Determining Policy Communication Effectiveness: A Lexical Link Analysis Approach

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Abstract: Military policies are often promulgated from the echelon II and III level, but it is often difficult to ascertain whether they are interpreted and implemented as intended. There is often a communication gap. This article seeks to determine if data mining tools such as lexical link analysis can measure that gap in quantitative terms. It starts by examining how lexical link analysis can determine how policies are communicated through the various echelons, assessing whether lexical link analysis can be used to determine if policies are interpreted and redistributed as intended, and exploring what this data tells us about policy communication and the implications for policy execution. The author uses lexical link analysis to reveal if there is a degree of policy mismatch at lower echelon levels and makes assessments about this mismatch based on established communication theory. This paper validated that Naval aircrew's understanding of policies is of vital importance and higher policy tends to be interpreted and reissued with greater specificity as it moves down the chain of command as exemplified between Echelons IV and V.

1 INTRODUCTION (Dyer, 2020)

The U.S. Navy is separated into multiple levels of leadership and organization. Upper-level policies are written and expected to be executed down the chain-of-command. Policies promulgated by echelon II and III commands may not have the desired effect originally intended. Discovering this communication mismatch often can be difficult and commonly it is not discovered until thousands, if not millions, of dollars are spent and many manpower and training hours are wasted. To mitigate this, big data analytics may help inform the Navy's organizational communication and make it more effective.

This paper assessed attributes of the current sociotechnical system (STS), or the technical, social, organizational, and environmental aspects of a system, used to conduct F/A-18 flight training events. The researchers emphasized the importance of interactions between hardware, software, and people, and related processes to support the interactions. The previous researchers also acknowledged system capability needs, recommended subsequent technical and social requirements, and suggested improvements to the STS and the administering of training events (Holness and Wood, 2018).

Training effectiveness depends on the quality of the training devices provided, instruction, syllabi, feedback systems, and the supporting resources that make up the vast majority of the U.S. department of defense (DoD) funding. In order to improve military capability, we need to fully grasp the efficacy of current Fleet operational training. We intend to do this by examining the effectiveness of the communication that dictates the syllabi and resources that apply to the operator's training.

This research identifies gaps and successes of organizational communication within the Navy Air Systems Command (NAVAIR) and other high-level commands as they pertain to the promulgation and execution of organization policies that affect and inform training syllabi and resources. An analysis of this communication results in recommendations regarding mismatches and how these may be remedied. This paper utilized big data analysis tools, specifically Lexical Link Analysis (LLA), to determine how the syllabi and supporting resources accomplish underlying readiness objectives set forth at the echelon II and III levels. The research resulted in recommendations and follow-on research that explore the environmental and

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organizational aspects of flight training with the goal of implementing an improved design for F/A-18 flight training events.

2 BIG DATA AND CONTENT ANALYSIS

There has been a good deal of research conducted to link big data with organizational communication, but the bulk of that research has centered around leveraging big data to improve marketing and public relations efforts (Wiencierz and Röttger, 2017). In their suggestions for future research, Wiencierz and Röttger suggest that data analysis could enable management, or any communicator for that matter, to analyze issues and influence such issues strategically. This implies that data analysis could identify misinterpretation of communication. A more specialized field of data analysis, content analysis, allows the researcher to objectively, systematically, and quantitatively extract meaningful content from large volumes of text (Neuendorf, 2016). Prior to 1997 much of content analysis was conducted in the field of journalism and that analysis was done manually (Guo et al., 2016). Today, there are a number of automated tools available to accomplish such analysis (Slapin and Proksch, 2014; Guo et al., 2016). Lexical link analysis (LLA) is an unsupervised topic modeling method detail in Section 3.

NAVAIR provided a list of possible documents related to the F/A-18 Strike Fighter Advanced Readiness Program (SFARP). After a review, the researchers selected and compared the 17 primary policies and instructions governing SFARP to determine correlation.

3 LEXICAL LINK ANALYSIS (LLA)

We use LLA as an example of deep models (Zhao et al., 2015) (Quantum Intelligence, 2015). In an LLA, we describe the characteristics of a complex system using a list of attributes or features with specific vocabularies or lexical terms. For example, we can describe a system using word pairs or bi-grams as lexical terms extracted from text data.

Figure 1 shows an example of such a word network discovered from text data. "human learning" and "human interface" are two bi-gram word pairs. For a text document, words are represented as nodes and word pairs as the links between nodes. A word center (e.g., "human" in Figure 1) is formed around a word node connected with a list of other words to form more word pairs with the center word "human." In contrast to human-annotated word networks, such as WordNet (Miller, 1995), LLA automatically discovers word pairs, divides them into clusters and themes, and displays them as word networks.

LLA is related to but significantly different from the methods such as bag-of-words (BOW) methods, Automap (CASOS, 2009), Latent Dirichlet Allocation (LDA) (Blei et al., 2003), Latent Semantic Analysis (LSA) (Dumais et al., 1988), Probabilistic Latent Semantic Analysis (PLSA) (Hofmann, 1999) and can be jointly used with named entity extraction (NEE) (InXight, 1997; MUC-7, 1998), part of speech (POS) methods (Toutanova and Manning, 2000). LLA is related to unsupervised learning algorithms such as k-means, principal component analysis (PCA), and spectral clustering (Ng et al., 2002). LLA can be applied to both structured and unstructured data. Because it uses an improved community detection method to find clusters, it can find more interesting groups than the traditional spectral based methods such as PCA, LDA, and LSA. LLA can also compare matches and gaps easily among documents or repositories of documents, which is the focus of this paper.

We applied LLA in use cases to facilitate the discovery of high-value information in different application domains. LLA outputs smart data such as semantic and social networks (Zhao et al., 2012), patterns such as rules, associations (Zhao et al., 2016a), themes and topics (Zhao et al., 2017b). The themes and topics discovered by LLA are further divided into the popular or authoritative, emerging and anomalous information categories. Information users can use authoritative information to discover leadership and archetypes in a social network (Zhao et al., 2016b), use emerging information to discover high-value information from crowdsourcing (Zhao et al., 2017a),

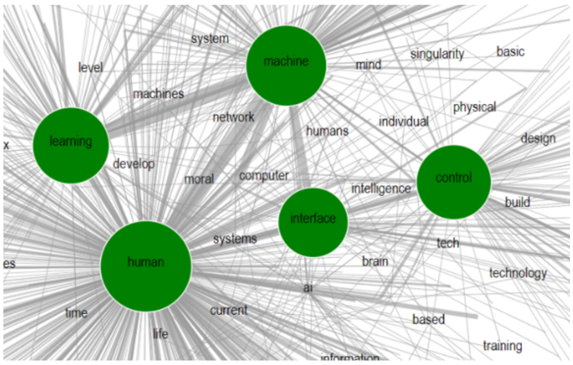

Figure 1: An example of lexical link analysis.

and use anomalous associations to identify fraudulent behavior and imposters (Zhao et al., 2016b).

The output of LLA includes a file of associations where word pairs (for unstructured data) or lexical features (for structured data) are linked together.

4 LLA RESULTS

4.1 Themes Discovered

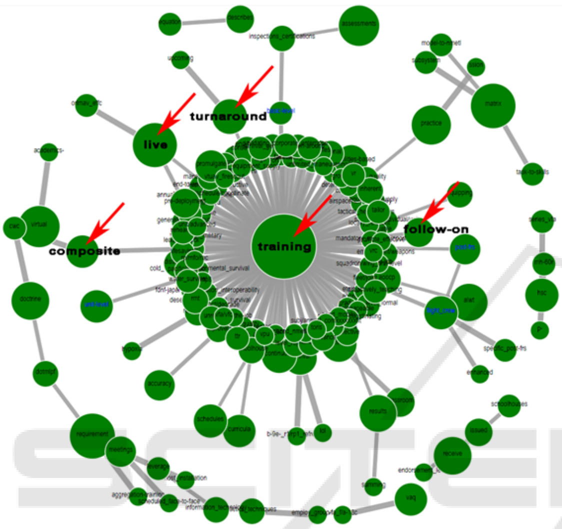

Figure 2: Theme 147 - Training Theme Word Cloud.

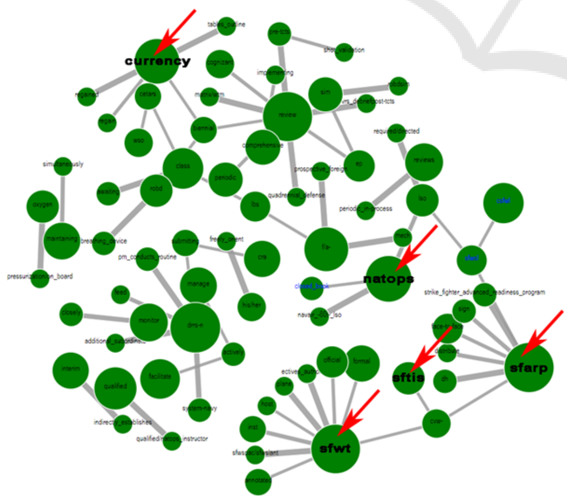

Figure 3: Theme 125 - SFARP Theme Word Cloud.

We observed correlation within the Word Cloud visualization from the LLA outputs. Figure 2, Figure 3, and Figure 4 display three of the key discovered themes found through LLA. The visualizations display a significant trend between the 17 instructions examined. Of particular note, Theme 147 in Figure 2, the training theme, displays that some of the most significant bi-grams found in this theme are live training, turnaround training, follow-on training, and composite training. This implies that significant emphasis was put on these themes throughout the 17 instructions. Furthermore, Theme 125 in Figure 3, the SFARP theme, reveals a trend between Strike Fighter Weapons and Tactics (SFWT), Strike Fighter Weapons and Tactics Instructors (SFTIs), Naval Air Training, Operating Procedures Standardization (NATOPS), and currency. Lastly, Figure 4 depicts Theme 1, the syllabus theme word cloud, revealing an emphasis on advanced, capable, near-peer threats throughout the training syllabi.

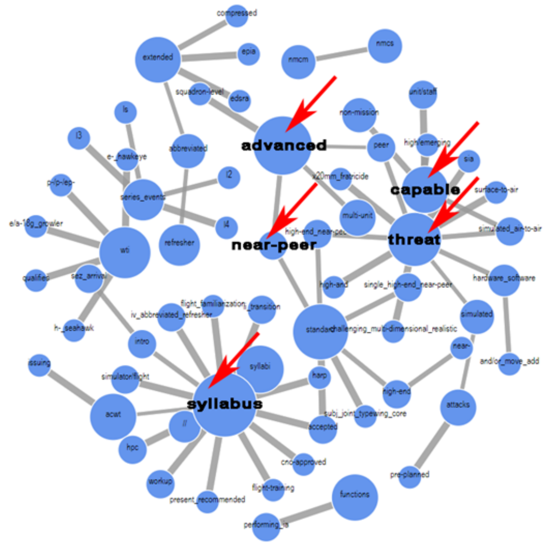

Figure 4: Theme 137 - Syllabus Theme Word Cloud.

Theme 147 in Figure 2, is perhaps the second most relevant theme of this study. The theme's keywords are "live training" and "training matrix." In this theme, 138 word pairs matched across the 17 documents and the consensus—percentage of words that matched between documents—was 17%. The highest consensus among all the themes was only 18%, i.e., Theme 113—readiness standards, conditions), indicating there is not exactly a high degree of homogeny across the 17 documents. As briefly mentioned above, authors expect this to an extent as higher echelons use more broad language to convey their intent while lower echelons interpret that intent and give their instructions using more specificity.

There is only 7% percent consensus for Theme 125 – SFARP. This is essential to the paper since the primary topic of the research is how these policies influence training, specifically SFARP. For this theme, CSFWPL 3710.14G, Joint Typewing Core Standard

Operating Procedures (SOP) scored the highest node match. Authors expected this high degree of node match since the publisher is at the echelon IV level which directly governs SFARP. CSFWPL 1525.1G, CNAL 5440.3, and SFWSPACINST 3500.3B scored the next highest on this theme. Again, this is generally expected because of their position in the chain of command.

Theme 137 in Figure 4, "syllabus," scores 10% which is relatively high compared to the highest consensus score. Naval Aviation Warfighting Development Center (NAWDC) had the highest node matches—actual word-for-word bi-gram matches between documents—on this theme (52) which is consistent considering it is the source of air combat training and tactics development, the primary source for training syllabi. COMNAVAIRLANT had the second highest node matches in this theme with a total of 47. Again, this is consistent with their mission to provide training to east coast squadrons.

4.2 Match Matrix

Figure 5 shows a match matrix view of the 17 documents. The numbers shown indicate a reference to the number of terms or word categories (i.e., themes) found among the documents. For example, in the first row of Figure 5, USFF_CPF_3501-3D matched across all documents for 725 themes out of 2510 themes (Uniqueness Score or total themes found in the document). Moving to the right across Figure 5, USFF_CPF_3501-3D has a match score with USFFC_300015A of 411 or about 16.4%.

4.3 Matches and Gaps between Echelons and Organization Relations

The instructions examined span across five echelons as depicted in Figure 6. Upon first inspection, one can glean from the Chord Diagrams from the LLA outputs that the instructions at the highest echelons have the greatest degree of symmetry. The further down the chain of command, the greater the divergence. For example, Figure 7 shows Commander U.S. Pacific Fleet (CPF)—an echelon II command—has a great deal of symmetry between itself and U.S. Fleet Forces Command (USFFC)—another echelon II command. The next highest degree of symmetry is between itself and Commander, Naval Air Forces Atlantic (CNAL)—an echelon III command. Further, Strike Fighter Weapons School Pacific (SFWSP) has the least degree of symmetry among all the instructions examined as seen in Figure 8.

Initially, Pearson's Correlation Coefficient (r) —the measure of linear relationship between two data sets—showed no or very weak correlation between the data sets. However, when compared between Match Score and Uniqueness Score or, algebraically in Figure 10, where x equals the Match Score and y equals the Uniqueness Score, the analyst notes a very strong correlation between Echelon I instructions and a progressively weaker correlation as the analyst moves down the echelons Figure 11 and this is consistent with previous research results (Frey, 2018).

The correlations and the Chord Diagrams visually reveal a strong linear relationship at higher echelons. This could be attributed to a higher degree of understanding at higher echelons. More likely, however, the lower r below Echelon III is due to a higher degree of specificity at lower echelons. In other words, higher echelons may be more correlated because they use broad, overarching language to relay their intent; while lower echelons interpret that intent and specifically state through their instructions how they are going to achieve the intent of their parent commands.

4.4 Match Matrix of Echelons

Figure 9 depicts the Match Matrix for the 17 instructions analyzed organized by echelon. The cells in yellow represent bi-gram matches between echelons one step apart. Those in pink represent bi-gram matches between echelons two steps apart. Those in green represent bi-gram matches between echelons three steps apart, whereas orange represents bi-gram matches between echelons four steps apart. The cells in grey represent bi-gram matches at the same echelon and will be disregarded as they generally do not issue direction to themselves or commands at the same echelon level. From this matrix, the researcher notes the highest degree of match at echelons one step apart (i.e., echelon II bi-grams have a higher degree of match with echelon I, echelon III have a higher degree of match with echelon II, etc.). This indicates that commands take the instructions from their parent commands and promulgate further guidance predominately based on those instructions and with a lesser regard to instructions two or three steps above them. Table 7 further accentuates this. Here, the researcher averaged each instruction's matches for each subordinate echelon and then averaged those averages (e.g., OPNAV 3500.31G has an average of 39.5 matches from echelon II instructions, USFFC 3000.15A has an average of 51.83 matches from echelon III instructions, and so on). The bold cells are the average of these numbers to account for each echelon's subordinate averages.

		Match Score	USFF_CPF_3501-3D	USFFC_3000-15A	CNAL_3502-1	CNAF_3500-38A	NAVANWARDEVCEN_3500-3J	CSFWP_3500-3A	CNAF_1500-12	CNAP_5450-42	OPNAV_3500-31G	CSFWPL_3500-7E	CSFWPL_3710_14G	CNAL_5440-3	OPNAVINST_3501-360A	OPNAVINST_3000-15A	CSFWPL_1525-1G	CNAL_3500-1	SFWSPACINST_3500-3B	Uniqueness Score
1	USFF_CPF_3501-3D	725	_	411	137	107	87	77	53	83	40	71	36	57	62	73	23	25	4	2510
2	USFFC_3000-15A	619	411	_	79	78	62	52	26	64	39	41	28	48	60	108	17	16	5	1792
3	CNAL_3502-1	414	137	79	_	124	77	61	56	60	45	102	38	39	23	15	35	49	10	925
4	CNAF_3500-38A	301	107	78	124	_	35	35	22	29	27	54	16	29	59	17	12	13	8	1174
5	NAVANWARDEVCEN _3500-3J	276	87	62	77	35	_	50	40	52	32	43	62	31	9	15	53	25	31	1466
6	CSFWP_3500-3A	257	77	52	61	35	50	_	56	37	33	33	42	62	11	10	29	21	13	1193
7	CNAF_1500-12	226	53	26	56	22	40	56	_	24	85	27	34	21	10	3	21	20	4	973
8	CNAP_5450-42	220	83	64	60	29	52	37	24	_	18	22	32	52	12	12	16	34	8	545
9	OPNAV_3500-31G	218	40	39	45	27	32	33	85	18	_	16	30	15	12	8	26	15	6	1569
10	CSFWPL_3500-7E	206	71	41	102	54	43	33	27	22	16	_	27	21	13	10	25	17	12	362
11	CSFWPL_3710_14G	200	36	28	38	16	62	42	34	32	30	27	_	38	6	2	36	8	10	2590
12	CNAL_5440-3	197	57	48	39	29	31	62	21	52	15	21	38	_	15	5	17	16	8	791
13	OPNAVINST_3501-360A	149	62	60	23	59	9	11	10	12	12	13	6	15	_	12	3	4	1	301
14	OPNAVINST_3000-15A	146	73	108	15	17	15	10	3	12	8	10	2	5	12	_	2	2	1	178
15	CSFWPL_1525-1G	133	23	17	35	12	53	29	21	16	26	25	36	17	3	2	_	21	8	506
16	CNAL_3500-1	105	25	16	49	13	25	21	20	34	15	17	8	16	4	2	21	_	6	329
17	SFWSPACINST_3500-3B	48	4	5	10	8	31	13	4	8	6	12	10	8	1	1	8	6	_	173

Figure 5: Match Matrix.

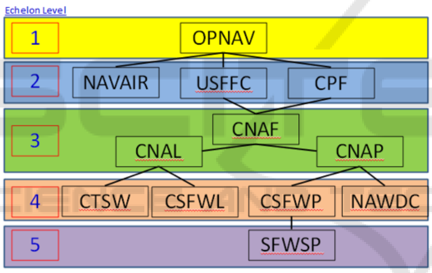

Figure 6: Echelon Level of Document Authors.

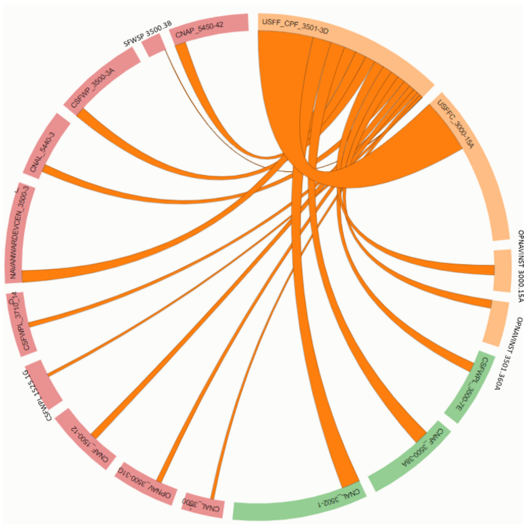

Figure 7: USFF-CPF 3501-D Chord Diagram Relation.

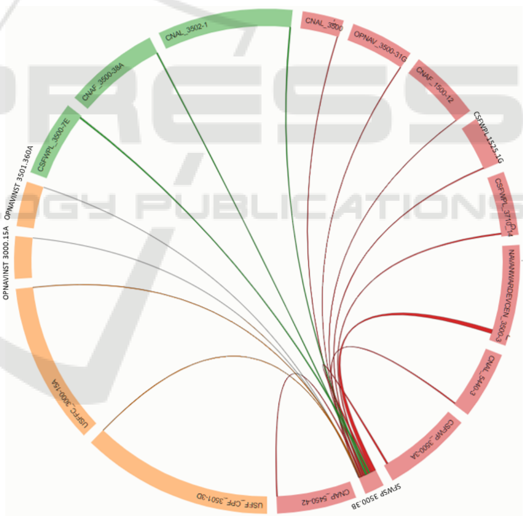

Figure 8: SFWSP Chord Diagram Relation.

5 CONCLUSION

Organizations typically use vertical communication and mass media to communicate policy, as is exemplified in Naval Aviation through promulgation via its use of email, message traffic, and command websites. However, at present, there is no verification that ensures policy being understood at lower levels (Whitworth, 2011). Naval aircrew's understanding of policies is still of vital import since higher policy tends to

	Match Score	OPNAV_3500-31G	OPNAVINST_3501-360A	OPNAVINST_3000-15A	USFF_CPF_3501-3D	USFFC_3000-15A	CNAL_3502-1	CNAF_3500-38A	CNAF_1500-12	CNAP_5450-42	CNAL_5440-3	CNAL_3500-1	NAVANWARDEVCEN 3500-3J	CSFWP_3500-3A	CSFWPL_3500-7E	CSFWPL_3710_14G	CSFWPL_1525-1G	SFWSPACINST_3500-3B	Uniqueness Score
Echelon I																			
OPNAV_3500-31G	218	–	12	8	40	39	45	27	85	18	15	15	32	33	16	30	26	6	1569
OPNAVINST_3501-360A	149	12	–	12	62	60	23	59	10	12	15	4	9	11	13	6	3	1	301
OPNAVINST_3000-15A	146	8	12	–	73	108	15	17	3	12	5	2	15	10	10	2	2	1	178
Echelon II																			
USFF_CPF_3501-3D	725	40	62	73	–	411	137	107	53	83	57	25	87	77	71	36	23	4	2510
USFFC_3000-15A	619	39	60	108	411	–	79	78	26	64	48	16	62	52	41	28	17	5	1792
Echelon III																			
CNAL_3502-1	414	45	23	15	137	79	–	124	56	60	39	49	77	61	102	38	35	10	925
CNAF_3500-38A	301	27	59	17	107	78	124	–	22	29	29	13	35	35	54	16	12	8	1174
CNAF_1500-12	226	85	10	3	53	26	56	22	–	24	21	20	40	56	27	34	21	4	973
CNAP_5450-42	220	18	12	12	83	64	60	29	24	–	52	34	52	37	22	32	16	8	545
CNAL_5440-3	197	15	15	5	57	48	39	29	21	52	–	16	31	62	21	38	17	8	791
CNAL_3500-1	105	15	4	2	25	16	49	13	20	34	16	–	25	21	17	8	21	6	329
Echelon IV																			
NAVANWARDEVCEN_3500-3J	276	32	9	15	87	62	77	35	40	52	31	25	–	50	43	62	53	31	1466
CSFWP_3500-3A	257	33	11	10	77	52	61	35	56	37	62	21	50	–	33	42	29	13	1193
CSFWPL_3500-7E	206	16	13	10	71	41	102	54	27	22	21	17	43	33	–	27	25	12	362
CSFWPL_3710_14G	200	30	6	2	36	28	38	16	34	32	38	8	62	42	27	–	36	10	2590
CSFWPL_1525-1G	133	26	3	2	23	17	35	12	21	16	17	21	53	29	25	36	–	8	506
Echelon V																			
SFWSPACINST_3500-3B	48	6	1	1	4	5	10	8	4	8	8	6	31	13	12	10	8	–	173

Figure 9: Match Matrix of Echlons.

$$r = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sqrt{\sum (x-\bar{x}) \sum (y-\bar{y})}}$$

Figure 10: Pearson correlation computation.

be interpreted and reissued with greater specificity as it moves down the chain of command as exemplified between Echelons IV and V.

In this paper, we hypothesized that there would be some degree of mismatch between policies at the various levels which was proven. The reason for this mismatch appears to be due to a higher degree of specificity in policies at lower level echelons as explained by their higher Uniqueness Scores.

Between Echelons I and IV, LLA does reveal common as well as uncommon vectors between documents from the various levels and subsequently, correlation and differentiation.

	Match Score	Uniqueness Score
Echelon I		
OPNAV-3000-15A	146	178
OPNAV-3500-31G	218	1569
OPNAV-3501-360A	149	301
Echelon II		
USFFC-CPF-3000-15A	619	1792
USFF-CPF-3501-3D	725	2510
Echelon III		
CNAF-1500-12	226	973
CNAF-3500-38A	301	1174
CNAP-L-3500-1	105	329
CNAP-1-3502-1	414	925
CNAP-5450-42	220	545
CNAL-5440-3	197	791
Echelon IV		
NAWDCINST-3500-3J	276	1466
CSFWP-1-CTSW-1525-1G	133	506
CSFWPL-3500-3A	257	1193
CSFWPL-3500-7E	206	362
CWFWPL-3710-14G	200	2590
Echelon V		
SFWSP-3500-3B	48	173
Pearson's Correlation Coefficient (r)		
Echelon I		0.999070695
Echelon II		1
Echelon III		0.694623236
Echelon IV		0.298599
Echelon V		N/A
Total *r*		0.67679746

Figure 11: Pearson's Correlation Coefficient by Echelon and Total r.

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