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The Relationship Between Air Traffic Control Communication Events and Measures of Controller Taskload and Workload

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Abstract

A study was conducted to determine whether air traffic control (ATC) communication events (number and duration of controller/ pilot communications) would predict subjective estimates of controller workload as well as taskload measures based on aircraft and controller activities. Analyses were conducted that compared different regression models' predictions of subjective workload estimates made by 16 subject matter experts for 8 samples of air traffic activity. The predictors in the regression models were different combinations of five taskload principal components computed from routinely recorded ATC data and two measures of pilot/controller voice communications. A series of model comparisons was conducted to determine whether a "reduced" regression model containing fewer variables would predict the workload ratings as well as the full model containing all predictors. Several reduced models predicted ATWIT ratings as well as the full model, but a reduced model containing only the communications variables was not as effective. The results suggest that certain voice communications measures add nothing to the prediction of subjective workload, over and above that of taskload.

Introduction

It is necessary to develop valid and sensitive workload measures for en route air traffic control (ATC) to identify negative effects on controllers of using new forms of automation or new procedures (Wickens, Mavor, & McGee, 1997). ATC workload can be influenced by numbers and configurations of aircraft moving through a sector, activities a controller performs to control the aircraft, and the controller's reaction to the air traffic situation.

Measures of ATC workload are typically based on subjective ratings made by controllers either while controlling air traffic or just afterwards. One problem with obtaining workload ratings while controlling traffic is that they may be influenced by the effort required to generate and record them. On the other hand, workload ratings provided after the controller finishes controlling traffic may be unduly influenced by events that occurred early or late in the traffic sample (e.g., due to proactive or retroactive inhibition).

Objective workload (taskload) estimates are being developed that may be used in place of subjective workload ratings. Taskload estimates are computed from routinely recorded ATC data that describe both aircraft and controller activities (Buckley, DeBaryshe, Hitchner, & Kohn, 1983; Galushka, Frederick, Mogford, & Krois, 1995; Mills, Pfleiderer, and Manning, in review; Stager, Ho, & Garbutt, 2001).

It is preferable to use objective taskload measures rather than subjective workload ratings for several reasons. First, it is often easier to obtain routinely-recorded ATC data than to recruit air traffic controllers for research projects. Second, objective taskload measures are better than subjective ratings because they are not influenced by rater errors, such as leniency/severity errors or errors of central tendency (Landry, 1989). Third, computing objective measures from recorded data does not interfere with controllers' activities (thus, will not affect their perceived workload).

Although using objective measures has certain benefits, the argument has been made that they do not sufficiently represent ATC workload because they cannot capture a controller's personal reaction to the air traffic situation (Stein, 1998). Stein contends that individual reactions that cannot be measured influence a controllers' perception of the effects of a particular taskload. However, other research has found significant correlations between objective taskload and subjective workload measures

(Stein, 1985; Manning, Mills, Fox, Pfleiderer, & Mogilka, 2001), suggesting that taskload measures may provide sufficient information to allow evaluation of the effects of new systems.

Communications between pilots and controllers and between controllers and other controllers are also recorded routinely and may be appropriate to include in a set of objective taskload measures. These include counts of the numbers and timing of the events, and their content.

Pilot-controller communications are thought to be related to ATC workload because complicated communications can increase workload (Morrow & Rodvold, 1998). Bruce (1993) found that traffic volume and complexity (both frequently-used indicators of ATC taskload) were significantly related to the number of pilot/controller communications. Cardosi (1993) used numbers of communications per hour to classify time periods as high- or low-workload.

Corker, Gore, Fleming, & Lane (2000) used communication time as an indicator of workload against which to assess alternative free flight conditions. Porterfield (1997) found a correlation of $r = .88$ between the amount of time spent communicating and on-line workload ratings, and concluded that communication duration time is a valid measure of workload.

Communication events may also be considered an indicator of workload because affective components could reflect the amount of effort the controller experienced at the time the event occurred. Thus, these measures may contribute some of the subjective component of workload that Stein (1998) argued is not accounted for by other taskload measures and may do so without interfering with the controller's task.

On the other hand, communications measures have some disadvantages. First, determining the number and duration of communication events requires a considerable amount of time and labor, and coding their content and affect requires even more effort (and introduces a subjective component). Thus, it may only be appropriate to include communication events in a set of taskload measures if they add significantly to the prediction of subjective workload. Second, recorded communication events do not account for all communication activity because some exchanges (e.g., radar (R) controller to data (D) controller) are not recorded. Thus, recorded communications may provide, at best, a lower-bound estimate for subjective workload.

The purpose of this study was to examine the relationship between communication events, subjective workload, and objective taskload measures. We proposed several hypotheses about the relationships between these measures. First, we expected that the total number and duration of communication events would be significantly related to busyness—as measured by both subjective workload and objective taskload. As the traffic situation gets busier, more communication events should occur, and more time should be spent communicating. Second, we expected that the average time for an individual communication event should be negatively related to both workload and taskload. As the situation gets busier, the amount of time a controller spends on a single communication should decline. Third, we expected that communication events would not contribute uniquely to the prediction of subjective workload, over and above the contribution of taskload measures. Thus, we expected that taskload measures alone would account for most of the variance in a set of subjective workload ratings and this prediction would not improve by adding communications measures to the set of predictors.

If communications measures do indeed add a unique component to the prediction of subjective workload, then it would be worth taking the time to analyze the transmissions. On the other hand, if they do not add a unique component to the prediction of subjective workload, it will not be necessary to analyze them.

Method

This study examined statistical relationships between communication events, objective taskload measures, and subjective workload measures. While the content of controller communications may contribute to the prediction of subjective workload, in this study, only the numbers and timing of communication events (including all pilot-controller, and controller-controller communications) were analyzed. The communication events and taskload measures were obtained from samples of routinely-recorded air traffic control data. The subjective workload measures were provided by subject matter experts (SMEs) who observed graphical displays and listened to voice communications of the same ATC data samples (hereafter called "traffic samples") and rated the workload they thought was experienced by the R controller responsible for the sector. Each component of the study is discussed in more detail below.

Traffic Samples

System Analysis Report (SAR) data and voice communication tapes were obtained for eight traffic samples recorded in January, 1999, at four sectors in the Kansas City Air Route Traffic Control Center (ARTCC). The ATC data were extracted by the Data Analysis and Reduction Tool (DART; Federal Aviation Administration, 1993) and the National Track Analysis Program (NTAP; Federal Aviation Administration, 1991). The resulting files were processed both by the Systematic Air Traffic Operations Research Initiative (SATORI; Rodgers & Duke, 1993) and Performance and Objective Workload Evaluation Research (POWER; Mills, Pfleiderer, & Manning, in review) programs. SATORI synchronizes data extracted by the DART and NTAP programs with tapes containing the R controller's voice communications, using the time code common to both data sources, while POWER uses data from a subset of the DART files to compute taskload measures. Two 20-minute experimental traffic samples were re-created for each sector, resulting in a total of 8 traffic samples.

Participants

Participants were 16 en route ATC instructors from the FAA Academy in Oklahoma City, OK. All were formerly fully-certified at an en route center. Two participants controlled traffic at some of the Kansas City Center sectors included in the study, though none worked at all the sectors in the study.

Sector training materials

Computerized training sessions were provided that described each sector's characteristics and procedures. Participants examined sector maps and the sector binder (containing additional information). Flight plan information (derived from recorded flight strip messages) was also available for each aircraft controlled by the sector.

Subjective workload

Participants provided subjective workload ratings using the Air Traffic Workload Input Technique (ATWIT; Stein, 1985). The ATWIT measures mental workload in "real-time" by presenting auditory and visual cues that prompt a controller to press one of seven buttons within a specified amount of time to indicate the amount of mental workload experienced at that moment. In this study, instead of rating their own workload, participants entered ATWIT ratings to indicate the amount of mental workload they thought the R controller experienced in reaction to the taskload that occurred during the traffic sample.

Objective taskload measures

The objective taskload measures used in this study were derived from the POWER software (Mills, Pfleiderer, & Manning, in review). The POWER measures included numbers of controlled aircraft; handoffs made and accepted; altitude changes; controller data entries and data entry errors; variations in aircraft headings, speeds, and altitudes; and average time aircraft were under control. In all, 23 POWER measures were analyzed.

Procedure

Participants reviewed a description of the study, completed consent and biographical information forms, then reviewed instructions for making the ATWIT workload ratings. Then, for each sector, participants reviewed training materials, observed an 8-minute training traffic sample, and observed two 20-minute experimental traffic samples. To ensure continuity, all traffic samples for a sector were shown as a block. The order of the blocks of traffic samples was counter-balanced, as was the order of the experimental traffic samples within each block.

During each traffic sample, the ATWIT aural prompt occurred every four minutes, and participants responded by entering a number between 1 and 7 on a keypad. Completing the training process and observing the traffic samples for each sector required about 1½ hours.

Data processing

Communication events for each traffic sample were transcribed. The number of transmissions and the identity of the speaker (i.e., controller, pilot, other) were recorded, as well as start and stop times for each communication event. The total number of communications, total time spent communicating, and mean time for individual communication events were computed for each 4-minute period. The 23 POWER measures were computed for the 4-minute segments in each traffic sample, and ATWIT ratings were averaged across participants for each 4-minute segment.

Results

Descriptive statistics

Communication events. Overall, 999 communication events (on the average, about 125 per traffic sample) were recorded. On average, the total amount of time spent communicating during a traffic sample was 346 seconds (SD = 93.3), or about 29% of the 1200 seconds in each traffic sample. The average duration of each communication event was 2.77 seconds (SD = 2.56).

Table 1 shows inter-correlations of communication events computed during the 4-minute segments. Total communications were highly correlated with total time spent communicating. Total communications were also negatively correlated with mean time for each communication. However, total communication time was not significantly correlated with mean time for each communication. Because total communications and total communication time were so highly correlated, total communication time was eliminated from further analysis.

Subjective workload. The mean ATWIT rating, averaged across the 4-minute time periods, was 2.76 (SD = .59). This value is significantly lower than 4 ($t(39) = -13.2$, $p < .001$), the midpoint of the 7-point workload scale, suggesting that participants thought workload was generally low during the traffic samples.

Table 1. *Inter-correlations of communication events.*

	Total N	Total time	Mean time
Total number of communications	1.0		
Total communication time	.83**	1.0	
Mean time for single communication event	-.35*	.19	1.0

** Correlation is significant at p <.01 level
* Correlation is significant at p <.05 level

Taskload. Table 2 shows descriptive statistics for the 23 POWER measures used in the study averaged across the 4-minute periods in each traffic sample. Some of the POWER measures (primarily certain kinds of data entries such as handoffs and altitude changes) occurred several times during the 4-minute periods. However, many other data entries (e.g., pointouts, data block offsets, Distance Reference Indicators [DRIs, also known as J-rings], track reroutes) and conflict alerts (both displayed and suppressed) occurred very infrequently. In fact, many of the variables occurred in fewer than 30% of the time segments, producing near-zero means and corresponding standard deviations that were greater than the means. Subsequent analyses excluded these infrequent variables.

A Principal Components Analysis was conducted to identify a smaller set of variables that would describe the relationships between the POWER measures more concisely while reducing their number. The results of this analysis should be interpreted with some caution because only 4-minute time segments were analyzed, and only 40 observations from 4 sectors were available. Subsequent analyses using larger data sets and longer time samples should be conducted to obtain more stable results. However, the primary purpose of conducting this analysis was to reduce the number of variables included in later analyses.

Table 2. *Descriptive Statistics for 23 POWER measures computed at 4-minute intervals.*

Power Measures	Descriptive Statistics Mean	*SD*
Total N aircraft controlled	7.20	2.73
Max aircraft controlled simultaneously	5.48	2.35
Average time aircraft under control	158.35	34.38
Avg Heading variation	1.06	0.86
Avg Speed variation	4.22	2.46
Avg Altitude variation	2.00	1.48
Total N altitude changes	3.50	2.20
Total N handoffs accepted	1.15	1.12
Avg time to accept handoff	25.91	27.58
Total N handoffs initiated	1.98	1.29
Avg time until initiated HOs are accepted	41.00	45.45
N Radar controller data entries	11.35	5.54
N Radar controller data entry errors	0.23	0.58
N Data controller data entries	1.93	2.04
N Data controller data entry errors	0.08	0.27
N Route displays	0.40	0.84
N Radar controller pointouts	0.08	0.27
N Data controller pointouts	0.08	0.47
N data block offsets	0.15	0.43
Total N CAs displayed	0.08	0.27
Number of CA suppression entries	0.05	0.22
N DRIs requested	0.05	0.22
N DRIs deleted	0.03	0.16

Table 3 contains the rotated component matrix for 5 components, transformed using the Varimax rotation method. The entries in the table are correlations between each POWER measure and the 5 components derived from the analysis. For ease of interpretation, correlations less than .3 were not displayed.

Component 1 was primarily related to numbers of aircraft controlled and controlled simultaneously, handoffs accepted, and R-controller data entries. To a lesser extent, the component was also related to the number of handoffs initiated, times to accept handoffs, and duration aircraft were controlled. This component was labeled "Activity" because the values of these measures were associated with more aircraft and controller activity.

Component 2 was related to variations in heading, speed, and altitude, and number of altitude changes. To a lesser extent, the component was also related to control duration. Component 2 was labeled "Arrivals" because variability in these measures was consistent with aircraft arriving at the St. Louis Lambert Airport.

Component 3 was primarily related to time to accept initiated handoffs and R-controller data entry errors. To a lesser extent, the component was related to numbers of handoffs initiated and was negatively related to D-side entries and Route Display entries. These conditions were consistent with busy R-controllers working alone and making more data entry errors. Thus, Component 3 was called "Overload."

Component 4 was primarily related to numbers of Route Display entries, handoffs initiated, and R-controller data entries, and was negatively related to control duration. These conditions were associated with activities involved in handling departing aircraft. Thus, Component 4 was called "Departures."

Component 5 was primarily related to the number of data block offsets and D-side data entries. To a lesser extent, the component was also negatively related to altitude variation. Thus, Component 5 was called "Overflights."

Table 3. *Rotated component matrix for 5 components representing reduced set of POWER measures.*

Power Measure	Comp 1: Activity	Comp 2: Arrivals	Comp 3: Overload	Comp 4: Departures	Comp 5: Overflights
Max aircraft controlled simultaneously	.93				
Total N aircraft controlled	.92				
Total N handoffs accepted	.74				
N Radar controller data entries	.69			.50	
Total N handoffs initiated	.52		.30	.61	
Avg time to accept handoff	.50				
Avg time aircraft under control	.44	.48		-.53	-.35
Avg Speed variation		.86			
Avg Heading variation		.81			
Total N altitude changes		.78			
Avg Altitude variation		.75			
Avg time until initiated HOs are accepted			.85		
N Radar controller data entry errors			.75		
N Data controller data entries			-.40		.72
N Route displays			-.37	.73	
N data block offsets					.83

*Correlations less than .3 are not displayed.

Prediction of mental workload

Table 4 shows correlations between the 5 taskload components, the two communication variables, and the ATWIT subjective workload rating. By definition, the orthogonally-rotated principal components are unrelated, so their inter-correlations are 0. The mean ATWIT rating had a correlation of .76 with Taskload Component 1 (Activity; $p < .01$), had a correlation of .47 with the total number of communications ($p < .01$), and had a correlation of .32 with mean communication time ($p < .05$). Other significant correlations were found between Mean communication time and Taskload Component 4 (Departures; $p < .05$), and between total number of communications and Taskload Component 1 (Activity, $p < .01$), Taskload Component 3 (Overload; $p < .01$), and Mean Communication time ($r = -.35$, $p < .05$).

Additional analyses assessed the effectiveness of alternative multiple regression models in predicting the subjective ATWIT ratings. Table 5 shows the results of these analyses. The first row shows the multiple correlation of the "full" regression model containing all taskload components and communication variables as predictors. The multiple correlation of the full model with the ATWIT dependent variable was $R = .85$, accounting for over 70% of the variance in the ATWIT ratings. Succeeding lines show multiple correlations between alternative "reduced" regression models containing fewer than the total number of predictors. The column containing F for the test of R^2 change compares the relative effectiveness of an alternative (reduced) model with the full model for predicting the ATWIT rating. If the probability is greater than .05 that the change in R^2 between the two models is significantly different from 0, then the reduced model is considered to be as effective as the full model. On the other hand, if the probability is less than or equal to .05 that the change in R^2 between the two models is significantly different from 0, then the reduced model is not considered to be as effective as the full model.

Table 4. *Correlations of subjective workload, taskload components, and communications measures.*

	ATWIT	Comp 1 - Activity	Comp 2 - Arrivals	Comp 3 - Overload	Comp 4 - Departures	Comp 5 - Overflights	Mean comm time	Total N comms
ATWIT	1.00							
Comp 1 - Activity	.76**	1.00						
Comp 2 - Arrivals	.24	.00	1.00					
Comp 3 - Overload	.12	.00	.00	1.00				
Comp 4 - Departures	.12	.00	.00	.00	1.00			
Comp 5 - Overflights	.02	.00	.00	.00	.00	1.00		
Mean comm time	.32*	.09	.25	-.11	.38*	.19	1.00	
Total N comms	.47**	.54**	-.09	.41**	-.14	-.10	-.35*	1.00

** Correlation is significant at the $p < .01$ level.
* Correlation is significant at the $p < .05$ level.

In the first comparison (Line 2), the reduced model containing only the taskload components had an R^2 of .66, compared with the full model's R^2 of .72. The F computed to assess the R^2 change of .06 had a value of .73, and the probability was .69 that the change in R^2 was greater than 0. Thus, the reduced model containing only the taskload components predicted ATWIT ratings as well as the full model. A second example is shown on line 3 of Table 5. The reduced model containing only the communication variables had an R^2 of .49, compared with the full model's R^2 of .72. The F computed to compare the R^2 change of .23 had a value of 2.08, and the probability was .05 that the change in R^2 was greater than 0. Thus, the reduced model containing only the communication variables did not predict the ATWIT ratings as well as the full model.

Table 5. *Results of analyses comparing alternative multiple regression models predicting ATWIT ratings.*

Regression model	R	R^2	R^2 change	F for test of R^2 change	df	p
1. Full model containing all taskload components and communication variables	0.85	0.72				
2. Model containing all taskload components	0.81	0.66	0.06	0.73	10, 32	0.691
3. Model containing communication measures	0.70	0.49	0.23	2.08	13, 32	0.046
4. Model containing only Component 1 (Activity)	0.76	0.58	0.14	1.22	14, 32	0.366
5. Model containing taskload Components 2, 3, 4, 5	0.29	0.08	0.64	6.75	11, 32	0.001
6. Model containing taskload components 2, 3, 4, 5, and communications measures	0.73	0.53	0.19	2.52	9.32	0.026

Reduced models containing all the taskload components, and those containing any combination of taskload components (as long as the Activity taskload component was included in the model) predicted ATWIT ratings as well as the full model. Reduced models that did not contain the Activity component (whether or not communications measures were included in the model) did not predict ATWIT ratings as well as the full model.

Discussion and Conclusions

We hypothesized that number of communications would be significantly related to both subjective workload and objective taskload. Examination of Table 4 showed that the total number of communication events significantly correlated with ATWIT ratings and was also significantly related to two of the taskload components.

We also predicted that the average time for an individual communication would be negatively related to both workload and taskload. While mean communication time was negatively related to the total number of communication events, it had both positive and significant correlations with ATWIT and the Departures component but was not significantly correlated with any of the rest of the taskload components.

We expected that communication events would not contribute uniquely to the prediction of subjective workload, over and above the contribution of the taskload components. As shown in Table 5, a reduced model containing only the taskload components predicted ATWIT ratings as well as the full model that contained both the communications measures and the taskload components. Furthermore, a reduced model containing only the communication variables did not predict ATWIT ratings as well as the full model.

An interesting finding from this analysis was that the Activity component must be present in any reduced regression model if it were to predict ATWIT ratings as well as the full model. This suggests that measures that increase as a function of the number of aircraft (such as handoffs, data entries, and pointouts) can affect the perception of workload.

If communications measures added uniquely to the prediction of subjective workload, then it would be worth taking the extra time needed to analyze the transmissions. On the other hand, these results suggest that variables derived from analysis of voice communications do not add a unique component to the prediction of subjective workload. Thus, it appears that it is not necessary to analyze them to successfully assess controller workload.

However, several factors should be considered when interpreting these results. First, numbers and duration of communications for controllers and pilots were combined. Analyzing transmissions separately for different speakers might result in differential prediction of subjective workload. Second, the selection of traffic samples and sectors was limited, which may reduce our ability to generalize these results to other sector types, traffic situations, and facilities. Third, SMEs rated others' subjective workload instead of their own. If those actually working the traffic had rated their own workload, the results may have differed. Fourth, we assumed that the ATWIT was the most appropriate method to describe subjective workload. If another workload procedure was used, such as the NASA TLX, the results might have been different.

Even if the numbers and timing of controller/pilot communications variables had been found to add to the prediction of subjective workload, this relationship can be expected to change in the near future. The use of Controller/Pilot Data Link Communications (CPDLC) will reduce the amount of voice communications. It has been proposed that using CPDLC will reduce controller workload, but more likely it will redistribute workload from an aural to a visual modality. Regardless of whether increasing the visual component of a controller's activity also increases their perceived subjective workload, the workload associated with the aural component of communications should be reduced significantly when most of the verbal communications are transferred to another modality.

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Scott Mills earned his Ph.D. in Experimental Psychology at the University of Oklahoma in 1995. From 1995 until 2000, he served as an Engineering Research Psychologist at the Federal Aviation Administration's Civil Aerospace Medical Institute, concentrating on human factors in air traffic control. Dr. Mills is currently a Senior Member of the Technical Staff in Human Factors at SBC Technology Resources, Inc.

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Elaine Pfleiderer is a graduate of the University of Central Oklahoma with a Masters degree in Experimental Psychology. Ms. Pfleiderer has spent the last six years as a research associate at the Civil Aerospace Medical Institute, working primarily on the development of objective measures of air traffic controller taskload using routinely-recorded National Airspace System (NAS) data.

Henry Mogilka is a Supervisory Air Traffic Control Instructor at the Federal Aviation Administration's (FAA) Training Academy in Oklahoma City, OK. He has worked for the FAA since 1983, starting as an Air Traffic Controller at the Albuquerque Air Route Traffic Control Center. He has a Bachelors of Individualized Studies degree from the University of Minnesota - Minneapolis, and a Juris Doctorate degree from the Oklahoma City University School of Law. He is licensed to practice law in the state of Oklahoma.