE L ANNUAL REPORT DATA

PRE-'60 REPORTS

VARIABLE	COMMUNALITY	SPECIFIC VARIANCE	FACTOR 1 LOADING	FACTOR 2 LOADING
P. ABIL	.72	.28	.84	.06
M.QUAL	.57	.43	.75	.10
LEADER	.74	.26	.85	-.15
A.ABIL	.66	.34	.81	.04
P.QUAL	.61	.39	.78	.10
REP.SD	.54	.46	-.15	.72
TIMREP	.12	.88	.33	.10

SAMPLE SIZE 677

POST-'60 REPORTS

VARIABLE	COMMUNALITY	SPECIFIC VARIANCE	FACTOR 1 LOADING	FACTOR 2 LOADING
ENERGY	.65	.35	.80	.05
RELIAB	.78	.22	.85	.22
COMMON	.72	.28	.84	.15
INTELL	.63	.37	.74	.29
INTIVE	.77	.23	.88	.01
LEADER	.90	.10	.89	-.32
EXPRES	.61	.39	.73	.28
O.ABIL	.70	.30	.82	.15
TACTCO	.50	.50	.70	.07
SOCATT	.45	.55	.66	-.14
REP.SD	.10	.90	-.27	.15
TIMREP	.09	.91	.25	.16

SAMPLE SIZE 768

TABLE APP. 16.3 FACTOR ANALYSIS of SAMPLE X ANNUAL REPORT DATA

APPENDIX 17

PRINCIPAL COMPONENT ANALYSIS

of

SAMPLE E

SELECTION and CONDENSED ANNUAL REPORT DATA

COMPONENT LOADINGS

VARIABLE	COMPONENT NO.				VARIABLE	COMPONENT NO.			
	1	2	3	4		1	2	3	4
GT35	.01	.01	.28	.31	S.INDB	-.03	0	-.08	-.07
SP96	.04	0	.17	.37	S.TRG	0	-.13	.21	.11
SP21	-.05	.12	.09	.10	FAT2	.01	.15	-.33	.29
SP117E	-.02	-.08	.04	.39	FBT2	-.01	-.10	.29	-.35
SP117M	-.03	-.13	.07	.42	FAT3	.17	.05	-.34	-.01
SP160	-.05	-.06	.20	.29	FBT3	-.18	-.05	.33	-.01
PRES	.30	-.06	.06	-.15	FAT4	.04	.12	-.35	.10
DP	.34	.02	.03	-.05	FBT4	-.04	-.13	.36	-.15
CS	.36	0	.08	-.09	FAT6	-.02	.38	.12	.03
EO	.34	-.04	.04	.13	FBT6	0	-.39	-.14	-.12
SO	.34	0	.08	-.04	FAT7	-.02	.39	.10	-.10
PSYCHO	.31	-.05	.05	.11	FBT7	-.01	-.40	-.17	.02
TO	.33	.06	.02	-.03	FAT8	.02	.35	.03	-.04
B.MARK	.39	-.03	.05	.03	FBT8	-.02	-.36	-.08	0

VARIANCES

COMPONENT NO.	VARIANCE	ACCUMULATED VALUE AS % OF TOTAL VARIANCE
1	6.2	22.1
2	4.2	37.2
3	3.0	48.1
4	2.2	55.7
5	1.6	61.5
6	1.4	66.5
7	1.2	70.9

TABLE APP. 17.1 PRINCIPAL COMPONENT ANALYSIS of SAMPLE E - SELECTION and CONDENSED ANNUAL REPORT DATA

APPENDIX 18

PRINCIPAL COMPONENT and ASSOCIATION ANALYSES

of

SAMPLE XES BIOGRAPHICAL and INTERESTS DATA

COMPONENT LOADINGS

VARIABLE	COMPONENT NUMBER			
	1	2	3	4
PR.ATT	.11	.06	.63	.06
CORPS	.02	-.51	.10	-.26
SOCS	.19	.31	.19	-.21
GAMES	.43	-.37	.18	-.03
PREF	.50	-.14	.12	-.22
ON.CH.	.13	.37	-.39	-.28
PAR.DD	-.08	.11	-.17	.03
FAT.RN	-.41	.19	.37	-.44
F.ARMY	-.15	-.43	-.32	.13
IMC.SC	-.53	-.23	.24	.13
B.PREF	-.14	-.23	-.19	-.73

VARIANCES

COMPONENT NO.	VARIANCE	ACCUMULATED VALUE AS % OF TOTAL VARIANCE
1	1.8	16.1
2	1.3	28.3
3	1.2	39.4
4	1.1	49.8
5	1.0	59.1

TABLE APP. 18.1 PRINCIPAL COMPONENT ANALYSIS of SAMPLE XES - BIOGRAPHICAL DATA

INTEREST CLUSTER	SAMPLE X			SAMPLE E			SAMPLE S		
	B.MARK	S.TRG	S.INDB	B.MARK	S.TRG	S.INDB	B.MARK	S.TRG	S.INDB
IAA	.21	.04	-.02	.07	.01	-.17	-.14	-.07	.05
IAB	-.09	-.14	-.10	-.02	-.17	-.12	-.07	.11	.11
IBA	-.02	-.09	.02	.09	.05	-.10	-.35*	-.14	.08
IBB	-.05	-.04	.05	.15	.03	-.12	-.16	.07	0
EAA	.04	-.14	.02	-.02	-.04	0	.30*	.12	-.13
EAB	-.08	0	-.23*	-.08	.04	0	-.16	.03	0
EBA	-.11	-.24*	-.01	-.19*	-.19*	.01	.16	.02	.07
EBB	-.24*	.08	.06	-.01	-.13	0	-.08	.27	.28*
IA	.11	-.04	-.06	.05	-.08	-.19*	-.13	.01	.10
IB	-.05	-.08	.04	.16	.05	-.14	-.28*	-.02	.03
EA	-.02	-.10	-.12	-.07	0	0	.09	.09	-.09
EB	-.18	-.18	.01	-.17	-.21*	.01	.10	.13	.17
I	.04	-.07	-.01	.12	-.02	-.21*	-.26	0	.08
E	-.12	-.17	-.07	-.14	-.12	.01	.11	.13	.05
INT	-.05	-.15	-.05	-.01	-.09	-.13	-.09	.08	.08

* Correlations which are significant at 5% level

TABLE APP. 18.2 CORRELATIONS of B.MARK, S.TRG, S.INDB with INTEREST CLUSTERS - SAMPLES X, E and S

SAMPLE X

		COMP. 1 +	COMP. 1 −	COMP. 2 +	COMP. 2 −	COMP. 3 +	COMP. 3 −	TOTAL
P	O	9	20	6	23	12	17	29
	E	12	17	11	18	12	17	
NP	O	25	30	25	30	22	33	55
	E	22	33	20	35	22	33	
Total		34	50	31	53	34	50	84
χ^2		1.95		5.65		0		
α				.02				

SAMPLE E

		COMP. 1 +	COMP. 1 −	COMP. 2 +	COMP. 2 −	COMP. 3 +	COMP. 3 −	TOTAL
P	O	32	13	16	29	28	17	45
	E	25	20	20	25	25	20	
NP	O	33	38	35	36	36	35	71
	E	40	31	31	40	40	31	
Total		65	51	51	65	64	52	116
χ^2		7.20		2.35		1.32		
α		.01						

SAMPLE S

		COMP. 1 +	COMP. 1 −	COMP. 2 +	COMP. 2 −	COMP. 3 +	COMP. 3 −	TOTAL
P	O	10	11	11	10	10	11	21
	E	9	12	14	7	10	11	
NP	O	12	20	24	8	15	17	32
	E	13	19	21	11	15	17	
Total		22	31	35	18	25	28	53
χ^2		0.32		3.18		0		
α								

SAMPLE XES

		COMP. 1 +	COMP. 1 −	COMP. 2 +	COMP. 2 −	COMP. 3 +	COMP. 3 −	TOTAL
X	O	34	50	31	53	34	50	84
	E	40	44	39	45	41	43	
E	O	65	51	51	65	54	52	116
	E	56	60	53	63	56	60	
S	O	22	31	35	18	25	28	53
	E	25	28	25	28	26	27	
Total		121	132	117	136	123	130	253
χ^2		5.25		10.8		4.92		
α					.005			

TABLE APP. 18.3 ASSOCIATIONS of P/NP and X, E, S with C_{123} SCORES of SAMPLE XES BIOGRAPHICALS

SAMPLE X

		COMP. 1 +	COMP. 1 -	COMP. 2 +	COMP. 2 -	COMP. 3 +	COMP. 3 -	TOTAL
P	O	12	18	15	15	21	9	30
	E	13	17	18	12	17	13	
NP	O	26	30	36	20	27	29	56
	E	25	31	33	23	31	25	
Total		38	48	51	35	48	38	86
χ^2		0.21		1.91		3.33		

SAMPLE E

		COMP. 1 +	COMP. 1 -	COMP. 2 +	COMP. 2 -	COMP. 3 +	COMP. 3 -	TOTAL
P	O	21	24	24	21	22	23	45
	E	24	21	20	25	21	24	
NP	O	43	30	28	45	32	41	73
	E	40	33	32	41	33	40	
Total		64	54	52	66	54	64	118
χ^2		1.31		2.32		0.15		

SAMPLE S

		COMP. 1 +	COMP. 1 -	COMP. 2 +	COMP. 2 -	COMP. 3 +	COMP. 3 -	TOTAL
P	O	13	8	10	11	15	6	21
	E	10	11	10	11	15	6	
NP	O	12	20	16	16	23	9	32
	E	15	17	16	16	23	9	
Total		25	28	26	27	38	15	53
χ^2		2.86		0		0		

SAMPLE XES

		COMP. 1 +	COMP. 1 -	COMP. 2 +	COMP. 2 -	COMP. 3 +	COMP. 3 -	TOTAL
X	O	38	48	51	35	48	38	86
	E	43	43	43	43	47	39	
E	O	64	54	52	66	54	64	118
	E	58	60	59	59	64	54	
S	O	25	28	26	27	38	15	53
	E	26	27	27	26	29	24	
Total		127	130	129	128	140	117	257
χ^2		2.65		5.21		9.80		
α						.01		

TABLE APP. 18.4 ASSOCIATIONS of P/NP and X, E, S with C_{123} SCORES of SAMPLE XES INTERESTS

BIOGRAPHICALS, Component No. 2

	+	-
X	.37	.63
E	.44	.56
S	.66	.34

INTERESTS, Component No. 3

	+	-
X	.56	.44
E	.46	.54
S	.72	.28

TABLE APP. 18.5 SIGNIFICANT ASSOCIATIONS of X, E, S with C_{123} SCORES of SAMPLE XES BIOGRAPHICALS and INTERESTS

APPENDIX 19

PRINCIPAL COMPONENT ANALYSES

of

GROUPS A, B and C SELECTION DATA

COMPONENT LOADINGS

VARIABLE	COMPONENT NO.		
	1	2	3
GT35	.12	.38	.45
SP96	.12	.38	.26
SP21	.04	.23	.63
SP117E	.09	.45	-.40
SP117M	.04	.47	-.37
SP160	.07	.44	-.16
B.MARK	.37	-.08	-.02

VARIANCES

COMPONENT NO.	VARIANCE	ACCUMULATED %
1	7.07	50.5
2	2.41	67.7
3	1.25	76.6
4	0.73	81.8

TABLE APP. 19.1 PRINCIPAL COMPONENT ANALYSIS of GROUP A SELECTION DATA

COMPONENT LOADINGS

VARIABLE	COMPONENT NO.		
	1	2	3
GT35	.15	.31	.50
SP96	.15	.39	.20
SP21	.09	.15	.69
SP117E	.09	.47	-.32
SP117M	.05	.52	-.30
SP160	.08	.42	-.15
B.MARK	.36	-.10	-.05

VARIANCES

COMPONENT NO.	VARIANCE	ACCUMULATED %
1	7.30	52.1
2	2.28	68.4
3	1.17	76.8
4	0.76	82.2

TABLE APP. 19.2 PRINCIPAL COMPONENT ANALYSIS of GROUP B SELECTION DATA

COMPONENT LOADINGS

VARIABLE	COMPONENT NO.		
	1	2	3
GT35	.43	.38	.07
SP70/23	.47	-.27	-.18
SP21	.36	.37	-.05
VMD	.43	-.39	-.02
SPR(E)	.42	-.02	-.46
B.MARK	.32	-.07	.86
AGE	.05	.70	-.02

VARIANCES

COMPONENT NO.	VARIANCE	ACCUMULATED %
1	2.65	37.9
2	1.29	56.3
3	0.87	68.7
4	0.76	79.6

TABLE APP. 19.3 PRINCIPAL COMPONENT ANALYSIS of GROUP C SELECTION DATA

APPENDIX 20

FACTOR ANALYSIS

of

GROUPS A, B and C SELECTION DATA

and

ROTATIONS of FACTOR AXES

VARIABLE	FACTOR LOADINGS			ORTHOGONAL ROTATED LOADINGS			OBLIQUE ROTATED LOADINGS		
	FACTOR 1	FACTOR 2	FACTOR 3	P	M	V	P'	M'	V'
GT35	.22	.70	.47	-.01	.17	.85	-.01	.33	.87
SP96	.24	.54	.15	.08	.28	.53	.08	.38	.56
SP21	.06	.33	.31	-.05	.01	.45	-.05	.10	.45
SP117E	.15	.62	-.45	.04	.77	.14	.04	.78	.28
SP117M	.02	.63	-.45	-.08	.76	.12	.08	.77	.26
SP160	.11	.55	-.19	-.01	.53	.26	-.01	.57	.36
B.MARK	.99	-.01	- 0	.96	.08	.23	.96	.13	.25

TABLE APP. 20.1 FACTOR LOADINGS for GROUP A

VARIABLE	FACTOR LOADINGS			ORTHOGONAL ROTATED LOADINGS			OBLIQUE ROTATED LOADINGS		
	FACTOR 1	FACTOR 2	FACTOR 3	P	M	V	P'	M'	V'
GT35	.31	.73	.44	0	.17	.89	0	.33	.91
SP96	.29	.55	.02	.09	.36	.50	.09	.45	.56
SP21	.18	.29	.24	.04	.03	.41	.04	.10	.41
SP117E	.16	.54	-.47	.05	.72	.13	.05	.73	.26
SP117M	.02	.64	-.56	-.10	.84	.09	-.10	.84	.25
SP160	.13	.43	-.26	.02	.48	.17	.02	.51	.26
B.MARK	.99	0	0	.93	.08	.33	.93	.15	.34

TABLE APP. 20.2 FACTOR LOADINGS for GROUP B

VARIABLE	FACTOR LOADINGS			ORTHOGONAL ROTATED LOADINGS			OBLIQUE ROTATED LOADINGS		
	FACTOR 1	FACTOR 2	FACTOR 3	P	M	V	P'	M'	V'
GT35	.70	.47	.02	-.02	.16	.83	-.02	.32	.84
SP70/23	.71	-.32	.14	-.14	.73	.28	-.14	.77	.41
SP21	.49	.28	.08	-.08	.15	.54	-.08	.25	.56
VMD	.64	-.43	-.02	.02	.76	.15	.02	.77	.30
SPR(E)	.57	-.05	.20	-.20	.44	.37	-.20	.51	.44
B.MARK	.47	-.03	-.54	.54	.35	.31	.54	.41	.37
AGE	.07	.39	.04	-.04	-.22	.32	-.04	-.16	.27

TABLE APP. 20.3 <u>FACTOR LOADINGS for GROUP C</u>

VARIABLES	VARIABLES							FACTORS		
	GT35	SP96	SP21	SP117E	SP117M	SP160	B.MARK	F1	F2	F3
GT35								75	37	57
SP96	19							67	28	75
SP21	11	30						82	44	47
SP117E	68	51	78					79	38	-54
SP117M	70	54	79	9				90	36	-54
SP160	52	36	62	17	19			79	22	-71
B.MARK	75	67	82	79	88	80		0	-90	-90

TABLE APP. 20.4 ANGLES BETWEEN VECTORS
and BETWEEN VECTORS and FACTOR AXES - GROUP A

VARIABLES	VARIABLES							FACTORS		
	GT35	SP96	SP21	SP117E	SP117M	SP160	B.MARK	F1	F2	F3
GT35								70	36	61
SP96	27							62	28	88
SP21	9	32						65	45	56
SP117E	69	43	76					77	43	-50
SP117M	73	49	81	11				88	42	-48
SP160	59	34	66	10	16			76	34	-60
B.MARK	70	63	65	77	88	75		0	-90	-90

TABLE APP. 20.5 ANGLES BETWEEN VECTORS and BETWEEN VECTORS and FACTOR AXES - GROUP B

VARIABLES	VARIABLES							FACTORS		
	GT35	SP70/23	SP21	VMD	SPR(E)	B.MARK	AGE	F1	F2	F3
GT35								34	56	89
SP70/23	58							26	-66	80
SP21	8	53						30	60	82
VMD	67	15	63					34	-57	-89
SPR(E)	42	20	36	34				20	-85	71
B.MARK	60	62	64	54	69			49	-87	-41
AGE	46	-77	50	-67	84	-89		80	12	84

TABLE APP. 20.6 ANGLES BETWEEN VECTORS and BETWEEN VECTORS and FACTOR AXES - GROUP C

VARIABLE	GROUP		
	A	B	C
GT35	.76	.83	.71
SP96	.37	.39	
SP21	.21	.17	.32
SP117E	.61	.54	
SP117M	.60	.72	
SP160	.35	.27	
B.MARK	.99	.99	.52
SP70/23	.62		
VMD	.60		
SPR(E)	.37		
AGE	.16		

TABLE APP. 20.6a. COMMUNALITIES of VARIABLES in 3-FACTOR MODELS of GROUPS A, B and C

T_A	.964	.087	.242
	-.250	.695	.676
	-.105	-.713	.695
T_B	.957	.087	.334
	-.317	.643	.695
	-.139	-.760	.636
T_C	0	.707	.707
	0	-.707	.707
	- 1	0	0
T_0	1	0	0
	0	.982	.191
	0	.191	.982

TABLE APP. 20.7 TRANSFORMATIONS for ORTHOGONAL and OBLIQUE ROTATIONS

SAMPLE	VARIABLE	GROUP A				GROUP B				GROUP C				SAMPLE SIZE		
		MEAN	MIN	MAX	SD	MEAN	MIN	MAX	SD	MEAN	MIN	MAX	SD	A	B	C
ALL	P	0	-2.62	2.69	1.03	0	-2.53	2.59	1.03	0	-3.62	3.99	1.54	519	252	227
	M	0	-3.64	2.93	1.16	0	-3.33	2.47	1.14	0	-4.03	2.32	1.19			
	V	0	-4.58	2.63	1.18	0	-3.42	2.82	1.15	0	-3.10	3.23	1.21			
ACCEPTED	P	0.50	-1.70	2.69	0.78	0.91	-0.43	2.59	0.72	1.19	-1.08	3.99	1.03	254	90	89
	M	0.23	-2.65	2.93	1.03	0.27	-0.26	2.47	1.03	0.53	-2.40	2.32	1.02			
	V	0.24	-2.72	2.63	1.08	0.39	-3.28	2.82	1.11	0.45	-1.60	3.23	1.00			
REJECTED	P	- .51	-2.62	2.00	0.99	-0.50	-2.53	1.61	0.80	- .76	-3.62	2.23	1.31	250	162	138
	M	- .25	-3.64	2.88	1.21	-0.14	-3.33	2.47	1.17	- .33	-4.03	2.32	1.17			
	V	- .29	-4.58	2.40	1.23	-0.23	-3.42	2.51	1.09	- .33	-3.10	2.72	1.23			

TABLE APP. 20.8 UNIVARIATE STATISTICS for DERIVED VARIABLES P M V in ALL GROUPS

SAMPLE	VARIABLE	GROUP A			GROUP B			GROUP C		
		σ	1.96σ	2.58σ	σ	1.96σ	2.58σ	σ	1.96σ	2.58σ
ALL	P	1.03	2.02	2.66	1.03	2.02	2.66	1.54	3.02	3.97
	M	1.16	2.28	2.99	1.14	2.24	2.94	1.19	2.34	3.07
	V	1.18	2.32	3.04	1.15	2.26	2.96	1.21	2.37	3.12
ACCEPTED	P	0.78	1.53	2.01	0.72	1.41	1.86	1.03	2.02	2.66
	M	1.03	2.02	2.66	1.03	2.02	2.66	1.02	1.98	2.63
	V	1.08	2.12	2.78	1.11	2.18	2.86	1.00	1.96	2.58
REJECTED	P	0.99	1.94	2.55	0.80	1.57	2.06	1.31	2.57	3.38
	M	1.21	2.37	3.12	1.17	2.30	3.02	1.17	2.30	3.02
	V	1.23	2.41	3.17	1.09	2.14	2.81	1.23	2.41	3.17

TABLE APP. 20.9 95% and 99% CONTOURS of P M V - ALL GROUPS

VARIABLE	SAMPLE X		SAMPLE E		SAMPLE S	
	MEAN	SD	MEAN	SD	MEAN	SD
P	.95	.68	.27	.77	.39	.67
M	.17	1.00	.49	.95	-.29	1.12
V	.41	.98	-.06	1.08	.61	1.08

TABLE APP. 20.10 UNIVARIATE STATISTICS for P M V SCORES of SAMPLES X, E and S

APPENDIX 21

TOPICS FOR FURTHER STUDY

TOPICS FOR FURTHER STUDY

1. Analysis of abilities associated with promotion to higher rank (i.e. Captain and higher).

2. Analysis of abilities associated with training success in a recently selected sample.

3. Design of psychological test batteries for present forms of entry.

4. Design of discriminant functions for use in present-day selection and placement.

5. Cross-validation of present studies as samples become available.

6. Study of the relevance of current measures of training success to long-term success in terms of abilities assessed.

7. Analysis of the relationship of qualities assessed on S206 reports to basic abilities in Samples X and S.

8. Design of career development monitoring procedures using predictor functions embracing selection and training scores and annual report markings.

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MULTIVARIATE ANALYSIS IN PERSONNEL SELECTION

A CONCEPTUAL REVIEW

by

Commander K E GARDNER, MA, FSS, CEng, MIEE, Royal Navy

ADDENDUM

to

thesis submitted for the degree of Ph D, Graduate Business Centre,

City University

MULTIVARIATE ANALYSIS IN PERSONNEL SELECTION

A CONCEPTUAL REVIEW

Contents | Page

Acknowledgement:-

Material for certain illustrations and examples has been taken from Harman (1960), Fruchter (1954) and Moroney (1951).

INTRODUCTION

1. Statistical method is now widely used in the scientific investigation of management problems, an application to which it is particularly relevant since the manager is commonly faced with the problem of making decisions from observed data in the face of uncertainty.

2. The branch of statistical method known as multivariate analysis owes much of its early development to the study of human abilities. There is consequently a close conceptual relationship between some of the techniques of multivariate analysis and the personnel management problems of selection, training and career development, in the study of which the researcher is concerned with quantifying and structuring the immense variety of human characteristics and with examining their relationship to achievement.

3. Considerable progress has been made in recent years with mathematical formalising of multivariate analysis and with development of computer facilities capable of handling the often massive calculations involved. As a result it is now possible to envisage wider applications of the various techniques, both singly and in combination.

4. It is the purpose of this paper to discuss the nature of multivariate analysis and the structure of human ability and to review and illustrate the relevance of multivariate modelling to the study of personnel selection, training and career development. Examples of a number of techniques have been included but primary emphasis has been placed on discussion of their conceptual nature and illustration of their potential application rather than on description of computational aspects. References have been given to statistical texts where details of the processes may be found. More complete treatments of the use of statistical method in the study of selection are given by DUNNETTE (1966) and HORST (1966), the emphasis in the former being on the psychological aspects and in the latter on statistical aspects.

MULTIVARIATE METHODS

What is multivariate analysis?

5. In a general sense the term might be construed as embracing almost the whole of statistical theory but it is customarily used in a much narrower sense than this. M G KENDALL (1965) has observed that two main features may be discerned.

(a) In a set of n individuals, each of which bears the value of p different variates, the multivariate character lies in the multiplicity of the p variates, not in the size of the set n.

(b) The variates are dependent among themselves so that we cannot split off one or more from the others and consider it by itself. The variates must be considered together.

6. Thus multivariate analysis may be defined as the branch of statistical analysis which is concerned with the relationships of sets of dependent variates. Like all statistics it embraces three distinct levels of activity; first the formulation or adoption of an appropriate mathematical model, second the derivation of results from the model using observed data and a suitable technique, and third the testing of the results for validity and reliability.

Some multivariate models

7. Before any analysis of observed data is undertaken it is essential to formulate or adopt a theoretical statistical model, the choice being dictated by the purpose of the analysis and to some extent by the nature of the data.

8. Much of the early development of multivariate analysis was a by-product of its applications in the first 40 years of this century and it is only in the past 20 years that mathematicians have brought some order to its structure. A large number of models has been formulated but they fall naturally into groups determined by the type of analysis for which they are designed. The main groups may be classified as follows:-

a. Factor Analysis

b. Principal Component Analysis

c. Cluster Analysis

d. Canonical Correlation Analysis

e. Discriminatory Analysis

The first three are primarily descriptive models and the last two predictive. A brief outline of each is given below.

Factor Analysis

9. Factor analysis is a way of getting an overview of a large number of correlation coefficients to see if the common variance which they express, which has been measured only in pairs of variables, taken two-by-two, can be described in broader terms. A fundamental consideration in factor analysis is to express the observed variables in terms of a smaller number of factors which adequately account for the correlations. By reducing the dimensionability of observations the method provides a valuable aid to understanding of multivariate data as well as to its description.

Principal Component Analysis

10. Principal Component Analysis is used to find linear combinations of variables with large variance and to determine how many components (or dimensions) are required to account for any given proportion of the variance. Principal components are linear combinations of variables which are uncorrelated, the first component being the normalised combination with maximum variance, the second, uncorrelated with the first, with maximum remaining variance, and so on. The method is useful for estimating the number of factors required for a factor analysis since the algorithm is computationally more efficient.

Cluster Analysis

11. Cluster Analysis is a simple form of correlational analysis which enables clearly defined clusters of variables to be identified by a technique which involves much less computation than factor analysis. Various techniques have been developed but one of the most common uses what is known as a B coefficient, which gives the ratio of the average intercorrelation of the

variables in a cluster to their average correlation with the variables not in the cluster. A B coefficient of 1.0 would indicate that the variables in the cluster correlate no more highly among themselves than they do with variables outside the cluster. It is customary to start a cluster with the two variables which correlate highest and to keep adding variables until the B coefficient shows a marked drop.

Canonical Correlation Analysis

12. Canonical correlation methods are concerned with investigation of the interrelation between two sets of variables referred to as the criteria and the predictors. Multiple regression analysis is a special case of canonical correlation analysis in which the criteria set contains only one member, the dependent variable, and the predictor set contains the independent variables.

13. Any desired partitioning of the variables may be specified. Mathematically there is no distinction between criteria and predictors but it is usual to regard the smaller set as criteria. It is usual to calculate a pair of canonical variates which are linear functions of criteria and predictor variables, chosen so as to maximise the correlation between them.

Discriminatory Analysis

14. The principle of discriminatory analysis is that an observation matrix can be partitioned into groups, defined as required, and an identification routine is then derived so that a new set of observations can be assigned to the groups in such a way that the probability of assignment to a wrong group is as small as possible.

15. A simple geometrical representation of the method for the two groups of observations of two variables is shown in Figure 1.

16. Each ellipse is the locus of points of equal density for a particular group. Thus the outer contour for group A might define the region within which 95% of group A lies and the inner contour the region within which 50% lies.

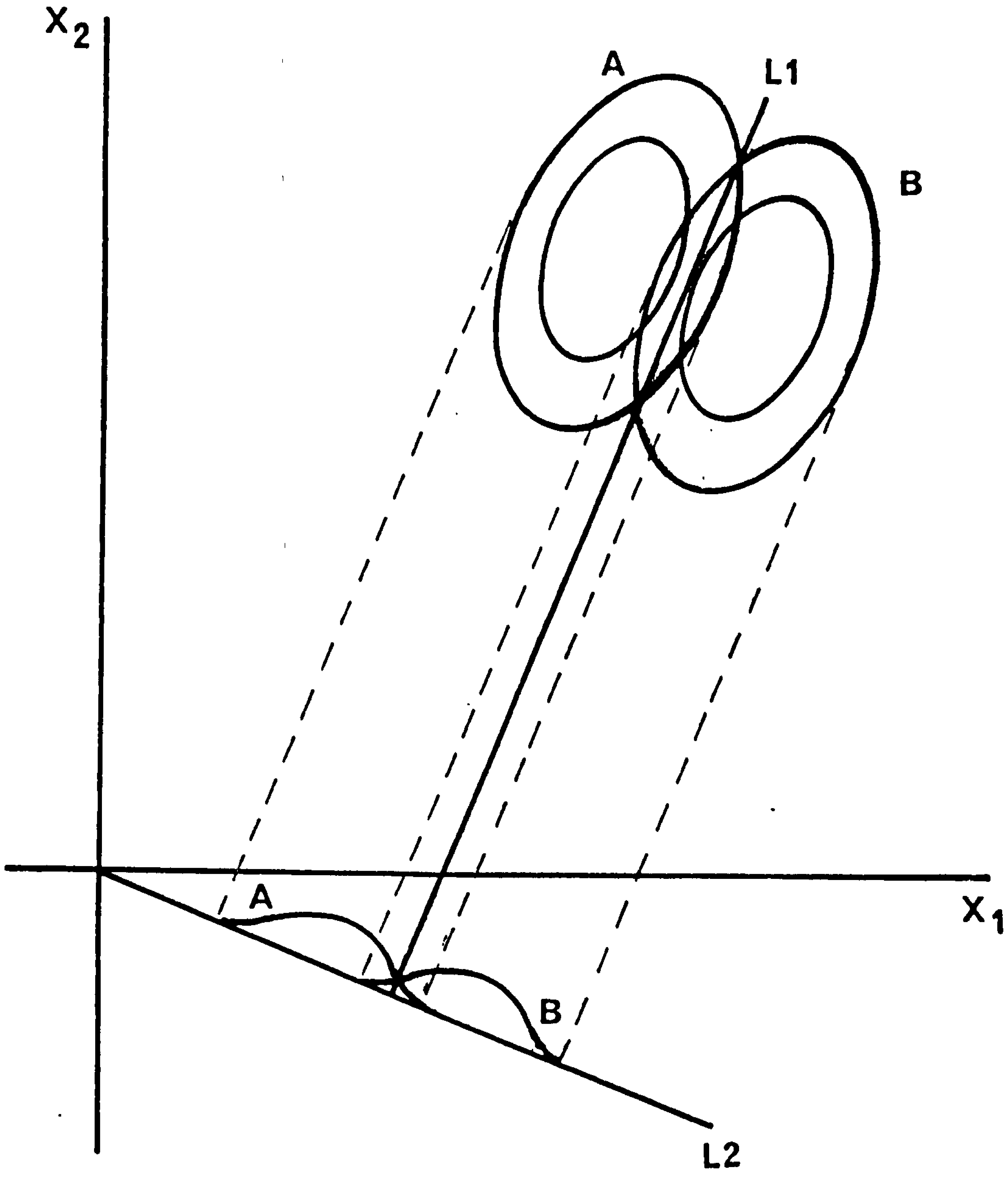


FIG 1 DISCRIMINANT MODEL

17. L1 is defined by the intersections of corresponding contours of the two groups. The distributions of points are projected onto L2 which is constructed perpendicular to L1 so that the overlap of distributions is smaller than it would be on any other line.

18. The discriminant function is defined so as to transform an observation (x_1, x_2) into a single discriminant score which represents the location of the observation on L2.

<u>General</u>

19. Because of a natural desire for elegance (ie simplicity) and because the mathematical formulation might otherwise become complex most of the theorists in this field have confined themselves to linear models. This paper is similarly confined.

HUMAN ABILITY and FACTOR THEORY

20. Factor analysis methods were originally conceived for the detection of the underlying variables needed to account for individual differences in measurements of human abilities or aptitudes in terms of test scores.

21. To understand the classical factor model it is helpful to view its development in the light of the concepts of human ability which it was designed to examine.

Evolution of Factor Theory

22. In the late 19th century GALTON and PEARSON devised the method of correlation for measuring agreement between two sets of scores. In 1901 WISSLER and THORNDIKE applied the method to mental functions and showed scarcely any correlation in their measures. Up to the 1930s the view persisted that abilities were highly specific, but during this period a number of theories began to germinate in this country. Much of the work was done by SPEARMAN, THOMSON and BURT and in 1927 SPEARMAN published "The Abilities of Man" in which he reviewed current theories and grouped them as follows:-

a. Monarchic - reduces all abilities to a single capacity of general intelligence or common sense - implies perfect correlation.

b. Oligarchic - mind ruled by a number of separate powers or facilities accounting for groups of abilities.

c. Anarchic - all abilities are specific.

d. SPEARMAN's two-factor - all abilities overlap to some extent (described as the g-factor) but at the same time each subject involves its own specific factor (s). The amounts of g and s in each ability in each person vary.

23. More recent work during the 1930s, in which STEPHENSON, EL KOUSSY and THURSTONE have figured prominently, has produced the concept of group factors accounting for overlap between some but not all subjects. THURSTONE at first tended to the view that there was no general factor, but later admitted a super-factor

representing communality of group factors. It was THURSTONE who gave the name factor analysis to the statistical processes used for investigating ability structures.

24. In the 1940s BURT evolved the hierarchical concept of abilities which may be depicted as in Figure 2. Here g is regarded as the total of a number of bonds - a property of the higher nervous system.

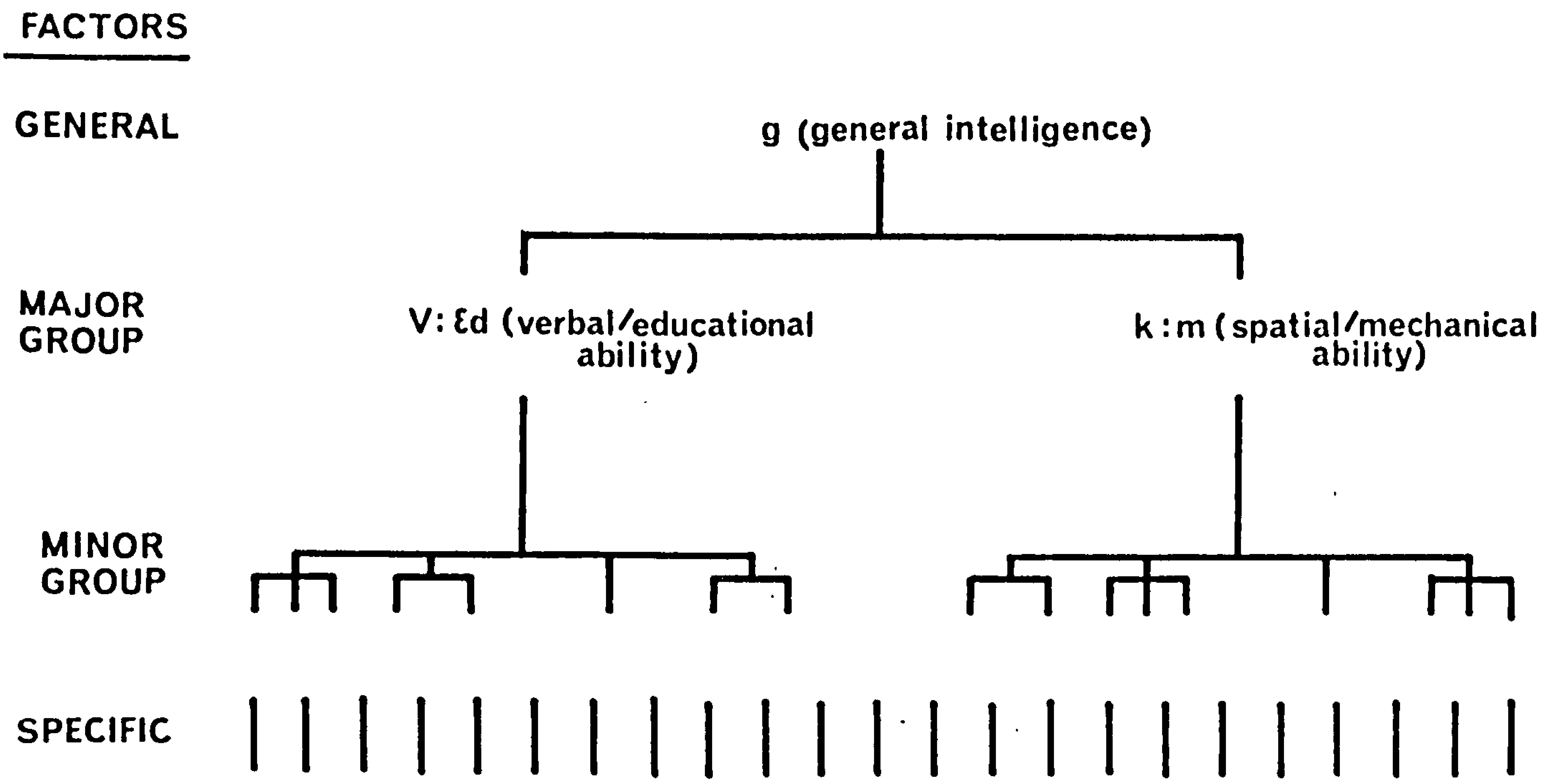


FIG 2 HIERARCHICAL CONCEPT of ABILITIES (BURT)

25. A great deal of work was done during the second world war in both USA and Britain in connection with personnel selection in the armed forces. Much of the British work has been described by P E VERNON (1947) who was a consultant to the services for many years.

26. In 1950 VERNON published an historical account of the study of human ability and gave his own interpretation of the structure of educational ability as in Figure 3.

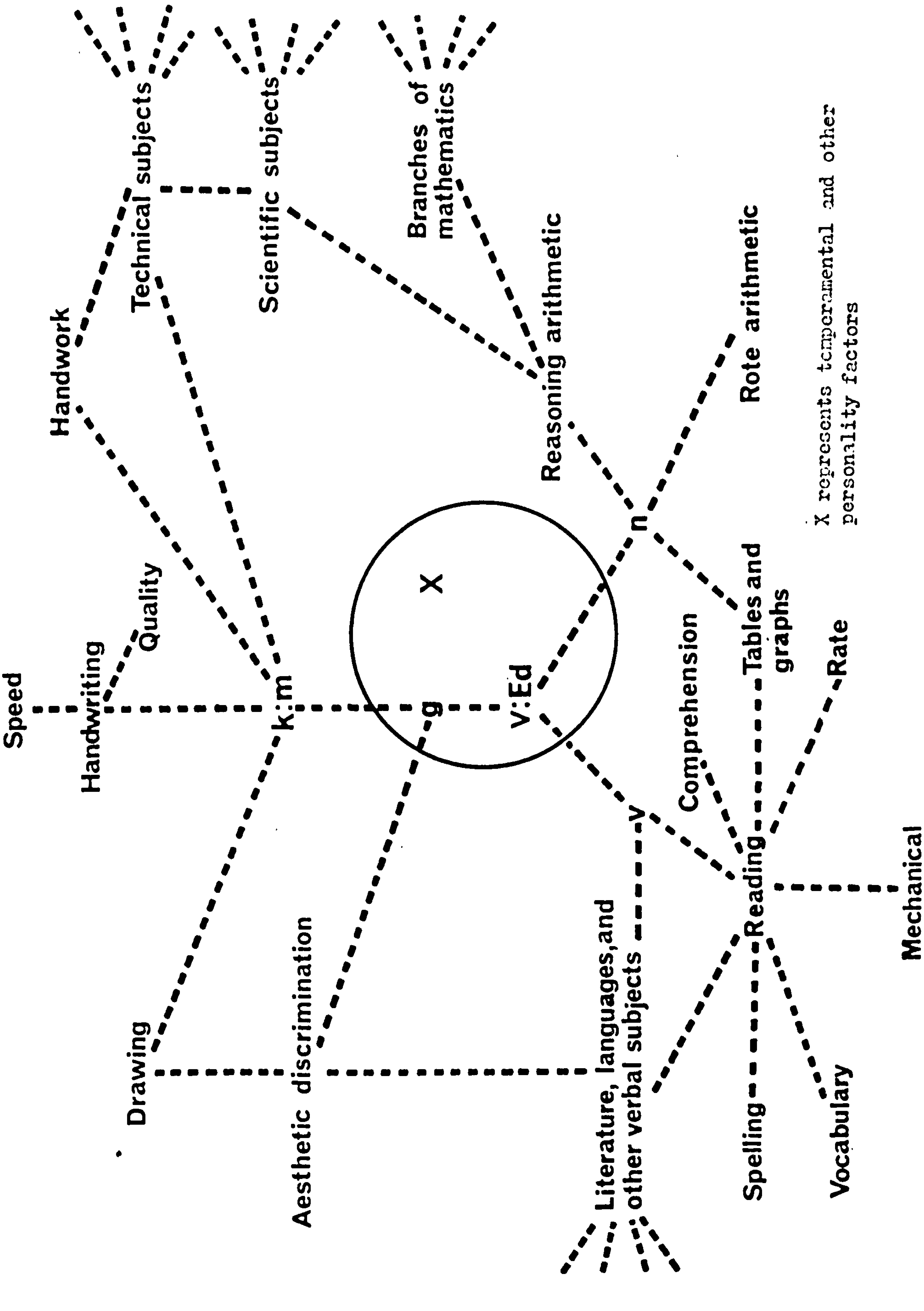


FIG 3   STRUCTURE OF EDUCATIONAL ABILITY (VERNON)

He drew the general conclusion from his extensive experience of design and analysis of tests that, though small group factors can be isolated fairly easily in many types of cognitive tests, no intellectual faculties beyond g and v were yet established as having much educational or vocational importance.

27. He showed how the educational ability structure could be related to occupational aptitude in another model (Figure 4).

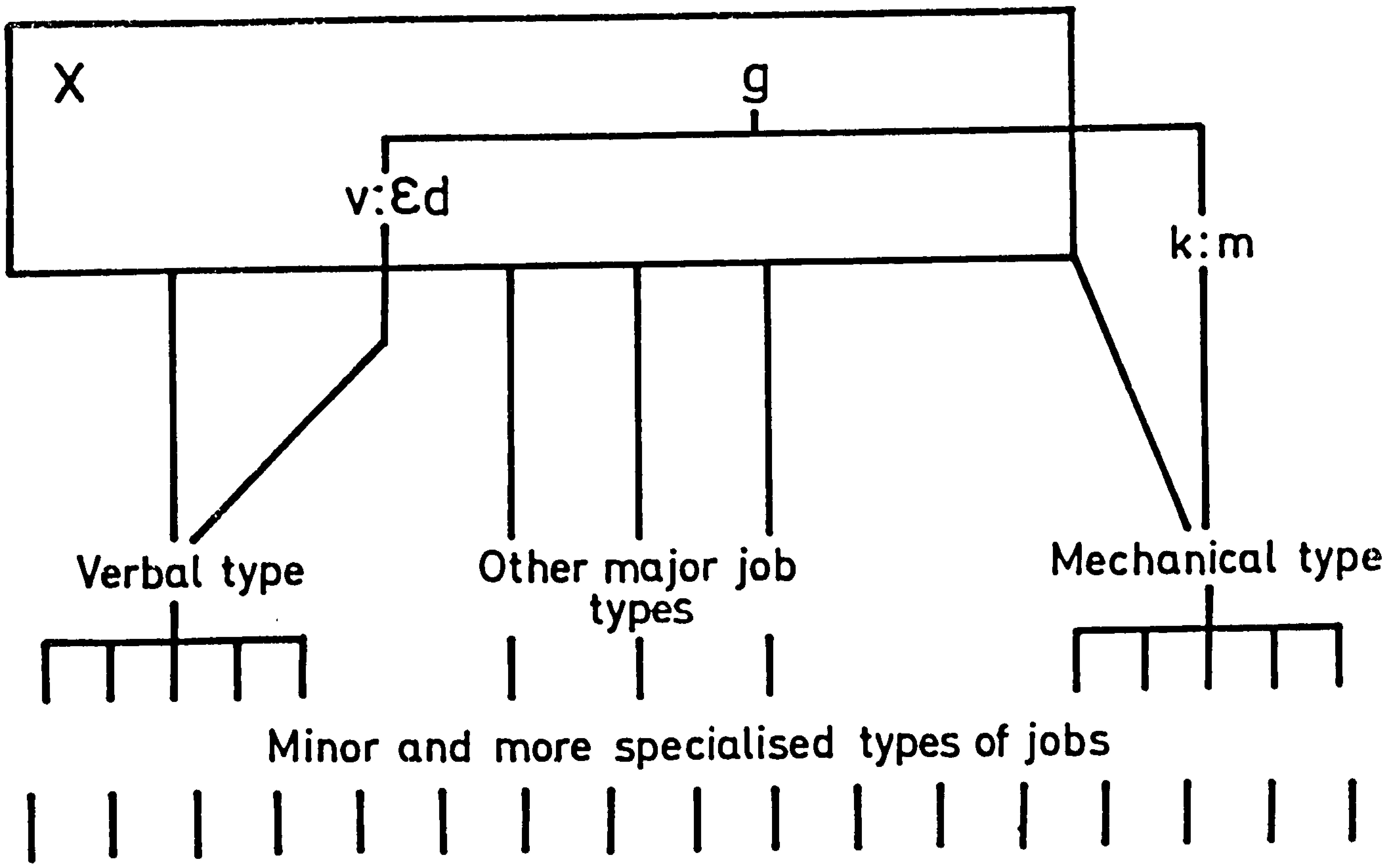


FIG 4 RELATIONSHIP of OCCUPATIONAL APTITUDE and EDUCATIONAL ABILITY (VERNON)

28. There appears to be no disagreement between the various schools on the essential requirements of mathematical models to deal with these ability concepts. Many American factorists do nowadays, like their British counterparts, find a g-factor. But it still remains true that British writers make g as large as possible and posit group factors only when the residuals

necessitate them, whereas American writers either introduce *g* as a second order factor, or if a primary one is unavoidable, tend to minimise it. Also British workers recognise larger or more comprehensive group factors with sub-factors descended from them, whereas Americans' primary factors more often all possess much the same status and variance.

29. The psychological problem which catalysed the development of factor analysis has been discussed at some length because it is relevant to personnel selection and because it provides a greater understanding of the nature of the factor model and of the reason for the existence of so many different techniques for deriving solutions. It is apparent, however, that there are many possible applications in management, where it is frequently desirable to simplify and reduce to a few primary factors a large number of variables. Indeed LAWLEY and MAXWELL claimed in 1963 that, although the protracted psychological controversy about the structure of ability had damped for a time the development of factor analysis, it was by then the most widely used of the multivariate techniques, particularly since the use of computers had facilitated the massive calculations involved even in relatively small problems.

The Concept of Correlation

30. Before going on to consider the factor model it may be helpful to recall the statistical concept of correlation which is central to all multivariate problems. To illustrate the concept an example of some educational data for ten schoolchildren is given in Figure 5.

Student	Exam % x_1	IQ x_2	Years % x_3
A	35	100	35
B	40	100	50
C	25	110	30
D	55	140	75
E	85	150	80
F	90	130	90
G	65	100	75
H	55	120	50
J	45	140	35
K	50	110	50
Mean	54.5	120	57
Standard Deviation	20.74	18.86	21.37

FIG 5 OBSERVATION MATRIX

In this observation matrix the three variables, x_1, x_2, x_3, are measures of educational interest on the ten individuals who, in this case, are members of a school class.

31. From the observation matrix a correlation matrix can be computed. If the individuals are designated i then the correlation coefficient of any two variables j and k is

$$r_{jk} = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{x_{ij} - \bar{x}_j}{\sigma_j} \right) \left(\frac{x_{ik} - \bar{x}_k}{\sigma_k} \right)$$

where N is the number of individuals.

The correlation coefficient is a measure of the extent to which variation in one of two variables is linearly related with variation in the other. It has a range of

$$-1 \leqslant r_{jk} \leqslant +1$$

32. The format and content of the correlation matrix are shown in Figure 6.

Variable	1	2	3
1	r_{11}	r_{12}	r_{13}
2	r_{21}	r_{22}	r_{23}
3	r_{31}	r_{32}	r_{33}

Variable	1	2	3
1	1	.54	.91
2	.54	1	.41
3	.91	.41	1

FIG 6 CORRELATION MATRIX

33. How is the concept of correlation used in the study of ability?

Suppose that two tests, one consisting of arithmetic reasoning problems and the other of reading-comprehension items, are given to a class of 100 students, and a correlation coefficient of +.50 is obtained between the two set of scores (Figure 7.a).

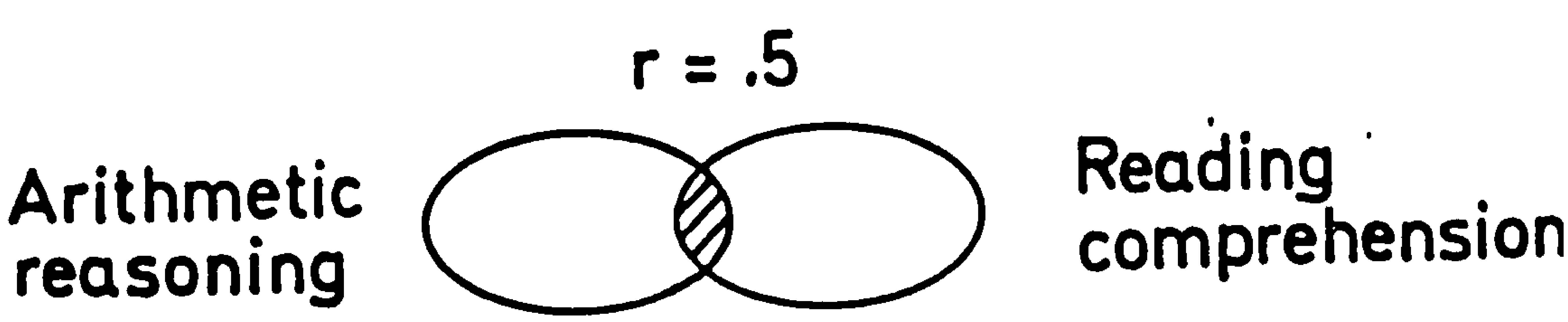


FIG 7.a

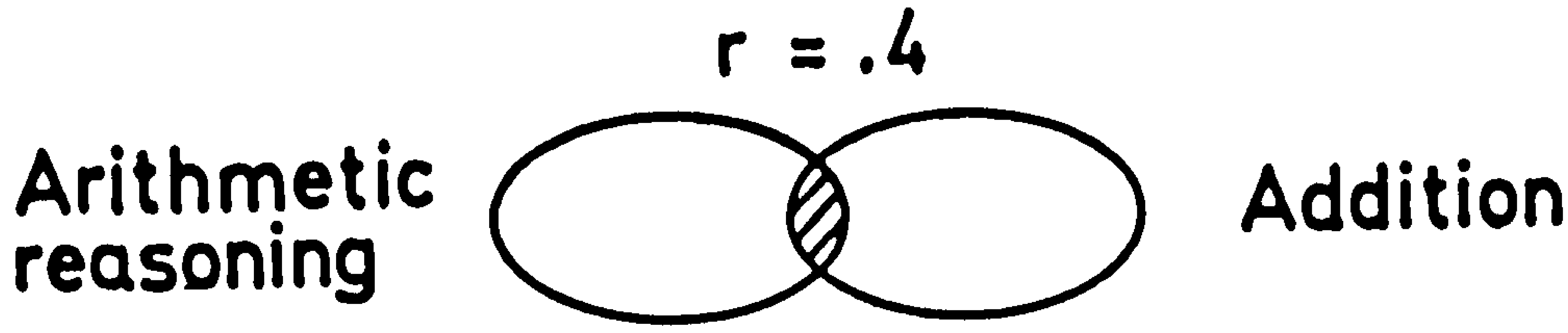


FIG 7.b

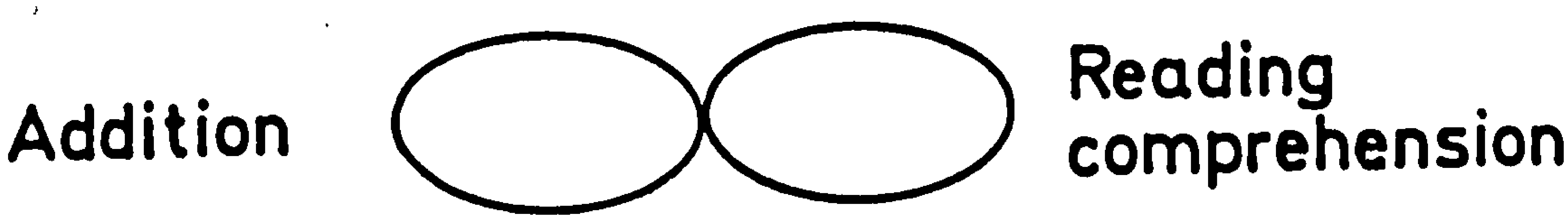


FIG 7.c

This indicates that the tests have something in common, which might be because they both assess reading-comprehension, or vocabulary, or reasoning ability, or speed of working. The correlation between two tests is not a sufficient datum for inference. If the arithmetic-reasoning test were also correlated with a test of simple addition it might yield a correlation coefficient of + .40 (Figure 7.b). Here the overlap might be due to arithmetic computation ability, numerical facility, etc. But if the correlation of addition and reading-comprehension is zero (Figure 7.c) then the overlap of each with arithmetic-reasoning is due to separate traits (Figure 7.d).

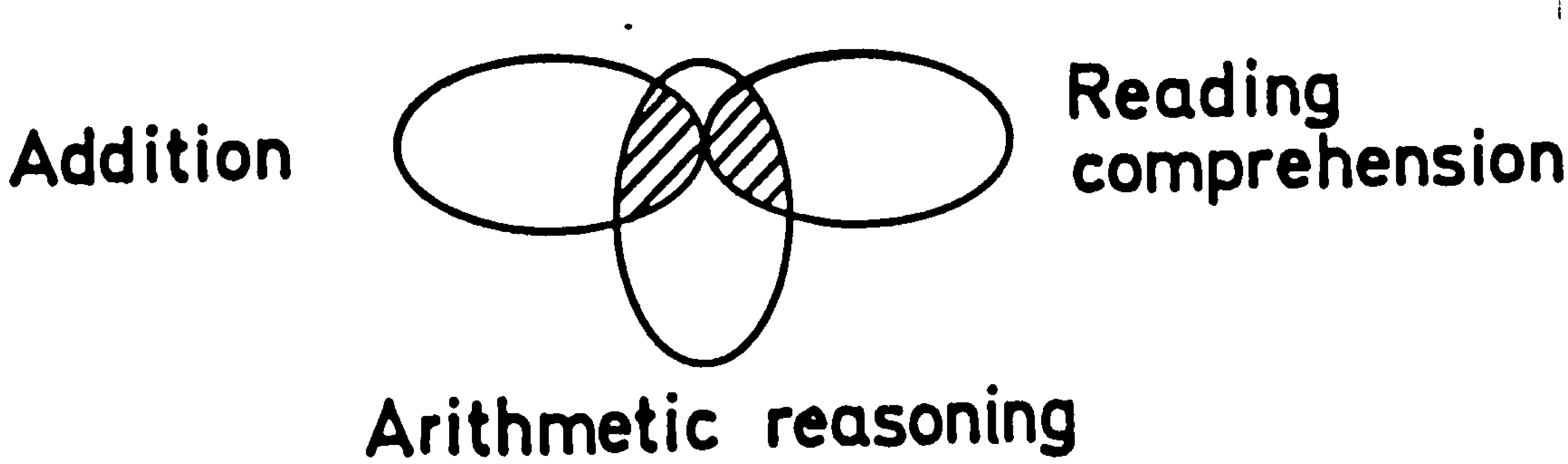


FIG 7.d

34. In real life situations there are often many variables and a large number of correlations to be considered. The various methods of factor analysis have been devised to provide a systematic way of doing this.

SPEARMAN's Two Factor Theory

35. SPEARMAN was one of the first to attack the factor problem by statistical methods. At first he worked with groups of four tests. Observing that tests of abilities tended to have positive intercorrelations he showed mathematically that the intercorrelations, as represented in the following table:-

Test	1	2	3	4
1		r_{12}	r_{13}	r_{14}
2	r_{21}		r_{23}	r_{24}
3	r_{31}	r_{32}		r_{34}
4	r_{41}	r_{42}	r_{43}	

could be, but were not necessarily, accounted for by a single source of variation (or factor) if the coefficients in any combination of two columns were proportional.

36. Thus, to satisfy the "criterion of proportionality":-

$$\frac{r_{31}}{r_{32}} = \frac{r_{41}}{r_{42}}\,; \quad \frac{r_{21}}{r_{23}} = \frac{r_{41}}{r_{43}}\,; \quad \frac{r_{21}}{r_{24}} = \frac{r_{31}}{r_{34}}$$

which may be written:-

$$r_{31}\, r_{42} - r_{32}\, r_{41} = 0$$
$$r_{21}\, r_{43} - r_{23}\, r_{41} = 0$$
$$r_{21}\, r_{34} - r_{24}\, r_{31} = 0$$

When these equations are satisfied, within the limits of sampling error, the four tests are assumed to have one factor in common. In matrix terminology this is the same as saying that the rank of the correlation matrix is one if all second-order minors vanish.

37. SPEARMAN and others found a considerable number of ability tests whose intercorrelations satisfied the criterion closely enough to be accredited a single factor. This factor was called g, the general intellectual factor. SPEARMAN's two-factor theory postulated that every test which satisfies the criterion contains two factors, g and s. His g factor is a general factor common to all intellectual tests. The s factor is specific to each test

and represents that portion of the reliable variance of a test which does not correlate with other tests.

38. The concepts underlying SPEARMAN's technique, which had a profound influence on the development of factor analysis, are illustrated by means of the correlations of six tests shown in Figure 8.a.

Test	1	2	3	4	5	6
1		.35	.21	.56	.28	.35
2	.35		.15	.40	.20	.25
3	.21	.15		.24	.12	.15
4	.56	.40	.24		.32	.40
5	.28	.20	.12	.32		.20
6	.35	.25	.15	.40	.20	

FIG 8.a

39. The g-loading of test j can be calculated from its correlations with two other tests k and l by the formula

$$g_j = \sqrt{\frac{r_{jk}\, r_{jl}}{r_{kl}}}$$

provided the proportionality criterion is satisfied (which it is).

40. The specific factors s_j can then be calculated from:-

$$g_j^{\,2} + s_j^{\,2} = 1.00$$

for a perfectly reliable test.

41. Thus for the six tests SPEARMAN's theory gives the results in Figure 8.b.

Test	Factor						
	g	s_1	s_2	s_3	s_4	s_5	s_6
1	.7	.714					
2	.5		.866				
3	.3			.954			
4	.8				.600		
5	.4					.917	
6	.5						.866

FIG 8.b

42. This might be shown schematically as in Figure 9.

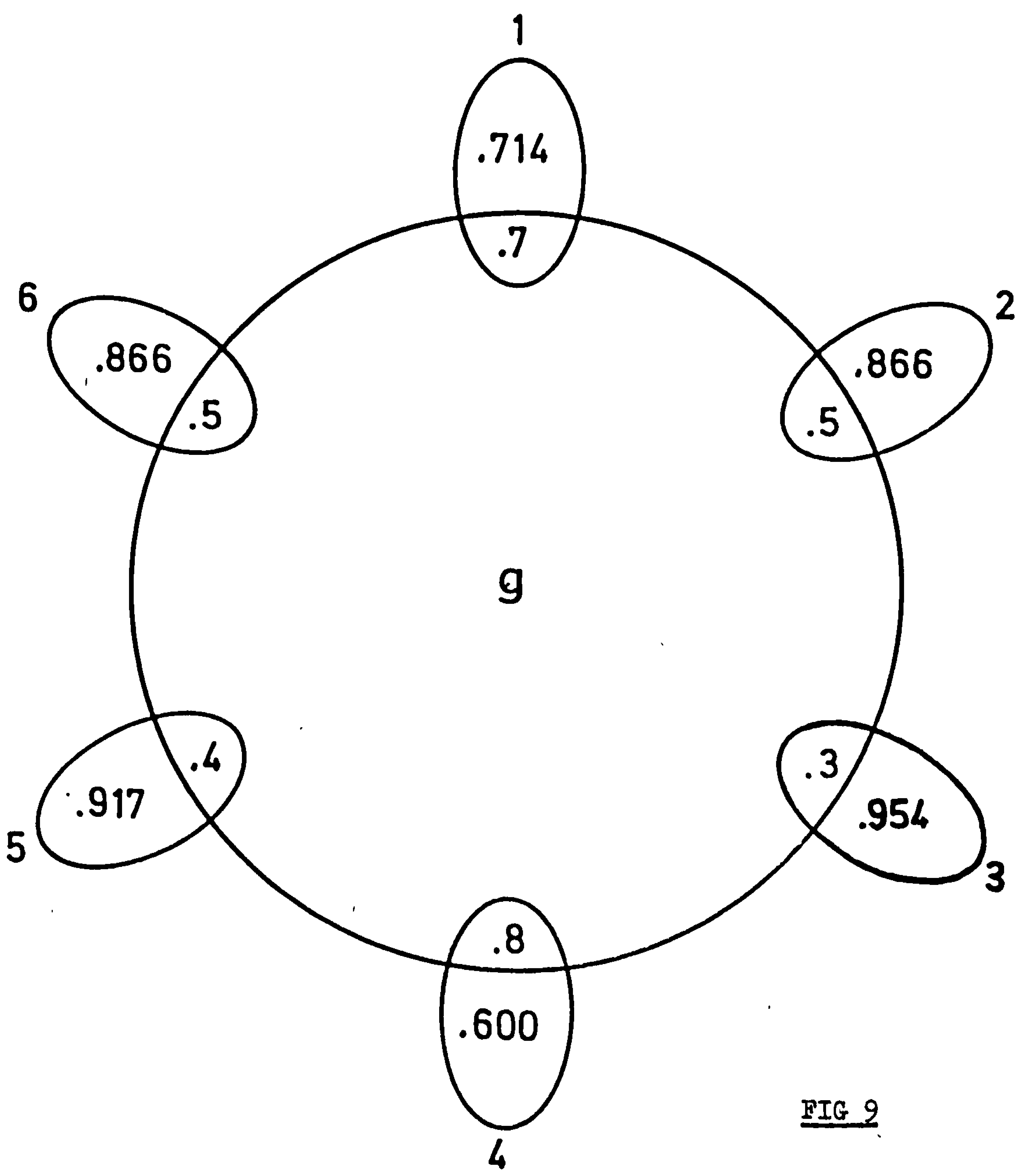


FIG 9

where the numbers inside both circle and ovals are the correlations of each test with g and the numbers in the ovals outside the circle are the loadings on specific factors, assuming perfectly reliable tests.

43. The correlations can be reproduced entirely from the g loadings. Thus $r_{12} = g_1 \; g_2$, etc.

HOLZINGER's Bi-Factor Theory

44. A major limitation of SPEARMAN's technique was the criterion of proportionality requirement. HOLZINGER realised that this limitation could be overcome if group-factors were postulated as well as a general factor. An example, in which there are two group-factors is shown in the table and diagram (Figures 10.a and b).

Test	Factors								
	g	c_1	c_2	s_1	s_2	s_3	s_4	s_5	s_6
1	.6	.3		.742					
2	.4	.4			.825				
3	.7					.714			
4	.5		.6				.625		
5	.6		.7					.387	
6	.3		.8						.520

FIG 10.a

In this case, for a perfectly reliable test j,

$$g_j^{\,2} + c_j^{\,2} + s_j^{\,2} = 1.00$$

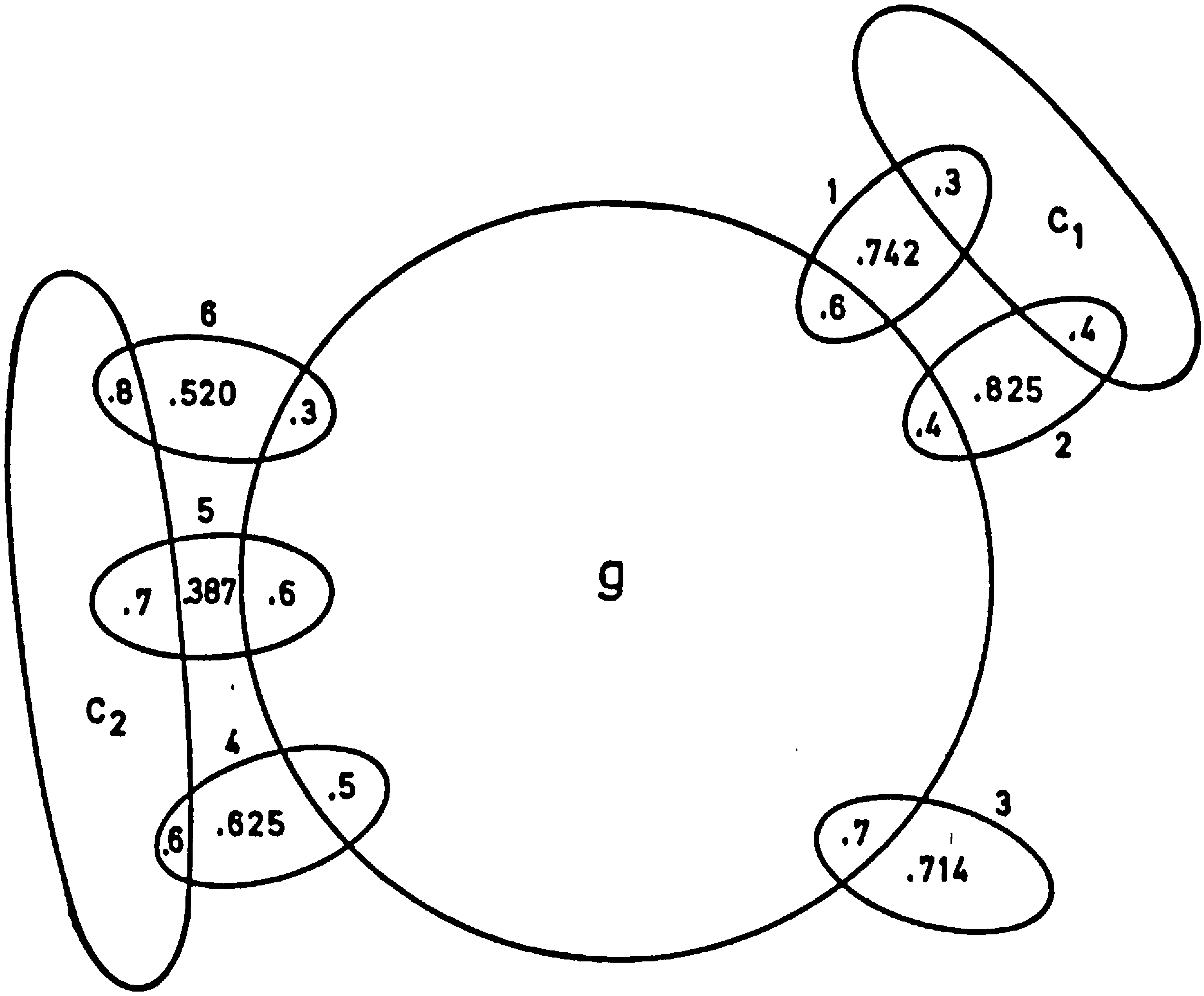


FIG 10.b

The correlation matrix could be reconstructed from the above data using the relationship:-

$$r_{jk} = g_j\ g_k + c_{j1}\ c_{k1} + c_{j2}\ c_{k2} + \ldots\ldots\ldots\ldots$$

Thus

$$r_{12} = g_1\ g_2 + c_{11}\ c_{12} + c_{21}\ c_{22}$$

$$= (.6 \times .4) + (.3 \times .4) = .24 + .12 = .36$$

45. What has been achieved in the SPEARMAN and HOLZINGER techniques?

In the SPEARMAN case the correlations of six tests are entirely accounted for by the products of loadings of these tests on one general factor, g.

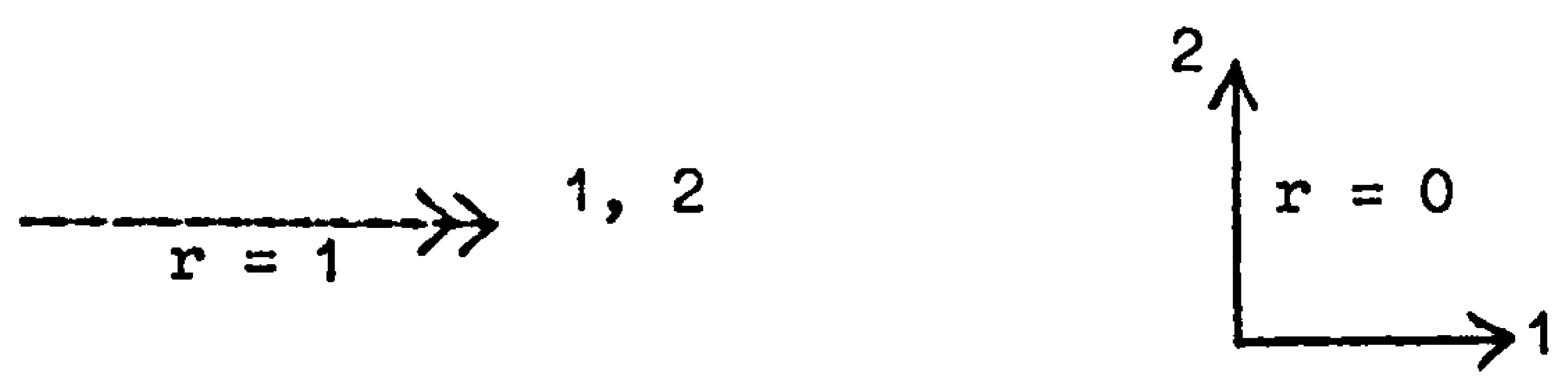
HOLZINGER's approach overcomes the limitations of SPEARMAN's by introducing group factors in addition to g.

In both cases it is possible to reproduce the correlation matrix from a number of factors which is smaller than the number of tests, or variables.

Geometrical Representation of Factors

46. The geometrical model most commonly used for illustrating correlation, particularly in the case of regression analysis, shows observations in relation to rectangular axes and represents the correlation coefficient by means of the slope of the regression line.

47. A useful alternative is a model in which r is represented by the cosine of the angle between vectors, ie the correlation of two unit variables may be represented by two unit vectors separated by an angle $\emptyset$ where $r_{12} = \cos \emptyset$. Thus collinear vectors represent $r = 1$ and orthogonal vectors represent $r = 0$.



48. Consider the correlation matrix of Figure 11.a for ten variables:-

Variable	1	2	3	4	5	6	7	8	9	10
1	1	.96	.60	.48	.64	.80	.36	.48	.00	.70
2		1	.80	.36	.48	.60	.48	.64	.00	.70
3			1	.00	.00	.00	.60	.80	.00	.50
4				1	.96	.60	.64	.48	.80	.86
5					1	.80	.48	.36	.60	.82
6						1	.00	.00	.00	.50
7							1	.96	.80	.86
8								1	.60	.82
9									1	.70
10										1

FIG 11.a

Here $r_{36} = r_{39} = r_{69} = 0$, so that variables 3, 6 and 9 are orthogonal.

49. If a three-dimensional vector diagram is constructed in which vectors 3, 6 and 9 are the axes, the correlations in the matrix can be represented by vectors as shown in Figure 11.b.

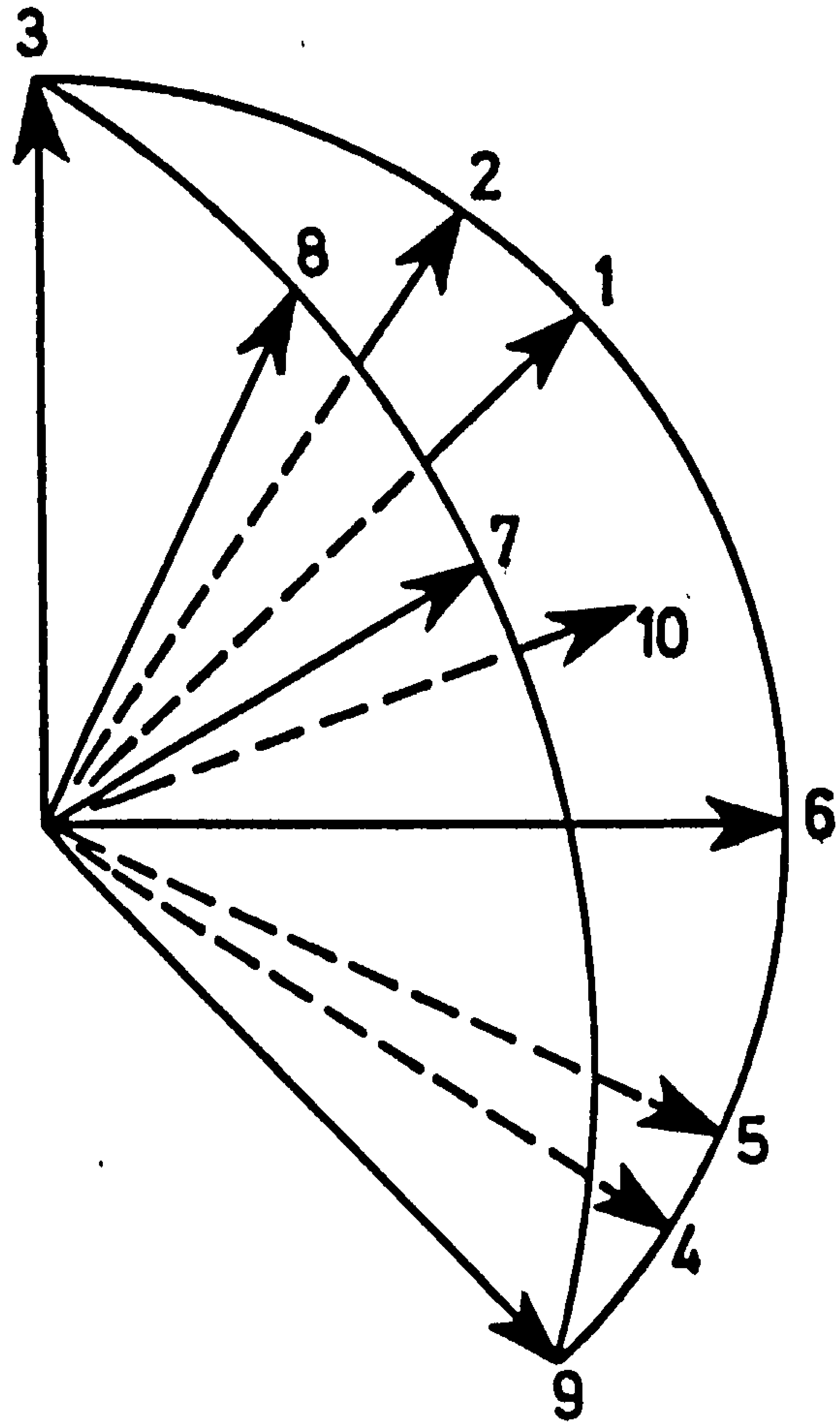


FIG 11.b

Vectors	1 & 2	are	orthogonal	to	vector	9,	so	are	in	the	plane	of	3 & 6
"	4 & 5	"	"	"	"	3,	"	"	"	"	"	"	6 & 9
"	7 & 8	"	"	"	"	6,	"	"	"	"	"	"	3 & 9

" 10 is not in any of the three planes.

50. Thus if vectors 3, 6 and 9 are used as reference vectors and called factors II, I and III respectively, the factor loadings are as shown in Figure 12.

Variable	Factor		
	I	II	III
1	.8	.6	0
2	.6	.8	0
3	0	1	0
4	.6	0	.8
5	.8	0	.6
6	1	0	0
7	0	.6	.8
8	0	.8	.6
9	0	0	1
10	.5	.5	.7

FIG 12

and all the correlations can be reproduced by adding the cross-products of factor loadings.

51. The example is a simplified one (in which the rank of the correlation matrix is 3) but it does bring out an important aspect of factor analysis, namely that, although there is only one configuration of vectors corresponding to any given correlation matrix, there is no unique location for the reference axes. The axes in the example could have been rotated to any desired position without changing the relationships of the correlations, but the factor loadings would have been different for each position of the axes.

52. It is therefore necessary to insert a frame of reference axes into the test configuration before a factor matrix can be deduced. Since the axes are determined by the observer and not by the data every factor matrix is an interpretation of the correlations and there is an infinite variety of possible interpretations. Each column of the factor matrix represents one axis of the chosen framework. Each row represents the orthogonal components of one test vector.

Factor Models

53. The psychological problem which led to the development of factor analysis has been outlined and the concepts used by SPEARMAN and HOLZINGER for representing correlations in terms of factors have been discussed. The geometrical significance of factors has also been examined. It is now possible to define the essential nature of factor analysis in more general terms.

54. HARMAN (1960) has described factor analysis as the resolution of a set of variables in terms of a smaller number of factors, which convey all the essential information of the originals, in order to attain economy of description. The model may be expressed in the form:-

$$x_i = \sum_{j=1}^{m} a_{ij} F_j + \mathcal{E}_i \qquad (i = 1, 2, \ldots\ldots n)$$

ie the n variables x_i are each expressed in terms of their loading on each of m factors F_j (where $m < n$) and a specific term $\mathcal{E}_i$. The common factors account for the correlations among the variables while each specific term accounts for the remaining variance (including error) in that variable.

55. The basic problem of factor analysis is the estimation of loadings of the common factors. Many methods have been developed for determining the axes and the loadings in order to satisfy various requirements. Some of the more important are listed below:-

Method		Characteristics
*1.	Principal component	All general factors
2.	Principal factor	All general factors
3.	Centroid	All general factors
4.	Maximum - likelihood	All general factors
5.	Minres	All general factors
6.	Triangular decomposition	Each successive factor involves one fewer variable
7.	Multiple - group	Group factors only
8.	Two-factor	One general factor
9.	Bi-factor	One general and m group factors
10.	Multiple-factor	Overlapping group factors

(*Principal component analysis is listed as a factor method by HARMAN, though its model has an important distinguishing feature. In factor analysis each of the p original variates is expressed in terms of m ($< p$) mutually uncorrelated common factors and a residual which is not correlated with either the common factors or the remaining variates. In principal component analysis the number of components is equal to the number of variates ($m = p$) and the residual vanishes.)

56. These and other methods have been described in detail by HARMAN (1960), HORST (1965) and KENDALL (1965). The choice of method in any particular application depends partly on the nature of the problem, partly on preference, and partly on available facilities (some of the methods are impracticable for manual calculation). It is important to remember, however, that a model which is mathematically elegant (ie it chooses reference axes to give the simplest expression of the configuration) is not necessarily the most suitable for interpretation of data in a real-life situation.

57. The background of factor analysis has been described at some length in order to demonstrate the nature of multivariate analysis and its application to personnel selection. In order to illustrate the use of factor methods an example has been worked using two of them, firstly the principal component and secondly the maximum - likelihood.

Principal Component Analysis

58. The method of principal components, developed by HOTELLING, uses the model

$$x_i = \sum_{j=1}^{n} a_{ij} F_j \qquad (i = 1, 2, \ldots\ldots n)$$

where each of the n observed variables is described in terms of n new uncorrelated components. Important properties of the method are:-

a. the components are orthogonal (ie are uncorrelated)

b. each component in turn makes a maximum contribution to the sum of variance of the n variables.

59. In effect the transformation of the observed vector to the vector of principal components amounts to a rotation of axes. The principal components are in fact the eigenvectors of the correlation matrix.

60. Thus principal component analysis is used to find linear combinations of variables with large variance. It does not in itself condense the data but it may be a useful preliminary to Factor Analysis, enabling the effective dimensionality of the test space, ie the number of significant factors, to be assessed for use in methods requiring an estimate of the number of common factors (eg maximum - likelihood).

61. To illustrate this point an example has been worked using some synthetic data designed to illustrate the results of five selection tests on a group of twelve candidates. In practice a considerably larger sample of candidates would normally be required.

62. The nature of the five tests and the scores of each candidate on them are tabulated in Figure 13. Mean scores and standard deviations for each test are also listed.

INDIVIDUAL	TEST				
	1 Mechanical Aptitude	2 Verbal Reasoning	3 Mechanical Comprehension	4 Mathematics	5 Verbal Comprehension
1	57	128	25	67	25
2	10	109	16	41	10
3	34	88	10	41	9
4	38	136	17	54	25
5	40	128	16	54	25
6	82	83	26	46	12
7	12	114	4	41	16
8	91	115	33	46	14
9	99	125	34	58	18
10	96	137	36	79	25
11	96	96	33	48	12
12	94	114	40	50	13
Mean	62.4	114.4	24.2	52.1	17.0
Standard Deviation	34.4	17.9	11.4	11.5	6.4

FIG 13 SELECTION TEST DATA

63. The first step is to normalise the test scores, that is to scale them so that each test has a mean score of zero and a standard deviation of unity. The reason for this is that there are normally no grounds for supposing that the differences between the variances of tests represent real differences in the importance of the qualities which the tests measure. The normalised scores are tabulated in Figure 14.

INDIVIDUAL	TEST				
	1	2	3	4	5
1	- .16	.76	.07	1.30	1.26
2	-1.52	- .30	- .71	- .96	-1.10
3	- .83	-1.48	-1.24	- .96	-1.26
4	- .71	1.21	- .63	.17	1.26
5	- .65	.76	- .71	.17	1.26
6	-1.76	.16	- .53	- .79	- .92
7	-1.47	- .02	-1.76	- .96	- .16
8	.83	.03	.77	- .53	- .47
9	1.06	.59	.86	.52	.16
10	.98	1.26	1.03	2.34	1.26
11	.98	-1.03	.77	- .36	- .79
12	.92	- .02	1.38	- .18	- .63

FIG 14 NORMALISED SELECTION TEST DATA

64. If the tests are visualised as orthogonal axes of a graph (which in this case would need to be five-dimensional), and each person's score as a point on this graph, the object of principal component analysis is to rotate the axes so that the first component or axis lies in such a direction that the sum of the square of the distances of the points from it is a maximum. The second component is then arranged to be at right angles to the first, again with maximum variance, and so on. A lucid description of the mathematical processes involved is given by HOPE (1968).

65. An essential preliminary is to derive the correlation matrix which is shown in Figure 15.

VARIABLE	1	2	3	4	5
1	1				
2	.01	1			
3	.93	.14	1		
4	.44	.69	.48	1	
5	.02	.86	.04	.78	1

FIG 15 CORRELATIONS of SELECTION TEST DATA

66. The results of principal component analysis are tabulated in Figure 16.

VARIABLE (Test)	COMPONENT				
	1	2	3	4	5
1	.33	.60	.06	.48	.54
2	.47	- .38	- .70	- .15	.35
3	.37	.57	- .33	- .21	- .63
4	.56	- .06	.59	- .56	.15
5	.47	- .41	.20	.63	- .41
Component Variance	2.82	1.81	0.23	0.11	0.03
Accumulated % of Total Variance	56.4	92.6	97.2	99.4	100

FIG 16 PRINCIPAL COMPONENTS of SELECTION TEST DATA

67. The table shows that the first two components account for almost 93% of the total variance, and consequently that a two-dimensional model can provide a satisfactory representation of the observed inter-relationships.

68. If the normalised observation matrix (Figure 14) is post-multiplied by the component loading matrix (Figure 16) the result is a matrix of normalised observations in principal component co-ordinates. The process is illustrated in Figure 17 and the result tabulated in Figure 18.

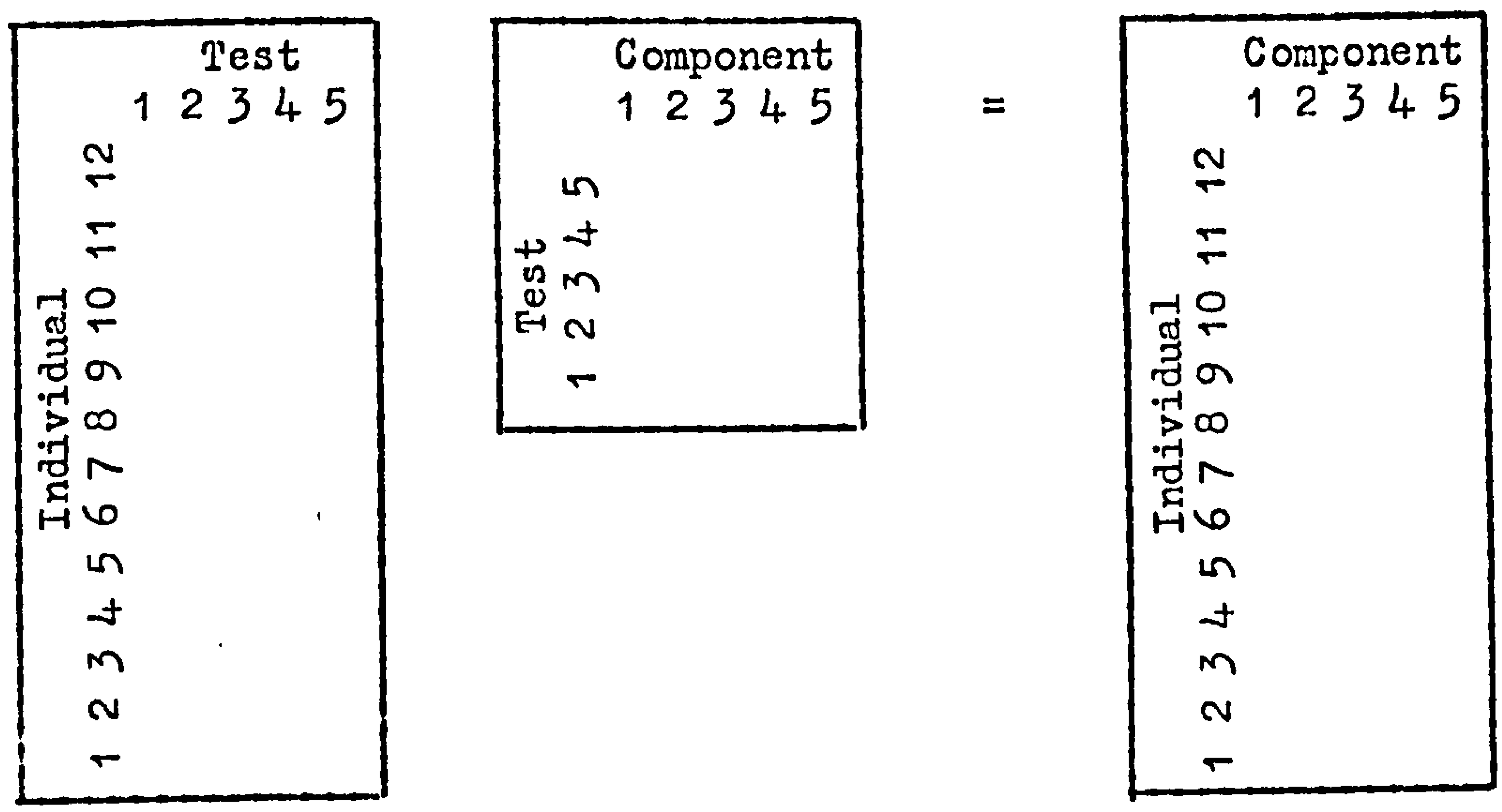


FIG 17 DERIVATION of COMPONENT SCORES

INDIVIDUAL	COMPONENT				
	1	2	3	4	5
1	1.65	- .94	.46	- .14	- .19
2	-1.97	- .69	- .44	- .69	- .18
3	-2.55	- .06	.56	- .17	.19
4	.79	-1.77	- .33	.31	- .06
5	.57	-1.61	.02	.42	- .13
6	-1.24	1.46	.74	.30	- .16
7	-1.76	-1.75	- .10	.11	.22
8	.06	1.15	- .64	.23	.09
9	1.31	.80	- .29	.05	.25
10	3.20	.03	.48	- .45	.15
11	- .45	1.76	.16	.16	- .04
12	.40	1.61	- .62	- .14	- .15

FIG 18 COMPONENT SCORES of SELECTION TEST DATA

69. The distribution of the twelve observations in the C_1C_2 hyperplane is shown in Figure 19. The third component (which is orthogonal to the paper) accounts for only 4.6% of the total variance and the largest co-ordinate is 0.74. Co-ordinates on the fourth and fifth components are still smaller. Hence the distribution of the points in the component space may be seen as an ellipsoid cloud, the shape resembling a discus.

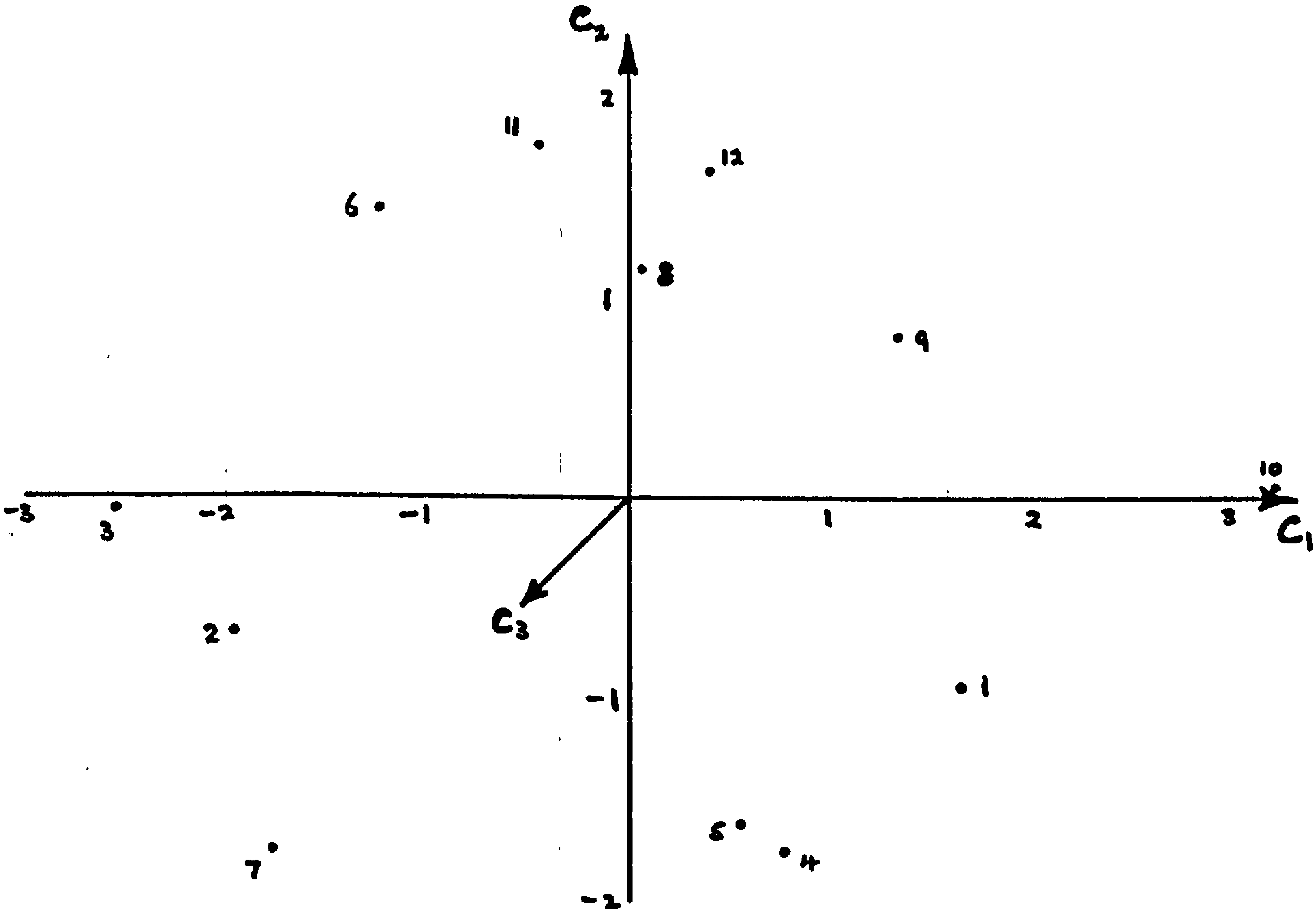


FIG 19 DISTRIBUTION of OBSERVATIONS in C_1C_2 PLANE

Maximum - likelihood Method

70. In contrast to the method of principal components, which is concerned with determining how many dimensions are required in the test space to account for any given proportion of the total variance, the method of maximum likelihood requires an estimate of dimensionality to be made. The method, developed by LAWLEY in the early 1940s, made a fundamental contribution to factor analysis by providing a statistical basis for judging the adequacy of the model with a specified number of factors to explain an empirical correlation matrix. Essentially, the derived factor loadings are such that the sum of the squares of the differences between observed and estimated correlations is as small as possible. An account of the mathematical processes involved is given by HARMAN (1960).

71. Using the same example of selection test results and specifying two factors, the method gives the matrix of factor loadings for normalised variates shown in Figure 20.

Variable (Test)	Factor 1	Factor 2	Communality $h^2 = F_1^2 + F_2^2$	Specific Variance $s^2 = 1 - h^2$
1	.41	.86	.90	.10
2	.82	-.29	.76	.24
3	.45	.87	.97	.03
4	.90	.08	.82	.18
5	.89	-.41	.98	.02

FIG 20 FACTOR LOADINGS of SELECTION TEST DATA

The high communalities for all five variables support the finding of the principal component analysis that the useful information derived from the five ability tests can be represented in a two-space.

72. Statistical adequacy of the factor solution is assessed by comparing observed and estimated correlation matrices, R and $\hat{R}$. The estimated correlations are obtained from the relationship $\hat{R} = AA'$, where A is the factor loading matrix. Values are tabulated in Figure 21 for comparison with the observed values given in Figure 15.

Variable	1	2	3	4
1				
2	.09			
3	.93	.12		
4	.44	.72	.48	
5	.02	.85	.05	.77

FIG 21 ESTIMATED CORRELATIONS

73. The test of adequacy proposed by LAWLEY requires calculation of a residual function U:-

$$U = N \sum_{i<j=1}^{p} \frac{\bar{r}_{ij}^{\,2}}{s_i^2 \cdot s_j^2}$$

where:- N is the number of observations from which the correlation matrix is computed. N is corrected to $N - \frac{p}{3} - \frac{2k}{3} - \frac{11}{6}$ for small samples.

$\bar{r}_{ij} = r_{ij} - \hat{r}_{ij}$, ie the difference between observed and estimated correlation coefficients of variables i and j.

s_i^2 is the specific variance of variable i.

p is the number of variables and k the number of factors.

U is distributed as χ^2 with $\left[(p - k)^2 - p - k\right] /2$ degrees of freedom.

74. In the present problem U = 2.7 with 1 degree of freedom, a value which indicates that the residuals are not significantly greater than might be expected by chance and hence that the two-factor solution is adequate.

75. The orientation of selection test vectors in the two-factor space is shown by plotting the factor loadings as in Figure 22. The graph shows the close relationship of tests 1 and 3 and of tests 2 and 5. (In this case the relationship could have been deduced by inspection of the correlation matrix, but in a problem involving many variables the factor solution is often an invaluable aid to understanding the data.)

76. It would be possible to rotate the factor axes to coincide with the centroids of these two pairs of variables. The F_2 axis, when rotated through 27°, might be labelled mechanical ability (M); the F_1 axis rotated through 23° might be labelled verbal ability (V). Test 4, a measure of mathematical ability, is seen to be loaded on both V and M.

77. It can be shown that the best estimate of factor scores (ie co-ordinates in the factor space) of the original observations is given by:-

$$Y = (A'A)^{-1} A'Z$$

where A is the factor loading matrix (Figure 20) Z is the normalised observation matrix (Figure 14).

The factor scores matrix Y is tabulated in F_1 and F_2 columns of Figure 23 and the distribution of the points is illustrated in Figure 24. The position of the M and V axes is also shown to illustrate how any particular individual might be described in terms of his scores on M and V in relation to the sample mean of these measures. The scores on the oblique axes may be calculated by means of the transformation

$$Y_t = T^{-1} Y$$

where T is the matrix of direction cosines of old versus new axes. For rotation to M and V axes the matrix T^{-1} is:-

$$\begin{matrix} 0.895 & -0.451 \\ 0.384 & 0.926 \end{matrix}$$

The rotated scores matrix Y_t is tabulated in the M and V columns of Figure 23.

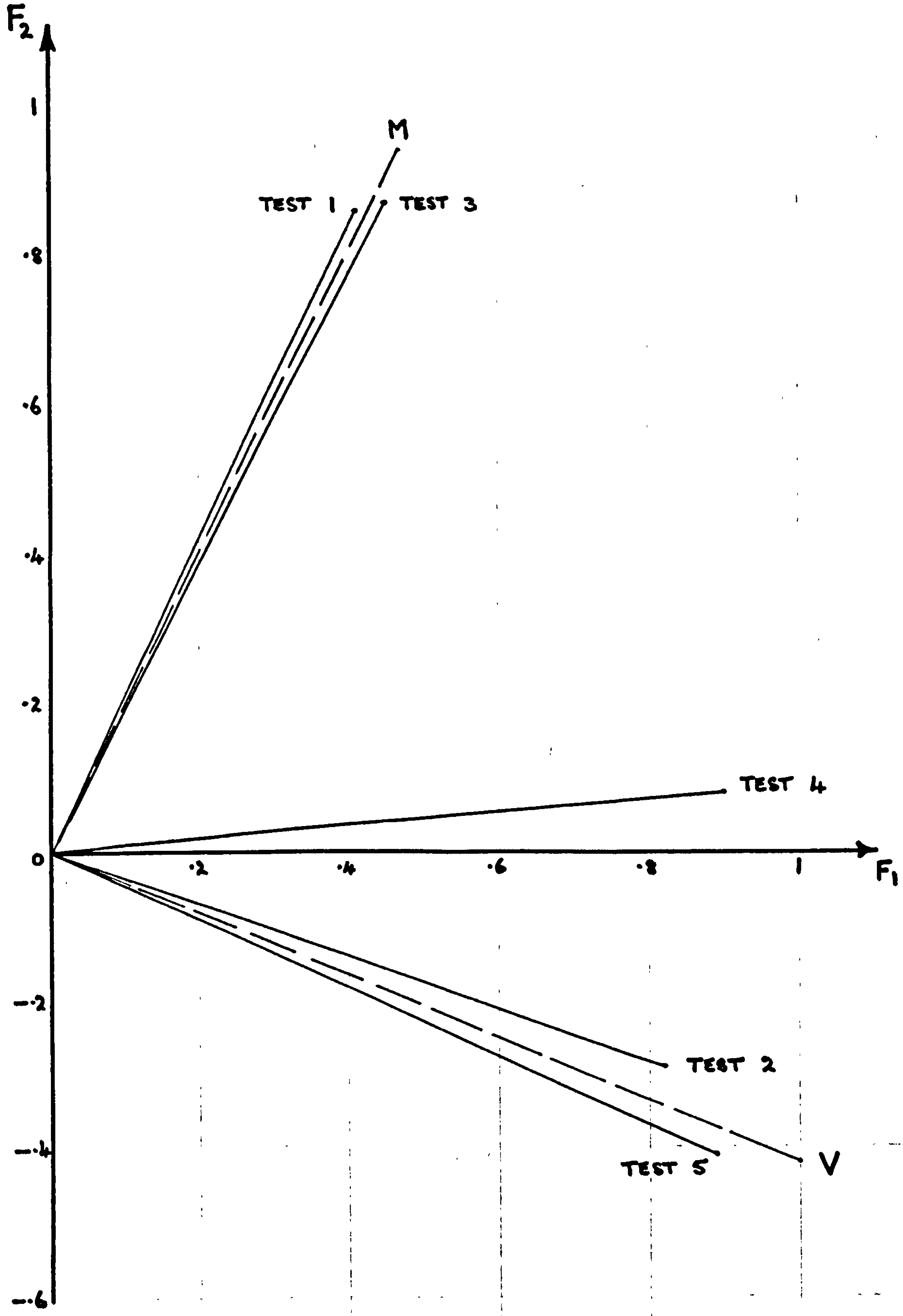


FIG 22 ORIENTATION of SELECTION TEST VECTORS in TWO-FACTOR SPACE

INDIVIDUAL	FACTOR AXES		OBLIQUE AXES	
	1	2	V	M
1	1.13	-1.52	1.69	- .97
2	-1.09	- .95	- .55	-1.30
3	- .54	- .34	- .33	- .52
4	.73	- .14	.72	.15
5	.58	.66	.22	.84
6	- .71	.93	-1.05	.59
7	- .79	- .52	- .48	- .79
8	-1.24	.89	-1.51	.35
9	-1.16	.76	-1.38	.26
10	1.90	0	1.71	.73
11	-1.50	1.27	-1.92	.60
12	.37	1.28	- .25	1.33

FIG 23 FACTOR SCORES of SELECTION TEST DATA

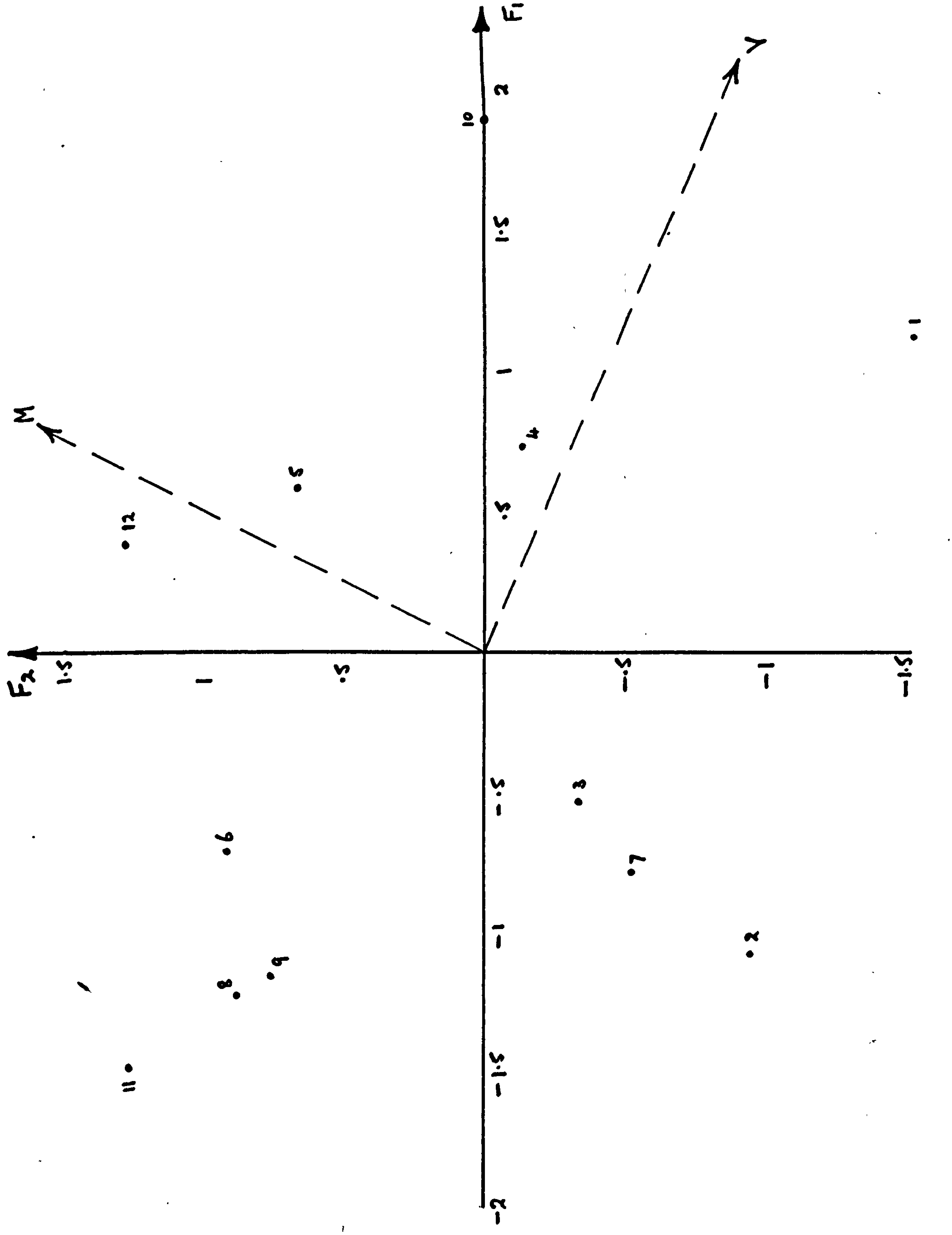


FIG 24 DISTRIBUTION of OBSERVATIONS in F_1F_2 PLANE

Summary

78. The example has shown how multivariate analysis may be used to reduce the dimensionality of observed data, and hence to produce a simplified descriptive model with meaningful axes. In the case examined it was found possible to express the information yielded by five typical selection tests in terms of two near-independent qualities which might be labelled verbal and mechanical ability.

79. Real-life cases would normally involve a much larger sample and often include many more variables.

80. Problems of such magnitude demand high speed computing facilities since the calculations are long, intricate and tedious. Factor analysis is capable of yielding elegant descriptions of suitable data but it is only since the computer has been available to cope with the mammoth manipulations, and since LAWLEY provided mathematical respectability by introducing the maximum likelihood method, that the method has come into its own.

THE PREDICTION PROBLEM

81. So far this paper has been concerned with the use of multivariate analysis as an aid to description of data.

82. A problem frequently encountered in the personnel selection field is the need to predict likely success of candidates and there are two techniques particularly appropriate for this purpose.

83. The first, and most commonly used, is multiple regression analysis, which is concerned with the estimation of an expected criterion score from candidates' scores on a number of predictors. The method is appropriate for predicting probable examination results, since these are measured on a near-continuous scale.

84. In certain instances the measurement of success on such a scale may be impracticable and a more appropriate approach may be to classify individuals as successful/unsuccessful. In such a case the technique known as Discriminatory Analysis, which is concerned with classificatory prediction, may be more suitable.

85. To illustrate the application of both multiple regression and discriminatory analyses examples have again been worked using the same selection test data as before. It is now assumed that the candidates, having been selected, underwent a period of training at the end of which their relative success was judged by their instructors and an aggregate mark was awarded. Furthermore, the candidates were then employed and during their working careers the more successful were promoted. A matrix showing the training mark, T_6, and career success, T_7, is given in Figure 25.

INDIVIDUAL	Training Success T_6	Career Success T_7
1	12	1
2	2	1
3	0	0
4	10	1
5	10	1
6	3	0
7	4	1
8	7	0
9	10	0
10	15	1
11	5	0
12	7	0

FIG 25 CRITERIA SCORES

86. In order to demonstrate the use of condensed data for predictive purposes examples have been included in which the V and M scores derived by factor analysis (see Figure 23) have been used as predictors. The advantage of using scores on these variables rather than the raw selection test scores given in Figure 13 is that the predictor functions can then readily be interpreted in terms of abilities. There is, however, some loss of information in the process of condensation.

Multiple Regression Analysis

87. The regression model:-

$$\hat{Y} = a + b_1X_1 + b_2X_2 \ldots\ldots + e$$

Where $\hat{Y}$ represents the conditional mean of the dependant variable for a specific set of observations on the predictor variables X_1, X_2 etc, embodies assumptions of additivity and linearity. The processes involved in estimating the values of the constant a and the coefficients b_1, b_2, etc. are described in many statistical texts and will not be reiterated here.

88. The results of such an analysis using training success as criterion and the selection test scores as predictors are discussed below. The optimum equation is:-

$$T_6 = .04T_1 + .09T_2 + .10T_4 + .26T_5 - 15.33$$

the multiple correlation coefficient being 0.998, with 7 degrees of freedom.

89. The t statistics of the coefficients (ie the ratio of the coefficients to their standard errors) are 9.46, 8.61, 5.26 and 6.83 respectively, showing that all four predictors contribute highly significantly. The value of t for the variable T_3 is, however, only 1.35 and this variable has consequently been eliminated from the predictor function.

90. Estimated values of T_6, derived by use of the equation, are compared with corresponding observed values in Figure 26, the dotted line indicating the locus of points for perfect prediction.

91. If such an equation were to be used for predictive purposes, eg as an aid to eliminating potential training failures at selection,

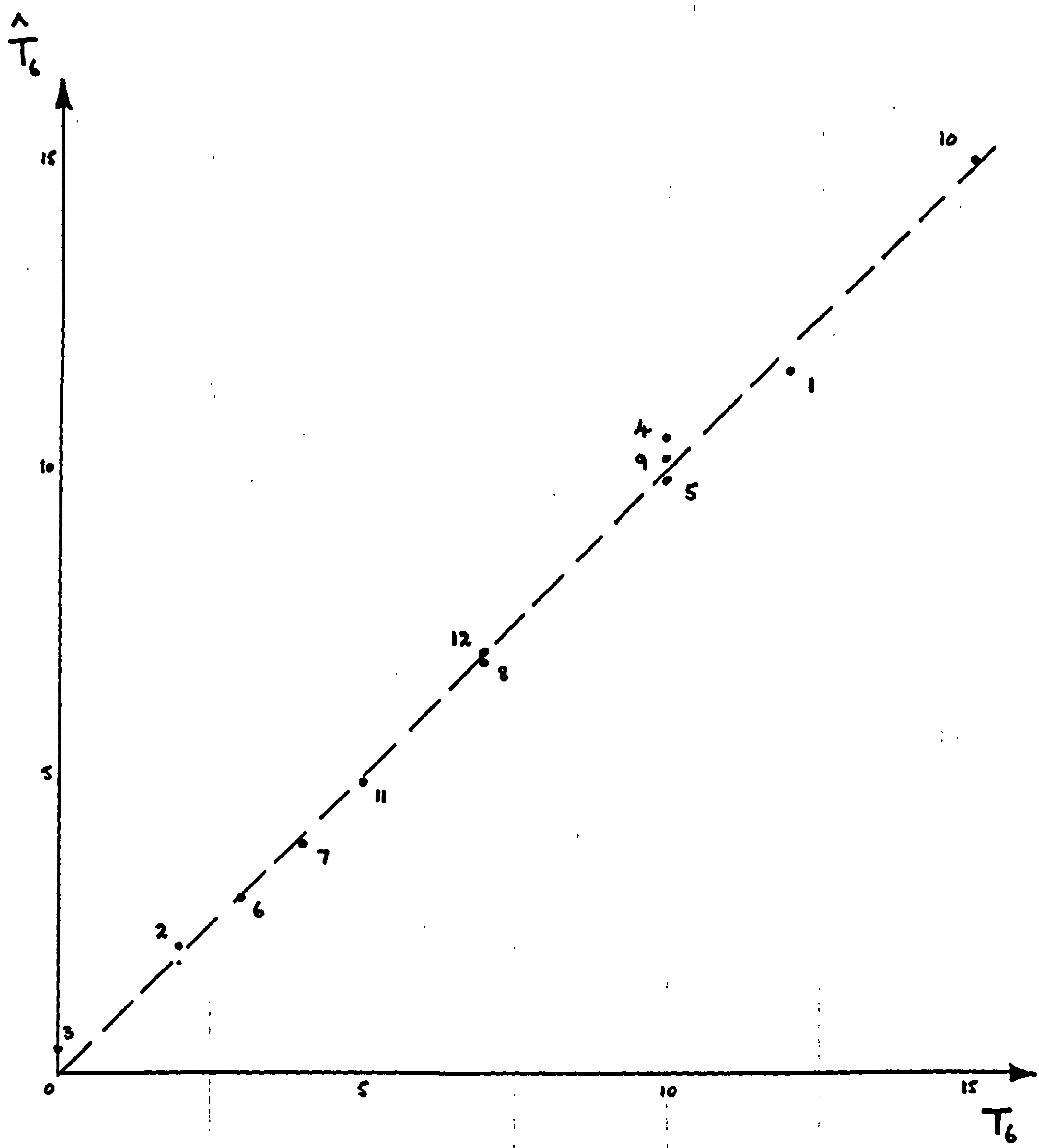


FIG 26 COMPARISON of ESTIMATED and OBSERVED TRAINING SUCCESS

it would be desirable to use a larger sample and to cross-validate the results on an independent sample to ensure that the high multiple correlation was not a result of capitalising on chance association.

92. In the case illustrated there is a strong probability that the coefficients would be found to be unstable because of the high correlation between T_1 and T_3 and between T_2 and T_5. The regression method derives predictor coefficients which minimise the error sum of squares between observed and estimated criterion values. When two predictors are highly correlated there is often a wide range of combinations of coefficients which give little variation in the error sum of squares. Consequently normal sampling variations may give equations which appear to be different though in practice they give similar results.

93. The point may be better appreciated by reference to the factor analysis, illustrated in Figure 22. This shows that the selection data is essentially two dimensional, and it is instructive to carry out a regression analysis using the rotated factor scores, V and M, as predictors instead of the raw selection data. The resulting equation is:-

$$T_6 = 2.58V + 2.39M = 7.50$$

the multiple correlation coefficient being 0.75 with 9 degrees of freedom.

94. The predictor function now clearly shows the dependance of training success on the qualities which have been labelled V and M, and though there has been some loss of prediction accuracy because of the loss of information in the process of condensation, the equation is likely to prove more stable.

95. Though the point is not illustrated by the example chosen, it is not unusual to find that a predictor may contribute negatively though there appears to be no reason to suppose a true inverse relationship with the criterion. Such a situation may arise where some other variable, though well correlated with the criterion, is also introducing an unwanted component of variance into the predictor function. The appearance of a negative coefficient is

then an indication that the variable concerned is acting as a suppressor of this unwanted variance. Again, in such a case, the use of condensed variables, derived by means of factor analysis, may give a much clearer interpretation of the inter-relationships.

Discriminatory Analysis

97. Although discriminatory analysis is essentially a regression method it differs from multiple regression analysis in that it is concerned with estimating probability of membership of defined categories. Thus it may be used as an aid to classification of candidates into such groups as probable success/failure, or probable success in various types of course, such as science/arts, or probable suitability for various types of career. For such categorical situations it is often difficult to construct the continuous measured criteria needed for multiple regression analyses.

98. To illustrate the application of discriminatory analysis the career success of the twelve candidates of the original selection tests has been indicated in terms of promotion/no promotion, shown as variable T_7 in Figure 25.

99. The analytical process has been described by HOPE (1968). In this case the V and M scores, derived by factor analysis and shown in Figure 23, have again been used as predictors. The resulting discriminant function is:-

$$D = 0.36V - 0.25M$$

Thus, in this case, although training success was found to be positively dependant on both verbal and mechanical ability, the latter is found to be a handicap to career success.

100. When the predictor function is applied to the original observations, ie the V and M scores of the twelve candidates, the D scores and probabilities of membership of "promotion" and "no promotion" categories obtained are as shown in Figure 27. The D scores corresponding to the centroids of the two groups are:-

Promoted	0.253
Not promoted	- 0.492

The results are illustrated in Figures 28 and 29, the former showing how the two-dimensional V M space is projected onto the one-dimensional discriminant, and the latter showing the relationship between D score and probability of membership of the two groups.

INDIVIDUAL	D SCORE	P (Promotion)	P (No Promotion)
1	.848	1	
2	.125	.89	
4	.220	.95	
5	-.127	.51	
7	.025	.78	
10	.431	.99	
3	.012		.24
6	-.522		.94
8	-.627		.97
9	-.558		.95
11	-.835		.99
12	-.419		.89

FIG 27 DISCRIMINANT SCORES of SELECTION TEST DATA

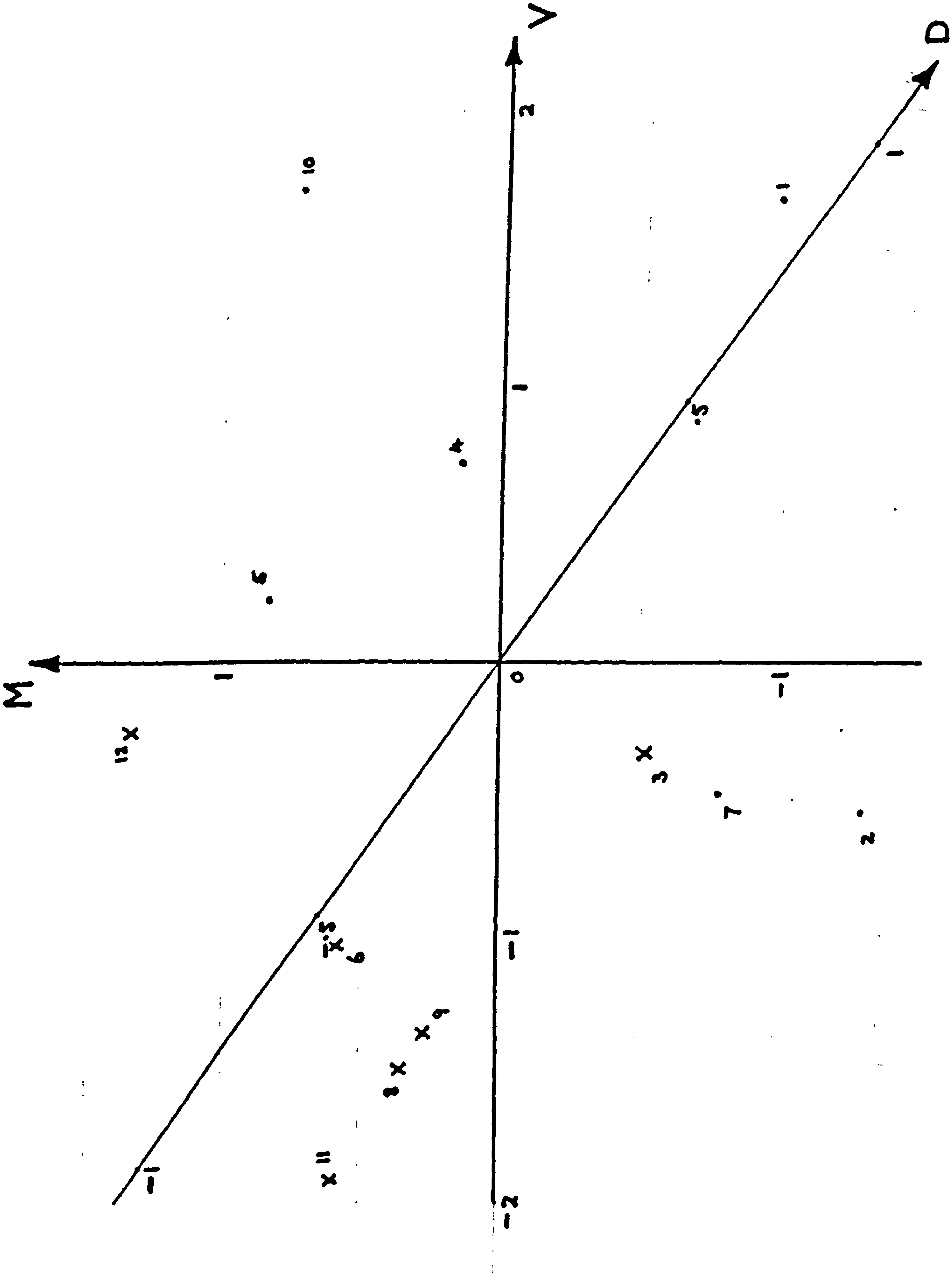


FIG 28 RELATIONSHIP of DISCRIMINANT to V and M

FIG 29 DISTRIBUTION of OBSERVATIONS in DISCRIMINANT SPACE

101. The prediction accuracy may be summarised in the form of a "hits and misses" table as shown in Figure 30.

		ACTUAL	
		Promoted	Not promoted
FORECAST	Promoted	6	1
	Not promoted	0	5

FIG 30

102. The incorrect forecast for individual number 3 indicates the existence of other influences which have not been taken into account in the use of V and M as predictors and it would be fruitful in a real-life case to attempt to assess the nature of this influence and to introduce a suitable variable into the predictor function.

103. Examination of Figure 29 shows that individual number 5 falls close to the position of equal probability of membership of either category. In a real-life situation a policy decision would be required to enable such marginal cases to be dealt with. Such a decision would be based on an assessment, in the prevailing circumstances, of the probable cost of wrong decision, either potentially good candidates rejected or potentially bad ones accepted.

104. As with multiple regression analysis the study would need to be based on a larger sample and would need to be cross-validated before it could confidently be used as a basis for actual selection.

105. In essence discriminatory analysis is a method of data condensation for classification purposes. In the example given the two-dimensional observations are projected onto a one-dimensional discriminant. In general there is no constraint on the dimensionality of the data (ie the number of observed variables n). The m observations may be classified into K groups where $K < m/2$. The n-dimensional test space is reduced to an r-dimensional discriminant space where $r = \min(K - 1, n)$.

106. Outside of scientific circles (where it is extensively used for such purposes as anthropomorphic classification) discriminatory

analysis is, as yet, a little known technique but applications seem likely to increase. It appears particularly suitable for use as an aid to personnel selection and placement.

CONCLUSION

107. This paper has outlined the conceptual relevance of multivariate analysis to the study of personnel selection, training and career development and by means of simplified examples has illustrated the use of multivariate analysis as an aid to descriptive and predictive modelling, and hence to understanding and decision making, in this field. A real-life study, in which the techniques have been extensively used, is described by GARDNER (1971).

108. There are many possible multivariate methods which may be used to analyse empirical data and to construct meaningful models in which the observations are presented in a logical structure. It is through the use of such quantitative techniques that the management decision making process may be lifted out of the realms of pure hunch and put on a scientific foundation.

109. It is important to remember, however, that in any scientific field the observed phenomena can be described in a great variety of ways which are mutually consistent. The choice of a particular interpretation must depend on its utility. MOULTON (1939) hit the nail on the head when he said:-

"If scientists would remember that various equally consistent interpretations of every set of observational data can be made, they would be much less dogmatic than they are, and their beliefs in a possible ultimate finality of scientific theories would vanish."

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