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Classification of Use Status for Dietary Supplements in Clinical Notes

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Abstract

Clinical notes contain rich information about dietary supplements, which are critical for detecting signals of dietary supplement side effects and interactions between drugs and supplements. One of the important factors of supplement documentation is usage status, such as started and discontinuation. Such information is usually stored in the unstructured clinical notes. We developed a rule-based classifier to identify supplement usage status in clinical notes. The categories referring to the patient's status of supplement use were classified into four classes: Continuing (C), Discontinued (D), Started (S), and Unclassified (U). Clinical notes containing 10 of the most commonly consumed supplements (i.e., alfalfa, echinacea, fish oil, garlic, ginger, ginkgo, ginseng, melatonin, St. John's Wort, and Vitamin E) were retrieved from the University of Minnesota Clinical Data Repository. The gold standard was defined by manually annotating 1000 randomly selected sentences or statements mentioning at least one of these 10 supplements. The rules in the classifier was initially developed on two-thirds of the set of 7 supplements (i.e., alfalfa, garlic, ginger, ginkgo, ginseng, St. John's Wort, and Vitamin E); the performance was evaluated on the remaining one-third of this set. To evaluate the generalizability of rules, we further validated the second testing set on other 3 supplements (i.e., echinacea, fish oil, and melatonin). The performance of the classifier achieved F-measures of 0.95, 0.97, 0.96, and 0.96 for status C, D, S, and U on 7 supplements, respectively. The classifier also showed good generalizability when it was applied to the other 3 supplements with F-measures of 0.96 for C, 0.96 for D, 0.95 for S, and 0.89 for U. This study demonstrated that the classifier can accurately classify supplement usage status, which can be further integrated as a module into the existing natural language processing pipeline for supporting dietary supplement knowledge discovery.

Keywords

Clinical Notes; Electronic Health Records; Regular Expression; Supplements Use Status; Natural Language Processing

I. Introduction

Over the last two decades, complementary and alternative medicine (CAM) has gained worldwide popularity. It has been reported that the use of herbal supplements in the United States has increased from 2.5% in 1997 to 18.6% in 2002 [1]. According to the American Botanical Council, the sale of dietary supplements has increased by 6.8% in the United States in 2014 [2]. Meanwhile, the use and sale of CAM has also risen dramatically in European countries, such as Spain [3], United Kingdom [4], and Germany [5]. As the most common type of CAM approach, dietary supplements are usually taken to complement conventional medicine to reach a better healthcare outcome.

Despite the extensive and widespread use of dietary supplements, there is very limited information about the safety and effectiveness of dietary supplements [6]. One reason for limited investigation is that dietary supplements are usually sold as medicine but regulated as food per DSHEA (Dietary Supplement Health and Education Act) of 1994 [7]. Thus, usual clinical trials for safety and effectiveness that are required for new drugs before marketing are not required for dietary supplements [8]. Most people think they are safe, but according to some clinical studies and case reports, concurrent use of prescribed medications and supplements might affect pharmacokinetic profiles and can lead to potentially dangerous drug and supplement interactions (DSIs) [9]. For example, warfarin has the potential to interact with many supplements like garlic, ginseng, ginger, ginkgo, and St. John's Wort, which can potentiate the effects of warfarin in multiple ways and can increase the risk of side effects such as bleeding [10], [11]. In addition, concomitant use of St. John's Wort with immunosuppressive drugs like cyclosporine will cause reduced plasma concentration [12], [13]. Undoubtedly, it is imperative to identify dangerous DSIs particularly in vulnerable populations, such as cancer patients and the elderly, who are at a greater risk of experiencing DSIs [14], [15].

Since clinical trials can have limitations in validating DSIs [16], electronic health record (EHR) systems provide a valuable source from which DSIs can be mined [17]. Information about medication usage is stored in structured medication tables, in contrast, most supplement usage information is documented in free clinical text. To detect adverse interactions between medications and supplements, or to determine the efficacy of supplements, it is clinically important to extract the history (e.g., past use) and the current status (e.g., active or discontinued) of supplement use. Clinical notes contain rich information about the status of supplement usage, which is important for both medical research and clinical decision support. For example, such information exists in the section of Current Medications, or other sections consisting of the observations of the past supplement use, problems associated with current or past supplement use, or future use. Both current use and past use may hold important information, which can provide hints to explain the current problems, such as adverse events and drug interactions. The supplement use information locked in free text makes it difficult to be analyzed by automated systems. Therefore, it is challenging to automatically extract and classify such information.

Previous efforts have focused on the medication status classification by using rule-based and machine-learning methods. Sohn *et al.* used rule-based and support vector machines (SVM)

with indication features to detect medication status change in free text [18]. Pakhomov *et al.* built a maximum entropy model with a variety of features to automatically identify five categories of medication status from clinical narratives and then applied it to rheumatic notes [19]. Stoddard *et al.* assumed that the patient has taken the supplements if the text positively mentioned the supplements, but did not further analyze the supplement status [17].

In this study, we developed and evaluated a classifier to automatically identify the four categories (i.e., continuing, discontinued, started, and unclassified) of supplements use status from clinical notes. We only focused on the ten most commonly consumed supplements (listed previously). We developed a reference standard that was independently annotated by two experienced reviewers. The gold standard was then used to develop and evaluate our classifier. To the best of our knowledge, this is the first study investigating the use status of supplements in clinical notes through a rule-based classifier.

II. Methods

A. Data Collection and Annotation

The clinical notes used in this study were retrieved from the University of Minnesota's Clinical Data Repository (CDR). IRB approval was obtained for accessing the clinical notes. The ten supplement names and their lexical variations (Table I) were first used to retrieve clinical notes for creating the data set. In this study, we randomly collected 1000 sentences and incomplete sentences (statements) (100 for each supplement). The names of the ten supplements in the sentences were normalized to their preferred names (Table I) for the following data analysis. We found that one sentence might contain more than one supplement of interest with the same status. For example, "She has stopped fish oil and Vitamin E". In this case, the sentence was counted for each supplement mention. Totally, there are 138 sentences with multiple supplements of interest. Specifically, among the 1000 sentences, there are 111 sentences for alfalfa, 109 for echinacea, 168 for fish oil, 159 for garlic, 117 for ginger, 136 for ginkgo, 120 for ginseng, 116 for melatonin, 111 for St. John's Wort, and 130 for Vitamin E. The entire total of 1000 sentences was divided into three sets. There were 623 sentences containing seven supplements including alfalfa, garlic, ginger, ginkgo, ginseng, St. John's Wort, and Vitamin E. Two-thirds of this collection was designated as the "training set" (415 sentences) and was used to develop the initial rules. The remaining one-third was labeled as testing set #1 (208 sentences), which was used to evaluate and refine the rules. The second part, named testing set #2, consisted of 377 sentences containing the other three supplements, including echinacea, fish oil, and melatonin; the objective of this set was to evaluate the generalizability of the classifier.

Two annotators were asked to manually classify the four categories of supplement use status: continuing (C) for supplement that is actively taken; discontinued (D) for supplement that is no longer consumed; started (S) for supplement that is initiated; and unclassified (U) for a supplement that does not provide sufficient information about use, such as, "recommended the use of Vitamin E" or "avoid triggers for lupus: sun, alfalfa". For each supplement mention, one of four categories was given according to the context and linguistic cues. Specifically, 100 out of 1000 sentences were randomly selected to develop the annotation guidelines which are shown in Table II. The disagreement was resolved by discussion to

reach a consensus. Inter-annotator agreement has been examined using Cohen's Kappa score and percentage agreement. The remaining 900 were equally split into two parts which were independently annotated by the two reviewers. A total of 1000 annotated sentences defines the gold standard set in this study against which the results of the classifier can be compared.

B. Development and Evaluation of the Classifier

Based on the training set, we found that there was a variety of linguistic features which can be used as status indicators. For instance, "He has continued on this heart Caps medications, which does include ginger, garlic, and lecithin", may indicate C status. "Discontinued simvastatin and fish oil on admission" and "Pt will stop taking ginseng" may indicate D status. "Pt started fish oil 2 days ago" may indicate S status. "Advised over-the-counter melatonin" may indicate U status. From the instances above, "continued", "discontinued", "stop", "started", and "advised" can be used as signals indicating the use status. Also, physicians often use abbreviations to save time and improve efficiency. For example, additional examples from the dataset use "DC" for "discontinue" and "d\ced" for "discontinued". These abbreviations were also considered when we developed the rules. Based on such features, rules were manually created in the training set and iteratedly evaluated in the development set until the performance would not improved significantly.

Several sentences contain more than one status indication feature for different supplements. For example, the sentence "He continues on Coumadin and also has recently started taking ginseng as he is concerned about the fatigue he will have during chemotherapy", has two status feature words "continues" and "started" indicating different statuses for "Coumadin" and "ginseng", respectively. In order to improve the accuracy of our rules, it is important to set the proximity boundaries for the occurrence of such words with respect to the supplement mentions, which means the number of tokens fall between the feature words and the supplements. If the feature word is too far away from the supplement, the feature word may not indicate the use status of the supplement. Without distance control ginseng in the example might be erroneously identified as "Continuing" status instead of "Started" status. In order to choose an optimal window size around the supplement mentions, we evaluated the distance ranged from 1 token to 9 tokens on the left side of supplement mentions since most of the sentences are in the active voice. The precision, recall, and F-measure of each status category were evaluated in the training set of seven supplements with the distance increasing by one token. For each distance, F-measure was also averaged based on the F-measure of each category. We chose the optimal distance value based on the averaged F scores.

The classifier was first tested on the testing set #1 (208 sentences). Tests were performed on both supplement level and category level. For each of the seven supplements, the precision, recall, and F-measure for the four status categories were calculated. The performance of the rules on the overall seven supplements in terms of the four categories was also calculated. To evaluate the generalizability of the classifier developed from the 7 supplements, we evaluated the classifier on testing set #2 (377 sentences) consisting of the other three supplements. We evaluated the classifier on the set #2 using the same evaluation metric. The

performance of the classifier on the overall three supplements in terms of the four categories was calculated as well.

III. Results and Discussion

Cohen's Kappa score is 0.93 and the percentage agreement is 95%, which indicates great agreement between two annotators. A total of 1000 annotated sentences (or statements) consists of 380 with Continuing (C) status, 156 with Discontinued (D) status, 139 with Started (S) status, and 325 with Unclassified(U) status.

Table III indicates the performance of the classifier, evaluated on the training set, with the various distances of 1 to 9 tokens to the supplement mentions. The F-measure increased with the distance until it reached the best (averaged F-measure: 0.943) when distance was 8. Thus we selected the window size of 8 tokens on the left side of supplement.

We generated 115 rules for the classifier. Specifically, there are 35 rules for C, 18 for D, 11 for S, and 51 for U. For each status category, the top three commonly used regular expression templates and their corresponding examples are listed in Table IV. For the C status, most frequently used feature words are "continue", "increase", "take", and their corresponding morphological forms. For the D category, "discontinue", "stop", "hold", and their corresponding morphological forms are frequently used. For the S status, most frequently used features words are "start", "resume", and "add". As for the U status, "avoid", "recommend", and some negated words like "deny" are most commonly used.

The performances of rules on both testing set #1 and testing set #2 were shown in Table V and Table VI, respectively. In Table V, F-scores for predicting the Continuing status of testing set #1 in seven supplements range from 0.83 for ginseng to 1 for both St. John's Wort and Vitamin E. For the Discontinued status, the F-scores have the lowest value of 0.80 for ginger and highest of 1 for five supplements including alfalfa, ginkgo, ginseng, St. John's Wort and Vitamin E. For the Started category, F-measures range from 0.67 for garlic to 1 for four supplements including ginger, ginkgo, ginseng, and St. John's Wort. For the Unclassified status, F-measure has the highest score of 1 for alfalfa, st. John's Wort, and Vitamin E and the lowest of 0.93 for ginger. To evaluate the performance of the rules on the four status categories in the seven supplements, we grouped the sentences based on their assigned classes. The performance of the rules on the overall seven supplements achieved the highest F-measure in Discontinued category (F-measure: 0.97) and the lowest in Continuing category (F-measure: 0.95).

The classifier can accurately classify for most supplements over 0.90; especially for St. John's Wort and Vitamin E, their F-measures were 1.00 for all categories. The classifier also performed well on others, such as Ginkgo (F-measure: 0.96–1). The classifier's performance was lower when identifying Started status for garlic (0.67) and alfalfa (0.80), Discontinued status for ginger (0.80) and Continuing status for ginseng (0.83).

Table VI indicates the performance of three supplements in testing set #2. The F-measures in Continuing status range from 0.91 for echinacea to 0.98 for fish oil. F-measures have the highest score of 0.97 for fish oil and the lowest of 0.73 for melatonin for Discontinued

category. For Started status, F-measures range from 0.91 for melatonin to 1 for echinacea. For Unclassified status, the rules achieved the highest F-measure of 0.92 for fish oil and the lowest of 0.87 for melatonin. The classifier on the overall three supplements performed with an F-measure ranging from 0.89 to 0.96, with the highest score in Continuing and Discontinued status and the lowest in Unclassified status.

The results of Table VI showed that our rules developed on seven supplements had good performance on the three supplements, especially for fish oil – its F-measures in the four categories were all above 0.92. The classifier also performed well on echinacea, with F-measures ranging from 0.89 to 1 in the four categories. The rules seemed to have a poorer performance with the Discontinued category of melatonin (0.73).

When comparing the results of the rules on three supplements in testing set #2 to those on seven supplements in testing set #1, the performance levels remained the same although the performance of three supplements is slightly lower in terms of recall in two status categories (Started and Unclassified). The reason might be that there were some patterns trained in the training set that were not representative in testing set #2 due to the sparseness of the training set and the differences of supplements. For example, “He supplements his diet with fish oil capsules, a multivitamin and vitamin E”, “I sent refill requests to Walgreens for sertraline and melatonin”, “Sleep is improving with addition of Melatonin”, and “Melatonin available as needed for insomnia”. These instances above are cases which were not common in the training set. Additionally, other missed patterns include passive syntactic structure like “melatonin has been stopped”, “Ginseng with Royal Jelly: again started taking this for energy support”, and “Melatonin and Ambien QHS continue”. However, there is a slight improvement of the F-measure in Continuing category in the three supplements. This might be due to the limited patterns of Continuing category in the three supplements. As for the supplements, our rules have a better performance on St. John’s Wort and Vitamin E in testing set #1 and fish oil in testing set #2. When we were implementing the regular expressions on supplements, we assumed that if the sentence didn’t belong to either category of Continuing, Discontinued, and Started, it should fall in the Unclassified class, which might explain the low precision and high recall of Unclassified category in the three supplements set since some missed patterns of other three categories (Continuing, Discontinued, and Started) were erroneously categorized into Unclassified class.

The main source of false negatives is the distance of feature words from the supplement; that is, the tokens between the supplement mention and the feature word were beyond the limit of 8 tokens. For example, “Started a new herbal supplement about a week ago which contains ginseng and green tea”, or “About 10 days ago started an herbal prep for her memory that includes multiple substances that can increase her INR ie cloves, fenel, garlic, ginkgo, ginseng, echinacea”. In both examples, our rules failed to correctly classify this supplement mention due to many intervening tokens in between. Another source of erroneous classification stems from sentences with more than one feature word that were both within 8 tokens of the supplement mention. For example, “He has stopped Coumadin and started fish oil”. The mention of fish oil is within the 8 tokens limit of both “stopped” and “started”. Additionally, we also failed to find some abbreviations used by doctors in the training data, such as “d’ced”, which means discontinued.

Not only did we successfully detect the use status of supplements, we have also attempted to identify the negated mentions of supplements. In the Unclassified category, there is a small portion of negated mentions of supplements that have been successfully detected by our rules. A set of rules with negated phrases or words, such as “deny”, “decline”, “refuse”, “no”, “not”, “without”, “instead of” and “avoid” were generated to detect the negations. Also, some recommendations or suggestions like “consider Vitamin E” or “advised melatonin for sleep” given by physicians may imply the future use of supplements.

Generally, the performance of the rules on three supplements achieved promising results with high scores of precision, recall, and F-measure, which indicated that the rules developed on seven supplements are generalizable to other supplements since most supplements share common expressions of supplement status. Therefore, the same rules can be applied in extracting the use status information of supplements in this study in future research.

The results demonstrated that our rule-based classifier is powerful in detecting and classifying the use status of supplements. Such classifier can be further integrated as a module into our NLP system for information extraction to support supplement research. In addition, there are a lot of advantages of the rule-based method, such as generating more generalized rules. Moreover, the rule-based system can be easily modified and transferred since they are standard across almost all implementations [20], [21]. Many rule-based systems such as MetaMap and SemRep are widely used in the healthcare informatics domain [22], [23]. Alternatively, machine learning based methods usually require a larger annotation corpus, which is time-consuming and costly to prepare.

Nevertheless, there exist few limitations in our study. First, the corpus of this study is relatively small and includes only ten popular supplements. It can cover more patterns when the sample size is larger and supplement species are broader, but collecting a more comprehensive gold standard is a costly, time-consuming process, as mentioned above. Second, we used free words in the search for clinical notes. Since we did not consider other names of the supplements, some information related to supplement use might have been missed. In addition, lexical variations, typos, non-standard free forms, acronyms, and abbreviations were ubiquitous in the clinical notes due to the nature of healthcare documentation. We did not solve these issues in the current study.

IV. Conclusions and Future Work

We developed and evaluated a rule-based classifier for supplement use status. The classifier was developed on seven supplements and then validated on both a testing set of seven supplements and a separate corpus with another three supplements. The results demonstrated that our classifier performs well (F-measures range from 0.95 to 0.97 for C, D, S categories) and was also generalizable to other supplements (F-measures range from 0.95 to 0.96 for C, D, S categories). This study shows that applying rule-based methods can unlock the rich and detailed information about supplement usage in clinical notes and that the rule-based method is a feasible solution to the classification of supplement use status.

Future work includes incorporating more sentences to enlarge the sample size not only for the already examined ten supplements, but also many other supplements. We will evaluate the generalizability on a relatively larger dataset as well as increase the performance of the classifier. The second direction is to use machine-learning methods to classify the supplement use status and compare the performance with the current study. We will also attempt to extract temporal information about supplement use in the near future.

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Table I

Supplement Name, Lexical Variations, and Preferred Name

Supplement	Variations	Preferred Name
alfalfa	alfalfa	alfalfa
echinacea	echinacea	echinacea
fish oil	fish oil	fish oil
garlic	garlic	garlic
ginger	ginger	ginger
ginkgo	ginkgo, ginko, gingko, ginkoba	ginkgo
ginseng	ginseng	ginseng
melatonin	melatonin	melatonin
St. John's Wort	St. John's Wort, St. Johns Wort, St. John Wort, St John's wort, St Johns wort, St John Wort	St Johns Wort
Vitamin E	Vitamin E, Vit E	Vitamin E

Table II

Annotation Guidelines for Supplement use Classification Task

Class	Definition	Examples
Continuing (C)	There is evidence showing that patient continues on the current supplement(s).	She continued on herbal supplements including echinacea. Decrease fish oil to 1 tablet daily. Has been drinking orange juice and eating garlic. Increase the dose of the garlic.
Discontinued (D)	The supplement is being stopped or is going to be stopped for some reason such as adverse interactions with the current medications or allergic reactions.	Stopped taking her garlic tablets a week ago. Pt will stop taking ginseng. Discontinued simvastatin and fish oil on admission. Please discontinue fish oil and garlic.
Started (S)	The patient is being started on or will be started on a supplement	Begin melatonin 10mg 1 hour before bedtime. Pt has started multiple herbal therapy, garlic TID, ginseng, iodine. Start ginkgo to help memory. Added garlic supplement.
Unclassified (U)	Supplements are mentioned in the notes, but do NOT indicate the use status or negation.	Advised over-the-counter melatonin. She asked about garlic and cranberries. Discussed options of benecol, garlic, and fish oil. Denies using st johns wort.

Table III

Performance of the Rules with the Distance to Supplement Terms

Distance from supplement terms	Category												Averaged F score
	Continuing (C)			Discontinued (D)			Started (S)			Unclassified (U)			
	P	R	F	P	R	F	P	R	F	P	R	F	
1	0.71	0.59	0.64	0.94	0.58	0.72	0.88	0.39	0.54	0.57	0.86	0.69	0.648
2	0.84	0.80	0.82	0.98	0.78	0.87	0.89	0.61	0.72	0.70	0.87	0.78	0.798
3	0.87	0.81	0.84	0.98	0.81	0.89	0.92	0.63	0.75	0.73	0.89	0.80	0.820
4	0.86	0.82	0.84	0.96	0.81	0.88	0.95	0.74	0.83	0.76	0.89	0.82	0.843
5	0.90	0.88	0.89	0.98	0.85	0.91	0.94	0.87	0.90	0.85	0.94	0.89	0.898
6	0.93	0.89	0.91	0.98	0.86	0.92	0.96	0.93	0.94	0.86	0.95	0.90	0.918
7	0.94	0.91	0.92	0.98	0.88	0.93	0.98	0.93	0.95	0.88	0.96	0.92	0.930
8	0.96	0.93	0.94	0.98	0.92	0.95	0.96	0.93	0.94	0.91	0.97	0.94	0.943
9	0.96	0.92	0.94	0.98	0.90	0.94	0.96	0.91	0.93	0.89	0.97	0.93	0.935
No distance control	0.97	0.92	0.94	0.98	0.88	0.93	0.96	0.93	0.94	0.90	0.98	0.94	0.938

Table IV

Selected Regular Expression Templates and Examples

Class	Top Three Frequently Used Rules	Examples
C (Continuing)	$(\text{continue} \text{continued} \text{continues} \text{continuing})(\backslash s+\backslash S)\{0,7\}\backslash s+\text{Sup}$	Continue fish oil to reduce inflammation.
	$(\text{increase} \text{increases} \text{increased} \text{increasing})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	Increase melatonin to 3 mg at night to help with sleep.
	$(\text{take} \text{takes} \text{took} \text{has}\backslash s+\text{taken} \text{taking})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	Pt takes low-dose aspirin and fish oil supplements, with the hope that these will help increase his HDL.
D (Discontinued)	$(\text{discontinue} \text{discontinued} \text{discontinues} \text{D}/\text{ced}/\text{DC})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	Pt discontinued the Vitamin E qd when he resumed taking his coumadin 2 weeks ago.
	$(\text{stop} \text{stops} \text{stopped} \text{stopping})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	Pt says she has stopped taking her fish oil and garlic.
	$(\text{hold} \text{holds} \text{held} \text{holding})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	Hold mobic, fish oil and other NSAIDS.
S (Started)	$(\text{start} \text{starts} \text{started} \text{starting})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	She was started on donepezil, mirtazapine, melatonin, Vitamin B.
	$(\text{resume} \text{resumes} \text{resumed})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	We have resumed fish oil from 1 g bid.
	$(\text{add} \text{adds} \text{added} \text{adding})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	Added ginseng, mushroom pill, MVI, B-complex to PTA list per patient report.
U (Unclassified)	$(\text{avoid} \text{avoided} \text{avoids} \text{avoiding})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	For supplements, avoid Vitamin E, fish oil, ginseng and ginkgo.
	$(\text{deny} \text{denies} \text{denied} \text{denying})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	Denies alfalfa.
	$(\text{recommend} \text{recommends} \text{recommended} \text{recommendations?})(\backslash s+\backslash S+)\{0,7\}\backslash s+\text{Sup}$	Recommend melatonin for sleep.

Note: "Sup" indicates the supplement names.

Table V

Performance of Rules on Testing Set #1

Supplement	N	Category																							
		Continuing (C)						Discontinued (D)						Started (S)						Unclassified (U)					
		P	R	F	N	P	R	F	N	P	R	F	N	P	R	F	N	P	R	F	N				
alfalfa	30	1.00	0.89	0.94	9	1.00	1.00	1.00	1.00	3	0.67	1.00	0.80	2	1.00	1.00	1.00	1.00	1.00	16					
garlic	42	0.92	1.00	0.96	12	1.00	0.90	0.95	10	1.00	0.50	0.67	2	0.95	1.00	0.97	18								
ginger	33	1.00	0.88	0.94	8	1.00	0.67	0.80	3	1.00	1.00	1.00	1.00	9	0.87	1.00	0.93	13							
ginkgo	39	1.00	0.92	0.96	12	1.00	1.00	1.00	1.00	4	1.00	1.00	1.00	5	0.95	1.00	0.97	18							
ginseng	37	1.00	0.71	0.83	7	1.00	1.00	1.00	1.00	6	1.00	1.00	1.00	5	0.90	1.00	0.95	19							
St. John's Wort	43	1.00	1.00	1.00	6	1.00	1.00	1.00	1.00	5	1.00	1.00	1.00	2	1.00	1.00	1.00	30							
Vitamin E	30	1.00	1.00	1.00	11	1.00	1.00	1.00	1.00	10	-	-	-	0	1.00	1.00	1.00	9							
Overall	254	0.98	0.92	0.95	65	1.00	0.95	0.97	41	0.96	0.96	0.96	25	0.93	1.00	0.96	123								

Table VI

Performance of Rules on Testing Set #2

Supplement	N	Category											
		Continuing (C)			Discontinued (D)			Started (S)			Unclassified (U)		
		P	R	F	N	P	R	F	N	P	R	F	N
echinacea	109	0.90	0.92	0.91	40	0.94	0.84	0.89	19	1.00	1.00	0.91	0.90
fish oil	168	0.98	0.98	0.98	93	0.97	0.97	0.97	32	1.00	0.89	0.94	19
melatonin	116	1.00	0.91	0.95	47	0.80	0.67	0.73	6	0.96	0.86	0.91	29
Overall	393	0.97	0.95	0.96	180	0.97	0.95	0.96	57	0.98	0.92	0.95	63
												0.83	0.95
												0.89	93