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This Annual Report describes two lines of research performed during Fiscal Year 1990 at the Naval Aerospace Medical Research Laboratory. One research line involved developing a generic model of human performance tests, such as those in the Unified Tri-service Cognitive Assessment Battery and the Walter Reed Army Institute of Research Performance Assessment Battery. Several performance-test models were developed using the plan of the generic task. The generic model might serve both as a vehicle for quantifying laboratory performance and a blueprint for analyses of operational systems.

A second research line focused on a risk identification study of 31 Navy and Marine aircraft carrier combat occupations. The data were from task analyses performed by Cooper, Schemmer, Fleishman, Yarkin-Levin, Harding, & McNelis (1987). The purpose was to examine whether knowledge of a stressor's effects on abilities might be used to predict those combat jobs most affected by the stressor. Notable among the abilities exhibiting

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19. substantial variation in importance across jobs (a necessary property for predicting differential stressor effects) were far vision, spatial orientation, flexibility of closure, and rate control. Examining the effects of stressors on these and related abilities may yield information of value in predicting the threats posed by stressors to different members of this set of occupations.

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CONTENTS

1. INTRODUCTION

This Annual Report covers work performed at the Naval Aerospace Medical Research Laboratory during Fiscal Year 1990. Our 1990 effort included (a) the development of models of human performance tests drawn from the Unified Tri-services Cognitive Assessement Battery and (b) a risk-identification study of 31 naval and marine aircraft carrier combat occupations. The modeling effort is described in detail in Stanny and Shamma (1990), a copy of which is attached to this Annual Report. The results of the study of combat occupations have not yet been described elsewhere. These results will be outlined here in the body of the Report.

Resources at hand are never sufficient to ensure that all combat personnel will be protected from all possible hazards. Thus, strategies must be developed to estimate the proportion of resources that should be devoted to countermeasures and to allocate those resources as well as possible. A basic problem in the development of such strategies is to identify those personnel most threatened by each different potential hazard. The assumption that different stressors will affect different abilities suggests that a taxonomy based on skills and abilities would be valuable in this regard (Cooper, Schemmer, Fleishman, Yarkin-Levin, Harding, & McNelis, 1987).

Given that the impact of a specific stressor can be expressed as a pattern of changes in a set of abilities, it should be possible to derive the relative impact of a stressor on each of a given set of jobs. The analyses presented here are based on the assumption that the magnitude of a stressor's threat to performance on task i increases with the number and importance of the skills affected by the stressor. That is,

$$t_i = f_k(\sum_j e_{jk} s_{ij}), \tag{1}$$

where t_i represents the threat to the ith task, f_k is a monotonically increasing function that may differ among stressors, e_{jk} is a dummy variable equal to 1 if stressor k affects skill j and 0 otherwise, and s_{ij} is the importance of the jth skill to task i. I do not mean to imply that Equation 1 should be regarded as a general model of stressor effects. It is, however, an assumption that should be consistent with a range of such models.

In this report, I will discuss three exploratory analyses of a data base of Navy and Marine air combat occupations (Cooper et al., 1987). Each was performed with an eye to determining which skills might be most informative in predicting differential risks posed by environmental stressors. The first analysis described here comprised an examination of the variation in the skills' importance ratings across jobs. The second analysis was performed by identifying clusters of jobs related by similarities in their patterns of skill requirements and then determining the variables that best distinguished between the job clusters. The intuition motivating this analysis was that using clusters of similar jobs as units of analysis might yield more stable predictions than those derived from analyses of individual jobs. In the third analysis, I identified clusters of skills related by their patterns of association across jobs and then examined the degree to which these skill clusters distinguished between the groups of jobs previously identified.

2. METHODS

Task analysis data. The data base of occupational task analyses used in the present study was developed by Cooper et al. (1987). The data base contains task analyses of 31 naval and marine combat jobs. The information on each job includes a rating of the importance of each of 44 skills and abilities to the performance of each job. These ratings were developed through interviews with experienced job incumbents.[1] The rating

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[1]The data base also contains information on substasks of jobs. Only the overall skills-and-abilities ratings were analyzed in this study.

scale ranged from one to seven (least to most important). The list of jobs is given in Table I; the list of skills for which the jobs were rated is in Table II.

(U) Table I. Navy and Marine Aviation Occupations in the Data Base. (U)

Aviation Boatswain's Mate	Helicopter Crew Chief
Aviation Electrician's Mate	Hospital Corpsman
Aviation Structural Mechanic	Landing Signal Officer
Aviation Ordnanceman	Marine Bulk Fuel Operator
Aviation Organizational Maint. Officer	Marine Helicopter Pilot
Aviation Fire Control Technician	Marine Harrier Pilot
Aviation Electronics Technician	Machinist Mate
Bombardier Navigator	Marine Prop Pilot
Catapult & Arresting Gear Officer	Navy Helicopter Pilot
Cryptologic Technician	Radioman
Data Systems Technician	Helicopter Search & Rescue Crew Member
Electrician's Mate	Sonar Technician
Electronics Technician	Torpedoman's Mate
Electronic Warfare Technician	Tactical Pilot
Fire Controlman	SEALS
Gunner's Mate	

Statistics. Principal Components Analyses (PCAs) were performed using BMDP 4M (Factor Analysis; Dixon, Brown, Engelman, Hill, & Jennrich, 1988). Recall that PCA yields a component for each variable. The first principal component (PC) extracted from the correlation matrix corresponds to the linear combination of the original variables that accounts for the largest proportion of the variance in the data. Subsequent components are statistically independent and account for smaller and smaller proportions of the variance. The scree test (the method of rootstaring; Cliff, 1987) was used to identify components that appeared to represent real phenomena. These PCs were then rotated by the varimax procedure. Varimax rotation produces components whose squared correlations with the original variables have the largest possible collective variance. This tends to produce "simple" components, components strongly correlated with a few of the original variables and weakly correlated with the others. Discriminant analyses (DAs) were performed with BMDP 7M (Dixon et al., 1988). Details specific to individual analyses are described in the next section.

3. RESULTS AND DISCUSSION

Table III contains the mean rated importance of each skill, calculated across jobs, in the Cooper et al. (1987) data base. The entries in Table I are sorted in descending order of average rating. One should be cautious about interpreting these means as general measures of "importance" because they are strongly influenced by the makeup of the specific sample of jobs selected for inclusion in the data base. The foregoing having been said, the head of the list is dominated by a set of perceptual/cognitive variables. The middle of the list contains a number of variables having to do with coordination, dexterity, and spatial orientation. Strength and stamina variables tend to be found in the lower third of the list. Notable exceptions to the preceding generalizations are math and writing, which are rated as comparatively unimportant. Reading, however, is rated as important.

Table IV contains a list of skills sorted in order of decreasing variability (across jobs) of their importance ratings. This list is of particular interest because the accuracy of predicting which jobs are likely to be affected by a stressor should increase with the systematic variance (across jobs) in the importance of the affected skills.

2

1	Oral comprehension	23	Time sharing
2	Written comprehension	24	Rate control
3	Oral expression	25	Arm-hand steadiness
4	Written expression	26	Manual dexterity
5	Fluency of ideas	27	Finger dexterity
6	Originality	28	Speed of limb movement
7	Memory	29	Static strength
8	Problem sensitivity	30	Dynamic strength
9	Mathematical reasoning	31	Explosive strength
10	Number facility	32	Trunk strength
11	Logical reasoning	33	Muscular flexibility
12	Information ordering	34	Equilibrium
13	Speed of closure	35	Gross body coordination
14	Flexibility of closure	36	Stamina
15	Spatial orientation	37	Near vision
16	Visualization	38	Far vision
17	Perceptual speed	39	Color vision
18	Control precision	40	Night vision
19	Multi-limb coordination	41	Depth perception
20	Reaction time	42	Glare sensitivity
21	Choice reaction time	43	General hearing
22	Selective attention	44	Sound localization

This point can be understood by reference to Equation 1. Examining Equation 1, one can see that, with other factors (including measurement error) held constant, the spread in threat magnitude across jobs, var(t_i), increases with the job-to-job variance in var(s_{ij}), the importance of a threatened skill. As the spread in threat magnitudes increases, for any reason other than an increase in measurement error, the accuracy of predicting those jobs for which the threat exceeds a critical value should also increase.

The most variable skills on the list of Table IV are a set of perceptual, psychomotor, and strength skills. Of note, most of the cognitive skills fall near the bottom of this list. This suggests that, at least in the present sample of jobs, it may prove easier to predict differential threats to performance from effects of stressors on perceptual and strength variables than from effects of stressors on cognitive variables.

I searched for clusters of related jobs by performing a PCA of a correlation matrix whose row and column headings were the 31 combat jobs. Each element, r_{ij}, of this matrix was, thus, the correlation between the 44 skill ratings of jobs i and j. High values of r_{ij} indicated jobs with similar skill requirements. This procedure resembles Q-factor analysis, a technique sometimes used in studies of individual differences (Guilford, 1954). Examining Fig 1., one can see that by the time the seventh PC was extracted, the magnitudes of the eigenvalues had decreased to a value effectively equal to 1.0. This value is 1/31 of the total variance (the 31 variables in the analysis were standardized so that each had unit variance). Because factors with unit eigenvalues account for no more variance than one of the original variables, nothing is to be gained by considering factors beyond the sixth. Indeed, the plot of eigenvalue magnitude versus eigenvalue number seems to contain a break-point in the vicinity of factor 3-5, which suggests that, perhaps, only the first four factors are real (Cliff, 1987).

Table shows the clusters of jobs that loaded on (correlated in excess of 0.5 with) each of the four PCs.

Skill	M	Skill	M
Selective attention	6.00	Fluency of ideas	4.35
Problem sensitivity	5.94	Finger dexterity	4.03
Near vision	5.87	Color vision	3.97
Time sharing	5.74	Far vision	3.97
Written comprehension	5.35	Speed of closure	3.90
Night vision	5.26	Originality	3.90
Memory	5.23	Number facility	3.90
Reaction time	5.00	Muscular flexibility	3.84
Logical reasoning	4.94	Visualization	3.74
Oral expression	4.94	Glare sensitivity	3.71
Information ordering	4.90	Static strength	3.68
Flexibility of closure	4.84	Rate control	3.45
General hearing	4.84	Sound localization	3.42
Control precision	4.74	Trunk strength	3.26
Depth perception	4.74	Gross body coordination	3.26
Oral comprehension	4.68	Arm-hand steadiness	3.26
Perceptual speed	4.61	Speed of limb movement	3.23
Multi-limb coordination	4.58	Written expression	3.19
Choice reaction time	4.58	Dynamic strength	3.00
Manual dexterity	4.55	Stamina	2.52
Spatial orientation	4.52	Mathematical reasoning	2.10
Equilibrium	4.45	Explosive strength	1.94

A group of technical jobs are associated with the first PC. An examination of this cluster suggests that the jobs in it are fairly high in their demands for logical analysis. The second cluster is dominated by pilot occupations and some closely related jobs. The third cluster is dominated by mechanical-technical jobs. The SEALS formed their own fourth cluster. Two jobs did not load to the criterion 0.5 on any of the PCs.

I used linear discriminant analysis (DA) to measure the distances between job clusters in terms of various combinations of the skill ratings. This appeared to be the direct approach to identifying variables that might discriminate between the clusters. Furthermore, it was unclear that simply factoring the skills intercorrelation matrix would

Figure 1. Eigenvalues from the principal components analysis of jobs.

produce similar results. The predictor variables used in the DA were the job skill-requirement levels. The grouping variable was job-cluster membership--the number of the PC with which each job was correlated. Cluster four of the jobs PCA was not used in the DA because it contained only the SEALS. The two uncategorized jobs also were not used. Thus, the resulting prediction equations were linear combinations of the original skill-requirement values that maximized the overall Euclidean distance (in within-group σ units) between the means of the groups defined by the PCA.
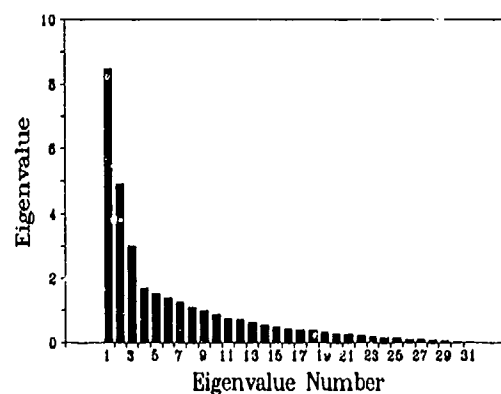
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Skill	sd	Skill	sd
Far vision	2.85	Reaction time	1.92
Rate control	2.72	Speed of limb movement	1.90
Stamina	2.66	General hearing	1.82
Glare sensitivity	2.49	Choice reaction time	1.74
Trunk strength	2.46	Finger dexterity	1.69
Depth perception	2.46	Flexibility of closure	1.61
Sound localization	2.42	Mathematical reasoning	1.59
Visualization	2.40	Perceptual speed	1.58
Static strength	2.35	Multi-limb coordination	1.56
Dynamic strength	2.29	Color vision	1.53
Explosive strength	2.29	Manual dexterity	1.52
Arm-hand steadiness	2.24	Written comprehension	1.33
Speed of closure	2.19	Number facility	1.23
Fluency of ideas	2.12	Memory	1.21
Gross body coordination	2.09	Oral comprehension	1.06
Originality	2.08	Information ordering	1.06
Spatial orientation	2.06	Time sharing	0.98
Equilibrium	2.06	Oral expression	0.95
Muscular flexibility	2.05	Near vision	0.83
Night vision	1.95	Selective attention	0.80
Written expression	1.94	Problem sensitivity	0.80
Control precision	1.93	Logical reasoning	0.72

I added one variable at a time to the prediction equation by forward stepping. A criterion $F_{(2,25)}$-to-enter of 9.12 was used to control the entry of variables. This is the Bonferroni-corrected critical value of F that yields an experimentwise significance level of $p \le .05$ when 44 such F ratios are available for comparison. (Note that, because the job clusters were not determined according to a priori criteria, this significance level may not reflect the actual significance of the DA.)[2] Five skills produced F ratios greater than 9.12. These were far vision, spatial orientation, arm-hand steadiness, rate control, and glare sensitivity. Far vision yielded the largest value of $F_{(2,25)} = 36.00$ and was, thus, entered into the prediction equation. Far vision would seem to distinguish flight-related jobs from other occupations. Consistent with this observation, when far vision was

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[2]An additional problem is posed by the fact that the number of skills (predictors) in the database exceeds the number of jobs (cases). Hence, the significance of the full-rank discriminant function cannot be calculated. This makes it difficult to assess the significance of the discriminators because the most compelling way to establish that one or more skills significantly distinguishes among the job clusters would be to establish the significance of the full-rank prediction equation(s). (See Larzelere and Muliak, 1977, for a discussion of this issue in the related context of multiple regression). A partial solution is to calculate the significance of prediction equations containing subsets of prespecified size, l, of the original m predictor variables. (Unfortunately, in exploratory analyses one can rarely supply an a priori rationale for setting l to any particular value, with the possible exception of 1.) For a subset of size $l = 1$ selected from m candidate predictors, a conservative, Bonferroni-style significance level can be estimated by determining p in the usual way and multiplying by m. For a subset of size 2 selected from m candidates by forward stepwise selection, the implied number of predictor equations examined is $m \times (m - 1)$ and the Bonferroni correction is $p \times m \times (m - 1)$. For $l = 3$, the implied number is $m \times (m - 1) \times (m - 2)$, and so on. Note that, if m is large and the predictors are correlated, this correction procedure rapidly becomes conservative as l increases.

Cluster 1
Aviation Electrician's Mate
Aviation Electronics Technician
Aviation Fire Control Technician
Aviation Organizational Maintenance
    Officer
Cryptologic Technician
Data Systems Technician
Electrician's Mate
Electronic Warfare Technician
Electronics Technician
Gunner's Mate
Hospital Corpsman
Radioman
Sonar Technician

Cluster 2
Bombadier Navigator
Catapult and Arresting Gear
    Officer
Helicopter Crew Chief
Helicopter Search and Rescue
    Crew Member
Landing Signal Officer
Marine Harrier Pilot
Marine Helicopter Pilot
Marine Prop Pilot
Navy Helicopter Pilot
Tactical Pilot

Cluster 3
Aviation Boatswain's Mate
Aviation Ordnanceman
Aviation Structural Mechanic
Machinist Mate
Torpedoman's Mate

Cluster 4
SEALS

entered into the equation, the F ratios for entering spatial orientation, rate control, and glare sensitivity (other clearly flight-related skills) dropped precipitously, from respectable values of 9.37, 10.06, and 10.68 to 0.08, 0.94, and 0.17, respectively.[3] The drop suggests that the information they contained was redundant to the prediction equation.

With far vision in the prediction equation, a criterion $F_{(2,24)}$-to-enter of 9.20 was used to control the entry of further variables. This is the Bonferroni-corrected critical value of F that yields an experimentwise significance level of $p \leq .05$ when 43 values of $F_{(2,24)}$ are calculated. The only variable that yielded an F-to-enter exceeding the criterion was flexibility of closure, a high-level cognitive variable ($F_{(2,24)} = 14.07$). This was somewhat higher than the F ratio this variable yielded before far vision was entered in the equation. All other variables had much smaller F-ratios (below 6.0). After flexibility of closure had been entered into the prediction equation, the values of $F_{(2,23)}$-to-enter for the remaining variables were substantially less than the next criterion value of 9.28 (3.15 and below).

To further investigate the variables distinguishing the three job groups, DAs were performed for each of the three possible pairwise contrasts between clusters. A criterion value of $F_{(1,21)} = 17.875$ was adopted, which corresponded to the Bonferroni-corrected critical value of F that yields an experimentwise significance level of $p \leq .05$ when 3 x 44 = 132 F tests with 1 and 121 degrees of freedom are performed. The contrast between

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[3]The F ratio for entering a variable into the prediction equation was the F from a one-way analysis of variance calculated using the variable's residuals, which is equivalent to the F produced by an analysis of covariance in which variables already in the prediction equation serve as covariates (Dixon et al., 1988).

6

the logic-demanding technical jobs and pilot-like jobs yielded four skills with F ratios exceeding the criterion. These were far vision, glare sensitivity, and rate control. Spatial orientation was only slightly below criterion, with an F = 16.42. All of these skills were rated as more important to the pilot-like jobs. The contrast between pilot-like jobs and mechanical-technical jobs yielded no variables with F ratios exceeding the criterion. Flexibility of closure had the highest F ratio, 14.33. This variable was rated as more important for the pilot-like jobs than for the mechanical-technical jobs. Interestingly, the mechanical-technical jobs were scored more like pilot jobs than were logical jobs with respect to those skills that distinguished logical jobs from pilot jobs (except for depth perception). The contrast between the two technical job clusters also yielded no F ratios exceeding the criterion. The largest F ratio in this case was associated with mathematical reasoning ($F(1,21)$ = 12.42), which was rated as more important for the logic-demanding jobs.

(U) **Table VI. Clusters of Skills Obtained by Principal Components Analysis (Titles are Component Numbers in Order of Extraction). (U)**

PC1	PC2	PC3
Rate control	Trunk strength	Flexibility of closure
Spatial orientation	Dynamic strength	Selective attention
Glare sensitivity	Muscular flexibility	Speed of closure
Far vision	Stamina	Perceptual speed
Depth perception	Gross body coordination	Near vision
Night vision	Sound localization	
Choice reaction time		
Visualization		

PC4	PC5	PC6
Oral expression	Manual dexterity	Originality
Oral comprehension	Finger dexterity	Problem sensitivity
Written expression	Static strength	Mathematical reasoning
Written comprehension		

PC7	PC8	PC9
Time sharing	Color vision	Arm-hand steadiness
Number facility	Night vision	Equilibrium
Written expression	Reaction time	

PC10	PC11	PC12
Information ordering	Memory	Logical reasoning
	Multi-limb coordination	

A second PCA was carried out to examine clusters among the skills. This PCA yielded 12 PCs with eigenvalues greater than one. A skree test disclosed no obvious breakpoint in the plot of eigenvalue versus component number (see Fig. 2). The clusters defined by the skills' correlations with the 12 PCs (r ≥ 0.5) are listed in Table VI. The first skill cluster contains several variables that were rated, on average, more important for the pilot-like jobs than for either of the technical jobs. The second skill cluster is dominated by a group of physical strength variables. These skills, on average, were rated somewhat more important for the mechanical-technical jobs than for the logical-technical jobs, and more important for the logical-technical jobs than for the pilot-like jobs. None of these skills discriminated well among the job clusters in the previous DAs. The third cluster contains a group of cognitive and sensory variables, among them flexibility of closure, a

potentially discriminating variable identified in a previous DA. The skills in this cluster were, on average, rated as somewhat more important for pilot-like jobs than for the logical-technical jobs, and more important for the logical-technical jobs than for the mechanical-technical jobs. The fourth cluster contains oral and written communication variables, none of which discriminated among the jobs. The fifth cluster contains two dexterity variables and static strength, which did not produce evidence of potential discriminating power. The sixth cluster is a set of cognitive variables that somewhat resembles cluster 3. Beyond this point, the clusters become increasingly difficult to interpret, suggesting that they may be largely noise.
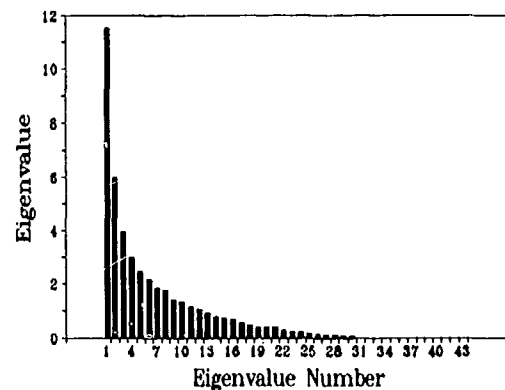

Figure 2. Eigenvalues from the principal components analysis of skills.

Six parallel discriminant analyses were performed on skill clusters identified by the PCA just described. The first was performed by forcing the apparently pilot-like skills of cluster 1 of Table VI into the equation, which yielded an approximate $F(10,42) = 5.038$. (This F ratio is an approximation to Wilks' λ that can be compared to ordinary F tables.) Had the pilot-like skills been selected by a priori criteria, the test would be significant at $p < .0006$, controlling, in Bonferroni fashion, for six, simultaneous F tests. A parallel discriminant analysis performed by forcing the strength-related skills of cluster 2 into the prediction equation yielded an approximate $F(12,40) = 1.32$. Even if the strength-related skills of cluster 2 had been selected by a priori criteria, this test would be nonsignificant. A third discriminant analysis performed by forcing the skills in cluster 3 into the prediction equation yielded an approximate $F(10,42) = 3.42$. Were the third cluster of skills selected by a priori criteria, this test would be significant at $p = .0138$, controlling for six tests. Discriminant analyses employing skill clusters 4 through 6 yielded F ratios of 3.02 and lower, which would also be nonsignificant.

4. CONCLUSIONS

The most important skills and abilities in the Cooper et al. (1987) data base of carrier combat occupations, as judged by their mean importance ratings, were a set of perceptual and cognitive abilities (see Table III). Coordination, dexterity, and orientation abilities tended to be rated as of intermediate importance. Strength and stamina variables tended to be rated as of lower importance. The skills and abilities that differed the most in importance from job to job were a group of perceptual, psychomotor, and strength skills, including far vision, rate control, stamina, glare sensitivity, and trunk strength.

Three primary clusters of carrier combat occupations were tentatively identified in a principal components analysis (Table IV). The first cluster contained a set of logic-demanding technical jobs. The second contained pilot-like jobs. The third contained mechanical-technical jobs. The SEALS formed their own cluster. Two jobs were not assigned to any cluster. An exploratory analysis of the skills distinguishing these clusters suggests that the best discriminator could be far vision. Spatial orientation, rate control, and glare sensitivity may provide lesser quantities of correlated predictive information. Somewhat surprisingly, the second best discriminator may be a cognitive skill, flexibility of closure. Discriminating between the pilot-like jobs and the logical-technical jobs was much easier than discriminating between the pilot-like jobs and the mechanical-technical jobs, or between the two clusters of technical jobs. Cognitive skills, as a group, displayed relatively little variation in rated importance from one job to the next.

Several clusters of skills and abilities were identified by principal components analysis (Table V). The first cluster was a group of apparently flight-related skills, including far vision, rate control, spatial orientation, and glare sensitivity. The second cluster contained a set of strength, stamina, and coordination skills, along with

8

auditory localization. The third cluster of skills contained several perceptual and cognitive abilities, including flexibility of closure (a potentially discriminating ability) and selective attention (the ability with the highest overall importance rating). Unsurprisingly, given the preceding analysis, the first and third ability clusters gave some evidence of distinguishing between the job clusters; the remaining clusters did not.

One should bear in mind that abilities that discriminate between jobs need not be the most important abilities overall. Conversely, abilities that are important, overall, need not discriminate between jobs. Clearly, the most useful predictions of *differential* threat will occur in cases where a stressor is found to affect abilities that are uniformly important in some jobs and uniformly unimportant in others. An ability whose importance is unevenly distributed in this way is unlikely to be regarded as among the most important overall. In the present data, cognitive abilities were highly rated, as a group, yet the variability of their ratings across jobs was comparatively low (compare Tables III and IV).[4] Thus, despite the uniformly high importance attributed to cognitive abilities, the present data suggest that abilities that were rated as of somewhat lower overall importance in these jobs might yield the best predictions of differential threats to performance.

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[4]The degree to which this may have been due to a compression of ratings at the upper end of the importance scale is an open question that warrants further attention.

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