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Statistical evaluation of control inputs and eye movements in the use of instrument clusters during aircraft landing

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Summary

Two different types of analyses were done on data from a study in which eye movements and other variables were recorded while four pilots executed landing sequences in a Boeing 737 simulation. Various conditions were manipulated, including changes in turbulence, starting position, and instrumentation.

In Part I, control inputs were analyzed in the context of the various conditions and compared against ratings of workload obtained using the Cooper-Harper scale. The results show clear differences as a function of conditions; manipulations of turbulence accounted for the major portion of the effects. A major portion of the workload rating variance could be predicted by the number of control inputs. There was also clear evidence for different strategies on the part of the pilots.

In Part II a number of eye-scanning measures including mean dwell time and transition from one instrument to another were entered into a principal components factor analysis. Eighteen orthogonal components were retained accounting for 73% of the variance. Factor scores were generated and entered into discrimination analysis. In contrast to the control input analysis, instrument changes were more easily discriminated than turbulence. Strategy effects were also observed.

Overall the results show a differentiation between control inputs and eye-scanning behavior. This shows the need for improved definition of workload and experiments to uncover the important differences among control inputs, eye-scanning and cognitive processes of the pilot.

Introduction

It is a fairly simple matter for an aeronautical engineer to determine what information a pilot needs during aircraft control. It is an entirely different matter to determine the optimal way of presenting the information. The optimal form will depend on a number of factors: the preferences of the operator including both individual differences and common preferences developed through experience with the airplane; ease of interpretation and therefore usefulness of the presentation; the layout; the conditions and situations to which the pilot must respond (the mission); and the purpose of the pilot (whether he is responding or controlling); the type of manuever he is performing as well as airplane parameters and differences between aircraft.

One obvious way to arrive at optimal displays is to ask the pilot. The problem with this approach is that the pilot cannot state with total accuracy how he gets his information. Any experienced pilot will, of course, understand the characteristics of the airplane and the demands placed on him and will have a good idea of the relative importance of the various informational components. In this sense, the pilot is very much like the aeronautical engineer; accordingly any report given by the pilot will be a composite of what he knows is necessary and of what he thinks he does in the cockpit (Dick & Bailey, 1976). However, as with any skilled operation, the situational and temporal demands are such that the pilot does not have time to think about what he is doing while he is doing it. By the time he could decide action to take at a conscious level, an emergency situation might lead to an unfortunate conclusion.

Examples of the intuitive approach to instrument panel design are apparent in the typical Instrument Flight Rule cockpit. The pilot has available at least two sources for glide slope information, horizontal guidance, altitude, and often airspeed. There is, of course, a difference in the form of the information displayed - relative or absolute, raw or derivative, predictive or current. The human, being flexible and adaptive as he is, can learn to deal with this array. Unfortunately he cannot tell us accurately what he does and what information he uses because he cannot simultaneously perform the task and think about what he is doing. On the one hand he does not have time to do both and on the other hand requiring him to tell us how he does the task may change what he does.

Clearly, more sophisticated procedures are required to monitor the pilot's performance, to study his acquisition of information, his utilization of that information and how hard he has to work at this task. An important step in the study of the information acquisition phase is the introduction of the oculometer in flight management research (Spady & Waller, 1973;

Waller & Wise, 1975). The oculometer provides a relatively unobtrusive means of measuring eye-scanning patterns while the pilot is performing various operations. With the oculometer it is possible to record in real time which instruments the pilot looks at during various flight segments as well as to build a data base about the sequence and the duration of the looks. The thrust of the approach is to determine how the pilot acquires and uses information about various states of the aircraft.

Several studies have been reported using the oculometer in a Boeing 737 simulation to study landing approaches (Dick & Bailey, 1976; Krebs & Wingert, 1976; Spady & Waller, 1973; Waller, 1976; Waller & Wise, 1975). The approaches in these studies have varied but basically fall into one of two general categories. The first includes data summaries of the oculometer results, representing averages across approximately five miles of approach. The second category represents the attempt to compare the oculometer results against subjective reports of the pilot which typically has involved use of the Cooper-Harper rating scale (Cooper & Harper, 1969) as an indicator of workload. There are, however, difficulties with both of these approaches.

The data reported are useful but only to the extent that the eye fixations are correlated with information utilization of the pilot. Unfortunately, these studies have not always found differences in frequency or duration of fixation time on various instruments which correlate with variations in the difficulties of the flight conditions (e.g., Krebs & Wingert, 1976). As the authors typically point out, these studies are but preliminary efforts toward understanding how the pilot functions during the landing segment.

These analyses demonstrate the usefulness and the potential of the oculometer in flight management research. However, they do not answer questions about how and when the pilot acquires information or about how he uses that information in controlling the airplane. The difficulty here is not in the usefulness of the summary data but rather in the (implied) basic assumption that every fixation on an instrument means exactly the same thing as every other fixation. For example, it might be reasonable to expect that the strategy of the pilot differs for different segments of the approach. In short, while it is obviously true that fixations in general are correlated with information acquisition, it is also true that the correlation is far from perfect.

Other investigators (e.g., Senders et al., 1966) have been concerned about the lack of a perfect correlation between eye movements and controlling and have developed laboratory situations in which the operator must detect a change in an indicator. The researcher can then apply latency measures and eye movement measures to assess the temporal difference (latency) between the point at which the experimenter changed the dial and the point in time the operator indicated he observed the change. Further, eye movements can be measured to determine the scan or search pattern in relation to such manipulations as probability of the instrument changing, the magnitude of change, etc. This type of task is basically a discrete one in as much as the experimenter has defined the initiation of a trial based on when the instrument was changed.

Aircraft are sufficiently more complicated than standard laboratory procedures so as to preclude direct application of any approach which requires discrete tasks. There is redundancy among the instruments in two forms: a) structural redundancy, similar information from two different instruments and b) shared or overlapping information. Because of the lack of independence of the sources of information, different classes of information may be obtained from the same instrument. This point has some important implications for the way in which the pilot scans the instruments.

The Present Approach

In order to improve the degree of correlation between scanning and performance and thereby understand what the pilot does, it is obviously necessary to consider the task in much more detail. This report is divided into two major sections. Part I deals with a preliminary analysis of control inputs; Part II reports an analysis of eye-scan data. Taken together, these analyses show how experimental manipulations of turbulence and of instrument changes affect pilot behavior in different ways.

We begin this extension by considering the assumptions involved in both existing and future analyses, followed by a brief discussion of what has been found. From this we derive some ways in which the analysis can proceed . Included in the present report is a critical review of some of the previous work, an evaluation of the assumptions made by various authors, and a description and some preliminary data from two new approaches to evaluate the function of the pilot, his information acquisition and his workload.

Some Theoretical Assumptions

It is an intuitively obvious argument that eye position and eye movements should be related to behavior. The issue, however, is complicated. On one side is the expectation that visual information acquisition will be directly related to eye position. This relation will be less than perfect to the extent that peripheral vision is used. Although we know that static acuity falls off markedly outside of the fovea, acuity for motion does not fall off quite so rapidly. If the pilot uses peripheral vision, information acquisition will not be directly related to eye position. Of course, the more peripheral vision is used the smaller the relation will be.

Clearly, use of peripheral vision will contaminate the degree to which eye position can be used to estimate information acquisition. There is a second aspect, however, which has not always been considered, namely that some eye movements may reflect cerebral or central events and activities, i.e., they are an end product and the result of information processing, not part of the initiation of the first stage. Hebb (1949), for example, has argued for this view. He suggested that learning requires the involvement of eye movements and that this pattern of movement is incorporated into a memory trace together with the material which is acquired as a result of the eye movement pattern. Subsequently, when the memory trace is activated, the eye movement pattern will also be activated with a consequent, almost reflexive, movement of the eyes. Because this type of eye movement is an end product it could be used to infer mental activities.

To test the implications of Hebb's suggestions, Bryden (1961) attempted to assess whether accuracy in a letter recognition task was related to eye movements following the letter presentation. He used a tachistoscope to present a row of letters for 100 msec. which is too short for a voluntary eye movement. The observers were instructed to fixate their eyes at a point midway between the ends of the display so movements toward either end could be observed. The observers were asked to report as many of the letters as they could. Bryden analyzed accuracy in terms of the number of letters correctly reported on the left and right sides of the display. He found a positive but moderate correlation between accuracy on the two halves and the direction of the eye movement. The results appear to support the motor outflow theory of Hebb. Similarly, consistent results have been reported by Kinsbourne (e.g., 1975) who looked at the direction of eye movements during verbal or spatial thought. The general implication of these data for the present examination of eye movements is that one can expect a less than perfect correlation between eye movements and behavior. Clearly, some eye movements are the result of central processes and have no relation to information acquistion but rather reflect information processing and information utilization. The inclusion of such eye movements will reduce the apparent relation between eye-scan and information acquisition.

A third characteristic of eye movements has to do with the task itself. The pilot's job is to watch the instruments and make decisions at several levels. If the instrument readings are within some acceptable tolerance he need do nothing except continue monitoring. If the instrument readings are outside the acceptable range he must make some control inputs to restore tolerance levels which in turn may lead to further monitoring and/or control inputs. The point is that some fixations will lead to action and some will not, thus probably negating the tacit assumption which has been made by treating all eye movements alike. It is certainly worth exploring the data to determine whether any underlying differences exist, such as duration or sequencing.

Finally, there seems to be an assumption about the relation of eye and limb movements. Megaw (1973) designed an experiment which required a subject to make an eye-movement response only, a manual response only, or a simultaneous eye and manual response. He found that the simultaneous condition demanded no additional processing time for either eye movements or manual tracking. Saccades were completed on the average in about 280 msec. while manual tracking took 350 msec. (Completion of saccade and peak acceleration were assumed to be an estimate of the termination of central processing.) It was also noted that most of the errors in tracking were motor direction reversals with almost no eye direction reversals. Megaw concludes that the eye movement and motor systems are more or less independent with evidence that there are two central processing modes by which either can operate: A fast, one-direction mode which is not concerned with the direction of response, or a slower two-directional mode in which there are fewer reversal errors. The degree of independence of eye and limb movements is of considerable importance to our understanding of how the pilot functions.

Some Procedural Assumptions

To measure workload many investigators have used "secondary" tasks which the pilot is to perform when he has time. There are two problems with this approach. First, there are often Performance trade-offs between tasks, i. e., both may suffer performance decrements when done together. Second, the pilot already has two tasks to perform when he is flying the airplane manually, eye scanning and control movements (Megaw, 1973).

Wiener (1975) has examined this latter issue in the context of monitoring vs. controlling. He used a monitoring task which consisted of detection of a visual signal which occurred on the average every one and one-half seconds interspersed with non-target visual stimuli. A one-dimensional tracking task was used as the secondary component in which the operator was required to set a pointer to locate a signal which was driven by summated sine waves. The frequency of the tracking signal movement was varied. Both tasks suffer when done together over the individual tasks, but these differences were not related to the frequency of performing the secondary task.

Putting this experiment in the context of the aircraft problem, these results imply that a pilot may be expected to miss some of the information available on the instruments when he must control the aircraft. In short, he should be more knowledgeble about position parameters when using the auto-pilot. The second aspect is that the frequency with which the signal moved in the tracking task had no influence on accuracy in the detection task. Both points have implications for approaches to analysis of eye movement data and of control inputs. We will consider both aspects. First, we will present some preliminary data to illustrate differences in eye movements for monitoring vs. controlling. Second, we will present in Part I a preliminary but detailed analysis of control inputs to illustrate the effect of certain types of experimental manipulations on control movements.

Monitoring vs. Controlling

An oculometer study was carried out on the Piedmont simulator using a number of their pilots. In this study pilots were asked to make a number of approaches in the manual mode and a number in the coupled (automatic) mode. Airspeed always is under pilot control and therefore the experiment represents an imprecise differentiation between monitoring only and monitoring plus controlling. Nevertheless, the oculometer data are of considerable interest.

Because airspeed is the only parameter under pilot control in the coupled appraoch, one would expect an increase in the percent of time the pilot looks at the airspeed indicator over the manual case. Motor workload has been reduced and therefore the pilot has more time to pay attention to this instrument. Even though the percent of time spent looking at the airspeed indicator increases, there are also increases in a number of other instruments at the expense of the flight director. The data are shown in Table 1. The segments in the table correspond roughly to those shown in Figure 1 (Dick & Bailey, 1976).

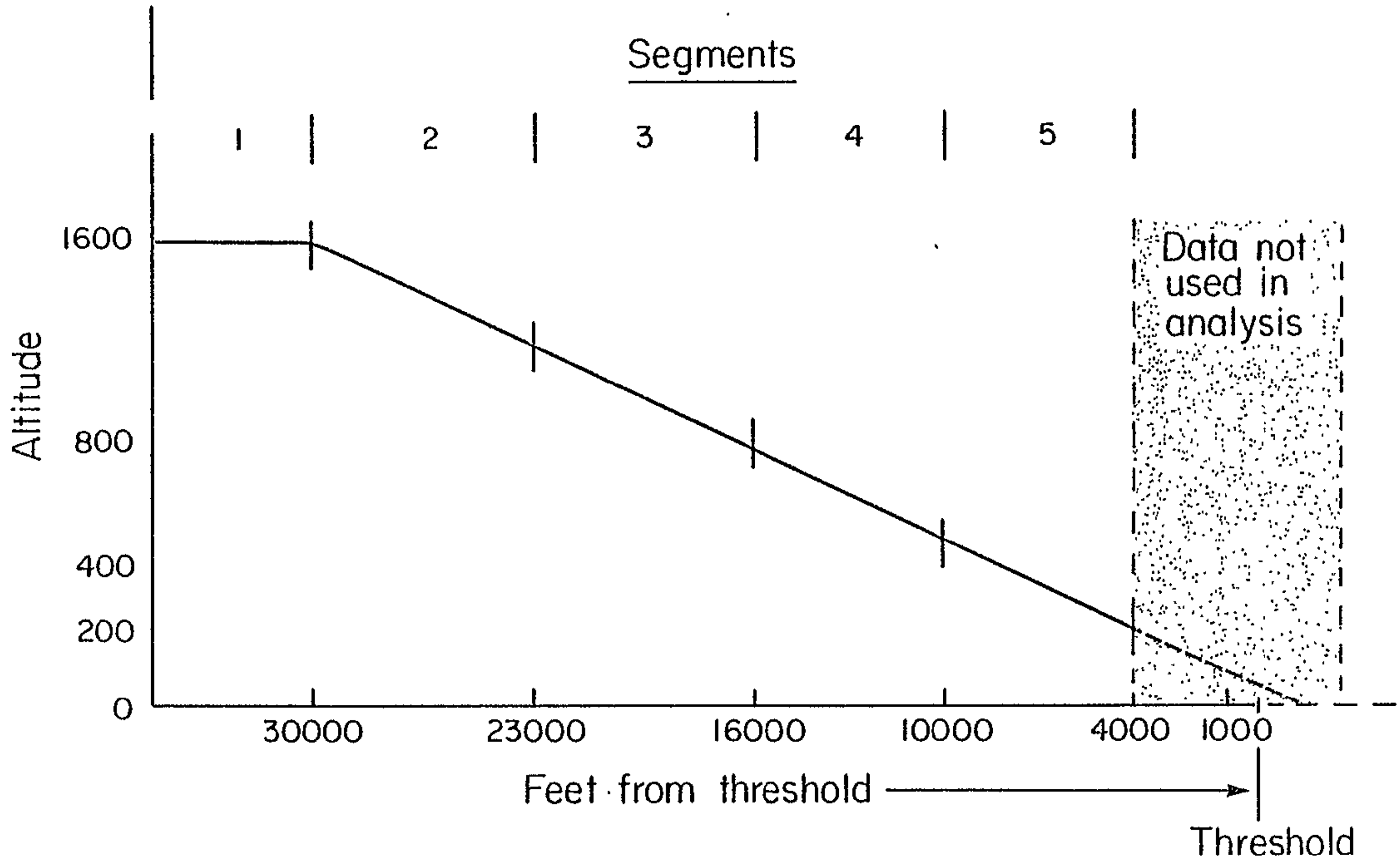
These data show the effects of changes in motor workload on eye-scan behavior. Generalizing from the data of Wiener (1975) one would expect the pilot to be more sensitive to certain types of changes such as airspeed under the coupled mode than under the manual mode. Whether this is true or not cannot be determined from the present analysis. One way to find out would be to measure the length of time it takes the pilot to discover a problem such as windshear.

There are also some implications for the source of the information. Under the manual mode the pilot tends to look for relative information from the flight director. When in the automatic mode he apparently is much less concerned with the relative information and spends more time on raw data. This result may occur because the motor workload is higher in the manual mode. This would be a logical conclusion if it can be shown that it is more difficult to extract information from the raw data instruments. When the pilot has been released from the major portion of his controlling duties by use of the autopilot, he has the time to deal with these instruments.

Table 1

Mean percent and (standard deviations) of time on instruments for automatic and manual flight modes as a function of segment. Data averaged for seven pilots in the Piedmont study.

		Air.	FD	Bar. Alt.	HSI	VSI	Radio Alt.	ADF
Manual	Seg. 1	11.36	67.60	6.28	6.63	4.21	.02	.88
		(7.85)	(10.45)	(4.85)	(8.35)	(3.26)	(.05)	(.97)
	Seg. 2	10.08	77.04	1.67	5.68	2.64	.00	.80
		(5.06)	(12.56)	(1.60)	(9.81)	(3.54)	(0.0)	(.83)
	Seg. 3	11.92	75.34	1.27	5.91	3.75	.04	.20
		(5.63)	(9.38)	(.99)	(8.82)	(3.24)	(.06)	(.10)
	Seg. 4	8.18	79.54	2.20	4.17	3.58	.47	.25
		(6.34)	(9.91)	(1.72)	(6.50)	(4.07)	(.99)	(.26)
Automatic	Seg. 1	19.07	49.83	6.32	11.88	4.22	.46	5.17
		(6.26)	(14.10)	(1.70)	(8.20)	(2.15)	(.44)	(7.25)
	Seg. 2	26.15	50.54	3.19	7.89	3.80	.06	4.82
		(10.03)	(17.18)	(2.26)	(8.09)	(2.97)	(.09)	(7.25)
	Seg. 3	24.72	52.30	3.90	6.60	6.52	.45	3.21
		(5.00)	(13.77)	(2.40)	(3.35)	(2.81)	(.62)	(5.33)
	Seg. 4	20.19	50.61	9.37	5.34	7.92	2.14	12.06
		(10.29)	(13.18)	(6.84)	(2.77)	(4.11)	(1.86)	(1.14)



Segments
1
2
3
4
5
Data not used in analysis
Altitude
1600
800
400
200
0
30000
23000
16000
10000
4000
1000
Feet from threshold
Threshold

PART I: Analysis of Control Inputs

The work of Megaw and Wiener suggests a considerable degree of independence between eye movements and motor behavior. For example, we may note specifically that a change in the frequency of the tracking task in Wiener's experiment had no effect on visual target detection. Translating these findings into the aircraft context, the implication is that eye-scan patterns could be stable while motor behavior (control inputs) might vary. One such example might be in heavy turbulence in which the pilot has to make more control movements to maintain the airplane level and on course than he does in smooth air. Although the number of control inputs may increase with turbulence, eye-scan behavior need not change.

Implicit in this argument is the assumption that the pilot is always scanning the instruments at or near his capacity. If he spends 80-90% of his time looking at the instrument cluster essential to landing in smooth air, there is little possibility for him to increase his time on instruments when in turbulent air. Our own thorough univariate analysis of time on instruments has failed to find any differences as a function of turbulence. Similarly, Krebs and Wingert (1976) showed no relation between eye-scan patterns and workload rating. These findings imply that eye-scan behavior is near saturation under normal conditions so that only small increases in the amount of time on instruments are possible. Nevertheless, motor behavior could change. To examine the motor behavior component a series of statistical analyses was carried out on the data from one pilot (Pilot #4) who participated in the workload study on the Langley Visual/Motion Simulator (Waller, 1976; Waller & Wise, 1973).

The Data

The data used were from the Langley Workload Study in which there were four pilots who were tested under each of six conditions. Table 2 lists these conditions (reproduced from Spady and Waller, 1973). The simulated position at initiation c the run was an altitude of 1600 feet at a distance of 33000 feet from the end of runway. Airspeed was 120 knots.

Because there may be changes in performance as a function c position on the glide slope, the flight path was segmented as shown in Figure 1. Segments ended at 30,000, 23,000, 16,000, 10,000, and 4,000 feet from threshold. Normal procedure require a pilot to make the transition to visual guidance at an altitude of 200 feet, and therefore the segments from that altitude to threshold were set aside.

The first step in the data analysis was to determine the number of control inputs Pilot 4 made in the various conditions.

Table 2

VMS Simulation Test Conditions

(from Spady & Waller, 1973)

Initial Conditions

X = 33,000 ft.

Altitude = 1600 ft.

Airspeed = 120 knots

Condition Label	Turbulence	Y-position	Others
I	None	0	No spd. cmd.
II	None	0	
III	None	500 ft.	No cmd. bars
IV	Moderate	500 ft.	
V	Heavy	500 ft.	No cmd. bars
VI	Heavy	500 ft.	

The data were run through a series of programs developed at Langley Research Center for conversion of the on-line recordings into usable form. Added onto the calibration programs was a pattern recognition program which identified the time and type of control maneuver the pilot made. The purpose of the pattern recognition program is to carry out analyses on control inputs in conjunction with the oculometer data. At the time these data were analyzed, however, the complete package was not ready; the program only printed out the occurence of each control input. Subsequent tabulations were made manually to determine the number and type of input for each of the segments in each of the conditions. Four categories of control input were used:

Aileron (A)

Aileron + Elevator (A + E)

Elevator (E)

Thrust (T)

The category "aileron + elevator" was forced on us by the data because it appeared that occasionally the two events were the result of one motor movement. Following these tabulations, the data were subjected to several statistical procedures.

Analysis of Variance

The purpose of using analysis of variance was to determine 1) if there were any significant differences in the number of control inputs as a function of condition each of which involves different levels of workload and 2) if this frequency changed as a function of the landing segment. Because pilots have indicated that they try to do things in a particular sequence, it was thought to be worthwhile to look for this possibility. The analysis of variance is provided in Table 3. The results show several significant effects, each of which will be discussed in turn.

There is a significant difference in the extent to which the various individual controls available to the pilot are used. The basis for the difference is simply that Pilot 4 uses the ailerons much more frequently than any other control. A limited amount of data from a second pilot shows a markedly different pattern. A second result which is important in confirming intuitions is the finding that there is a significant difference in the total number of inputs as a function of the segment.

A highly important finding is the significance of the main effect of conditions. This is the first analysis reported on these data in which conditions can be differentiated statistically. Again the data are consistent with what one would expect: the heavy turbulance conditions (V and VI) show the largest number of control inputs, as is shown in Table 4. Extensions of the analysis of variance were used to confirm this conclusion. It may be noted that the mean number of inputs does

Table 3

Analysis of variance on control inputs for one pilot in the Langley VMS Workload Study.

(There were five runs in each of six conditions. Each run was broken into five segments. Four categories of control were analyzed. Entries into the analysis consisted of the number (by type) of control inputs in each segment.)

Source	SS	df	F	p
Runs	22.93			
Type Control Inputs	2910.80	3	226.20	.0000
Error	51.47	12		
Segments	54.39	4	8.90	.0008
Error	24.44	16		
Conditions	556.27	5	13.87	.0000
Error	218.17	20		
Type x Segment	120.38	12	4.34	.0002
Error	111.03	48		
Type x Condition	1138.97	15	13.83	.0000
Error	329.37	60		
Segment x Condition	57.71	20	1.39	.1523
Error	166.06	80		
Type x Seg x Cond	201.86	60	1.69	.0033
Error	477.19	240		

Table 4

Means and standard deviations for control inputs by conditions and segments in Langley Workload Study for one pilot.

	Type of Control Inputs				
Conditions	A	A+E	E	T	Overall
I	3.120	0.240	2.520	0.320	1.550
	2.646	0.510	2.098	0.469	1.723
II	3.800	1.200	3.800	0.520	2.330
	2.843	0.812	1.249	0.424	1.619
III	2.560	0.160	2.080	0.320	1.280
	1.738	0.374	1.568	0.648	1.229
IV	3.440	0.600	1.720	0.480	1.560
	2.349	0.632	0.927	0.600	1.336
V	10.840	1.240	3.880	0.480	4.100
	2.814	0.906	2.358	0.400	1.901
VI	9.680	1.640	3.200	0.680	3.800
	3.156	1.720	2.437	0.678	2.198
Overall	5.573	0.847	2.867	0.467	2.459
	2.630	0.935	1.861	0.548	

not coincide precisely with the pilot's estimate of the workload (Table 5). Discussion of this point will be presented later.

The final important result is the significance of the interaction between the type of input and conditions. As can be seen in Table 4, when turblence is heavy, the major increase in the number of inputs occurs with the aileron. This interaction suggests that the major increase in total or subjective workload for this pilot is due to the necessity of working harder to keep the plane level.

Regression Analysis

The availability of the workload ratings provides an opportunity to examine the extent to which workload ratings are related to the number of control inputs. It may be recalled that Krebs and Wingert (1976) did not find any systematic relation between eye-scanning behavior and workload rating in their study.

The second type of statistical analysis used was multiple (linear) regression (Cohen & Cohen, 1975). It provides us with information different from that of the analysis of variance. Whereas the analysis of variance tells us about differences the regression tells us about predictability from the number of control inputs onto the Cooper-Harper rating. Multiple regression analysis determines the best linear combination of the

Table 5

Data comparing the NASA test pilot's rating of workload with the number of control inputs he made during the corresponding flight conditions.

Condition Label	Workload Rating	Mean # Control Inputs
I	3.0	29.8
II	2.5	49.0
III	4.0	25.8
IV	3.5	28.4
V	7.0	78.0
VI	5.0	68.5

independent variables which can be used to predict the dependent segments yielding just four values for each of the runs available. The independent variables then consisted of the four categories of control inputs; the dependent variable was the workload ratings on the conditions.

The results of this analysis are shown in Table 6. As can be seen in the table the number of aileron inputs accounts for some 63% of the variance (cumulative R square). An additional 10% of the variance can be predicted when the aileron + elevator inputs are added into the equation to give a total of 73% of the variance being accounted for by the two variables. This in itself is remarkable for two reasons. First the workload scale cannot be considered to be either a ratio or interval scale measurement; the difference between 3 and 5 is not the same as the difference between 5 and 7). However, such an assumption about scale is made automatically when using multiple regression. Second, the Cooper-Harper workload rating represents more than quantitative workload - note the difference in the rating between Conditions V vs. VI in Table 5.

The following equation which represents just the statistically significant components will account for 73% of the variance in the Cooper-Harper ratings:

Wrk rating 1 2.46 + .08(Ail. freq) - .16(Ail. + Elev. freq)

Table 6

Correlation Matrix

	Ail	Ail + Elev	Elev	Thru	C-H
Aileron	1.00	.683	.442	.205	.794
Ail. + Elev.	.683	1.00	.460	.528	.307
Elevator	.422	.460	1.00	.252	.224
Thrust	.205	.528	.253	1.00	.105
Cooper Hrpr	.794	.307	.224	.105	1.00

Regression Results

Variable	Coef.	Stan. err. of coef.	F	Cumulative R square
Aileron	.088	.011	68.93	.631
Ail. + Elev.	-.197	.058	11.53	.734
Thrust	.160	.111	2.09	.753
Elevator	-.013	.025	.26	.756

These results may be interpreted as indicating that a sizable portion of the workload evaluation is based on the number of control inputs the pilot makes. This is what we called quantitative workload and is apparently a major factor in determining overall workload. If the workload rating were on a ratio scale one could use the present equation to determine an estimate of cognitive workload. This could be done simply by letting the number of control inputs go to zero in which case the regression would be determined entirely by the constant, for these conditions, 2.46. We may note that this value is similar to the workload rating for Condition II which this pilot considers to be the easiest.

There are other reasons for suspecting that the Cooper-Harper workload rating does not reflect just quantitative workload. For example the rating goes up when the command bars are removed, as in Condition V as compared with Condition VI. In Condition V the pilot must get his information from other instruments which would increase his cognitive workload.

Throughout our discussion we have emphasized the importance of pilot strategies. To illustrate this point we will briefly describe a limited analysis done on data from another pilot who showed differences in the number of control inputs as a function of conditions. For reasons not fully known, the frequency of inputs was about 1/2 that of Pilot 4. Of more interest, the second pilot's strategy for controlling the airplane was quite different. When we did the regression of control inputs against workload rating we obtained comparable results - 71% of the variance accounted for by two types of inputs. The control input categories, however, were different from the previous case.

For Pilot #1:

$$\text{C-H rating} = 3.03 + .24\ (\text{Elev. freq}) - .38\ (\text{Thrust freq})$$

These results show that the workload rating of one pilot may have general implications for the performance of another pilot, however, the details underlying the performance may differ markedly. Naturally, when the data from the two pilots are combined the regression fares less well, a result which is to be expected when such strong individual differences are involved.

Suppression

One final point should be made about these results. There is evidence in the data for a phenomenon called suppression. Suppression can occur in several ways. One of these, the so called classical case, is the situation in which event A is correlated with event B; event B is correlated with event C; but events A and C are not correlated with each other. For this example, C is suppressing the degree of relation between A and B by virtue of the fact that some of the B variance is common to A and some of the B variance is common to C. Removal of the B variance common with C causes the relation of A and B to be statistically greater.

Although the situation is not dramatic in the present example there is evidence for suppression as indicated by a positive correlation between aileron and aileron + elevator as contrasted with the negative weight given to aileron + elevator in the final equation for Pilot 4. This result is probably due to the fact that the pilot cannot make both an aileron and an aileron + elevator input simultaneously. This kind of "forced" mutually exclusive event leads to the suppressing effects. There is also suppression in the data of Pilot 1 but for different reasons. Pilot 1 appears to be using the elevators and thrust as alternate means of controlling airspeed.

Discussion

The data speak strongly to the need for an improved, elaborated and more precise definition of workload. A variety of definitions have been attempted yet none are fully satisfactory. The present results imply that workload is not a unitary concept.

In the present example, a major portion of the workload rating can be predicted by the number of control inputs.

However, there is a sizable portion left. We can get some insights into the nature of workload by examining the data in some detail. For example, the workload rating goes up when the command bars are removed. This can be seen in Table 5, especially for conditions V vs VI. Note, however, that the number of control inputs does not correlate perfectly with the rating. We suggest that the imperfect correlation (or the residual 30% of the variance) is due to a qualitatively different component of workload which we will call "cognitive workload." This, of course, is a speculation and it will require more experimentation, first to establish the differentation more firmly and second to establish better indices of the relative contribution of the two components.

Roughly speaking, one part of workload is related to the motor system, i.e. the number of control inputs required to control the aircraft. The other part is imperfectly represented by eye-scan behavior in a manner parallel to Hebb's suggestion that eye movements may reflect central (cortical) activity. Apparently in the Langley VMS the major changes in the motor system come about as the result of manipulation in turbulence. (As we shall see later the situation is different for eye-scan; the most prominent differences come about as the result of instrument changes.)

The dissociation of workload into two qualitatively different components is reasonable in the context of Megaw's (1973) data. Because of the considerable degree of independence between motor behavior and eye-scanning it is not surprising to find that eye-scanning behavior is relatively constant while control inputs change as a function of turbulence.

Despite the compelling aspects of the data, it is equally reasonable to suggest the two systems cannot be totally independent as evidenced in the manual and compiled data. After all, a major portion of the information a pilot receives is through his scanning of the instruments. It becomes critical therefore that the relation between control inputs and eye-scan behavior be analyzed. A thorough analysis will not only yield information about how the pilot acquires information but also provide background about the trade-off between the two types of workload we have defined.

PART II: Evaluation of Eye-Scan Data

As we indicated earlier, univariate analyses did not yield any significant findings in the eye movement data. Accordingly, we adopted a set of multivariate procedures which are more complicated but also more appropriate. Because these procedures have not been used frequently in human factors research, we will devote some discussion to an introduction of the procedures. The present discussion of the factor analysis technique is entirely intuitive. Readers wishing more detail are advised to consult Harmon (1967) for a thorough presentation or Kroth (1975) or Rummel (1967) for an introduction.

Factor Analysis

When considering any set of empirical data there is usually more than one way to analyze and to describe the data adequately just as there is usually more than one useful theory. Although factor analytic procedures have typically been used in behavioral sciences and Fourier analysis in engineering, there is no particular reason why this need be the case. The major difference between the mathematics underlying factor analysis and frequency analysis is the basic equations. There are generally some assumptions made in frequency analysis which are not made in factor analysis. Both, however, assume linearity which can be accomplished by data transformations if necessary. They may be considered as alternate techniques to evaluate the same data. As with most alternatives there are some advantages and disadvantages associated with each, depending upon the purpose of the investigator. In engineering terms, factor analysis is akin to quantum theory (Rummel, 1967) whereas frequency analysis is derived from calculus. Several investigators (e.g. Clement, et al. 1971; Senders et al. 1966) have developed theories of display design and eye movement behavior and then determined the degree of fit between the theory and the empirical observation. In both cases the fit between the model and the eye movement data is quite good, however, their procedures require several assumptions which apparently have not been evaluated. For example, Senders et al. (1966) used time on instruments without worrying about linking (transition) probabilities; Clement et al. (1971), although they considered linking probabilities, did not take into account what happens when the instruments are redundant and overlapping. Because factor analysis is a technique designed specifically to deal with correlation (covariance), it is especially useful for examining redundancies and comes closer to the Senders et al. (1969) ideas on queueing theory than to other models.

A Brief Description of Factor Analysis

In large part, factor analysis is a descriptive procedure in which a primary aim is parsimony. A major function of the analysis is to reduce a large set of variables to a smaller set of factors or components each of which is related to one or more of the original variables. It usually involves the simplest mathematical model, a linear one, which takes the form:

$$Z_j = A_{j1} F_1 + A_{j2} F_2 + \ldots + A_{jN} F_n \qquad (1)$$

Where Z = the original variable to be approximated,

j = 1,n the number of original variables,

Aj. = a weight applied to the factor,

F. = new unrelated or othogonal components.

An important property of the method is that each component in turn makes a maximum contribution to the sum of variances of the n variables. Although technically n components are required to reproduce the correlations among the variables, in practice only 1/3 or less are required to account for a major portion of the variance. The solution is accomplished by analysis of the correlations among the variables.

Readers familiar with linear regression will see immediate similarities between the equation and the generalized regression expression. That is, whereas in regression the evaluation is on each variable separately, factor analysis first groups like variables into a combined component and then uses these mathematically defined components to provide the linear equation. In regression the idea is to maximize variance accounted for, whereas in factor analytic techniques the idea is to maximize variance accounted for and simultaneously to reduce the number of variables. In the analysis to be discussed we started with seventy variables and retained eighteen components while accounting for slightly more than 70% of the variance in the data matrix.

Because there exists a number of models of factor analysis it is important to specify the details. The particular factor analytic model used was principal components analysis (Dixon, 1975). Other models will not necessarily provide identical solutions. A feature of principal components is that the first component extracted accounts for the largest percentage of variance with each successive factor accounting for a lesser percentage. A second feature is that the main diagonal of the correlation matrix is composed of 1.0's, that is, a variable is assumed to be perfectly correlated with itself. A third feature is the orthogonality (independence) among the resulting components. The cutoff point or the decision to stop generating additional components is Kaiser's Eigenvalue = 1.0 rule, which when used does not permit a component to account for less variance than would be contributed theoretically by any one variable. Of great importance, a Varimax rotation was used which retains orthogonality among the components. Rotation has the feature of increasing interpretability by adjusting the loadings so each component is as mathematically close as possible to one of the axes in n-dimensional space. It optimizes the uniqueness of each component.

Reasons for Application

One of our prime goals is to reduce the number of variables. We have, of course, no a priori assurance about the existence of a simpler, latent structure in the data but if one exists the analysis will be useful in helping to uncover it. A second reason for using the technique is to determine some of the characteristics about the relations among the various instruments; specifically we want to examine how the pilot uses the redundant instrument information available to him.

A third and more general reason which encompasses the first two is in the context of theoretical development. As a long term goal we want to be able to specify what the pilot does to acquire and utilize information. One such attempt to do this is embodied in the use of the workload ratings on workload. In Part I we showed that the workload rating could be predicted better by the number of controls inputs than by specific use of instruments. (Krebs & Wingert, 1976). In a different approach (Dick & Bailey, 1976) pilots rated the instruments in order of use. Although they were quite consistent in what they said about the instruments, their ratings did not correlate well with objective (oculometer) measures on the percent of time they looked at the instruments. One need not look far for an explanation of why comparisons of verbal reports and eye movements have not fared well. The pilot must control the aircraft in a number of dimensions simultaneously; he can deal with these parameters one at a time, two at a time or even three at a time. For example, he could be concerned with being on the glide slope or he could be concerned with both vertical and horizontal position depending on where he is on the glide path, wind conditions, etc. To complicate the issue further once he has "set up" or brought a primary concern under control, a pilot can monitor in a secondary manner by making sure other parameters remain under control. The interactive effects between the parameters permit him to use instruments in an analogous interactive manner. Concern about two parameters simultaneously may require a different use of the instruments than concern about either parameter individually. Use of only percent time on instruments automatically eliminates even the possibility for discovery of coordination among parameters. Their discovery requires analysis of correlation.

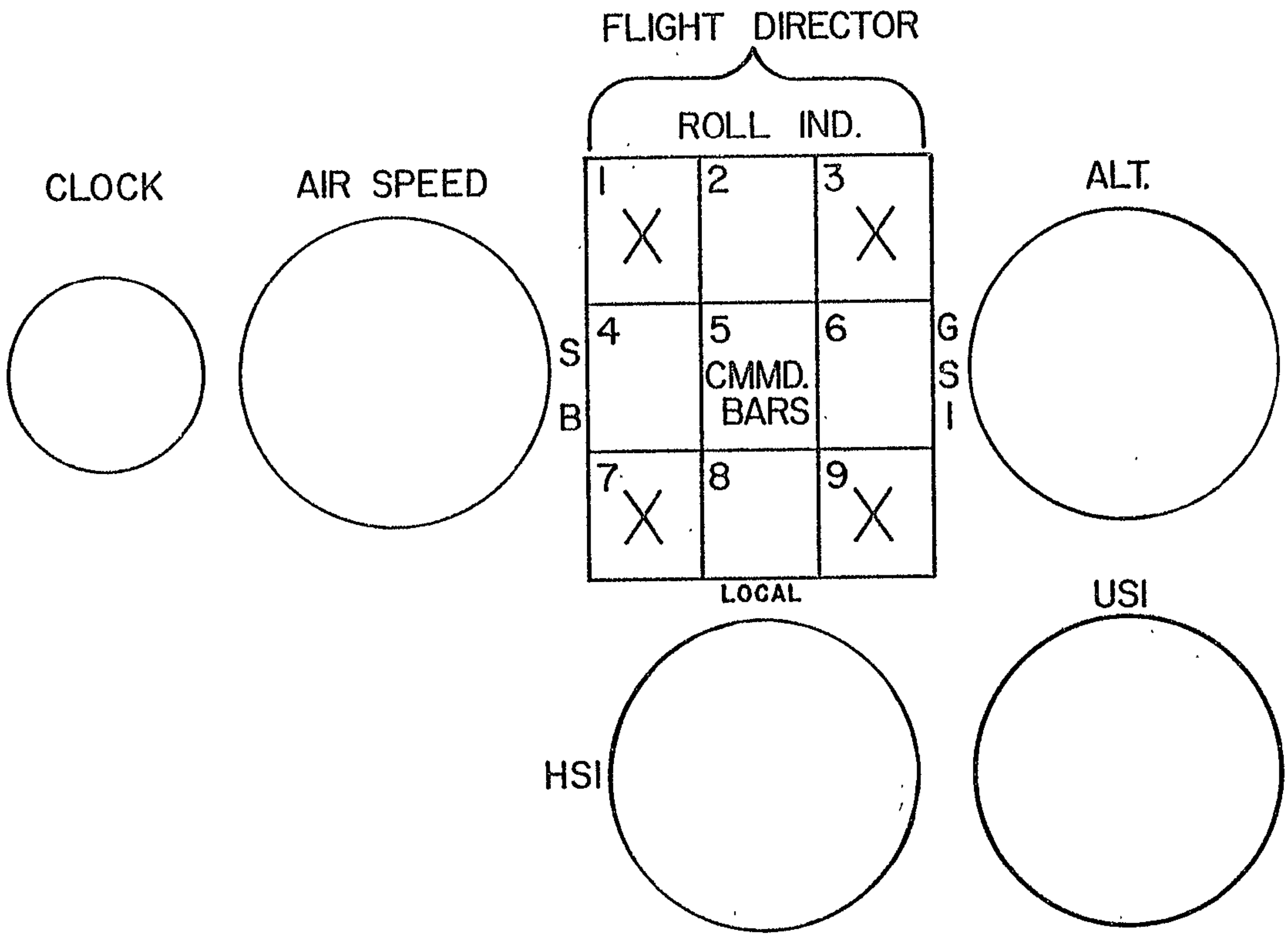
The Data

The data used were from the Langley Workload Study in which four pilots were tested under each of six conditions. Table 2 lists these conditions (reproduced from Spady and Waller, 1973). The simulated position at initiation of the run was an altitude of 1600 feet at a distance of 33000 feet from the end of runway. Airspeed was 120 knots. A total of 205 approaches was used.

The oculometer data were transformed into "look points" or instrument positions using programs developed at the Human Factors and Simulation Branch at Langley Research Center. Retained in the data transformations were the "from/to" characteristics or linking probabilities of eye-scan patterns. A preliminary analysis showed some cells to be 0.0 in all positions; these were accordingly discarded. Those not used are indicated in the table. There are two reasons why a variable may be 0.0: 1) the pilot does not use that combination of instruments and 2) the data analysis routines which convert the oculometer data into look points will classify a transition through an intermediate instrument into another category.

Because the flight director contains several separate instruments, this instrument was separated out and broken down into the spatial arrangement shown in Figure 2. The reader may wish to note that some of the transition probabilities from an empty cell to other cells in the flight director were discarded. In addition, mean dwell times were available. This measure ignores where the eye was previously; that is, the from component, and gives average time spent on each instrument. Finally, the standard deviation of dwell time was available and used because of its independence from mean dwell times.

Because it was felt that there may be some changes in the pattern of eye movements as a function of position on the glide



Schematic of Instrument layout.

slope, the flight path was segmented as shown in Figure 1. Normal procedure requires a pilot to transition to visual guidance at an altitude of 200 feet; therefore the final segments from 4000 feet to threshold were set aside. Aircraft position was obtained at the end of each segment; the parameters used were:

Altitude

Distance from Center Line

Localizer Error

Glide Slope Error

Airspeed

The complete list of variables was composed of 96 different observations and is given in Appendix A. This list was reduced to 70 by eliminating variables which were consistently zero.

Results

The major results are shown in Table 7 which lists the organization of the variables into orthogonal components. In the table only the primary loadings are shown; only 66 of the 70 variables showed loadings of .40 or better. Some of the variables displayed secondary (smaller) loadings on other components but these have been ignored in the table. The complete factor loading tables are provided in Appendix B.

Table 7

An abbreviated factor loading table.

The variables are grouped according to their primary membership in the factorial cluster. A suggested label and the percent of variance accounted for (related) is provided in the heading. The numerical entries are the rotated factor loadings. (The loading is a correlation coefficient of the variable with the component.) The complete table of factor loadings is given in Appendix B.

Component 1 "Vertical Velocity"	7.1%
Rate of Climb - Rate of Climb	.895
Flight Director - Rate of Climb	.891
Rate of Climb - Flight Director	.861
Stand. Dev. Rate of Climb	.828
Mean Dwell Rate of Climb	.784

Component 2 "Airspeed I"	6.5%
Airspeed - Airspeed	.939
Flight Director - Airspeed	.919
Airspeed - Flight Director	.913
Mean Dwell Airspeed	.868
Stand. Dev. Airspeed	.848

Component 3	"Vertical Guidance"	6.3%
Glide Slope - Glide Slope		.881
Stan. Dev.	Glide Slope	.857
Mean Dwell	Glide Slope	.823
Glide Slope - Command Bars		.811
Command Bars - Glide Slope		.790

Component 4	"Monitoring"	5.4%
Speed Bug - Command Bars		.795
Flight Director - Altimeter		.793
Command Bars - Speed Bug		.787
Altimeter - Flight Director		.778
Localizer - Glide Slope		.519

Component 5	"Roll"	5.4%
Roll - Roll		.908
Roll - Command Bars		.875
Command Bars - Roll		.869
Stand. Dev.	Roll	.785
Mean Dwell	Roll	.715

Component 6	"Horizontal Situation"	5.2%
Stand. Dev. HSI		.854
HSI - HSI		.843
Mean Dwell HSI		.799
Flight Director - HSI		.667
HSI - Flight Director		.655

Component 7	"Flight Director"	4.9%
Flight Director . Mean Dwell		.773
Command Bars Stand. Dev.		.741
Flight Director Stand. Dev.		.699
Command Bars Mean Dwell		.690
Flight Director - Flight Director		.544
Command Bars - Command Bars		.542

Component 8	"Localizer"	4.7%
Localizer - Localizer		.782
Localizer Mean Dwell		.767
Localizer Stand. Dev.		.647
Localizer - 7		.613
Localizer - 9		.505
Speed Bug - 7		.503

Component 9	"Airspeed II - Relative"	4.6%
Speed Bug Mean Dwell		.899
Speed Bug Stand. Dev.		.899
Speed Bug - Speed Bug		.865

Component 10	"Altitude"	4.1%
Altimeter - Altimeter		.872
Altimeter Stand. Dev.		.787
Altimeter Mean Dwell		.738

Component 11	"Angle and Speed of Approach"	3.2%
HSI - Rate of Climb		.788
Rate of Climb - HSI		.758
HSI - Airspeed		.514

Component 12	"Flight Path Deviation I"	3.0%
Distance from center line		.948
Localizer error		.947

Component 13	"Horizontal and Height"	2.5%
Altimeter - HSI		.738
HSI - Altimeter		.692

Component 14 "Flight Path Deviation II"	2.2%
Glide slope error	.779
Aircraft Airspeed	-.709

Component 15 "Relative Angle and Rate"	2.1%
Localizer - Speed Bug	.766
Glide Slope - Localizer	.745

Comp. 16 "Vertical/Horizontal Guidance"	2.0%
Glide Slope - Localizer	.628
Localizer - Command Bars	.403
Command Bars - Localizer	.447

Component 17 "Glide Slope Acquisition"	1.9%
Roll to 3	.815
Glide Slope - 3	.805

Component 18 "Rate of Descent"	1.6%
Rate of Climb - Airspeed	.598
Rate of Climb - Altimeter	-.445

Total variance 72.7%

We will not discuss each and every component because the interpretation of the components is, in most cases, straightforward. Let us consider the first component as an example. We have labeled it "Vertical Velocity" as a result of the heavy emphasis on rate of climb. There are several interesting characteristics in this component. First, not all of the transition measures on rate of climb enter into the component. Second, the flight director fits because it provides pitch information, but note the absence of airspeed.

Generally, we may note that the ordering of the components does not reflect time on instruments in any straightforward manner. This result occurs because factor analysis maximizes the variance accounted for; obviously, the variance is not necessarily related to the percent of time on each instrument. The components appear in most cases to be related to the pilot's concerns in landing the aircraft.

To understand the results more fully in terms of their generalizability we need to consider a number of issues. The first is the task itself. In four out of the six conditions the initial starting point is 500 ft. off the centerline. This experimental condition results in Component 5, "Roll." Without the offset, the roll indicator would not be an important consideration and probably would not appear as a component if the situation did not include the offset. Similarly, Component 6, "Horizontal Situation," plays an important part in later analyses for the same reasons. It stands to reason, of course, that the results are only as representative as the task which produced the data.

Another point has to do with the treatment of the data which will translate through to the interpretation. To illustrate this, let us consider Component 17 which we labeled "Glide Slope Acquisition." The issue involves the definition of the boundries of the instruments and their spatial arrangement. It is reasonable, of course, to expect the pilot to be concerned with roll as part of glide slope acquisition so that he can bring the airplane into the proper position. When considering the spatial arrangment of these two instruments in the flight director (Figure 2) we see that the pilot has two routes between cells 2 and 6 (roll and glide slope respectively). He can transition through 3 which is empty or he can go through 5 which contains the command bars. With the present data reduction procedures, all we can say about Component 17 is that it is probably an underestimate of the pilot's concern with glide slope acquisition. That is, any transitions between 2 and 6 which happen to go through cell 5 will be counted as two transitions, 2-5 and 5-6 and will end up in Components 3 and 5. Thus the magnitude of the components will be influenced by assumptions in data analysis about the size of instruments.

The role of the command bars is problematical. The term as used here denotes a physical location on the instrument panel but this physical location actually contains two instruments so it cannot be determined precisely which the pilot is using when he looks at that position. The command bars enter Components 3 and 4. Because of the different characteristics of the two components, however, it is unlikely that the same meaning should be attached to the scanning behavior for these and other components.

A final point which needs to be drawn out is the relation between the components as yielded by factor analysis and the per cent of time on instruments. The per cent of time on instruments loses its impact in factor analysis because all measures are normalized prior to factor analysis. Thus these difference have been removed. Although it could be argued that such differences should be left in the analysis, let us consider the case for their removal. Early eye movement studies showed that the optimal look-point was in the middle of the display, which in the present study, happens to be the flight director. (Although the data are from a different study, the manual condition shown in Table 1 is representative of the amount of time the pilot spends on the flight director.) The amount of time on instruments is partially confounded - it represents more than just information acquisition. By normalizing, the importance of unwanted contributions is reduced, although not eliminated. An even more telling argument is the relatively unsuccessful attempt to use raw measures involving time on instruments to predict workload (e.g., Krebs & Wingert, 1976).

Instrument Redundancy

Most previous analyses have emphasized time on individual instruments. By definition, the approach ignores the existence of redundancy - there is more than one source for the same information. A major benefit of the correlational analysis is in the result that the structurally redundant instruments are not always used in a coordinated fashion. If a pilot used a relative instrument to decide to look at a raw instrument, we should see components which contain both. The components are orthogonal and therefore there cannot be large correlations between these instruments or they would have ended up in the same component. It appears therefore the pilots treat them independently. For example, compare Component 2 with Component 9 (Airspeed I vs Airspeed II).

Interpretation

What about the utility of these components? What do they tell us about how the pilot operates the aircraft? To evaluate these questions, factor scores were generated and used in discriminant analysis. Factor scores represent normalized composites of each of the 70 variables mapped onto the eighteen components. The primary emphasis in Factor Score 1 will be vertical velocity; Factor Score 2, airspeed; etc. These scores were generated by the factor analysis program and written on tape for later use in discriminant analysis.

Discriminant Analysis

A statistical procedure which does not appear to have been used in human performance is that of discriminant analysis. The procedure is similar in some ways to signal detection theory and is related to multiple regression and analysis of variance. In effect, discriminant analysis allows us to develop decision rules (or equations) based on the data and further permits us to evaluate the usefulness of the rules.

In the present situation, the independent variables consisted of the factor components and the data values were the factor scores. Accordingly, one way to view the analysis is in terms of evaluation of the usefulness of the factor components generated from oculometer data. Several group classifications (dependent variables) were possible; the factor scores were labeled according to pilot, segment, and condition. Accordingly, several different discriminant analyses were run and each will be discussed in turn.

Step-wise discriminant analysis was used but in a simultaneous fashion (Dixon, 1975). The advantage of this procedure is the sequential output; the results are printed as the variables are entered with the ordering being determined by the statistical significance of the individual variables. One can then examine how the equation develops and see the contributions of each variable in turn including the possibility of suppression. Although it is not possible to present all of the results from this procedure we have preserved as much as possible.

Results

As with the factor analysis results, it is not our intention to discuss each and every significant point. Rather our intent is to discuss some of the interesting results partly to illustrate the usefulness of the technique and partly as a tutorial exercise so the interested reader can pursue the remainder as he wishes.

Pilots

Because of their varied experience, the first question to be answered was, Do pilots differ? The answer is yes. Table 8 shows the classification matrix which resulted from inclusion of

Table 8

Pilot Classification Matrix

Original "Group"	Percent Correct	Number of Cases Classified by Equation Pilot 1	2	3	4	N
Pilot 1	73.0	208	10	38	30	285
Pilot 2	80.4	15	205	1	34	264
Pilot 3	93.7	7	8	239	1	255
Pilot 4	84.8	6	25	4	195	230
Total	82.6	236	247	282	260	1025

The entries are F ratios and provide an index of the distance between pairings.

Degrees of Freedom = 18, 1004

	Pilot 1	Pilot 2	Pilot 3
Pilot 2	57.37		
Pilot 3	56.10	107.07	
Pilot 4	48.99	26.15	104.22

all the factor components in the analysis. The presentation in the table is readily understandable. The labels down the side represent the objective categories (pilots) which were entered into the computer program. The labels across the top represent the categories as calculated by the equations. The entries are frequencies. The main diagonal represents the number of times the equations were able to categorize correctly. The lower half of Table 8 provides a matrix which gives F ratios calculated between all pairings of two pilots. The entries can be used as an index of the distance (or difference) between any two pilots.

Table 9 provides the classification functions for the pilots by the components. The F values are multivariate and provide an index of the relative importance of the components for making the discrimination given the preceeding components. From the table it can be seen that the pilots differ significantly on all Components except for 17 and 18. The most important in terms of the F ratios (where the pilots differ most) are Vertical Velocity, Vertical Guidance and Horizontal Situation.

By studying the patterns of the normalized coefficients one can detect a considerable diversity among the weightings each pilot applies to the instruments. We may recall the differences in the two multiple regression functions derived from the control input analysis. Pilot 4 (for whom we had the most data) shows a positive weighting on Horizontal Situation and a negative

Table 9

Pilot Classification Functions

The Entries are Normalized Coefficients

Factor	Pilot 1	Pilot 2	Pilot 3	Pilot 4	F to Remove DF=3,1004
1 Vertical Velocity	1.22	-1.73	1.98	-1.79	304.28
2 Airspeed I	-0.27	0.24	-0.32	0.43	12.21
3 Vertical Guidance	-0.33	-1.33	2.21	-0.57	202.83
4 Monitoring	-0.47	1.25	-0.88	0.17	83.36
5 Roll	0.17	-0.72	1.16	-0.69	56.81
6 Horizontal Situation	0.22	-0.12	-1.30	1.30	116.01
7 Flight Director	0.50	0.28	-1.40	0.62	86.04
8 Localizer	-0.36	0.42	-0.43	0.46	19.72
9 Airspeed II-Relative	-0.14	0.36	-1.41	1.34	106.76
10 Altitude	-0.45	-0.05	0.27	0.32	21.01
11 Angle & Speed of App.	0.33	-0.59	0.60	-0.42	26.00
12 Flight Path Dev. I	0.69	-0.38	-0.12	-0.30	35.89
13 Horizontal & Height	-0.25	-0.33	0.97	-0.39	36.89
14 Flight Path Dev. II	0.28	-0.50	0.28	-0.11	14.49
15 Relat. Angle & Rate	-0.26	0.83	-0.58	0.04	36.86
16 Vert./Horiz. Guid.	-0.24	0.61	-0.79	0.51	32.21
17 Glide Slope Acq.	-0.03	-0.07	0.23	-0.14	2.04
18 Rate of Descent	-0.02	0.20	-0.23	0.06	2.73
CONSTANT	-2.32	-3.05	-4.35	-3.04	

weighting on Vertical Velocity. He was the pilot who used the ailerons a great deal. In contrast, Pilot 1 who used primarily elevators shows a positive weight for Vertical Velocity and an indifferent one for Horizontal Situation. The data show consistency between the control inputs and the eye movements and emphasize pilot differences. The patterning of eye movements differs among pilots as does the use of controls.

Segments

The factor scores were entered into discriminant analysis as a function of segments. The classification matrix in Table 10 shows not only that the discriminant analysis did not fare as well (53%, chance = 20%) as for pilots but also why. The selection of the cut points for segments is entirely arbitrary from the pilots point of view; his task is, after all, a continuous one. Priorities change over the flight path but there are no clear boundaries and accordingly misclassifications are likely to occur between adjacent segments. The main characteristics of Table 10 are recast in Table 11 to show the frequency of mistakes between adjacent and nonadjacent segments.

Table 12 provides the complete set of coefficients for the classification functions together with F values for significance. The results can be interpreted simply: there are some systematic changes in eye-scanning as a function of glide slope segment.

Table 10

Segment Classification Matrix

Original "Group"	Percent Correct	Number of Cases Classified into Group by Equation				
		Seg 1	Seg 2	Seg 3	Seg 4	Seg 5
Seg 1	80.5	165	25	6	4	5
Seg 2	52.2	29	107	42	19	8
Seg 3	32.2	17	51	66	44	27
Seg 4	50.2	11	9	29	103	53
Seg 5	49.8	2	6	29	66	102
Total	53.0	224	198	172	236	195

The entries are F ratios and provide an index of the distance between pairings.

Degrees of Freedom = 18, 1003

	Seg 1	Seg 2	Seg 3	Seg 4
Seg 2	16.11			
Seg 3	21.23	2.82		
Seg 4	33.61	16.25	8.57	
Seg 5	48.63	26.47	14.03	3.62

Table 11

Evaluation of Misclassification of Segments

	Number of Cells	Number of Cases	% Total	% Misclass.
Adjacent Segments	8	339	33	70
Non-adjacent Segments	12	143	14	30
Correct	5	(543)	53	-
Total	25	1025	100	100

Table 12

Segment Classification Functions

The Entries are Normalized Coefficients

	Factor	Segment 1	2	3	4	5	F to Remove DF=4,1003
1	Vertical Velocity	-1.33	-0.04	0.14	0.49	0.74	67.07
2	Airspeed I	0.04	0.18	0.09	-0.03	-0.28	4.08
3	Vertical Guidance	0.12	-0.06	-0.04	0.00	-0.02	0.74
4	Monitoring	-0.35	-0.18	-0.03	0.16	0.40	8.59
5	Roll	0.63	0.03	-0.03	-0.24	-0.40	15.86
6	Horizontal Situation	-0.22	-0.02	0.02	0.17	0.05	2.47
7	Flight Director	-0.11	-0.03	-0.00	0.07	0.08	0.59
8	Localizer	-0.38	0.15	0.08	0.10	0.06	6.09
9	Airspeed II-Relative	-0.78	0.10	0.10	0.27	0.31	22.30
10	Altitude	-0.72	-0.33	0.12	0.12	0.81	35.26
11	Angle & Speed of App.	-0.30	-0.00	0.07	0.03	0.21	3.92
12	Flight Path Dev. I	1.12	0.32	-0.15	-0.51	-0.77	55.57
13	Horizontal & Height	-0.29	-0.18	-0.09	0.22	0.32	7.06
14	Flight Path Dev. II	-0.44	-0.90	-0.51	0.84	1.01	89.34
15	Relat. Angle & Rate	-0.34	-0.20	0.08	0.20	0.27	7.10
16	Vert./Horiz. Guid.	-0.15	-0.06	-0.04	0.09	0.16	1.56
17	Glide Slope Acq.	-0.04	0.17	-0.00	-0.04	-0.09	1.65
18	Rate of Descent	-0.49	-0.24	0.02	0.19	0.52	15.18
	CONSTANT	-3.06	-2.03	-1.76	-2.03	-2.58	

However, these changes occur gradually and do not always occur at precisely the same point which produces the difficulty in discriminating the adjacent segments.

More detailed comparisons show that components, in order of importance, are the major components which permit discrimination:

14 - Flight path deviation - II (localizer error, X(95)),

1 - Vertical velocity

12 - Flight path deviation - I (Glide slope error, X(94) and aircraft airspeed, X(96))

9 - Airspeed II - Relative

5 - Roll

18 - Rate of descent

The other components do not contribute as greatly. We may note that Flight Path Deviation - I and Roll result from the 500' offset for Conditions III through VI (Table 2). This is the only discriminant analysis in which aircraft position parameters (Components 14 and 12) play a role in the discrimination.

Conditions

The third and most interesting way of looking at the factor scores is in terms of conditions. Table 13 shows the classification matrix resulting from entry of all eighteen

Table 13

Condition Classification Matrix

Original Group	Percent Correct	Number of Cases Classified by Equation into Condition					
		I	II	III	IV	V	VI
Cond I	91.5	151	10	0	3	0	1
Cond II	72.7	10	160	5	36	5	4
Cond III	65.0	1	3	91	12	19	14
Cond IV	64.7	4	29	15	110	1	11
Cond V	59.4	1	1	38	23	104	8
Cond VI	52.3	1	11	2	48	12	81
Total	68.0	168	214	151	232	141	119

The entries are F ratios and provide an index of the distance between pairings.

Degrees of Freedom = 18, 1002

	Condition				
	I	II	III	IV	V
Cond II	93.67				
Cond III	127.96	38.45			
Cond IV	111.62	14.08	29.53		
Cond V	150.99	48.55	9.13	24.74	
Cond VI	115.83	31.46	31.65	12.66	21.69

components. Overall, 68.0% of the cases were correctly classified (chance = 17%).

The ability of the discriminant analysis to categorize the conditions fits with changes in instrumentation but is more poorly related to turbulence. Condition I (without the speed bug) loads heavily on the "Airspeed" component (after this variable is entered most of the Condition 1 cases are correctly categorized.) Conditions III vs. V present some difficulties as do Conditions IV vs. VI; the command bars are out for Conditions III and V and are in for IV and VI.

Table 14 shows the normalized coefficients for the classification functions. The strongest discriminating component is "Airspeed I" which shows a positive weight for Condition I. The absence of the speed bug forces the pilot to use the airspeed indicator. For these same reasons, this component does not discriminate well between Conditions III and V or between IV and VI. The second strongest is "Horizontal Situation" which has a similar difficulty with III vs. V and IV vs. VI. Within the pairings they differ only in the amount of turbulence. Between the pairings, the difference is the presence or absence of the command bars. The difficult-to- discriminate conditions using eye-scan data are precisely those which are easy to discriminate in terms of number of control inputs and workload ratings. Reasonably accurate categorization of the difficult pairs is

Table 14

Condition Classification Functions

The Entries are Normalized Coefficients

	Factor	Condition I	II	III	IV	V	VI	F to Remove DF=5,1002
1	Vertical Velocity	1.40	0.02	-0.53	-0.33	-0.39	-0.24	19.14
2	Airspeed I	7.78	-0.18	-2.13	-1.53	-2.45	-1.67	559.70
3	Vertical Guidance	-0.56	0.27	0.83	-0.05	0.33	-0.85	31.91
4	Monitoring	-0.70	-0.39	0.59	0.14	0.68	-0.15	16.80
5	Roll	-0.26	-0.31	0.08	-0.07	0.62	0.02	9.76
6	Horizontal Situation	-2.04	-0.92	2.42	-0.68	2.07	-0.29	173.60
7	Flight Director	1.26	1.32	-0.87	-0.05	-1.20	-1.01	88.51
8	Localizer	-0.21	0.12	0.24	-0.47	0.10	0.25	9.97
9	Airspeed II-Relative	-1.68	-0.11	-0.27	0.73	0.79	0.50	44.76
10	Altitude	0.91	0.25	-0.26	-0.21	-0.40	-0.42	11.20
11	Angle & Speed of App.	-0.49	-0.15	0.00	-0.08	0.32	0.47	7.53
12	Flight Path Dev. I	-0.40	-0.26	-0.25	-0.02	0.17	0.85	18.45
13	Horizontal & Height	-0.45	-0.27	0.12	-0.20	0.46	0.45	10.47
14	Flight Path Dev. II	0.59	0.29	-0.02	-0.02	-0.63	-0.29	11.54
15	Relat. Angle & Rate	-0.21	-0.18	-0.16	0.20	0.29	0.08	4.66
16	Vert./Horiz. Guid.	-0.05	0.24	0.26	-0.17	0.05	-0.39	6.66
17	Glide Slope Acq.	0.21	-0.08	0.16	-0.13	-0.01	-0.10	1.52
18	Rate of Descent	0.25	-0.03	-0.04	0.00	-0.10	-0.08	0.68
	CONSTANT	-10.12	-2.75	-3.98	-2.64	-3.79	-3.25	

possible, but it takes a number of components to do the job. The strongest of these are 7, 9, and 3 in order of significance. The labels attached to these are "Flight Director", "Relative Airspeed", and "Vertical Guidance". Overall the discrimination among the conditions is good; this is the result of consistency among the pilots in spite of the fact that the pilots themselves show differences.

Conditions and Pilots Together

Individual discriminant analyses were done on pilots, conditions and segments. To evaluate how the components relate to the three classification schemes we rank ordered the components by means of their relative importance (F ratios) in the classification functions (Tables 9, 12, and 14). Spearman rho correlations were then done on the three possible pairings. The ordering of the components for segments was unrelated to pilots (rho = -.04) or to conditions (rho = -.08). Pilots and conditions, however, showed a significant correlation on the relative importance of the components (rho = .54; .05 % p % .01, one-tailed).

Accordingly, one other analysis was run. The intent was to determine to what extent predictability can be improved among conditions by the consideration of pilots. We presented some evidence in an earlier section showing results on two pilots who use different strategies in controlling the airplane. Such a strategy difference might be reflected in the use of instruments. By considering both pilots and conditions together we can determine the extent to which strategies contribute to the condition classification errors.

Factor scores were used again, this time with 24 "groups" (the product of 4 pilots by 6 conditions). The table associated with the results has been put in Appendix C for the interested reader. The final classification matrix shows 68% of the cases to be correctly classified. This is about the same accuracy as conditions alone, but chance is now down to 4%. Intuitively, this would seem to be an improvement. To our knowledge there are no statistical tests available in the literature to evaluate such cases, so we developed and applied information theory statistics.

Basically the notion is simple. First, we can calculate the amount of information transmitted or shared between the input variables (actual labels) and the classification function output (the computed labels). Table 13 presents one example. Second, having computed the two-dimensional discriminant analysis we have a 24 x 24 matrix, representing the classification of conditions x pilots. If we ignore pilots and collapse the matrix we are left with a 6 x 6 matrix representing conditions. The extent to which the new, collapsed matrix differs from the matrix in Table 13 provides an index (positive or negative) of the effect of considering pilots and their different approaches in performing the task. By calculating the information transmitted in the new matrix, we have an index which is in a form comparable to that obtained from Table 13. An approximation to Chi-square can then be applied to these H statistics to assess significance (Attneave, 1959).

Similar analyses were done for pilots and conditions. The results are shown in Table 15. Both information analyses show significant gains in the amount of information transmitted when both pilots and conditions are considered in the classification. In statistical terms, this represents an interaction between the two variables. Stated differently, the results suggest that each pilot has his own strategy or preference in his use of instruments and these strategies vary somewhat across conditions.

Discussion

A number of eye-scan measurements were entered into a principal components factor analysis. For this experiment 18 components accounted for more than 70% of the variance in the data matrix. The components show little direct relation to the percent time on instruments but appear to be related to concerns

Table 15

Evaluation of the interaction between
pilots and conditions.

Amount of Information (H) in bits

	Actual (rows)	Computed (columns)	Total in Situation	Transmitted	X2 on Difference
Conditions (Original)	2.570	2.544	4.005	1.109	
Conditions (Computed)	2.570	2.571	3.879	1.263	218.13
Pilots (Original)	1.996	1.997	2.843	1.150	
Pilots (Computed)	1.996	1.999	2.702	1.292	201.78

(df on X2 = 3 (pilots); 5 (conds.); p %% .01 for both) of a pilot while landing; that is the factors seem to make intuitive sense which is typically the first criterion applied to factor analysis.

A more rigorous test is whether the components can be used to discriminate among the various experimental variables. Factor scores were generated and entered into discriminant analysis. These analyses showed that pilots, segments, and conditions could be differentiated. Further analysis indicated the existence of an interaction between pilots and conditions which supports the suggestion that different pilots use somewhat different strategies in the various conditions.

As a technique, the approach to data analysis seems quite successful. There are, however, certain problems which need to be evaluated before the full value of the components analysis can be realized. The first issue has to do with the relativity of the components. We have already alluded to several of the components which appear to come about as a result of the 500' offset of the airplane at the initiation of the run. As the amount of offset is varied, the relative importance of components will also vary. The second issue revolves around validity. Due to its importance we will deal with this issue separately.

We have also stated that changes in instrumentation are detected by the eye-scan data analysis. This result has implications for other experiments and a more general solution to the issue of how the pilot uses the instruments. Although different instrument packages contain more similarities than differences they do vary somewhat. These changes may well result in a somewhat different outcome of the factor analysis. While we would expect similar results overall, the specifics should change both in the order of the components and in their relative importance. The whole issue revolves around the fact that the analysis is constrained by the data entered into it.

Finally, although the components do a good job in discriminating among the conditions, we lack a needed link between the components and reality. The difficulty here is the lack of a bench mark telling us what pilots are concerned about. We know that percent time on instruments does not correlate well with what pilots tell us about the way they use the instruments (Dick & Bailey, 1976). Before the results of analyses such as those reported here can be applied to instrument design with confidence we need a better link between the way the information is presented and the way pilots use that information.

Implications and Speculations

Perhaps the most important implication of the present work is the differentiation between two types of workload. Analysis of control inputs differentiates turbulence manipulations whereas analysis of eye movement differentiates among instrument manipulations. The additional study of the relation between control inputs and eye-scanning may well yield many important answers about instrument design.

The pilots did not use the structurally redundant instruments in a correlated manner. Pilots treat them independently, looking at one or the other depending on the circumstances in some unknown way. Further, when controlling, the pilots do not appear to have as much time to look at raw data instruments. Setting aside the issue of cross-checking, it would appear that the instrument panel could be simplified.

The present analysis and virtually every other report have only played lip service to the differentiation between monitoring (open-loop) and controlling (closed-loop) fixations. The data in Table 1 illustrate the problem. The pilot changes the way he looks at the instruments in the coupled approach from what he does in the manual approach. We can be fairly confident about the same kind of differences between monitoring and controlling fixations within the manual condition. Indeed, one of the factor components appears to be described best as "monitoring". We have no assurance, however, that the monitoring part of the manual condition is the same as we would get from a pure monitoring condition.

The present results are compatible with the Senders et al. (1969) queueing model. The essential difference is in the use of instrument clusters as represented by the factor components. That is, rather than use individual instruments as Senders et al. (1969) did, it appears more appropriate to consider the components. Before proceeding in this direction, however, a number of questions need to be answered. The central issues revolve around the relations among control inputs, eye-scanning, and the cognitive processes of the pilot.

References

Atteneave, F. Applications of information theory to psychology. New York: Holt, Rinehart & Winston, 1959.

Bryden, M. P. The role of post-exposure eye movements in tachistoscopic recognition. Canadian Journal of Psychology, 1961, 15, 220-225.

Clement, W. W., Allen, R. W., & Graham, D. Pilot experiments for a theory of integrated display format. Systems Technology, Inc. Technical Report 183-2. JANAIR Report 711107, 1971.

Cohen, J., & Cohen, P. Applied multiple regression/correlation for the behavioral sciences. Hillsdale N. J.: L. Erlbaum Associates, 1975.

Cooper, G.E., & Harper, R.D., Jr. The use of pilot rating in the evaluation of aircraft handling qualities. N.A.S.A. Technical Note TND-5153, 1969.

Dick, A. O., & Bailey, G. A comparison between oculometer data and pilot opinion on the usefulness of instruments during landing. Center for Visual Science Technical Report #3-76, N.A.S.A. Grant # NSG - 1211, 1976.

Dixon, W. J. (Ed.) BMD-P biomedical computer programs. Berkeley: University of California Press, 1975.

Kroth, B. Exploratory factor analysis. In D. J. Amick & H. J. Walberg (Eds.), Introductory multivariate analysis. Berkely, Calif.: McCutchan Pub. Co., 1975

Guilford, J. P. Psychometric methods. New York: McGraw-Hill, 1954.

Harmon, H. Modern factor analysis. Chicago: University of Chicago Press, 1967.

Hebb, D. O. The organization of behavior. New York: Wiley, 1949.

Kinsbourne, M. The mechanism of hemispheric control of the lateral gradient of attention. In P. Rabbitt, & S. Dornic (Eds.), Attention and performance. New York: Academic Press, 1975.

Krebs, M. J. & Wingert, J. W. Use of the oculometer in pilot workload measurement. NASA CR-144951, 1976.

Megaw, E. D. Simultaneous tracking of random step-input by saccadic eye movement and manual tracking systems. Journal of Experimental Psychology, 1973, Rummel, R.J. Understanding factor analysis. Conflict Resolution, 1967, 11, 444-480.

Senders, J., Carbonell, J.R., & Ward, J.L. Human visual sampling processs: a simulation validation study. N.A.S.A. CR-1258, 1969.

Senders, J. W., Elkind, J. I., Grignetti, M. C., & Smallwood, R. An investigation of the visual sampling behaviour of human observers. NASA CR - 434, 1966.

Spady, A. A., & Waller, M. C. The oculometer, a new approach to flight management research. AIAA paper No. Sept. 1973.

Waller, M. C. An investigation of correlation between pilot scanning behavior and workload using stepwise regression analysis. NASA TM X-3344, 1976.

Waller, M. C., & Wise, M. A. The oculometer in flight management research. AIAA paper No. 75-107, Jan. 1975.

Wiener, E. I. On simultaneous monitoring and tracking. Journal of Applied Psychology, 1975, 60, 100-105

Appendix A

The complete list of variables available. Those eliminated are marked. The variable label, X(n), corresponds to labels in the computer output in Appendix B.

Transition Probabilities

From	To	Variable Label	
Airspeed	Clock	X(1)	not used
Flight Director	Clock	X(2)	not used
Altimeter	Clock	X(3)	not used
Hor. Sit. Ind.	Clock	X(4)	not used
Rate of Climb	Clock	X(5)	not used
Airspeed	Airspeed	X(6)	
Flight Director	Airspeed	X(7)	
Altimeter	Airspeed	X(8)	not used
Hor. Sit. Ind.	Airspeed	X(9)	
Rate of Climb	Airspeed	X(10)	
Airspeed	Flight Director	X(11)	
Flight Director	Flight Director	X(12)	
Altimeter	Flight Director	X(13)	
Hor. Sit. Ind.	Flight Director	X(14)	
Rate of Climb	Flight Director	X(15)	
Airspeed	Altimeter	X(16)	not used
Flight Director	Altimeter	X(17)	
Altimeter	Altimeter	X(18)	

Hor. Sit. Ind.	Altimeter	X(19)	
Rate of Climb	Altimeter	X(20)	
Airspeed	Hor. Sit. Ind.	X(21)	not used
Flight Director	Hor. Sit. Ind.	X(22)	
Altimeter	Hor. Sit. Ind.	X(23)	
Hor. Sit. Ind.	Hor. Sit. Ind.	X(24)	
Rate of Climb	Hor. Sit. Ind.	X(25)	
Airspeed	Rate of Climb	X(26)	not used
Flight Director	Rate of Climb	X(27)	
Altimeter	Rate of Climb	X(28)	
Hor. Sit. Ind.	Rate of Climb	X(29)	
Rate of Climb	Rate of Climb	X(30)	
Airspeed	Mean Dwell	X(31)	
Flight Director	Mean Dwell	X(32)	
Altimeter	Mean Dwell	X(33)	
Hor. Sit. Ind.	Mean Dwell	X(34)	
Rate of Climb	Mean Dwell	X(35)	
Standard Dev. Dwell	Airspeed	X(36)	
Standard Dev. Dwell	Flight Director	X(37)	
Standard Dev. Dwell	Altimeter	X(38)	
Standard Dev. Dwell	Hor. Sit. Ind.	X(39)	
Standard Dev. Dwell	Rate of Climb	X(40)	
Transitions within the Flight Director			
Roll Ind.	Roll Ind.	X(41)	
Speed Bug	Roll Ind.	X(42)	not used
Cmmd. Bars	Roll Ind.	X(43)	

Glide Slope	Roll Ind.	X(44)	not used
Localizer	Roll Ind.	X(45)	not used
Roll Ind.	Cell 3	X(46)	
Speed Bug	Cell 3	X(47)	not used
Cmmd. Bars	Cell 3	X(48)	not used
Glide Slope	Cell 3	X(49)	
Localizer	Cell 3	X(50)	not used
Roll Ind.	Speed Bug	X(51)	not used
Speed Bug	Speed Bug	X(52)	
Cmmd. Bars	Speed Bug	X(53)	
Glide Slope	Speed Bug	X(54)	not used
Localizer	Speed Bug	X(55)	
Roll Ind.	Cmmd. Bars	X(56)	
Speed Bug	Cmmd. Bars	X(57)	
Cmmd. Bars	Cmmd. Bars	X(58)	
Glide Slope	Cmmd. Bars	X(59)	
Localizer	Cmmd. Bars	X(60)	
Roll Ind.	Glide Slope	X(61)	not used
Speed Bug	Glide Slope	X(62)	not used
Cmmd. Bars	Glide Slope	X(63)	
Glide Slope	Glide Slope	X(64)	
Localizer	Glide Slope	X(65)	
Roll Ind.	Cell 7	X(66)	not used
Speed Bug	Cell 7	X(67)	
Cmmd. Bars	Cell 7	X(68)	
Glide Slope	Cell 7	X(69)	not used
Localizer	Cell 7	X(70)	

Roll Ind.	Localizer	X(71)	not used
Speed Bug	Localizer	X(72)	not used
Cmmd. Bars	Localizer	X(73)	
Glide Slope	Localizer	X(74)	
Localizer	Localizer	X(75)	
Roll Ind.	Cell 9	X(76)	not used
Speed Bug	Cell 9	X(77)	not used
Cmmd. Bars	Cell 9	X(78)	
Glide Slope	Cell 9	X(79)	
Localizer	Cell 9	X(80)	
Mean Dwell	Roll Ind.	X(81)	
Mean Dwell	Speed Bug	X(82)	
Mean Dwell	Cmmd. Bars	X(83)	
Mean Dwell	Glide Slope	X(84)	
Mean Dwell	Localizer	X(85)	
S.D. Dwell	Roll Ind.	X(86)	
S.D. Dwell	Speed Bug	X(87)	
S.D. Dwell	Cmmd. Bars	X(88)	
S.D. Dwell	Glide Slope	X(89)	
S.D. Dwell	Localizer	X(90)	
Altitude		X(91)	
Distance from Threshold		X(92)	not used
Distance from Centerline		X(93)	
Glide Slope Error		X(94)	
Localizer Error		X(95)	
Airspeed		X(96)	

Appendix B

Complete (rotated) factor loading table. Loadings represent the correlation between the variables and the component. Like any other correlation coefficient, the loading can be squared to determine the per cent of variance accounted for by a variable in a component. For example, X(6) shows a loading on Factor 2 of .939 which when squared yields .88. This means 88% of the Factor 2 variance can be accounted for by X(6). Note, however, that Factor 2 itself only accounts for 6.5% of the total variance.

ROTATED FACTOR LOADINGS (PATTERN)

		FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5	FACTOR 6	FACTOR 7	FACTOR 8	FACTOR 9	FACTOR 10
X (6)	6	0.139	0.939	0.038	-0.019	-0.038	-0.064	0.003	-0.022	-0.049	0.108
X (7)	7	0.033	0.913	0.049	0.091	-0.039	-0.108	-0.054	-0.044	-0.076	0.043
X (9)	9	-0.004	0.110	-0.037	-0.035	0.108	0.204	0.107	-0.042	0.043	0.033
X (10)	10	0.100	0.201	0.076	-0.011	0.041	-0.020	-0.059	0.028	-0.017	0.069
X (11)	11	0.034	0.919	0.048	0.089	-0.045	-0.096	-0.054	-0.048	-0.069	0.053
X (12)	12	-0.163	-0.020	0.147	0.075	-0.016	-0.298	0.544	-0.150	0.173	-0.034
X (13)	13	-0.095	-0.002	-0.021	0.778	0.003	-0.127	-0.111	-0.094	-0.182	0.362
X (14)	14	-0.026	-0.180	-0.030	0.479	0.084	0.655	-0.247	0.065	0.058	-0.152
X (15)	15	0.861	0.062	0.195	-0.065	0.055	-0.146	-0.060	-0.067	-0.041	0.018
X (17)	17	-0.111	-0.015	-0.032	0.793	-0.011	-0.121	-0.104	-0.082	-0.177	0.333
X (18)	18	0.041	0.098	0.129	0.096	0.049	-0.058	-0.078	-0.025	-0.080	0.872
X (19)	19	-0.027	-0.056	-0.034	-0.060	-0.027	0.016	-0.107	-0.034	-0.034	0.116
X (20)	20	0.218	0.118	0.078	-0.005	0.083	0.016	-0.075	-0.027	-0.083	0.333
X (22)	22	-0.069	-0.167	-0.013	0.487	0.081	0.667	-0.238	0.065	0.043	-0.149
X (23)	23	-0.015	0.003	-0.016	-0.016	0.009	0.069	-0.058	-0.006	-0.023	0.087
X (24)	24	-0.077	-0.090	-0.014	-0.057	0.093	0.848	-0.149	-0.006	0.073	-0.031
X (25)	25	0.220	-0.065	-0.159	0.013	-0.032	0.064	-0.180	0.035	0.016	-0.093
X (27)	27	0.891	0.064	0.173	-0.086	0.062	-0.130	-0.076	-0.076	-0.009	0.049
X (28)	28	0.235	0.018	-0.045	-0.004	-0.024	0.032	-0.057	0.079	-0.089	0.330
X (29)	29	0.078	-0.020	-0.109	0.384	-0.021	0.064	-0.183	0.042	-0.075	-0.092
X (30)	30	0.895	0.163	0.118	-0.081	0.044	-0.075	-0.047	-0.052	-0.055	0.095
X (31)	31	0.142	0.848	0.012	-0.052	-0.046	-0.024	0.083	-0.030	0.059	0.140
X (32)	32	-0.219	-0.082	0.045	-0.124	-0.068	-0.243	0.773	-0.016	0.025	-0.090
X (33)	33	0.039	0.207	0.185	-0.041	-0.005	0.017	-0.010	-0.001	0.047	0.738
X (34)	34	-0.167	-0.032	0.176	-0.149	-0.039	0.799	-0.093	0.087	0.157	0.079
X (35)	35	0.784	0.171	0.140	-0.116	0.006	0.049	0.048	-0.055	-0.066	0.057
X (36)	36	0.173	0.868	-0.009	-0.023	-0.020	-0.034	0.036	-0.037	-0.025	0.098
X (37)	37	-0.206	-0.049	0.064	-0.117	-0.034	-0.252	0.699	0.071	0.094	-0.023
X (38)	38	0.113	0.127	0.109	0.031	-0.001	-0.008	-0.058	0.011	-0.030	0.787
X (39)	39	-0.035	-0.075	0.098	-0.125	0.010	0.854	-0.154	0.008	0.058	0.036
X (40)	40	0.828	0.123	0.119	-0.104	0.035	-0.028	-0.015	-0.036	-0.084	0.070
X (41)	41	-0.015	-0.023	0.031	-0.033	0.908	0.053	-0.061	-0.046	0.030	-0.003
X (43)	43	-0.077	-0.076	-0.039	0.016	0.869	0.040	-0.092	-0.117	-0.028	0.031
X (46)	46	0.035	0.019	0.007	-0.000	0.030	-0.027	-0.014	0.007	0.010	0.049
X (49)	49	-0.006	0.003	0.079	-0.013	0.015	-0.010	-0.016	-0.030	-0.026	-0.021
X (52)	52	-0.130	-0.100	-0.070	0.141	0.010	0.101	-0.048	-0.050	0.865	-0.068
X (53)	53	-0.100	0.102	-0.039	0.787	-0.037	-0.001	-0.110	-0.055	0.361	-0.150
X (55)	55	-0.015	-0.033	-0.023	0.008	-0.007	0.050	-0.029	0.050	0.014	-0.059
X (56)	56	-0.072	-0.074	-0.039	0.013	0.875	0.047	-0.094	-0.123	-0.032	0.028
X (57)	57	-0.101	0.101	-0.029	0.795	-0.037	0.003	-0.116	-0.068	0.337	-0.143
X (58)	58	0.055	0.146	-0.194	-0.016	-0.127	-0.025	0.542	-0.522	0.093	-0.026
X (59)	59	0.142	0.088	0.811	0.295	0.059	0.041	-0.131	-0.118	-0.032	0.109
X (60)	60	-0.103	-0.148	-0.267	0.215	-0.039	0.274	-0.320	0.286	-0.250	-0.032
X (63)	63	0.144	0.041	0.790	0.266	0.075	0.032	-0.153	-0.162	-0.067	0.164
X (64)	64	0.237	0.061	0.881	-0.109	0.048	-0.003	-0.087	-0.071	-0.139	0.132
X (65)	65	-0.021	-0.002	0.111	0.519	-0.074	0.100	0.116	0.135	0.019	-0.050
X (67)	67	-0.071	-0.026	-0.047	0.096	-0.012	0.071	-0.044	0.503	0.088	-0.044
X (68)	68	-0.080	0.011	-0.059	0.116	-0.026	-0.065	-0.052	0.076	-0.034	0.036
X (70)	70	-0.081	0.043	-0.048	0.044	-0.056	-0.001	-0.019	0.613	0.040	-0.071
X (73)	73	-0.091	-0.118	-0.261	0.216	-0.086	0.328	-0.281	0.305	-0.230	-0.058
X (74)	74	0.012	-0.024	0.084	-0.021	-0.100	-0.028	-0.074	0.132	0.017	0.105
X (75)	75	-0.139	-0.118	-0.205	-0.088	-0.141	0.012	-0.230	0.782	-0.179	0.031
X (78)	78	0.503	0.020	0.060	0.107	0.023	-0.010	-0.058	-0.081	0.031	-0.007
X (79)	79	0.304	-0.135	0.362	0.026	-0.068	0.184	-0.090	0.053	-0.233	0.241
X (80)	80	0.279	0.067	-0.044	-0.001	-0.103	-0.013	-0.068	0.505	-0.076	0.089
X (81)	81	0.235	-0.032	0.157	-0.045	0.715	-0.007	-0.062	-0.071	0.080	0.003
X (82)	82	-0.030	-0.026	-0.114	0.023	0.056	0.092	0.018	-0.100	0.899	-0.015
X (83)	83	0.130	0.036	-0.269	-0.055	-0.145	-0.056	0.690	-0.161	-0.139	-0.080
X (84)	84	0.158	0.005	0.823	-0.171	0.027	0.058	0.044	-0.059	-0.048	0.032
X (85)	85	-0.053	-0.076	-0.099	-0.079	-0.068	0.028	-0.076	0.767	-0.089	-0.008
X (86)	86	0.174	0.001	0.125	-0.045	0.785	-0.004	-0.044	-0.040	0.041	-0.012
X (87)	87	-0.042	-0.056	-0.091	0.045	0.006	0.082	0.027	-0.069	0.899	-0.020
X (88)	88	0.070	0.065	-0.275	-0.083	-0.155	-0.095	0.741	-0.170	-0.101	-0.060
X (89)	89	0.121	0.011	0.857	-0.148	0.033	0.050	0.008	-0.059	-0.031	0.043
X (90)	90	-0.126	-0.059	-0.100	-0.106	-0.181	0.092	0.091	0.647	-0.105	0.077
X (91)	91	-0.320	0.060	0.020	-0.121	0.164	-0.050	-0.031	-0.047	-0.147	-0.237
X (93)	93	0.004	-0.066	-0.034	0.015	0.171	0.054	-0.029	-0.037	0.040	0.049
X (94)	94	0.051	-0.002	-0.103	-0.006	-0.083	0.026	-0.037	-0.057	-0.006	-0.078
X (95)	95	0.044	-0.053	-0.022	0.010	0.124	0.045	-0.020	-0.025	0.054	0.014
X (96)	96	-0.008	0.040	-0.148	0.031	0.090	0.046	-0.159	0.000	0.179	-0.089

		FACTOR 11	FACTOR 12	FACTOR 13	FACTOR 14	FACTOR 15	FACTOR 16	FACTOR 17	FACTOR 18		
X(6)	6	-0.002	-0.018	0.001	-0.002	-0.009	-0.010	0.001	0.071		
X(7)	7	-0.016	-0.009	-0.037	0.013	0.020	-0.021	-0.013	-0.029		
X(9)	9	0.614	-0.070	-0.168	-0.174	0.058	0.209	0.011	0.055		
X(10)	10	-0.020	-0.022	0.043	0.045	-0.004	-0.149	-0.030	0.598		
X(11)	11	-0.002	-0.014	-0.044	0.005	0.024	-0.020	-0.007	0.013		
X(12)	12	-0.457	-0.027	-0.318	-0.052	0.076	0.114	-0.024	0.102		
X(13)	13	0.039	0.084	-0.164	0.060	0.054	0.020	-0.002	0.011		
X(14)	14	-0.098	0.009	0.155	-0.080	0.046	0.064	0.019	0.011		
X(15)	15	-0.064	-0.001	-0.036	0.017	-0.017	-0.032	-0.012	0.026		
X(17)	17	0.038	0.078	-0.164	0.058	0.057	-0.015	0.002	0.072		
X(18)	18	-0.033	0.122	0.029	0.007	-0.007	0.027	0.006	-0.044		
X(19)	19	0.121	0.059	0.692	0.109	-0.010	-0.032	-0.021	-0.140		
X(20)	20	-0.031	-0.048	0.124	-0.045	-0.030	0.117	-0.010	-0.445		
X(22)	22	-0.113	0.006	0.139	-0.087	0.012	0.075	0.024	-0.017		
X(23)	23	0.029	-0.027	0.738	-0.084	0.050	-0.004	-0.018	0.089		
X(24)	24	0.272	0.022	0.063	0.005	0.013	0.021	-0.002	-0.019		
X(25)	25	0.758	0.072	0.153	0.087	-0.049	-0.082	-0.014	0.026		
X(27)	27	-0.028	0.009	-0.023	0.023	-0.017	0.012	-0.020	0.029		
X(28)	28	0.032	-0.028	0.139	0.074	-0.042	-0.227	0.045	-0.288		
X(29)	29	0.788	0.032	0.160	0.031	-0.059	-0.086	-0.015	-0.046		
X(30)	30	0.119	0.004	0.004	0.001	-0.028	-0.018	-0.006	-0.046		
X(31)	31	0.013	-0.040	-0.014	-0.063	-0.043	0.015	0.022	0.050		
X(32)	32	-0.024	-0.031	-0.002	0.056	-0.043	-0.003	-0.019	0.013		
X(33)	33	-0.059	-0.044	0.147	-0.041	-0.059	0.029	-0.012	0.030		
X(34)	34	0.070	0.034	-0.035	0.047	-0.029	-0.003	-0.037	-0.006		
X(35)	35	0.079	-0.038	-0.003	0.017	-0.046	-0.050	0.037	-0.118		
X(36)	36	0.007	-0.035	0.018	-0.012	-0.024	-0.006	0.028	0.035		
X(37)	37	-0.024	-0.055	-0.012	0.085	-0.060	0.068	-0.012	0.085		
X(38)	38	-0.045	-0.011	0.023	0.048	0.013	0.066	0.031	0.002		
X(39)	39	0.095	0.046	-0.010	0.025	-0.018	-0.047	-0.035	-0.013		
X(40)	40	0.111	-0.001	0.011	0.038	-0.036	-0.027	0.046	-0.082		
X(41)	41	-0.059	0.149	-0.011	-0.002	-0.080	-0.035	0.011	-0.012		
X(43)	43	0.211	-0.046	-0.009	-0.049	0.116	-0.003	0.004	-0.014		
X(46)	46	-0.005	-0.007	-0.039	0.004	-0.005	-0.044	0.815	0.021		
X(49)	49	-0.006	-0.014	0.008	0.003	-0.002	0.016	0.805	-0.047		
X(52)	52	0.008	0.011	-0.022	-0.058	0.001	-0.065	-0.008	-0.059		
X(53)	53	-0.014	-0.037	-0.031	-0.035	0.088	-0.069	-0.032	-0.074		
X(55)	55	-0.022	0.012	0.031	0.051	0.745	0.062	0.005	-0.002		
X(56)	56	0.212	-0.032	-0.005	-0.058	0.077	0.004	0.011	-0.008		
X(57)	57	0.004	-0.046	-0.037	-0.021	0.122	-0.058	-0.037	-0.065		
X(58)	58	-0.269	0.019	-0.236	-0.061	0.068	0.036	-0.020	0.106		
X(59)	59	-0.042	-0.001	0.038	0.010	-0.057	0.022	0.044	0.008		
X(60)	60	0.093	-0.043	0.280	-0.157	0.108	0.403	0.012	0.199		
X(63)	63	-0.077	0.007	-0.015	0.031	-0.041	-0.044	0.025	0.020		
X(64)	64	-0.042	-0.045	0.008	0.011	-0.021	-0.026	0.045	0.005		
X(65)	65	0.058	-0.051	0.271	-0.045	-0.083	0.139	0.036	0.079		
X(67)	67	-0.059	-0.005	0.038	-0.184	0.308	-0.234	-0.008	-0.038		
X(68)	68	-0.024	-0.036	-0.003	-0.058	0.766	-0.003	-0.012	0.021		
X(70)	70	0.055	0.004	-0.030	0.016	0.234	0.081	0.009	-0.010		
X(73)	73	0.078	-0.059	0.252	-0.152	0.088	0.447	0.030	0.178		
X(74)	74	-0.040	-0.028	-0.039	0.120	0.037	0.628	-0.044	-0.263		
X(75)	75	0.060	-0.035	0.136	0.028	-0.059	0.153	-0.007	-0.004		
X(78)	78	0.086	0.112	-0.012	0.044	-0.030	0.175	0.002	0.253		
X(79)	79	-0.052	-0.160	-0.092	-0.075	0.025	-0.059	-0.053	0.103		
X(80)	80	-0.047	0.023	-0.102	0.028	0.049	0.421	0.008	-0.157		
X(81)	81	-0.157	0.199	-0.002	-0.031	-0.085	-0.070	0.027	0.031		
X(82)	82	-0.023	0.069	-0.031	-0.050	-0.012	0.011	-0.011	0.053		
X(83)	83	-0.085	0.008	-0.048	0.011	-0.036	-0.159	-0.001	-0.115		
X(84)	84	-0.076	-0.003	-0.053	0.001	-0.029	0.045	0.022	-0.002		
X(85)	85	0.032	-0.033	-0.032	-0.020	-0.088	-0.091	-0.029	0.026		
X(86)	86	-0.162	0.116	-0.003	-0.014	-0.082	-0.048	0.015	0.025		
X(87)	87	-0.032	0.004	-0.027	-0.044	-0.002	0.009	-0.001	0.059		
X(88)	88	-0.067	0.007	-0.064	0.015	-0.044	-0.134	-0.002	-0.076		
X(89)	89	-0.075	0.006	-0.018	-0.005	-0.005	0.023	0.013	0.011		
X(90)	90	-0.113	-0.036	-0.093	-0.001	-0.047	0.268	-0.013	0.141		
X(91)	91	-0.062	0.315	-0.114	-0.394	-0.110	-0.048	0.020	-0.177		
X(93)	93	0.016	0.948	0.006	-0.024	-0.014	-0.014	-0.016	0.013		
X(94)	94	-0.014	0.007	0.017	0.779	-0.005	-0.037	0.067	0.066		
X(95)	95	0.029	0.947	0.025	-0.034	-0.000	-0.012	-0.013	0.015		
X(96)	96	0.007	0.046	0.037	-0.709	0.032	-0.112	0.067	0.057		
	VP	4.978	4.526	4.444	3.815	3.808	3.650	3.463	3.278	3.191	2.857
		2.274	2.100	1.726	1.517	1.474	1.434	1.355	1.095		

THE VP FOR EACH FACTOR IS THE SUM OF THE SQUARES OF THE ELEMENTS OF THE COLUMN OF THE FACTOR PATTERN MATRIX CORRESPONDING TO THAT FACTOR. WHEN THE ROTATION IS ORTHOGONAL, THE VP IS THE VARIANCE EXPLAINED BY THE FACTOR.

Appendix C

P1						P2						P3						P4						
C1	C2	C3	C4	C5	C6	C1	C2	C3	C4	C5	C6	C1	C2	C3	C4	C5	C6	C1	C2	C3	C4	C5	C6	
36.	4.	0.	0.	0.	0.	1.	0.	0.	2.	0.	1.	0.	1.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	45.
3.	36.	0.	2.	0.	2.	0.	1.	0.	0.	0.	2.	0.	3.	0.	0.	0.	0.	0.	0.	0.	0.	1.	0.	50.
0.	0.	40.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	2.	1.	1.	0.	0.	0.	0.	1.	0.	0.	0.	45.
0.	2.	0.	33.	0.	2.	1.	3.	0.	0.	0.	0.	0.	0.	0.	1.	0.	0.	0.	0.	0.	2.	0.	6.	50.
0.	0.	0.	0.	17.	10.	0.	0.	0.	1.	1.	0.	0.	0.	0.	0.	4.	0.	0.	0.	8.	0.	4.	0.	45.
0.	1.	0.	12.	1.	35.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	1.	0.	0.	50.
0.	1.	0.	0.	0.	0.	44.	0.	0.	0.	0.	2.	0.	0.	0.	0.	0.	0.	3.	0.	0.	0.	0.	0.	50.
0.	2.	0.	3.	0.	0.	0.	27.	0.	1.	0.	0.	0.	0.	0.	0.	0.	0.	0.	1.	0.	0.	0.	1.	35.
0.	0.	0.	0.	0.	0.	0.	0.	12.	2.	9.	3.	0.	0.	0.	0.	0.	0.	0.	0.	0.	3.	0.	1.	30.
0.	0.	0.	5.	0.	0.	2.	1.	4.	14.	5.	7.	0.	0.	0.	0.	0.	0.	1.	0.	0.	1.	0.	5.	45.
0.	0.	0.	1.	0.	0.	0.	0.	3.	2.	30.	10.	0.	0.	0.	0.	0.	0.	0.	0.	0.	2.	0.	2.	50.
0.	0.	0.	0.	0.	0.	0.	2.	0.	5.	6.	24.	0.	0.	0.	0.	0.	0.	0.	1.	0.	5.	0.	2.	45.
0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	41.	0.	0.	0.	0.	1.	3.	0.	0.	0.	0.	0.	45.
0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	1.	48.	1.	5.	1.	0.	4.	0.	0.	0.	0.	0.	60.
0.	0.	3.	0.	0.	0.	0.	0.	0.	0.	0.	2.	0.	2.	4.	1.	5.	3.	0.	0.	0.	0.	0.	0.	20.
0.	0.	0.	1.	0.	0.	0.	0.	0.	0.	0.	1.	0.	9.	2.	28.	4.	0.	0.	0.	0.	0.	0.	0.	45.
0.	0.	4.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	1.	3.	4.	33.	0.	0.	0.	0.	0.	0.	0.	45.
0.	0.	0.	0.	0.	0.	0.	0.	1.	0.	0.	2.	0.	0.	0.	0.	0.	36.	0.	1.	0.	0.	0.	0.	40.
0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	1.	0.	0.	0.	0.	24.	0.	0.	0.	0.	0.	25.
0.	0.	2.	0.	0.	0.	0.	2.	0.	0.	0.	2.	0.	0.	0.	0.	0.	0.	1.	43.	5.	5.	0.	15.	75.
0.	0.	1.	0.	3.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	32.	0.	9.	0.	45.
0.	0.	0.	1.	0.	0.	0.	2.	0.	0.	0.	1.	0.	0.	0.	0.	0.	0.	0.	7.	0.	17.	0.	2.	30.
0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	6.	1.	28.	0.	35.
0.	0.	0.	2.	0.	0.	1.	2.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	0.	2.	0.	1.	0.	12.	20.
39.	46.	50.	60.	21.	49.	49.	40.	20.	27.	51.	57.	42.	67.	11.	40.	47.	40.	36.	55.	52.	38.	42.	46.	1025.