Working Words: Real-Life Lexicon of North American Workers

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Objective: *This study describes a new computer methodology for analyzing workers' free text work descriptions.* ***Methods:*** *Computerized lexical analysis was applied to work descriptions of participants in the Lung Health Study, a smoking-cessation study in persons with early chronic obstructive pulmonary disease. Text was parsed and analyzed as single term roots and pairs of roots commonly occurring together.* ***Results:*** *The frequencies of terms reflect the work of a population; our subjects' most frequently used terms included "sale, office, service, business, engine[er], secretary, construct, driv[e], comput[e], teach, truck." Standard classification schemes (NAICS and SOC) and textbooks use terms inconsistent with those of actual workers. Many common empirical terms imply both industry and job information content, although traditional coding schemes separate industry and job title.* ***Conclusions:*** *Formal analyses of language may facilitate communication, identify translation priorities, and allow automated work coding.* (J Occup Environ Med. *2005;47:859–864*)

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Understanding work activity is critical for clinical practice, occupational health surveillance, and epidemiologic research. Identification of the terms commonly used to describe work should greatly facilitate these endeavors. Attention to the language of work is needed for several reasons. Clinical occupational medicine increasingly involves workers with widely diverse occupational backgrounds. In the past, epidemiologic studies typically were based upon narrowly defined worker cohorts that required only a limited array of job classifications. More recently, many studies are community rather than industry cohort based, requiring understanding of a large number of terms. Furthermore, workers now frequently change jobs, requiring a larger vocabulary to summarize their work. Therefore, we conducted an empiric analysis of terms actually used by American workers to describe their work. We also compared the terms actually used to those in standardized coding schemes and occupational medicine textbooks.

Materials and Methods

Information was obtained from subjects in the Lung Health Study, a randomized clinical trial of smoking-cessation and bronchodilator therapy in persons with early chronic obstructive pulmonary disease (COPD).[1–3] Study participants came from 10 centers in North America (one in Canada, the remainder in the United States).

Each subject underwent a standardized interview at baseline. The questionnaire included a section concerning occupation. In addition to 11 occupation specific questions (eg, "How many years have you worked as a firefighter"), it included 6 free text questions dealing with work: 3 dealt with "current or most recent" job, and 3 dealt with "usual occupation." This analysis is based upon the questions describing current job; 5887 subjects completed this question set. Three questions were asked: "Job or Occupation," "Position or job title," and "Business, Field or Industry." Although not explicitly constrained, relatively short answers were collected.

Computer programs were developed to process the text input files using a relational database (Microsoft Access) and Visual Basic for Applications (Microsoft). Text processing was conducted in the following stages: The three responses for each subject were combined into a single text string. This string was then parsed to identify all unique term roots (morphemes) for the person by removing suffixes and non-alphabetic characters. Several individual terms may share a common morpheme. For example, "nursing," "nurse," and "nurses" have a common basic unit. Then, certain terms that convey little relevant occupational information (eg, "worker," "assistant") were eliminated. A root was listed only once for the subject even if he/she used it multiple times. The one root (1R) file was prepared by combining the unique root list from all subjects.

The root pair (2R) list was based upon pairs of terms used by each of the subjects. Certain "real-life" terms are most meaningful if they include more than one individual word or root (eg, "auto salesman" conveys more information than either "automobile" or "salesman" independently). Some terms, such as "Vice President" have a very different meaning than if based upon the first word only. All pairs of term roots for an individual subject were identified regardless of proximity (eg, an individual with five unique term roots would have nine unique root pairs). Order was ignored (eg, "truck driver" is equivalent to "driver truck," and only one of these pairs was included in the 2R list).

For comparison of the empiric lexicon of "real workers," the job descriptors used in several standardized coding schemes were also evaluated. The standardized systems for coding job title (ie, Standardized Occupational Classification, [SOC])[4,5] and the NAICS (North American Industrial Classification System) coding scheme for industry (a derivative of the former Standardized Industrial Classification System [SIC])[6] were used. Both of these are hierarchical structures and are meant to be both exclusive and exhaustive for classification.[7] For analysis purposes, all terms from both of these classification schemes were added to a single database, called standard terms (ST). Each record constituted a single entry in the source databases (1389 job titles came from SOC and 2401 industry titles came from NAICS).

The congruence of textbook terms to those actually used by workers was evaluated by determining how frequently the words most commonly used by the subjects were in the indices of several major occupational medicine textbooks.[8–11] The 100 most commonly used terms were tested. The term was considered present in the textbook if a term with the same root and meaning was identified.

Work descriptive information traditionally is separated into several distinct domains, ie, job, industry, exposure agent, and task. For illustrative purposes, the domain relevance of selected terms was assessed in two ways: "expert opinion" and "empiric use." First, a team of three investigators scored each of the 100 most frequent terms for percentage of implied information content for each of the four domains. For example, "sales" was rated to completely describe a job, whereas "construction" was felt to imply both job (construction worker) as well as industry content. Second, the manner in which subjects empirically used terms was determined. The 200 most frequently used terms were scanned to identify those which were frequently used in response to more than one question, even if by different subjects. The number of times each term was used in response to the separate questions about business/industry, job, and title was tallied.

Results

The frequencies of individual word roots (1R) and pairs of roots (2R) are shown in Table 1. The most common word root was "sale," closely followed by "office." Work traditionally associated with respiratory hazards, such as mining, was relatively infrequent. For example, "min" and "farm" were used only 15 and 47 times respectively. "Weld" was used by 50 subjects. The term "asbestos" was used only once, and "asphalt" appeared 8 times.

The frequency of root pairs is summarized in Table 1b. A root pair represents the appearance of two terms in the free-text concatenated string for an individual. In general, root pairs imply more specificity than single terms. The most frequent root pair was "real estate." Many other meaningful terms, such as "truck driver," appeared frequently. In many instances, however, the root pairs were redundant, such as "educate" and "education." Figure 1 shows the cumulative frequency of single roots. The total number of words used by subjects was 35,922, with 3,453 unique terms. However, only 513 terms account for the 80% of single roots actually used.

The most commonly used roots are shown stratified by gender in Table 2. Results are expressed by rank within gender rather than by absolute frequency because the number of men in the study was twice that of women. As shown, gender differences are evident: "construction" is more common in men, whereas "teach" is much more common in women. "Bookkeep" ranked seventh in women but ranked 584 among men. Only 3 terms were among the top 10 for both sexes.

TABLE 1
Frequency of Single and Double Roots

1a. Single Roots				1b. Root Pairs				
#		*n*	Cum%	#	Root1	Root2	*n*	Cum%
1	SALE	790	2%	1	ESTATE	REAL	141	0%
2	OFFICE	541	4%	2	EMPLOY	SELF	108	0%
3	SERVICE	464	5%	3	DRIV	TRUCK	102	1%
4	BUSINES	366	6%	4	SALE	SALESMAN	96	1%
5	ENGINE	325	7%	5	EDUCAT	TEACH	87	1%
6	SECRETARY	322	8%	6	REPRESENTATIVE	SALE	74	1%
7	CONSTRUCT	313	9%	6	SCHOOL	TEACH	74	1%
8	COMPANY	291	10%	8	RETAIL	SALE	65	1%
9	DRIV	283	10%	9	SALE	SELL	62	1%
10	COMPUT	282	11%	9	PRESIDENT	VICE	62	1%
11	TEACH	274	12%	11	BUSINES	SALE	53	1%
12	TRUCK	274	13%	12	OFFICE	SECRETARY	50	1%
13	ESTATE	260	13%	13	EDUCAT	SCHOOL	49	1%
14	REAL	260	14%	14	ESTATE	SALE	47	1%
15	INSURANCE	244	15%	14	REAL	SALE	47	2%
16	SALESMAN	242	15%	16	OFFICE	POST	41	2%
17	MAINTENANCE	240	16%	16	CARE	HEALTH	41	2%
18	SCHOOL	220	17%	18	DATA	PROCESS	40	2%
19	HOME	208	17%	19	OFFICE	SALE	39	2%
20	HOMEMAK	189	18%	20	DRIV	TRANSPORTAT	38	2%

The most common word roots based upon single words (1R) and pairs of roots (2R) are shown. *n* indicates the number of subjects using the term; cum, cumulative; #, rank.

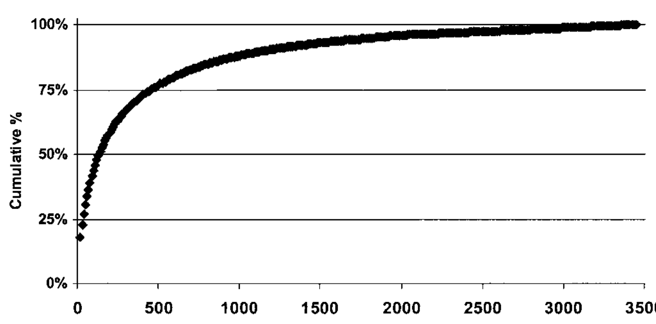

Fig. 1. Cumulative frequency of word roots. Shown is the cumulative frequency of word roots used.

TABLE 2
Most Common Terms By Gender

Males Rank	WORD	Females Rank	Females Rank	WORD	Males Rank
1	SALE x	3	1	SECRETARY	1088
2	SERVICE x	6	2	OFFICE x	8
3	ENGINE	97	3	SALE x	1
4	CONSTRUCT	103	4	HOMEMAK	*
5	TRUCK	97	5	HOUSEWIFE	*
6	DRIV	60	6	SERVICE x	2
7	BUSINES	11	7	BOOKKEEP	584
8	OFFICE x	2	8	HOME	69
9	SALESMAN	368	9	SCHOOL	52
10	MAINTENANCE	139	10	TEACH	20

The most common single words for males and females are shown.
*Not used at all by men. x = included in top 10 for both genders.

Comparison of the terms in the standardized classification systems (SOC, NAICS) and terms used by subjects showed considerable differences. Notably, 13 of the 100 highest ranking individual empiric terms did not appear at all in the standard system. Commonly used terms that were not in the standard schemes even once include the following: attorney, housewife, secretary, and president. Furthermore, 53 of the most frequently used 101 empirically derived root pairs were not present in the standardized schemes.

Table 3 summarizes the frequency with which the 100 most commonly used terms were present in the index of major textbooks. As shown, words and phrases that are often used by actual workers to describe their work are poorly reflected in standard textbooks of occupational medicine. For example, "sales," "engine," and "secretary" were not present in any of the four. Among the four textbooks, 44–74 of the 100 most common terms were not present. This suggests a need for reorienting the emphasis of text-

TABLE 3
Frequency of Workers' Commonly Used Words in Textbooks

Results for 10 Most Frequently Used Terms

	# With Term (of 4 books)	Average Hits
SALE	0	0
OFFICE	2	0.75
SERVICE	1	0.25
BUSINES	0	0
ENGINE	0	0
SECRETARY	0	0
CONSTRUCT	4	1
COMPANY	0	0
DRIV	1	0.5
COMPUT	3	0.75

Results for 100 Most Frequently Used Terms

	Book 1	Book 2	Book 3	Book 4
No. of terms not in book index	44	74	58	68
Total hits	139	41	99	82

The table shows the frequency with which commonly used terms appear in the indices of 4 major textbooks. Results are shown for the 10 most commonly used work descriptive terms and in aggregate for the 100 most commonly used terms.

book information to include topics relevant to current workers.

Table 4 shows the results of the information content analyses. Both analytic methods showed that many terms implied information for both job and industry rather than for just a single domain. However, as shown in Table 4a, subjects rarely used terms implying exposure agent information per se.

Discussion

This work summarizes application of lexical analysis to workers' descriptions of their work. This novel approach, focused upon the actual empiric words, provides insight into how occupational data may be used. Lexical analysis is effective at describing work characteristics. The American workforce is increasingly urban and works in the service sector rather than in manufacturing, agriculture, and mineral extraction (mining) sectors. This trend is reflected in the terms derived from the subjects (eg, the high frequency of "sales" and "office").

Workforces also increasingly are ethnically and linguistically diverse. The most frequently used words should be given highest priority for translation into multiple languages. Lexical analysis also helps identify culturally appropriate terms even within a language.

A relatively small number of terms accounts for the majority of words used by workers. Only 513 roots accounted for 80% of the words used by workers. This result enhances the potential for translation of work relevant terms and even automated text decoding.

"Controlled vocabularies" are increasingly used in medicine. When entering information in a controlled vocabulary system, users may only use terms contained in the vocabulary. An early example is SNOMED, a designated set of terms that pathologists may employ to classify histologic diagnoses.[12–14] Controlled vocabularies are being developed for many other areas to facilitate use of electronic medical records. Knowing actual work terms will help inform development of a "controlled vocabulary" for occupational health.

Automated Coding

The need for tedious coding by highly trained human experts may be obviated if a computer system with natural language-recognition capability can automatically code information.[15] Although natural language processing (computer-based interpretation of text) has severe limitations when applied broadly, it may work effectively in a more narrowly defined application,[16–20] such as work description. We are experimenting with an automated system of aggregating individuals into exposure groups for dust and other exposures as an extension of this current project.[21]

The traditional classification schemes (eg, SOC, NAICS) do not reflect the work done by the current workforce. The disparity in terms and emphasis indicates this incongruity; many of the commonly used terms are not included in the standard classification systems.

An arbitrary distinction between job title and industry classification is not supported by the empiric data. Traditionally, questionnaires treat occupation (job title) and industry as totally separate entities. For example, one classification scheme is used for occupational titles (SOC), whereas an entirely separate scheme is employed for classifying and analyzing industries (NAICS).

As shown in Table 4, many terms are used to describe both job and industry. Many of the terms actually used by workers convey both industry and job title information (eg, "nurse" and "nursing" have the same occupational health significance, although one is a job and the other an industry; similarly, the word root "bak" implies both a job title, ie, baker, and an industry, ie, baking). In addition to semantic implications to facilitate coding, these findings also suggest that a structural change is needed. Because natural language often reflects reality, this implies a single work classification scheme including both job and industry may be preferable to separate schemes for each.

Lexical Analysis Method

The methods used for lexical analysis in this project are straightforward and can be replicated in other

TABLE 4
Information Domain Analysis
a. Domain Relevance of Common Terms

Term	Content Relevance (%) Job	Industry	Agent	Task
Average for 100 most frequent terms	43%	47%	1%	9%
Examples for frequent terms				
SALES	100%	0%	0%	0%
OFFICES	50%	50%	0%	0%
SERVICES	30%	50%	0%	20%
BUSINESS	20%	80%	0%	0%
ENGINES	0%	70%	30%	0%
SECRETARY	100%	0%	0%	0%
CONSTRUCTION	50%	50%	0%	0%
COMPANY	0%	100%	0%	0%
DRIVING	55%	0%	0%	45%
COMPUTERS	50%	50%	0%	0%
TEACHING	50%	50%	0%	0%
TRUCKS	50%	50%	0%	0%
ESTATE	15%	85%	0%	0%
REAL	15%	85%	0%	0%
INSURANCE	40%	60%	0%	0%
SALESMAN	100%	0%	0%	0%
MAINTENANCE	50%	0%	0%	50%
SCHOOLS	0%	100%	0%	0%
HOMES	100%	0%	0%	0%
HOMEMAKING	90%	0%	0%	10%
HOUSEWIFE	100%	0%	0%	0%

The relevance of each term to several domains determined by raters is shown based upon distribution of 100% among the four domains. The table shows that terms often convey meaning in several domains.

b. Terms Used By Subjects to Describe Multiple Domains

Term	Business	Job	Title
FINANCIAL	56	54	60
METAL	50	68	62
HIGH	18	52	34
CONTRACT	52	70	62
AIRCRAFT	30	42	36
BUILD	46	150	90
SYSTEM	86	80	84
GENERAL	110	114	112
NURS	38	92	60
COMPUT	106	282	176
RESEARCH	42	70	50
PLANT	46	108	66
LEGAL	42	32	34
REPAIR	34	232	100
SECURITY	62	92	64
HEAVY	24	34	24
FACTORY	16	62	28
SMALL	14	64	26
FARM	40	76	40
CAR	22	120	42
PAINT	56	90	44
DATA	50	70	36
TRUCK	174	248	126
MARKET	66	82	44
TRAVEL	18	94	30

The table shows the number of times that subjects used these frequent term roots in response to separate questions about job, business/industry, and job title.

settings. The methods used are purely syntactic (depending only upon structure); adding semantic processing, which depends upon actual understanding of the terms, will significantly facilitate disambiguation in the future.[22,23]

The parsing technique used was relatively conservative. Removal of a larger number of suffixes or use of iterative cycles rather than just a single pass would have further reduced the number of roots and root pairs needed to create a lexicon. As seen in Table 1, several terms are actually similar. However, more aggressive parsing would increase the degree of ambiguity of some terms.

There are several limitations to this study. Subjects were volunteers in a smoking cessation clinical trial and may not reflect the entire North American population. For example, the high prevalence of sales related terms may be the result of a disproportionate number of sales persons who have been smokers or desire to quit smoking. Geographic biases are reduced because the subjects were recruited from 10 cities across North America; however, there may be a bias toward urban individuals since universities conducted the project. Diversity of subjects was aided by the recruitment strategies, which differed among the 10 centers. Some specifically targeted blue-collar occupations, helping to assure a broad array of participants. The initial data were collected more than 10 years ago, and therefore the relative frequency of terms used may not completely reflect the current situation (eg, no "dot-com" terms).

In summary, this study describes a new methodology for applying lexical analysis to understanding of work. Knowing the terms used by patients and workers enhances the ability of clinicians and non-clinical occupational health professionals (eg, industrial hygienists) to communicate effectively with employees. Explicitly assessing language also provides insight into how data should be coded for research.

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Appendix

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