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Semi-Automated Content Analysis of Pharmacist-Patient Interactions Using the Theme Machine Document Clustering System

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This chapter describes an automated system for extracting thematic features from computer-readable text. The system, dubbed the 'Theme Machine', is based on methods for document clustering that were originally developed to facilitate information retrieval (Hearst & Pedersen, 1996; Rasmussen, 1992; Salton, Allan, Buckley & Singhal, 1994; SPSS Inc., 1997; Voorhees, 1986; Willett, 1988). Preliminary studies indicate that the methods may also be useful for content analysis. In order to encourage further experimentation with similar methods, this chapter offers a methodological introduction and an example application of the Theme Machine. Specifically, we show how the Theme Machine can be used to illuminate issues that arise in medication counseling interactions between pharmacists and patients.

Pharmacist-Patient Interaction

This is the age of chronic illness (e.g., heart disease, cancer, hypertension, diabetes, etc.), and by far the most common treatment for chronic illness is drug therapy. Prescription and over-the-counter drugs, when used properly, can safely, effectively, and efficiently relieve suffering and cure disease. However, the (legal) drug use process is not without risks. When used improperly, patients may suffer harmful and even fatal consequences from drug therapy (Manasse, 1995). There is now general agreement among health professionals and consumer advocates that the best way to reduce the risks of drug therapy is for health professionals and patients to engage in an ongoing, two-way dialogue about the safe and effective use of medications (Kessler, 1991).

Doctors, nurses, and pharmacists (among others) share the responsibility for talking with patients about their medications. In the case of doctors and nurses, a fair amount is already known about what works and what doesn't when it comes to medication counseling (Landis, 1996; Roter & Hall, 1992). Much less is known about pharmacist-patient interaction (Schommer & Wiederholt, 1995; Smith, Salkind & Jolly, 1990). The purpose of the following content analysis is, therefore, to add to our understanding of pharmacist-patient interaction. Three research questions guided the work: What content themes arise in pharmacist-patient interaction? How do normative (i.e., idealized) models of medication counseling compare to actual practice? How are various content themes related to the outcomes of pharmacist-patient interaction?

A Normative Model of Medication Counseling Behavior

Although there are few good descriptions of what *actually* goes on in pharmacist-patient interactions, experts agree on what *should* go on. The U.S. Pharmacopeia (USP), the organization that sets drug information standards in America, has recently released a set of medication counseling behavior guidelines (U. S. Pharmacopeia, 1997). These guidelines, created by an interdisciplinary panel and intended for all health professionals, are designed to help "enhance communications with patients when providing information about the safe and effective use of medications" (U. S. Pharmacopeia, 1997). The guidelines include a comprehensive medication counseling assessment inventory, listing 23 content and 12 process items that should be included in an ideal counseling scenario. This study focused only on the 23 content items (See Table 1).

Insert Table 1 about here.

Previous research on provider-patient interaction, exemplified by the work of Roter and Hall (Roter & Hall, 1992), has been primarily process-oriented. Process-oriented coding systems tend to examine the amount of positive and negative talk by doctors and patients, the number of questions and statements made by each, the nonverbal behavior of the participants, etc. Such coding systems count the number of "informational utterances" in an interaction, but they may not distinguish between informational utterances that carry different content (e.g., "You have the flu." vs. "You have cancer.").

In contrast, the majority of items on the USP counseling assessment inventory are content-specific items. Because previous work emphasized process over content, little is known about the relative import of various content items. According to developers of the USP guidelines, "research needs to be conducted to determine the relative significance of the individual counseling behaviors comprising the assessment inventory" (U. S. Pharmacopeia, 1997). This chapter demonstrates how we used the Theme Machine to build a content-based coding scheme for pharmacist-patient interaction. We then used the coding system to examine the relationship between content themes and outcomes.

Relationship between Content and Outcomes

Among health professionals, the last decade has witnessed an explosion of interest in health outcomes. Traditional outcomes such as morbidity and mortality have in many instances been supplanted by measures of satisfaction, understanding, compliance, and quality of life (Stewart & Ware, 1992). This study focuses on three outcomes of medication counseling that can be measured immediately after an interaction has occurred: involvement, satisfaction, and understanding. The importance of these outcomes has been amply documented. Greater involvement in decision making is associated with greater satisfaction, adherence to regimens, and control of symptoms (Greenfield, Kaplan & Ware, 1985; Kaplan, Gandek, Greenfield, Rogers & Ware, 1996). Greater satisfaction is associated with greater adherence to regimens and with the tendency to stay with a given health plan (Rubin et al., 1993). Greater understanding is associated with improved memory, satisfaction and adherence (Ley, 1988). Our hypothesis follows directly from the normative USP guidelines:

H1: Greater elaboration of content items identified in the USP guidelines is associated with higher levels of satisfaction, understanding, and involvement.

Method

Design, Site, Sample and Procedures

We designed a cross-sectional, observational study to identify content themes in pharmacist-patient interaction and to relate these content themes to outcomes of satisfaction, involvement and understanding. Seventy-six regularly scheduled medication counseling interactions between pharmacists (or pharmacy students) and patients were recorded on audio tape. Interactions took place in private patient consultation rooms in the main ambulatory pharmacy clinic at the University of Illinois at Chicago. Before the counseling session began, patients were approached and asked to participate in the study. Consent was obtained orally, according to procedures approved by the university's institutional review board. When the counseling session ended, taping ceased, and patients completed a brief interview about their visit-specific satisfaction, understanding, and involvement in decision-making. Demographic data were collected at this time as well. We used 3 communication-specific items from the 9-item Medical Outcomes Study visit-specific rating questionnaire to measure satisfaction (Rubin et al., 1993). We used an original six item questionnaire to measure understanding. Patients were asked to rate their overall understanding as well as their understanding of how to take the drug, when to take it, how it worked, and how long it would take to work. We measured involvement with a 9-item questionnaire developed by Martin (Martin, Lepper & DiMatteo, 1994).

The average age of respondents was 45.65 (SD = 16.06). Sixty-eight percent of the patients were women. Seventy percent were African American, 13.5% were white, and 13.5% were Hispanic. The majority of patients (84%) had income of less than $15,000 per year, and 73.6% were insured by either Medicare or Medicaid. Forty-eight percent had completed high school. Due to technical problems (running out of tape, inaudible voices, etc.) recordings of 9 interactions were unusable. Thus, N = 67 transcripts were available for subsequent analyses of talk and outcomes.

Overview of Content Analysis Method

Computation of term weights, interdocument similarities, and clusters was done using the Theme Machine, a set of computer programs written primarily in the programming language Lisp (Lambert, 1996b). Analyzing data with the Theme Machine involved several steps: (a) transcription, (b) unitization, (c) tabulation of term frequencies, (d) removal of common terms, (e) reduction of terms to stem form, (e) assignment of term weights, (f) creation of an inverted file, (g) creation of an interdocument similarity matrix, (h) clustering of documents, (i) identification of a prototypical clause for each cluster and (j) grouping of micro-themes into macro-themes.

Transcription and Unitization

Tape recorded pharmacist-patient interactions were transcribed into plain (ASCII) text. Once transcribed, the discourse was segmented into units. Units can be defined at any grain size the analyst chooses (e.g., phrase, clause, sentence, turn, paragraph, chapter, etc.). We selected the independent clause as the unit of analysis (Lambert, 1995; Lambert, 1996a; Lambert & Gillespie, 1994; Saeki & O'Keefe, 1994). Evidence from both oral and written discourse suggests that the independent clause (or perhaps the slightly smaller "tone unit") can be construed as the smallest linguistic unit that expresses a complete thought (Chafe, 1994; Hillocks, 1986). Five transcripts were unitized by two independent coders. The reliability of unitization, using Guetzkow's U, was 0.01, reflecting a 1% rate of unitizing disagreement (Guetzkow, 1950).

Tabulation of Term Frequencies

The frequency of occurrence of each unique term in the collection was computed using the GAWK text processing language (Robbins, Close, Rubin & Stallman, 1992, p. 164). Frequency information was used to decide how many of the most common words should be removed from the collection and to calculate term weights.

Removal of Common Words

Grammatical function words (e.g., a, the, an, and, not, but, is, are, etc.) occur frequently in almost all English sentences; therefore, the presence of these words in a document carries little useful information. Standard lists of common words (called stop or drop lists) are readily available (Frakes & Baeza-Yates, 1992). These words are ordinarily deleted before documents are analyzed. In our analyses, custom stop lists have been constructed by removing the most frequently occurring words from the collection. In the present study, the 50 most frequent words were deleted.

Reduction of Terms to Stem Forms

Automated analysis of texts can be made more efficient and effective by removing suffixes from the words that remain after common words have been deleted (Frakes, 1992). This operation is referred to as stemming because it reduces words to their lexical stems. A single stem normally takes the place of several full terms. The stemming algorithm used here is a variant of Porter's algorithm, which removes common suffixes (e.g., -s, -es, -ing, -tion, -ed) (Frakes, 1992; Porter, 1980). Both the stemming and the stopping algorithms are freely available (Frakes, 1995). As an example, below is the same unit before stopping, after stopping, and after stemming.

Original: *and it looks from the computer here that these are the same medications you've been taking right along?*

Post-stopping: *looks from computer here these same medications you've been taking along*

Post-stemming: *look from comput here these same medic you'v been take along*

Assignment of Term Weights

After stopping and stemming, each document was represented as a vector of numeric term weights. It is possible to use a term's raw frequency as its value in a document vector, but more sophisticated term weighting schemes improve the analysis of texts. For the purpose of clustering and discrimination, a term is useful if it occurs frequently in certain documents but rarely in others. Term weights were calculated according to a standard inverse document frequency formula (IDF) (Harman, 1992; Sparck Jones, 1979):

$$\mathrm{IDF}_i = \log_2 \frac{\max n}{n_i} + 1 \qquad (1)$$

where maxn is the maximum frequency of any term in the collection and n_i is the overall frequency of the ith term in the collection. This function yields large weights for rare terms and small weights for common terms.

Creation of an Inverted Index

A collection is usually represented as a list of documents. Associated with each document is a list of terms (and term weights) that occur in that document. In some computations, however, it is useful to have an inverted index. An inverted index is a list of the unique terms in the collection. Associated with each term is a list of documents in which that term occurs (Harman, Fox, Baeza-Yates & Lee, 1992).

Computing the Interdocument Similarity Matrix

A matrix of interdocument similarities was computed. The cosine of the angle between weighted term vectors (i.e., the vector correlation) was used to define inter-document similarity (Harman, 1992):

$$\text{Cosine}(x, y) = \frac{\sum_{i=1}^{n} x_i \, y_i}{\sqrt{\left(\sum_{i=1}^{n} x_i^2\right)\left(\sum_{i=1}^{n} y_i^2\right)}} \tag{2}$$

where x_i and y_i are term weights from documents x and y, and n is the number of unique terms in the collection. For a collection of N documents, N(N - 1)/2 unique similarities must be computed and stored. An inverted index was used to guide the computation of interdocument similarities such that only nonzero similarities were computed (Rasmussen, 1992). The similarity matrix for most collections will contain relatively few nonzero similarities, so when an inverted index approach is used, the efficiency of the similarity computations is considerably better than the worst case implied by N(N - 1)/2. For experiments reported here, each similarity value was represented with 16 bits of precision (i.e., similarity values took on integer values between 0 and (2^{16} -1). Thus, N(N -1) bytes of memory would be needed to store an interdocument similarity matrix for N documents.

Clustering Documents and Identifying Cluster Centroids

The clustering procedures in the Theme Machine are based on Voorhees description of the group average and complete linkage clustering methods (Voorhees, 1986). These methods are governed by three rules: (a) merge the two closest objects (where an object can be an individual document or a cluster of documents), (b) unless no more objects exist, go to (a), and (c) if no more objects exist, stop. The Theme Machine also has a threshold-based stopping criterion. When no more objects can be merged at a similarity greater than or equal to the user-specified threshold, then clustering stops. The rules are the same for both methods. The two hierarchical agglomerative methods, group average and complete linkage, differ from one another only in the way that they define similarity between non-singleton clusters. Group average defines similarity as the average pairwise similarity between all documents in Cluster A and all documents in Cluster B. Complete linkage defines similarity as the minimum similarity between any member of Cluster A and any member of Cluster B (Rasmussen, 1992; Voorhees, 1986; Willett, 1988). Finally, to facilitate subsequent analyses, a prototypical, centroid clause was identified for each cluster. The prototypical member of a cluster was defined as the clause whose average similarity to all other clauses in the cluster was maximum.

Analysis Plan

Only pharmacist talk was examined. We studied the 100 most frequent clusters resulting from a complete linkage clustering of transcribed, segmented pharmacist talk using a similarity threshold of 0.1. The first step in the analysis was exploratory. The goal was to get an idea of what themes were being elaborated by pharmacists and to see how these themes compared to those described in the USP guidelines. Each cluster in the top 100 was then assigned to one of the 23 USP content categories. For each content category, we created a theme elaboration score, defined as the number of units in a given transcript belonging to a given theme. Each transcript was thus represented as a vector of 23 theme elaboration scores (i.e., counts). Once we identified which USP content categories were well represented in our data, we examined correlations between theme elaboration, demographic characteristics, and outcomes. Where significant zero-order correlations were found, we built hierarchical multiple linear regression models to predict outcomes from a combination of theme elaboration and demographic variables. All statistical tests used a significance criterion of alpha = .05. With N = 67, tests had 80% power to detect a medium-sized effect (r = .35) (Cohen, 1988).

Results

Performance of the Theme Machine

Data reduction. The original data set contained 7,422 clauses, 51,494 total words, and 2,489 unique words. After removing the 50 most common words and standard suffixes, the collection contained 5,745 clauses, 20,384 total words, and 1,897 unique words. The fifty most common words in the collection are displayed in Figure 1. Note that 1,677 clauses were deleted as a result of removing stop words. Most of these were one- or two-word clauses (e.g., “OK”, “All right”, “Right”). Complete linkage clustering of the data with a similarity threshold of 0.1 and a minimum cluster size of 10 produced 189 clusters. This was a 97% reduction in dimensionality as compared to the original data set. The mean number of clauses per cluster was 17.21 (SD = 10.58). The largest cluster contained 123 clauses. Due to the effect of the threshold, 2,493 clauses, roughly 33% of the original data, were not clustered. The experiments reported here required 31.5 megabytes of main memory to represent the similarity matrix. Clustering took 2 hours and 14 minutes on a PC with dual Pentium Pro processors and 500 megabytes of main memory. The CLISP compiler was used to compile Theme Machine Lisp code (Haible & Stoll, 1997).

Insert Figure 1 about here.

Good and bad clusters. Some clusters were much more interpretable and cohesive than others. Cluster 5, for example, whose prototypical member was "How often do you take it", was a very good, easily interpretable cluster (see Figure 2). Cluster 25, on the other hand, was not so easily interpretable because similarity between clauses was overly influenced by one word, in this case the word "I'll" (see Figure 3). Focusing on one word was the most significant failure of the Theme Machine on this data set. This behavior is caused in part by the complete linkage clustering method and in part by the term weighting formula. The term weighting formula assigned large weights to relatively rare words. Often, the large weight associated with a single term such as "I'll" was enough to create clusters such as the one in Figure 3. This flaw could be overcome in the future by using alternative term weighting procedures that do not give as much weight to single terms.

Insert Figure 2 about here.

Insert Figure 3 about here.

USP Macro-Themes and Outcome Measures

Each of the 100 largest clusters was assigned to one of the 23 content categories from the USP guidelines or to an "other" category. In the end, 56 clusters were assigned to a USP category, and the remainder were coded as "other." Many of the "other" clusters were non-substantive contributions such as "Uh-huh", "Fine", "Yes", "No", "I see", etc. The rest of the clusters in the "other" category were not coherent enough to be coded unambiguously or they did not fit any USP category. Six of the USP categories had at least 4 clusters assigned (see Table 2). Descriptive statistics for these 6 USP macro-themes and the three outcome measures are given in Table 3.

Insert Table 2 about here.

Insert Table 3 about here.

Correlations between Demographics, Themes and Outcomes

Correlations between selected demographic variables, themes, and outcomes are given in Table 4. The three outcome measures were highly intercorrelated. Demographic characteristics were not significantly correlated with any of the outcomes. There was a significant positive association between involvement and USP content themes 4, 8, and 11. Satisfaction and understanding were not significantly correlated with any content themes. As expected, elaboration scores for the six USP content themes were moderately intercorrelated (see Table 5).

Hierarchical Multiple Regression Models

Multiple linear regression models were constructed to examine the impact of demographics and theme elaboration on involvement. The first model included demographic variables only (i.e., health status, gender, age, ethnicity, and education). This model did not provide a good fit to the data ($F(5, 56) = 0.85$, ns, Adj. $R^2 = -.01$). Elaboration scores for six USP content themes were then added to the model. Tests for multicollinearity among the 6 theme elaboration scores revealed no serious problems. The resulting model produced a significantly better fit to the data ($F(11, 50) = 2.28$, $p<.05$, Adj. $R^2 = .19$). Table 6 displays the parameter estimates for both models. Once demographic characteristics were controlled, USP theme 8 (i.e., assessing problems and concerns that were important to the patient) and theme 11 (i.e., assisting the patient in developing a plan for taking the medication) were significantly associated with involvement, but USP theme 4 (i.e., obtains pertinent initial drug-related information) was not.

Limitations

The participants in this study were primarily middle-aged, low income, African American women without a college education. It is unlikely that the results can be safely generalized beyond this sample. When interpreting these results, it is also important to note that power to detect correlations smaller than .35 was quite low, and thus the likelihood of making type II errors with respect to smaller correlations is substantially greater than 20%. There were several problems with the Theme Machine itself. Most notably, the system could not cope with synonymy or polysemy (Deerwester, Dumais, Landauer, Furnas & Harshman, 1990), and it was unduly influenced by single, relatively rare words. What's more, setting the adjustable parameters to the Theme Machine is still something of a black art. The cluster solution would have been markedly different had we chosen a different threshold, a different clustering method, a different number of stop words, etc. Systematic research must be done to make these choices more principled. Before that research can proceed, we need to define a measure of "cluster quality" that can be optimized (Everitt, 1993). Even though the Theme Machine dramatically reduces the dimensionality of text data, the resulting cluster solutions are still complex and hard to analyze. Better tools for visualizing and manipulating large text hierarchies are needed (Gershon & Eick, 1995). In addition, the clustering methods used here may be too computationally demanding. Not all researchers have access to a PC with 500 megabytes of main memory, and without such resources, clustering large text collections will not be possible. This difficulty can be overcome by analyzing subsets of large collections, by defining units of analysis at courser levels of abstraction (e.g., the turn or paragraph rather than the independent clause), or by using less computationally complex methods (Hearst & Pedersen, 1996).

Discussion and Conclusions

A substantial amount of language use, especially in routinized contexts like pharmacist-patient interaction, is idiomatic and patterned. Document clustering methods such as those used by the Theme Machine can identify patterns in verbal communication and render them in a categorical representation that facilitates subsequent quantitative analyses. In this chapter we have shown how the Theme Machine can identify content themes in pharmacist-patient interaction that were strongly associated with patient involvement in decision-making, an important and consequential outcome. Specifically, pharmacists who (a) assessed concerns that were potentially important to patients and (b) assisted patients in making plans to integrate drug therapy into their routines, significantly increased patients' feelings of involvement in decision making. We believe that the general strategy of taking a normative model, comparing it to actual practice, and feeding back results to academics and practitioners, is an effective way of improving both theory and practice. The Theme Machine is a vitally important part of this strategy, and we hope to have demonstrated both its usefulness and its limitations.

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Table 1

<u>Medication Counseling Assessment Inventory: Introductory and Counseling Content Items</u>

	Item
1.	Conducts appropriate counseling introduction by identifying self and the patient or patient's agent
2.	Explains the purpose of the counseling session
3.	Reviews the patient record prior to counseling
4.	Obtains pertinent initial drug-related information
5.	Warns patient about taking other medications which could inhibit or interact with the prescribed medication
6.	Determines if the patient has any other medical conditions which could influence the effects of this drug or influence the likelihood of an adverse reaction
7.	Assesses the patient's understanding of the reason(s) for therapy
8.	Assesses any actual or potential concerns or problems of importance to the patient
9.	Discusses the name and indication of the medication
10.	Explains the dosage regimen, including scheduling and duration of therapy when appropriate
11.	Assists the patient in developing a plan to incorporate the medication into his/her daily routine
12.	Explains how long it will take for the drug to show an effect
13.	Discusses storage recommendations and ancillary instructions
14.	Tells patient when s/he is due back for a refill
15.	Emphasizes the benefits of completing the medication as prescribed
16.	Discusses potential significant side effects
17.	Discusses how to prevent or manage side effects is they do occur
18.	Discusses precautions
19.	Discusses significant drug-drug, drug-food, and drug-disease interactions
20.	Explains in precise terms what to do if the patient misses a dose
21.	Explores with the patient potential problems in taking the medication as prescribed
22.	Helps generate solutions to potential problems
23.	Provides accurate information

Note. Based on USP Medication Counseling Behavior Guidelines (U. S. Pharmacopeia, 1997). Table does not include counseling process items.

Table 2

Clusters (Micro-Themes) Assigned to Selected USP Content Categories

USP Category	Cluster Numbers and Prototypical Clauses
1. Conducts appropriate counseling introduction by identifying self and the patient or patient's agent	13: My name is S? 27: I'm one of the Pharmacy students, 28: I'm a pharmacist. 29: Hi
4. Obtains pertinent initial drug-related information	11: It's a new one? 36: Have you taken this before? 48: The insulin, you know 62: What else do you take- 75: When was the last time you had your blood pressure checked. 79: For how long? 90: Did they change it? 96: Have you ever had to do that before?
7. Assesses the patient's understanding of the reason(s) for therapy	12: Did you tell your doctor that? 46: And why do you take it? 52: That is high. 77: What did the doctor say?
8. Assesses any actual or potential concerns or problems of importance to the patient	3: Do you have any questions? 9: What do you do when you have chest pain? 19: How are you doing? 20: Is it helping you any? 24: Today? 57: Any problems with that? 61: Any dizziness or- 89: You been sleeping OK?
10. Explains the dosage regimen, including scheduling and duration of therapy when appropriate	5: how often do you take it? 7: How many times a day do you take it? 16: ? or ? 500 mg. 26: OK, in the morning? 34: Just once a day? 41: And your syringes. 51: Just 2 days? 56: A half of a tablet? 71: This is twice a day- 76: '52? 81: It's 1.2 ml by mouth. 83: And did you drink? 93: You can take 1 or 2 every 6 hours,
11. Assists the patient in developing a plan to incorporate the medication into his/her daily routine	21: How do you eat? 33: After meal? 50: Write it down so that you know, 80: And yeah, you can take food with it.

Table 3

Descriptive Statistics for Macro-Themes and Outcome Measures

Variable	N	Mean	Std. Dev.	Sum	Min	Max
Themes						
USP-1	67	1.36	1.37	91	0	5
USP-4	67	2.31	2.20	155	0	9
USP-7	67	1.21	1.75	81	0	8
USP-8	67	2.96	2.98	198	0	14
USP-10	67	3.75	4.07	251	0	24
USP-11	67	1.21	2.79	81	0	20
Outcomes						
Involvement	75	40.48	4.28	3036	28	45
Satisfaction	76	13.40	2.04	1019	9	15
Understanding	64	24.95	5.10	1597	14	30

Table 4

Correlations between Outcomes, Demographic Variables, and Themes

Characteristic	Outcome Involvement (n = 66)	Outcome Satisfaction (n = 67)	Outcome Understanding (n = 58)
Outcomes			
Involvement	-		
Satisfaction	0.61**	-	
Understanding	0.67**	0.76**	-
Demographics			
Health Status	-0.16	-0.05	-0.23
Gender	0.15	0.17	0.15
Age	0.03	-0.02	-0.01
Ethnicity	-0.01	0.01	-0.07
Income	0.06	-0.01	-0.02
Themes			
USP-1	0.06	0.06	0.01
USP-4	0.32**	0.04	0.12
USP-7	0.04	0.19	-0.02
USP-8	0.33**	0.22	0.02
USP-10	0.13	0.03	0.01
USP-11	0.31**	0.17	-0.05

**p<.01

Table 5

Correlations between Themes

	Theme (n = 67)				
Theme	USP-1	USP-4	USP-7	USP-8	USP-10
USP-1	-				
USP-4	.16	-			
USP-7	.18	.49**	-		
USP-8	.16	.38**	.30**	-	
USP-10	.32**	.26*	.28*	.39**	-
USP-11	.03	.27*	.55**	.21	.18

*p < .05, **p < .01

Table 6

Summary of Hierarchical Regression Analysis for Variables Predicting Patient Involvement in Decision Making (N = 62)

Variable	B	SE B	Beta
Step 1			
Health Status	-.54	0.44	-0.17
Gender	2.32	1.31	0.24
Age	0.02	0.04	0.07
Ethnicity	-0.87	1.28	0.09
Income	0.01	0.35	0.00
Step 2			
Health Status	-0.57	0.43	-0.17
Gender	2.16	1.23	0.23
Age	0.02	0.04	0.09
Ethnicity	0.11	1.23	0.01
Income	0.36	0.34	0.14
USP-1	0.14	0.39	0.05
USP-4	0.54	0.31	0.27
USP-7	-0.63	0.39	-0.23
USP-8	0.44	0.21	0.31*
USP-10	-0.13	0.14	0.13
USP-11	0.86	0.36	0.32*

Note. R^2 = .07 for Step 1 (ns); ΔR^2 = .26 for Step 2 ($p < .05$).

*$p < .05$

Figure 1

Fifty Most Common Words Deleted from Transcripts of Pharmacist Talk

you	the
ok	to
and	it
a	that
have	is
your	of
do	this
in	for
so	right
how	take
i	or
what	on
just	one
if	with
all	are
any	it's
they	know
be	yeah
good	like
at	that's
get	you're
can	then
day	because
going	but
about	not

Figure 2

Example of a Good Cluster: Cluster 5 ("How often do you take it")

How often do you take that?
OK, and how often do you take that?
And how often do you take that?
How often do you do it?
How often do you do this one?
How often do you-
And how often do you take that?
And how often do you take this?
how often do they do that?
And how often do you take that?
How often do you take it?
And how often do you take that one?
How often do you do it?
How often.
And how often is that?
how often do you take it?
How often are you taking that?
How often is she taking that?
How often should you be taking it?
So that you're not going as often.
How often do you take these?
How often do you have that feeling?
So how often is she getting this?
How often do you use this one?

Note. Only 25 of 37 clauses from cluster 5 are shown. The entire cluster output file is available by anonymous ftp from ftp://ludwig.pmad.uic.edu/pub/rph-units.d50.t.1.clink.out.

Figure 3

Example of a Bad Cluster: Cluster 25 ("I'll get that for you.")

I'll have her come in
I'll have them come in
I'll check for you.
and, then, I'll know you
I'll get that for you.
I'll be right back.
I'll be right back.
I'll be right back,
I'll be right back,
and I'll be right back.
I'll be right back.
I'll get you one more.
But I'll give this to you-
I'll give this one to you.
so I'll give this to you today
I'll be darned.
I'll just warn you.
I'll get the lady
I'll be here a month from now.
I'll have to check to see if we do have the tablets.
I'll check to see if we have a round tablet
I'll go get you a calendar
and I'll write it on a calendar for June for you so that you know.
And while they come back in and ask you a couple of questions, I'll go write this on a calendar for you,

---

Note. This cluster contained only 24 clauses.