A Comparison of Self-reported Medication Use to Actual Prescription Records

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Abstract

The present study examined the congruence of self-reported current medications with actual prescription claims. The sample included 1,603 members of an HMO who also participated in the seventh wave of the Seattle Longitudinal Study (SLS). Self-reports of current medications were collected using a brown bag protocol during SLS testing and were compared to HMO prescription records for the five weeks prior to testing. The sample had a mean age of 61.6 years (range = 22-96), was 54.5% women, and was 94% white. Generally high levels of congruence were found between the two sources of medication information. However, the proportion of the sample who self-reported a drug class that was also included in the HMO prescription records varied by drug class. An average of 12% of the prescription claims data was not represented in the self-reports, and an average of 36% of the self-reported medications were not included in the prescription claims data.

Self-reports of current medications are often obtained in research studies using what is called the “brown bag” method (e.g., Bosworth & Schaie, 1995; Gerbert, Stone, Stulbarg, Gullion, & Greenfield, 1988; Jobe et al., 2001; Pahor, Salive, & Brown, 1995). This method involves asking participants to collect their current prescription medication containers in a brown paper bag that they then bring to a testing site, where research staff then record the items. This type of information is useful to researchers because it can provide information about the physical health status and comorbidities of their samples (Clark, Von Korff, Saunders, Baluch, & Simon, 1995).

Obviously, for self-report data to be accurate, the participants must be willing to provide complete information to the researcher. A few studies have examined the validity of self-reported medication data (e.g., Caskie & Willis, 2001; Gurwich, 1983; Landry et al., 1988; Opdycke, Ascione, Shimp, Boyd, & Malloch, 1994) and found that self-reports were reliable ways of obtaining information about current medications. However, Gerbert et al. (1988) concluded that patient reports were unreliable compared to chart audits, physician interviews, and videotaped physician visits. These previous studies have either used an age-restricted sample, a sample where participants were prescribed at least one medication, or have focused on a limited set of condition-specific medications. The present study included a large sample with a wide age range (22 years to 96 years) and was interested in a broad range of possible medications. Statistical methods used in prior studies to assess congruence also needed to be adapted to accommodate a healthy sub-sample of adults with no medications being included in the total sample and a wide range of possible medications.

Thus, the purpose of the present study was to assess the congruence between the brown bag method of obtaining self-reported medication data and the medications that have been prescribed to and filled by an adult sample containing a wide age range. Self-report medication data were collected using the brown bag method as part of an ongoing longitudinal study, the Seattle Longitudinal Study (SLS; Schaie, 1996). Because the majority of the SLS sample was recruited from the membership rolls of a health maintenance organization (HMO), prescription claim data were available for the SLS participants who were currently enrolled in the HMO at the time of the brown bag data collection. This allowed us to compare the self-report medication data collected via the brown bag method with the prescription records from the HMO.

This study addressed three research questions. First, what proportion of a pre-defined set of drug classes has congruent information when comparing self-report data and prescription claims data? Second, are a greater proportion of discrepancies identified in the self-reported medication data or in the prescription claims data? Finally, does the congruence between self-report medications and the prescription claims data vary by drug class? These research questions were examined for twelve major therapeutic drug classes.

Method

Sample

The analysis sample for this study was 1,603 members of the Group Health Cooperative (GHC) of Puget Sound who participated in the seventh wave data collection for the Seattle Longitudinal Study (SLS) in 1997-98. Only SLS participants who were enrolled in GHC at the time of the brown bag data collection were included in this analysis. The average age of the sample was 61.6 years old (*SD* = 16.0 years, *range* = 22 to 96 years). The sample was predominantly white (94.4%) and had a median income of $50,262. Women comprised 54.5% of the sample, and 66.5% of the sample were married.

Procedure

Brown bag medication data were collected during cognitive testing for SLS. Computerized prescription records from GHC were examined for participants for the five weeks prior to the date of testing. Each prescription medication in the GHC data had a code to indicate its therapeutic purpose, using GHC's in-house coding system. Each medication had three levels of codes, depending on the level of therapeutic specificity. The first level indicated the major therapeutic drug class (e.g., antihypertensives), and lower levels indicated minor or more specific therapeutic drug classifications (e.g., vasodilators). Each brown bag medication was also coded using the GHC coding system.

For both the prescription claims data and self-report data, a participant was assigned a 0 or 1 for each of the 12 drug classes examined, indicating whether the participant had at least one medication in that class (i.e., score of 1) or no medication in that class (i.e., score of 0). Over-the-counter items were excluded from the brown bag data used for this analysis. These items were not commonly filled as pharmacy prescription items and would have falsely inflated discrepancies between the two methods.

Measures of Congruence

Several measures of the congruence between the pharmacy prescription records and the self-report brown bag data were calculated in this study. These measures are described below.

Agreement score. This score is defined as the degree of identical information in both the prescription records and the brown bag self-report data and is calculated considering all drug classes examined rather than for a single drug class (Ascione, Kirscht, & Shimp, 1986; Gerbert et al., 1988; Opdycke et al., 1994). The agreement score, ranging from 0 (no agreement) to 1 (total agreement), was calculated using the following formula:

$$\text{Agreement Score} = \frac{\text{Number of Agreements Between GHC and Brown Bag data}}{\text{Number of Drug Classes Compared}}.$$

Because we were interested in the pattern of congruence for either the absence *or* the presence of medications within a pre-defined set of drug classes, the denominator in the above equation (i.e., the number of drug classes compared) was 12 for all individuals. This practice differed from previous studies where the denominator varied for each person, depending on the total number of drug classes reported in either data source.

One benefit of the agreement score is that the same overall measure of the agreement can be used for each person, despite differences in what medications were being taken by individuals. Another benefit is that, unlike the percent agreement and the kappa coefficient described below, an agreement score is generated for each person rather than as a sample statistic. However, because the agreement score does not define one data source as more accurate (i.e., a “gold standard”), it does not indicate which source is the cause of any discrepancies between the two databases. This problem can be overcome with an analysis of omission and commission scores, which are described next.

Omission/Commission error scores. These scores were used to obtain information about the source of reporting errors that may be responsible for discrepancies between the self-reports and the prescription-refill records. Scores were calculated on a per person basis, with values of 0 indicating no error in the reporting of medications and a value of 1 representing 100% error (Hulka et al., 1975; Hulka, Cassel, Kupper, & Burdette, 1976; Opdycke et al., 1994). The three types of matches or mismatches between the two data sources considered in this method are described in Table 1. Because we were considering congruence in a *set* of drug classes that were relevant to this sample, individuals with no prescription drugs were given error scores of 0 to avoid removing them from this analysis.

Percent agreement. An overall percent agreement was calculated as the percentage of the total sample whose self-report data was congruent with the GHC data for a given drug class either for the presence or the absence of a prescription within a given drug class. Additionally, two more specific types of percent agreement were also computed. First, for cases that had a prescription in a given drug class in the GHC data, the proportion of individuals who also reported that drug class in the brown bag data was calculated as the “percent agreement for cases with a prescription.” Second, for cases that did not have a prescription in a given drug class in the GHC data, the proportion of individuals who also did not report that drug class in the brown bag data was calculated as the “percent agreement for cases without a prescription.”

Kappa coefficient. The kappa coefficient is a measure of agreement between the classifications made by two independent data sources and takes into account the agreement expected by chance (Gerbert et al., 1988; Wickens, 1989). Values range from 0 to 1, with higher values indicating greater agreement. The classifications examined from the two data sources were whether or not a drug class had been reported (yes/no) by that source for a particular individual.

Results

Three research questions were investigated in this study. First, the proportion of a set of drug classes that were congruent for each individual in both the self-reports and the prescription records was examined using agreement scores. Second, the source of any discrepancies was investigated with an analysis of the errors of omission and commission. Finally, the congruence (i.e., percent agreement and kappa coefficient) between the self-report data and the prescription claims data was explored within each of the 12 major drug classes.

Prevalence of drug classes

As shown in Table 2, the prevalence of the 12 major drug classes in this sample ranged from 2.5% to 21.7%. Of these 12 drug classes, the three most prevalent in the self-report data were: (1) hormones (21.7%), (2) autonomic agents (17.2%), and (3) diuretics (15.2%). In the prescription claims data, hormones (9.3%) and autonomic agents (8.2%) were among the top three categories, but the most prevalent category was anti-inflammatory agents (9.4%). GHC utilizes a unique drug coding system that separates the cardiovascular drugs into several categories. When these categories were combined, cardiovascular drugs was the largest class in both databases. The number of major drug classes present for each individual ranged from 0 to 8 in each database. About 35% of the sample had no prescriptions in either database.

Proportion of congruent drug classes in self-report data and prescription claims data

In this section of results, we examined the proportion of drug classes that were congruent in the two databases. An average of 92% agreement (i.e., 11 of 12 classes) was found between the self-report and prescription claims data (*SD* = 10%). Perfect (100%) agreement between the self-report data and the prescription-refill records was found for 47% of the sample. Although agreement scores ranged from 42% to 100%, which indicated that fewer than half of the 12 drug classes were congruent for some individuals, 88% of the sample had congruent information for at least 9 of the 12 drug classes examined.

Discrepancies in self-reports and prescription claims data

To identify the source of any discrepancies between the self-reported medications and the prescription claims data, we next calculated an omission error score and a commission error score for each individual. On average, 12% of the information present in the prescription claims data was not included in the self-report data. Although 8% of the sample failed to report any of the drug classes found in the prescription claims data, 84% of the sample self-reported all of the drug classes found in the prescription claims data. On average, 36% of the information in the self-report data was not included in the prescription claims data. For 27% of the sample, none of the self-reported drug classes were found in the prescription claims data (i.e., 100% discrepancy). However, for 55% of the sample, all drug classes present in the self-reports were also present in the prescription claims data.

Congruence between self-report data and prescription claims data: By drug class

Finally, we examined congruence separately within each of the 12 major drug classes. Within each of these drug classes, percent agreement was investigated in three ways: (1) what proportion of the total sample had congruent information overall (i.e., both GHC and the self-report data were coded 0 or both were coded 1), (2) of the cases with a prescription in a drug class in the prescription-refill records (i.e., GHC=1), what proportion also self-report that drug class, and (3) of cases without a prescription in a drug class in the prescription-refill records (i.e., GHC=0), what proportion also do not self-report that drug class? We also examined the kappa coefficients for each drug class. These results are presented in Table 3.

The overall percent agreement for the presence or absence of a particular drug class was high for all major therapeutic drug classes studied, ranging from 85.5% to 96.5%. For cases where a medication was prescribed in the drug class, the percent agreement ranged from 35.4% to 98.3%. For cases where no medication was prescribed in a drug class, the agreement between the self-report and prescription-refill data was generally high (85.1% - 97.3%). The kappa coefficients ranged from .33 to .65 and were significant at a 95% level of confidence for all 12 classes, indicating significantly more agreement between the two databases than would be expected by chance.

Discussion

Three research questions were addressed in this study. First, agreement between the self-reported medications (i.e., brown bag) and the pharmacy prescription records (i.e., GHC) as to what proportion of drug classes were reported for each individual in both databases was examined. Second, we explored the source of reporting errors in both the self-report data and the prescription-refill records. Finally, the congruence between the two medication databases was examined separately for each drug class.

The congruence of self-reported medications and pharmacy records is an important issue because of the frequency with which self-report measures are employed as a proxy for health status or the presence of chronic disease, especially where pharmacy records are not available. Despite the widespread use of self-reports of medications, relatively few studies have examined their congruence with pharmacy records, and the samples used are often limited by age, medication type, or medical condition. The present study contributes to this literature by examining congruence in a sample that includes a wide age range, from young adults to old-old adults, and that is relatively healthy.

Almost half of the sample had perfect agreement between their self-reports and the prescription claims data for the set of 12 drug classes examined. Overall percent agreement within each of the drug classes was also generally high. When examining only the participants who had a prescription for a drug class in the prescription claims data, agreement varied more by class, with anti-infectives and analgesics having the lowest percent agreement and antilipemics having the highest percent agreement. This finding may reflect the differences in the severity of the conditions for which these drug classes would be prescribed. Previous research has found that drugs taken for less serious conditions or on an intermittent or short-term basis, as many of the drugs in these classes might be, are less likely to be reported (Green, Mullen, & Friedman, 1986; Kelly et al., 1990).

Discrepancies associated with using the brown bag method versus prescription data were also examined. Across the 12 drug classes, the proportion of information not included by the self-report data was lower than the proportion of information not included by the prescription claims data. Medication noncompliance may account for some of the discrepancies between the two sources of medication information (Coons et al., 1994; Cooper, Love, & Raffoul, 1982). If individuals were not taking the medications on the prescribed dosing schedule, this could result in the self-report data containing more medications than the prescription records for the month prior to the brown bag data collection. Another alternative explanation is that individuals might be obtaining medications from other sources that would not be recorded in the prescription claims data, such as samples from their physician.

Contributions of this study are that congruence was examined at both the individual and aggregate levels and that our analyses included a large proportion of healthy, age-diverse participants who do not take medications. This study also included several limitations. One limitation of this study was that our sample was drawn from a health maintenance organization. Stuart and Grana (1998) found that prescription coverage may increase the likelihood that medical conditions would be treated with prescription medications. Second, agreement of the brown bag data with the prescription records was only examined for selected drug classes. Finally, Choo et al. (1999) and Christensen et al. (1997) have found that using computerized prescription records as a proxy for current medications can be problematic, mainly because filled prescriptions cannot verify the actual taking of the drug. Christensen et al. also found that medication compliance was difficult to assess in periods less than 60 days.

These findings have several implications for the use of the brown bag method to collect medication information. The difference between the brown bag and prescription data may vary by the class of medication being considered. Results also showed higher agreement of self-reports and prescription records for medication classes that were not prescribed than those that were prescribed. Further research needs to be done examining congruence within age groups and for more specific levels of drug classes. Also, demographic variables, cognitive ability variables, or health status should be investigated as predictors of congruence to aid in identifying sub-samples were the brown bag method will be accurate.

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Table 1. *Omission/Commission Analysis*

Notation	Error Name	Description
A		Number of classes that were self-reported and were in the pharmacy records
B		Number of classes person did not report that were in the pharmacy records
C		Number of classes the person reported that were not in the pharmacy records
B / (A + B)	Omission	Proportion of error attributed to the self-report
C / (A + C)	Commission	Proportion of error attributed to the pharmacy records
(B + C)/(A + B + C)	Combined	Combined errors of omission/commission

Note. The omission/commission method applied to medication data by Hulka et al. (1975, 1976) was adapted to include individuals with no prescribed and/or reported medications. These individuals were given error scores of 0.

Table 2. *Prevalence of examined drug classes in the prescription records and self-report data*.

Therapeutic Class	Self-report	GHC
Analgesics	8.8	7.0
Antihypertensives	10.8	5.5
Anti-infectives	5.1	7.0
Anti-inflammatory agents	12.7	9.4
Antilipemics	7.0	3.6
Autonomic agents	17.2	8.2
Cardiovascular agents (Calcium channel blockers)	5.7	2.9
Cardiac agents	5.5	2.5
Diuretics	15.2	5.1
Gastrointestinal agents	9.9	7.1
Hormones	21.7	9.3
Psychotherapeutics	11.0	6.6

Note. GHC = Prescription records from Group Health Cooperative of Puget Sound.