

Enhancing Fulfillment Data in Community Practices for Clinical Care and Research Final Progress Report¹

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Structured Abstract (249 words)

Purpose: To evaluate the availability and usefulness of medication prescribing and fulfillment data obtained from community-based electronic health records (EHRs).

Scope: Practices in the DARTNet distributed network participated in a web-based survey to assess the availability of medication fulfillment data in their existing EHRs. Three community-based practices and one academic practice were ultimately selected for data extraction. A pre-visit decision support focused on anti-hypertensive medication adherence in hypertensive patients was pilot tested.

Methods: The REDCap system was used to develop a web-based survey to assess the availability of medication fulfillment data. Patient demographics, diagnoses, encounters, medication prescriptions and fulfillment data were extracted from 7/1/2007 thru 2/1/2014. An existing paper-based pre-visit decision support tool was expanded to include alerts for potential medication non-compliance for hypertensive patients on anti-hypertensive medications.

Results: Medication fulfillment data is present in a minority of community-based practices. Drug fulfillment data became more widely available with the release of Meaningful Use requirements. Cost for obtaining and integrating medication fulfillment data were the most cited barrier. Significant data quality issues occurred across multiple data extractions due to a third-party data repository that existed between the EHR and the investigators. Lack of confidence in the completeness of the data extractions severely limited the conclusions drawn from the available data, limiting the study to overall descriptive statistics. Despite issues with false positive alerts, the pilot clinicians found the drug adherence decision support pilot of value and worth expanding.

Key Words: Medication fulfillment, medication adherence, electronic health records, clinical decision support

¹ Format based on "AHRQ Grant Final Progress Report Template" (<http://www.ahrq.gov/funding/grant-mgmt/reptemp.html>)

Purpose

Nearly all current medication-related literature, especially medication adherence studies, use payer-based medication fulfillment billing records. With the rapid expansion of electronic health records and the widening use of e-prescribing and electronic medication fulfillment data exchanges, EHR-based data may enable more clinically-relevant relationships between medication prescribing and medication fulfillment activities to be explored and may provide a different perspective on prescribing/fulfillment behaviors that cannot be assessed with administrative medication fulfillment billing records alone.

While prescription data represent what clinicians have prescribed for patients (ideally, the intended prescription medication regimen), fulfillment data represent what patients have received from the pharmacy (ideally, the actual prescription medication regimen). Comprehensive medication fulfillment data may help clinicians provide better coordination of care by revealing what other clinicians have prescribed for a patient and may better inform care by revealing whether a patient has been able to adhere to prescribed drug regimens. Because fulfillment data represent exposure to medications, they are also very important in observational comparative effectiveness research. Community practices that use fully electronic prescribing (eRx) are obtaining new access to fulfillment data, and federal efforts are actively promoting the adoption of eRx. However, many questions remain about the actual accessibility, comprehensiveness, and utility of these fulfillment data for clinical care and research.

This study had three specific aims:

Specific Aim 1: In all DARTNet organizations, use surveys and interviews to assess the actual status, organizational plans, and barriers for full eRx, capture of fulfillment data, and clinician use of fulfillment data.

Specific Aim 2: In five DARTNet organizations receiving fulfillment data through the eRx-based process, the consent-based process, or both, assesses the data's comprehensiveness and clinical utility.

- SA 2a: Assess and compare comprehensiveness of fulfillment data by matching with prescribing data
- SA 2b: Assess the completeness of fulfillment data by sampled manual audits
- SA 2c: Calculate adherence and persistence measures for three classes of medications - anti-hypertensives, HMG Co-A reductase inhibitors (statins), and antidepressants.
- SA 2d: Explore the utility of using prescribing data and fulfillment data to identify unintended continuation and duplication of therapy for anti-hypertensive medications.

Specific Aim 3: In one DARTNet organization capturing fulfillment data, develop and pilot test a patient-level report used using clinical, prescribing, and fulfillment data to improve the management of hypertension during the clinical encounter, with subjective assessments of utility by interviews with clinicians.

The three specific aims focused on assessing the availability of medication fulfillment data in community-based electronic health records (Aim 1), assessing the accuracy and completeness of medication prescribing and fulfillment data to measure medication adherence (Aim 2), and exploring the usefulness of EHR-based medication prescribing and fulfillment data to implement a clinical decision support tool based on medication adherence (Aim 3). The aims of this project focused explicitly addressed AHRQ's interest in "health IT to improve the quality and safety of medication management via the integration and utilization of medication management systems and technologies" and "health IT to improve health care decision making through the use of integrated data and knowledge management."

Scope

We leveraged existing relationships between multiple community-based practices and the Distributed Ambulatory Research in Therapeutic Network (DARTNet) to assess the prevalence of medication fulfillment data in current EHR systems. Based on the results of this survey, we selected four community-based general practices and one academic-based general practice to obtain EHR-based medication prescribing and fulfillment records. One community-based practice was eliminated due to insufficient medication fulfillment data observed following the initial data extraction. Using proprietary CINA clinical data repositories (CDR), which had been installed in all DARTNet sites at the time of this study to hold site-specific EHR data in a common standardized format (Figure 1, Step 3), we extracted data to examine issues of medication prescribing and fulfillment availability, data completeness and accuracy, and clinical usefulness for decision support. (Figure 1, Step 4). The four selected clinical practices collectively represented 132,171 unique patients overall (36,354 patients with hypertension, 29,172 patients with dyslipidemia, and 15,063 patients with depression, the three disease-specific targeted patient cohorts). More detailed definitions of the patient cohorts and medication classes and the observed study population demographics are presented in Table 1, Table 2, and Table 3.

Methods:

We initially created a web-based survey to assess the availability and use of medication fulfillment data in existing DARTNet practices. Based on these responses, we selected five practices for further analysis. We used retrospectively collected observational data obtained from electronic health records. Prior to the start of this project, data were extracted from each practice's commercial EHR by CINA Inc, a third party HIT services organization used by DARTNet, into a proprietary CINA clinical data repository (the CINA CDR). From the CINA CDR, we extracted patient demographics, encounter, diagnosis, medication prescribing, and medication fulfillment records from July 1, 2009 thru February 1, 2014. Based on the inconsistent availability of medication fulfillment data until October 1, 2012, we later restricted our analysis to data from that date onward. Multiple members of the CINA technical staff performed a total of 16 data extractions (4 data extraction rounds x 4 DARTNet data sites). A data analyst from the DARTNet Institute performed the three final data extractions (1 data extraction round x 3 DARTNet data sites). All data tables and findings presented below are based only on the final data extractions performed by the DARTNet Institute personnel. Numerous data quality assessment methods were applied including plots of medication prescriptions and fulfillment records by time, time from first prescription to first fill for same drug class, and time from last fulfillment to closest previous prescription. The potential impact of \$4.00 medications, which do not result in a fulfillment record were examined. A number of "control" settings where the time between prescriptions and fulfillment is expected to be small were examined. Despite concerns about data completeness, we calculated the Proportion of Days Covered (PDC) and Medication Possession Ratio (MPR) medication adherence measures for three patient cohorts: the use of antihypertensive medications in patients with a diagnosis of hypertension; the use of lipid lowering medications in patients with a diagnosis of dyslipidemia; and the use of anti-depression medications in patients with a diagnosis of depression. We used the definitions for PDC and MPR as described by Raebel [1]. Encounter-based ICD9-CM billing codes were used to define patient cohorts (Table 1); The Medi-Span Electronic Drug File Generic Product Identifier® (GPI) codes by Wolters Kluwer were used to define anti-hypertension, dyslipidemia, and anti-depression medication classes for both medication prescribing and medication fulfillment records (Table 2). The PDC and MPR medication adherence measures also used the same GPI codes from Table 2.

Results:

Aim 1: The survey used to assess the availability of medication fulfillment data within DARTNet partners' EHRs can be viewed at URL #1 in Table 7. The underlying REDCap data dictionary, which includes conditional logic that suppresses additional questions based on previous responses, is available on the AHRQ ARRS web site or can be downloaded from URL #2 in Table 7. At the time of the survey, a minority of DARTNet practices had established electronic links to integrate medication fulfillment data directly into their EHR. Of the 20 networks and practices that responded to the online-survey, only 6 reported some form of medication fulfillment data in their EHR. For networks without fulfillment data, the most commonly cited barriers were the costs for EHR vendor interfaces, configuration services, maintenance, and transaction fees associated with linking these external data providers to their EHR system. The most common mechanism for obtaining medication fulfillment data involved pulling data for patients 24-48 hours before their next scheduled visit, a workflow that impacts analytic methods. Although DARTNet has been pursuing a consent-based model for receiving fulfillment record between scheduled visits, none of the participants had implemented this model. The academic medical center only obtained medication fulfillment data from patients who filled their prescriptions at the institutional pharmacy, which accounted for less than 10% of all patients. For this small group of patients, fulfillment records were available in the EHR as soon as the fulfillment event was completed. When the very small number of patients using the in-house pharmacy for fulfillment was verified, this data partner was dropped from the final analysis. Thus, medication fulfillment data is not widely implemented in community practices and in some practices only represents specific patient subgroups based on fulfillment location.

Aim 2: Table 4, Table 5, and Figure 2 provide overview descriptive statistics for the number of medication prescription events that were initiated by the practice and all fulfillment events. Table 4 and Table 5 provide overall and cohort-specific numbers (rows) by medication class (vertical columns). Cells along the diagonal, highlighted in gray background, provide counts of prescription (fulfillment) events for the drug class directly associated with the cohort (e.g., anti-hypertensive medications in the hypertension cohort). Off-diagonals represent the use of one of the other medication classes not directly associated with the cohort (e.g., anti-depression medications in the hypertension cohort). Figure 2 shows the changes in the number of prescription and fulfillment events by month from 7/1/2009 to 3/1/2014. This figure shows the rapid increase in the number of monthly medication fulfillment records starting around 4/1/2012. In discussions with data partners, this increase coincides with the introduction of Meaningful Use Stage 1 electronic prescription (eRx) measures. For this reason, many of our analyses were restricted to the period between 11/1/2012-10/31/2013. The fall-off in fulfillment records after 11/1/2013 in the absence of a similar fall-off in prescription records is thought to be an artifact of the fulfillment record downloads, which only occurs at the time on the next clinic visit. Many of the patients who received prescriptions after 11/1/2013 have not yet returned to the clinical for a follow-up visit and therefore have not yet had their fulfillment records loaded into the EHR.

The vast majority of effort in this project was consumed with discovering, analyzing and attempting to solve (or work around) significant and eventually unsolvable barriers in obtaining accurate and complete data extractions for the CINA CDR (Figure 1, Step 4). A preliminary small data extraction from the EHR to the CINA CDR to study-specific extracts showed high accuracy when compared to chart review (Specific Aim 2b). The detailed protocol used to validate the pilot medication prescribing and fulfillment data extracts is available at URL #3 in Table 7. Despite excellent correspondence with the pilot extract, subsequent data extractions six months later had multiple data anomalies and inconsistencies that were not present in the preliminary data pulls. We provide only a small sample of the analyses performed to understand the data anomalies that were not present on the pilot extraction but appeared in every subsequent extractions until those performed by DARTNet Institute personnel during the second no-cost extension.

A major source of data anomalies were incorrectly formatted or nonsensical NDC codes (e.g., NDC codes that had no relationship to the text drug name) and multiple records, sometimes 10-15 repeats) with the same start/stop date with identical medication names but different drug SIG information. An example Excel spreadsheet that illustrates attempts to understand and rectify observed 9-, 10- and 11-digit NDC codes is available from URL #4 in Table 7. A valid NDC code is a 10-digit number divided into 3 segments separated by dashes. The first segment can be 4 or 5 digits, the second segment is 3 or 4 digits and the third segment is 1 or 2 digits. NDC codes have one of the following groupings of segments: 4-4-2, 5-3-2, or 5-4-1. CMS created an 11-digit variation that adds a leading zero to the appropriate segment to create a fixed 5-4-2 group (e.g. 4-4-2 → (1+4)-4-2; 5-3-2 → 5-(1+3)-2; 5-4-1 → 5-4-(1+1), where "1+" indicates the location of the additional leading zero). An 11-digit NDC code cannot be transformed back into a 10-digit standard format without examining/comparing product names. The Excel spreadsheet in URL #4 in Table 7 shows NDC code values with character lengths < 10, >=10 and >=12. Using convoluted logic that tried all variations of placement of dashes and removal of zeros, we were able to match 91-98% of medication fulfillment codes but only 50%-74% of prescription codes. Even with the very high match rate, confidence in the quality of the data extract across other data variable was still low.

An independent data completeness check we performed calculated the time between a prescription record and the closest fulfillment record for the same medication subclass (GPI-6 or GPI-8). An analogous quality check looked at a fulfillment record and determined the time of the closest prescription record. Table 6 defines and illustrates these two data quality checks.

The expected findings were that for most medications, the Rx→Fill and Fill→Rx times would be relatively short, with most medications filled within 0-7 days. For both methods and for all three cohorts-medication classes (e.g., hypertensive cohort-antihypertensive medications), over 50% of Rx→Fill and Fill→Rx pairs did not have a match. That is, over half of the prescriptions did not have a corresponding fill event in the 6-month time window. Similarly, over half of the fulfillment events did not have a corresponding medication event (same GPI-8 - drug class). When an Rx→Fill or Fill→Rx match was found, the mean and median times between these two events hovered around 15-20 days, longer than expected but not extremely long (Figure 3). To better explore this data quality measure, we examined three specific "control" cases where we used medications that do not have a generic equivalent, are not a \$4.00 medication, and are expected to be filled almost immediately due to the acute and serious medical indications for these medications: esomeprazole/Nexium®; oxycodone; and hydrocodone/acetaminophen/Vicodin®. Figure 4 plots the time between first prescriptions and first fills only for oxycodone, a potent oral narcotic given to relieve acute severe pain. The same pattern seen with our cohorts -- a large number of missing Rx→Fill pairs (62%) and longer than expected prescription to fill times -- suggests significant missing fulfillment data.

While drug prescription records had more data quality issues than drug fulfillment records, large gaps in both types of records suggested significant missing data in the EHR → CINA CDR data extraction routines (Figure 1, Step 3) that were "upstream" to the project CINA CDR → Analytic Data Set data extraction routines (Figure 1, Step 4).

During the course of the project, CINA had serious business challenges that resulted in the eventual departure of our key internal resource (Cathy Bryan), who continued with the team as an external consultant but without direct access to internal CINA resources or processes. Eventually the Founder/CEO, two project managers, and two key technical resources all left CINA during the project period. At the same time CINA decided to exit the clinical research space and licensed their CDR data query tools to the DARTNet Institute, a 503c non-profit organization formed by the DARTNet distributed network partners. During our second no-cost extension, members of the DARTNet Institute, in collaboration with Gerald Pulver, a member of our team, provided the final data extract that forms the

basis for the Tables and Figures in this report. Even with direct access to the CINA CDR and to the data analyst, DARTNet Institute personnel could not fix issues with data extraction from the EHR -> CINA CDR. For example, critical data fields for medication prescribing were not available in coded format in the CINA CDR but only as unformatted and non-standard text strings. Data quality ultimately limited the ability to draw significant conclusions, leading to mostly descriptive statistics regarding the state of medication prescribing and fulfillment data in community practices.

Because data completeness seemed to be better between November 1, 2012 thru October 31, 2012 (Figure 2), we used this restricted time interval to calculate two widely used drug adherence measures: proportion of days covered (PDC) and medication possession ratio (MPR). Figure 5 plots PDC for all three cohorts by all drug classes (anti-hypertensive, HMG Co-A reductase inhibitors). Figure 6 shows the traditional MPR where MPR values > 1 are set to 1.0. Figure 7 plots the raw MPR. For all three measures, compliance was lowest in the depression cohort across all medication classes. That is, patients in the depression cohort were least likely to be adherent to anti-hypertensive medications and HMG co-A reductase inhibitors in addition to anti-depression medications. For both the PDC and MPR, the area under the curve for values less than 1.0 indicates noncompliance. In all plots, a significant number of patients showed medication noncompliance (PDC=1.0 ~ 20% in all plots). Because of concerns about missing data, we cannot be sure if the observed non-compliance actually represents missing fulfillment data rather than true non-compliance. One counter-argument to missing data during the restricted time interval is the significant number of patients with MPR>1.0. An MPR>1.0 indicates that a patient is accumulating additional days of medications across successive fulfillments. For example, if a patient with a 60 day supply refills their prescription on Day 50, he will have 10 additional days of medications, resulting in a calculated MPR>1.0. If there were a significant number of missing fulfillment records, there should be very few patients with MPR values > 1.0. We see a significant "right tail" for MPR>1.0 in Figure 7, suggesting good fulfillment data coverage. Understanding the differences in data quality across the entire data set versus during the restricted time period remains as future work.

Aim 3: Despite barriers in accurate data extraction, a pilot clinical decision support tool that alerted physicians when a potential lapse in medication adherence in the use of anti-hypertensive medications was successfully implemented. Figure 8 provides a high-level and detailed description and graphical illustration of the decision support logic. In brief, the logic determines that the patient has filled previous anti-hypertensive medications (past 180 days). If so, the logic examines each of the major anti-hypertensive drug subclasses (ACE inhibitors, Angiotensin II receptor blockers -- ARB, calcium channel blockers, beta blockers or diuretics), calculates the expected date that existing medications should run out based on the days supplied in the most recent fulfillment record, adds an additional 45 days "grace period" and alerts if the current date exceeds this time interval. The "alert" was added to an existing paper-based pre-visit decision support report (Figure 9). Three physicians in three separate practices agreed to include this additional decision support logic in their existing pre-visit reports. Over a 3-month pilot implementation period, the clinicians noted that the decision support alert is dependable when it does NOT flag an adherence issue but it is less accurate when it flags a potential adherence issue. Based on an alert, physicians would ask about medication adherence and would discover valid reasons why the alert was inaccurate, such as a change in pharmacy or use of accumulated medications. Even with a relatively high false alerting rate, physicians found the decision support tool useful, which provides an opportunity for further implementation and formal analysis. It is unclear if the high false positive rate would be tolerated if the CDS were to be deployed to more clinicians or was expanded to include a wider range of medications. However, there was sufficient interest in incorporating fulfillment information in the pre-visit report that future implementation of this feature seems warranted.

List of Publications/Products: No publications have resulted from this work at this time. A very late-stage data extraction (fourth extraction by DARTNet Institute in February 2014) has provided more

dependable data that will continue to be analyzed and could lead to future publication beyond the grant funding period.

We have submitted the web-based survey used to determine the availability of medication fulfillment data in community EHRs to the AHRQ ARRS system. The full data dictionary and executable survey is available from that site.

Cited references

- 1 Raebel MA, Schmittiel J, Karter AJ, *et al.* Standardizing Terminology and Definitions of Medication Adherence and Persistence in Research Employing Electronic Databases: *Medical Care* 2013;**51**:S11–S21. doi:10.1097/MLR.0b013e31829b1d2a

Figures

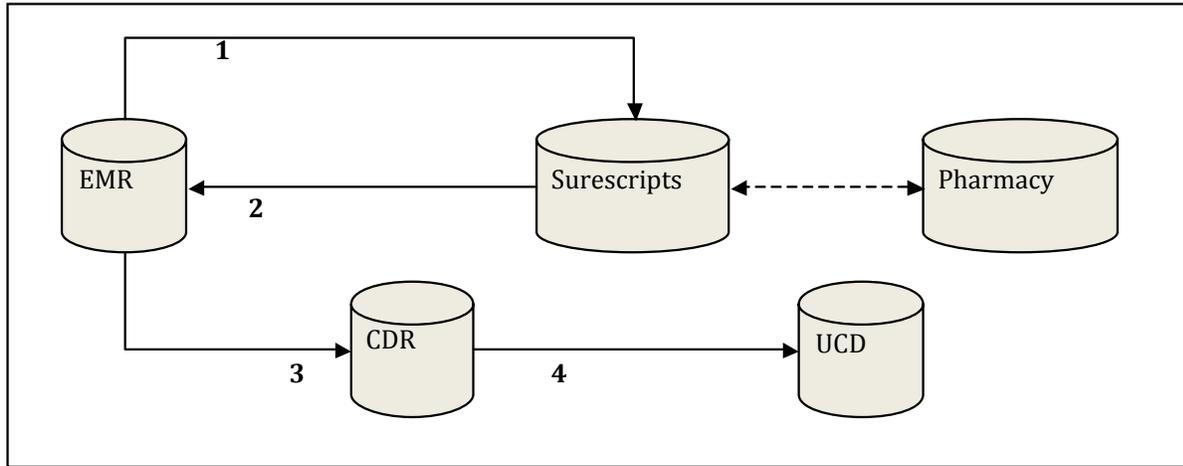


Figure 1: Data flows and key components in integrating medication fulfillment data from a pharmacy billing vendor (SureScripts). Diagram from the original grant proposal.

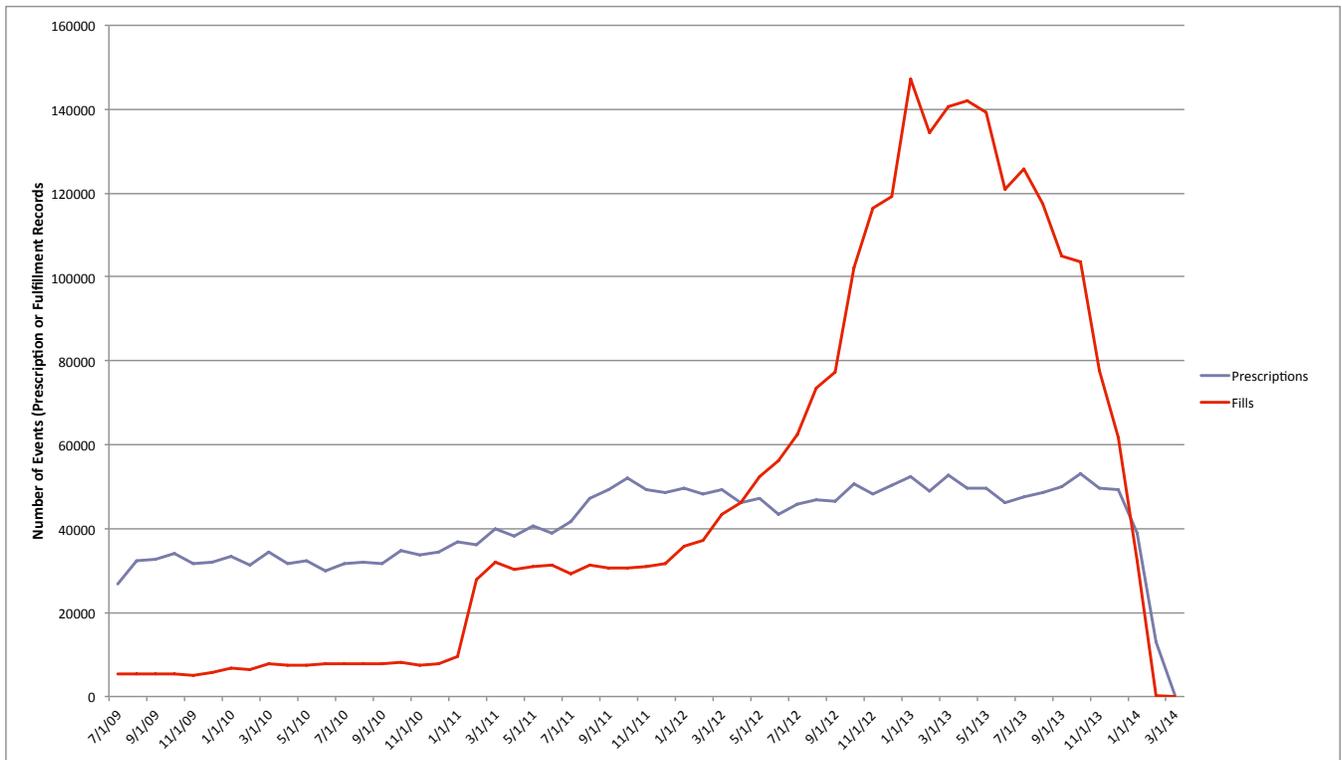


Figure 2: Plot of Medication Prescription and Fulfillment Events by Month (all medications).

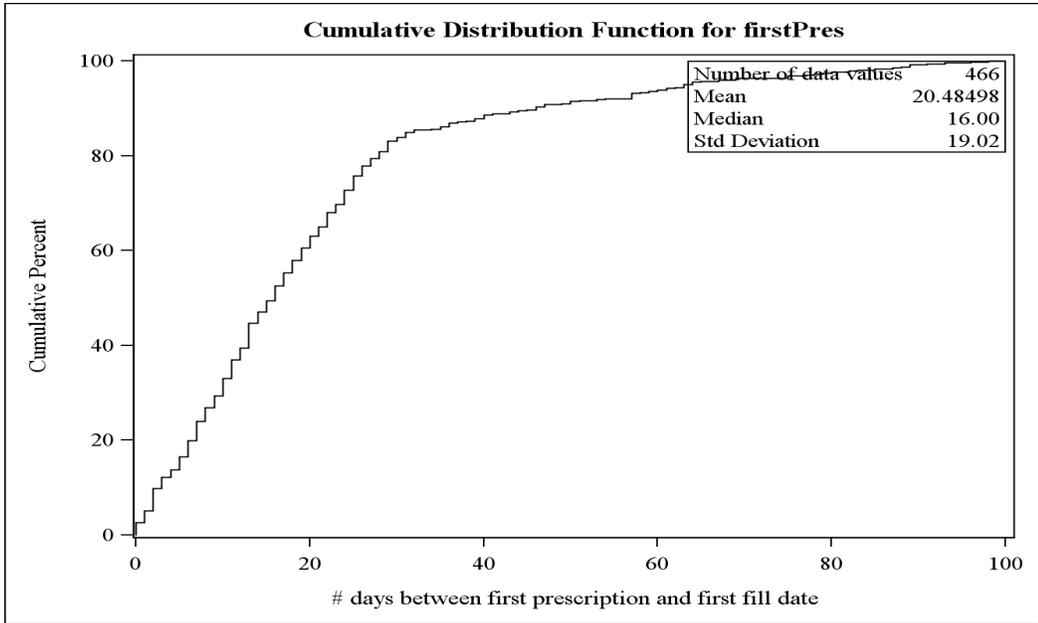


Figure 3: Time from first prescription to first fill for anti-hypertensive medications for patients in the hypertensive cohort. Over 51% of prescription records had no matching fulfillment records in a 6-month interval (not shown in this plot). Similar patterns of large amount of missing data and longer than expected mean and median time to fill in other cohorts and medication classes suggests significant missing data.

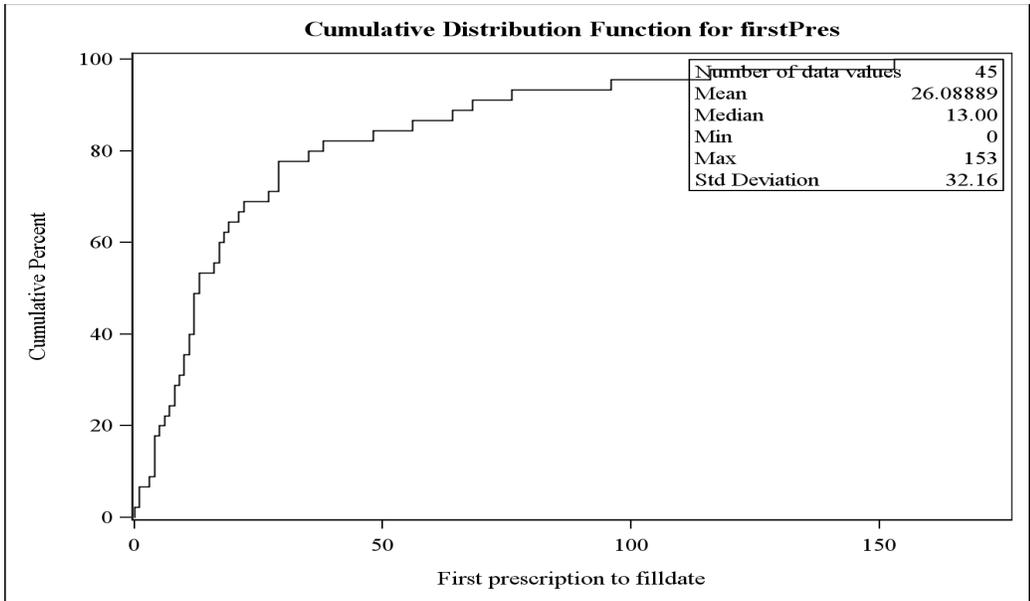


Figure 4: Time from first prescription to first fulfillment record for oxycodone, a potent narcotic used for treatment of acute severe pain. The much longer-than-expected mean and median fill times suggest missing data. More than 62% of prescription records had no matching fulfillment record (not shown), suggesting missing data. The same pattern was seen in two other "control" medications: esomeprazole/Nexium and hydrocodone/acetaminophen/Vicodin (not shown).

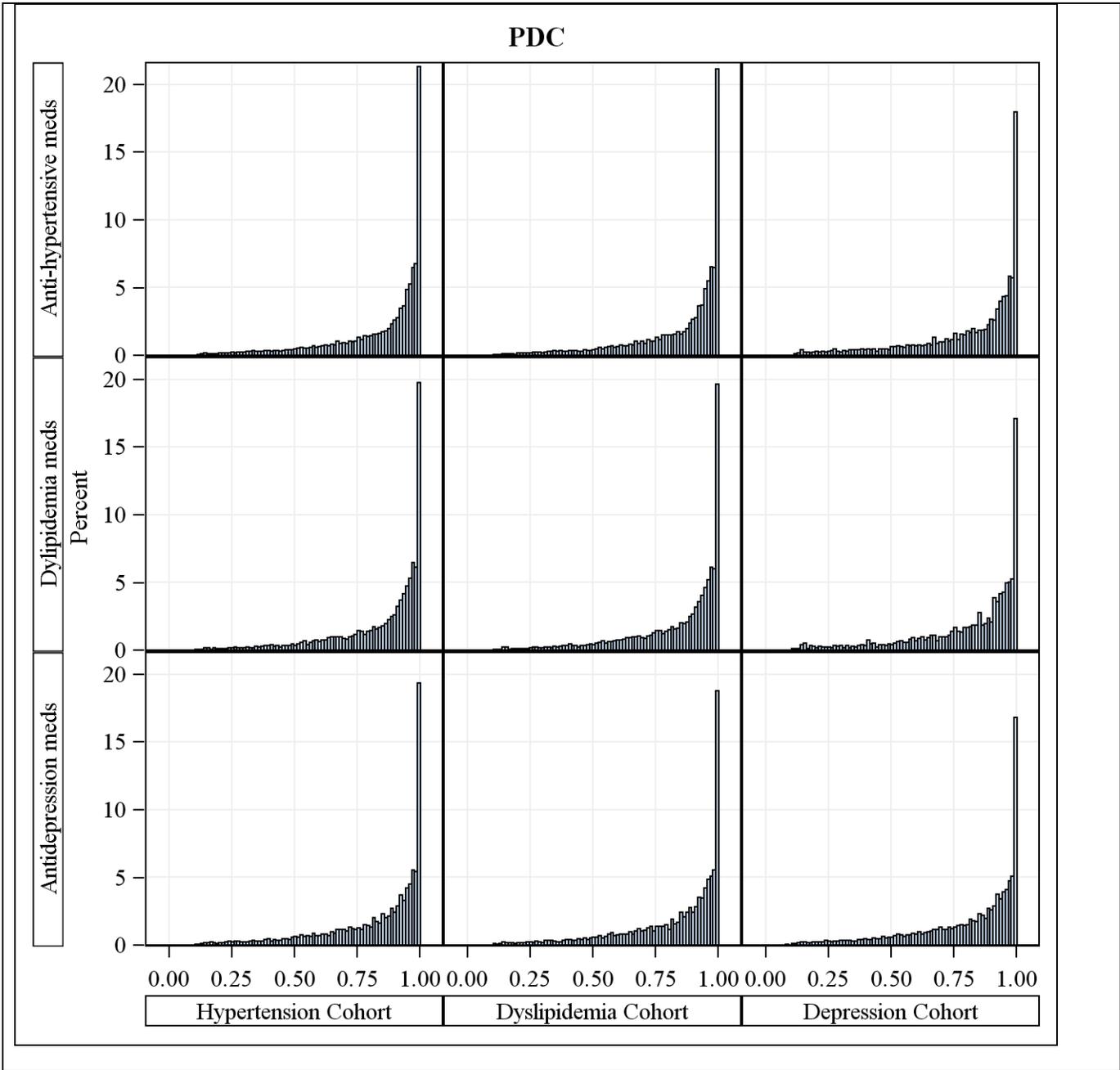


Figure 5: Proportion Days Covered (PDC) medication adherence measures by cohort (x-axis) by medication class (y-axis) based on EHR medication fulfillment records. Diagonals represent medication classes associated with disease cohort. Off-diagonals represent medical classes associated with other disease cohorts.

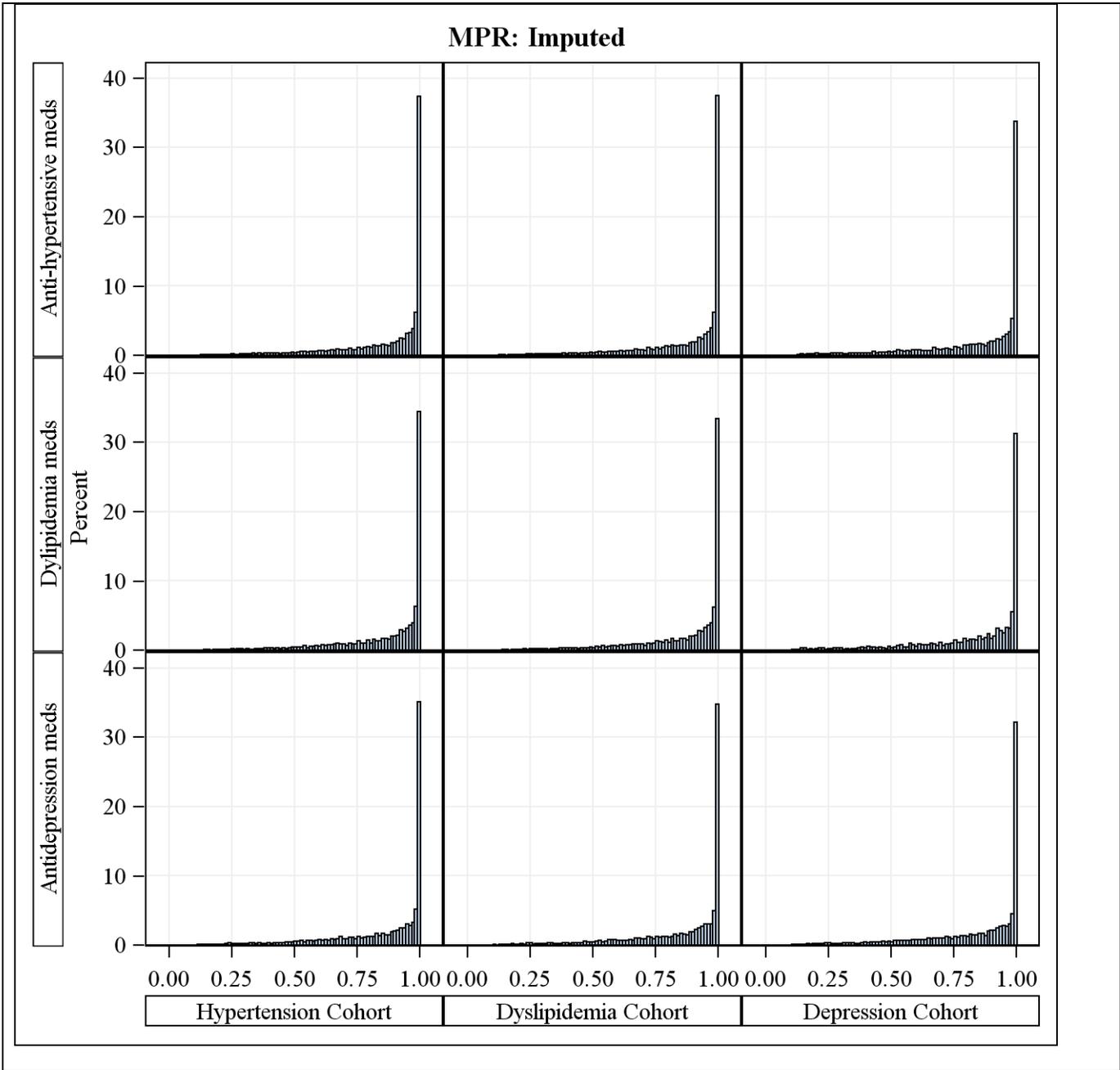


Figure 6: Medication Possession Ratio (MPR) based on EHR medication fulfillment records. MPR > 1 set to 1 per convention. Diagonals represent medication classes associated with disease cohort. Off-diagonals represent medical classes associated with other disease cohorts.

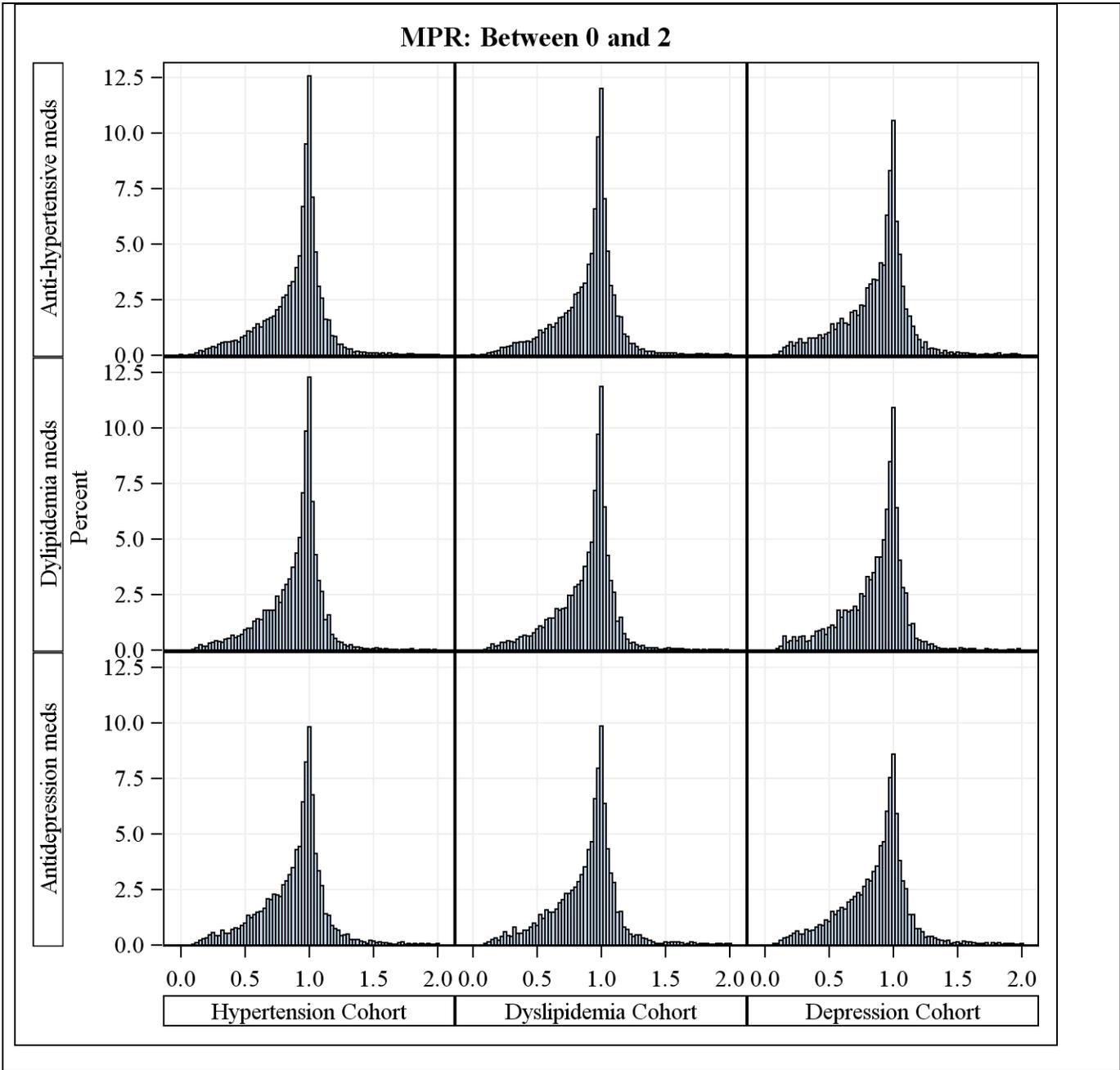


Figure 7: Same plot as previous figure that does not reset $MPR > 1$ to $MPR = 1$, showing intervals where patients have accumulated medications over time ($MPR > 1$). Diagonals represent medication classes associated with disease cohort. Off-diagonals represent medical classes associated with other disease cohorts.

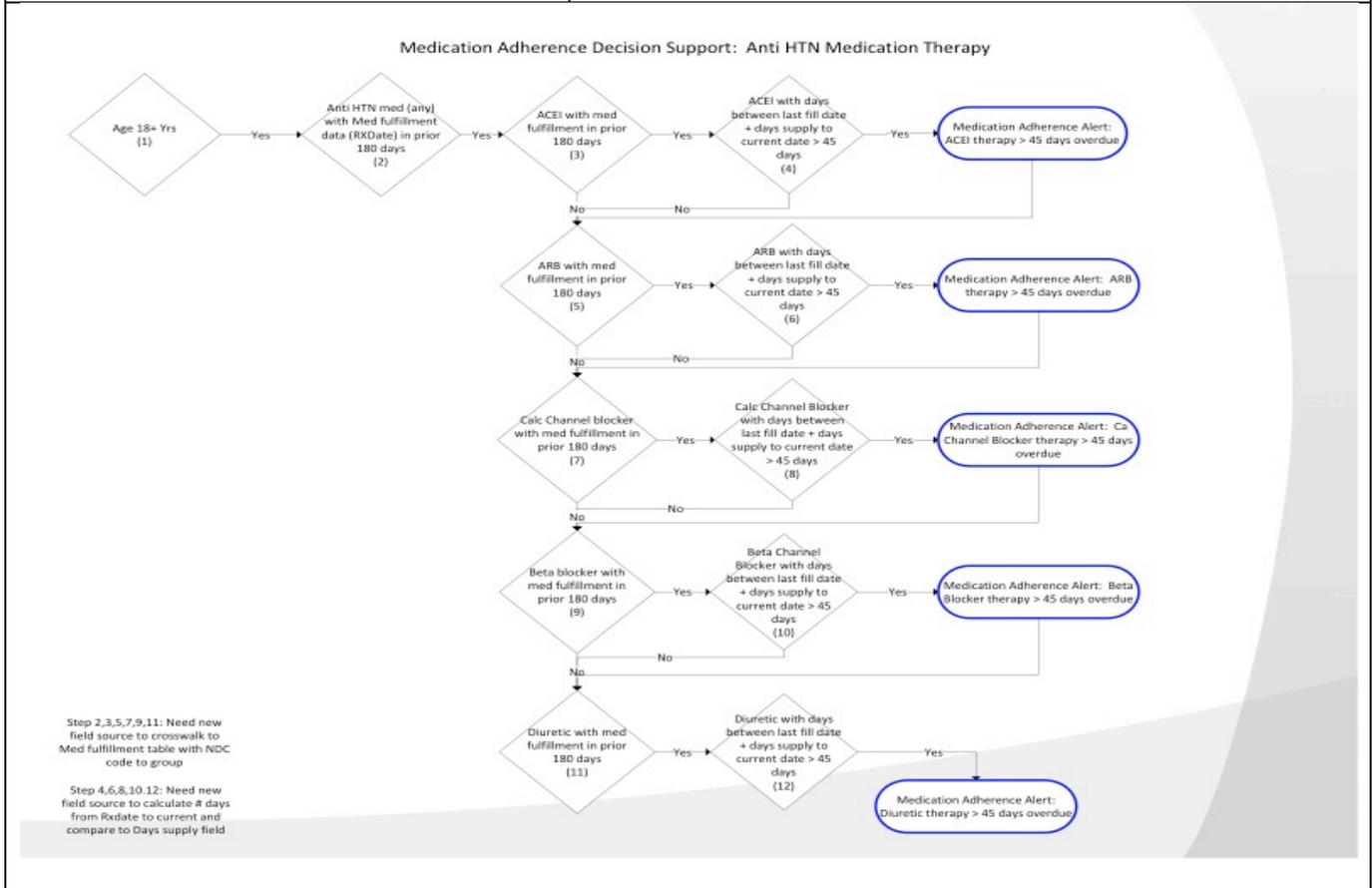
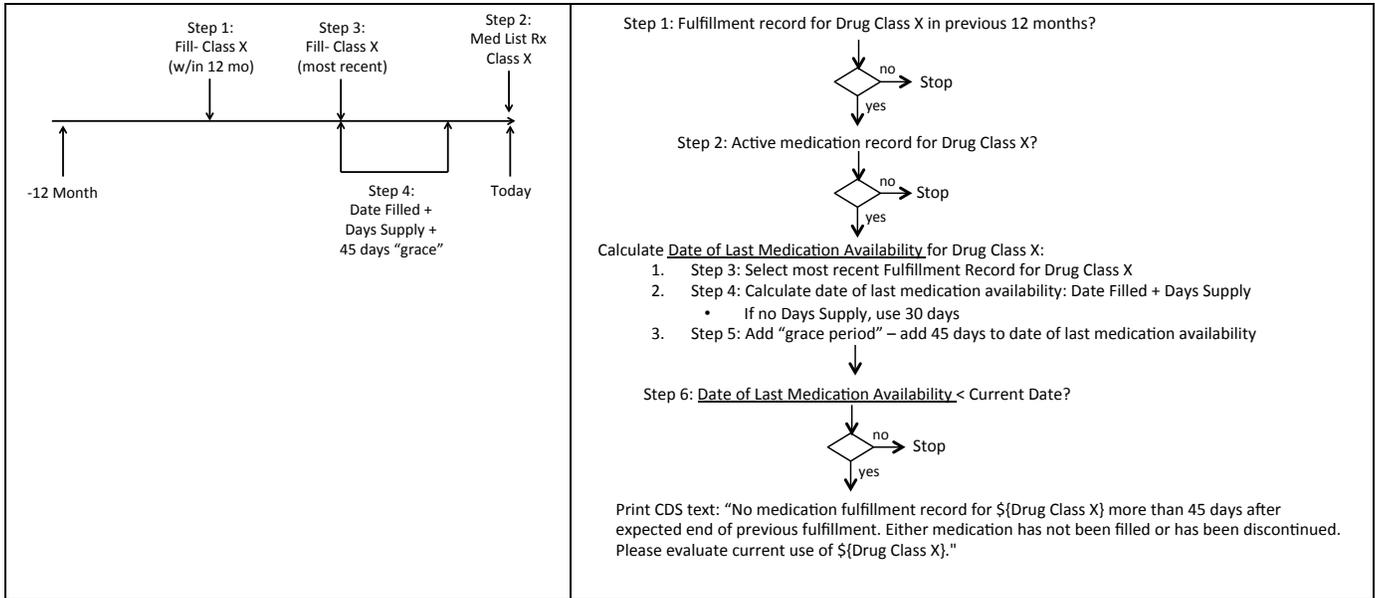


Figure 8: Decision support logic for alerting for potential medication non-adherence. Top two panels are high-level descriptions. Bottom panel is the complete decision logic by medication subclass.

Patient Recommendation Report

001890002 [REDACTED] DOB: [REDACTED] Age: 76 Sex: F Seen By: Webster, Brian
 Appointment Date: 8/9/2013 9:00:00 AM Report Date: PCP: Webster, Brian MD

<p>Active Diagnoses</p> <p>DIABETES MELLITUS (250.00) CONGESTIVE HEART FAILURE (428.0) FAILURE, DIASTOLIC HEART, CHRONIC (428.0) HYPERTENSION (401.1) HYPERTENSION, BENIGN ESSENTIAL (401.1) Atrial Fibrillation ATRIAL FIBRILLATION (427.31) MIXED HYPERLIPIDEMIA (272.2) ABNORMAL RESULTS OF FUNCTION STUDY ACUTE BRONCHITIS (486.0) ACUTE PHARYNGITIS (462.0) ACUTE SINUSITIS (461.0) ACUTE UPPER RESPIRATORY INFECTION ALLERGIC RHINITIS, CAUSE UNSPECIFIED MORE</p>	<p style="text-align: center;">Risk Factors</p> <p>CHD 10Yr Risk > 20% Lt Ventricular EF not documented Colon CA (age 50-60) Pneumonia (Age > 64 OR Risk Dx)</p>																																							
<p>Active Meds</p> <table style="width: 100%; border-collapse: collapse;"> <tr><td>MetFORMIN HCl 500 MG</td><td>two ti</td><td>02/25/13</td></tr> <tr><td>Losartan Potassium 100</td><td>ca ly</td><td>06/27/13</td></tr> <tr><td>Eplerenone 50 MG</td><td>ca ly</td><td>05/28/13</td></tr> <tr><td>Lasix 40 MG</td><td>once d</td><td>05/03/13</td></tr> <tr><td>Toprol XL 50 MG</td><td>two ti</td><td>06/24/13</td></tr> <tr><td>CloNIDine HCl 0.1 MG</td><td>as nee</td><td>05/28/13</td></tr> <tr><td>Pravachol 40 MG</td><td>ca ly</td><td>12/31/12</td></tr> <tr><td>Coumadin 5 MG</td><td>CC 15</td><td>07/09/13</td></tr> <tr><td>Citracal + D 315-200 MG-</td><td>ca ly</td><td>02/21/06</td></tr> <tr><td>Daily Multiple Vitamins</td><td>ca ly</td><td>02/21/06</td></tr> <tr><td>Ep Pen 2-Pak 0.3 MG/0.3</td><td>pm</td><td>06/08/11</td></tr> <tr><td>Ipratropium Bromide 0.0</td><td>n each</td><td>06/27/13</td></tr> <tr><td>Lanoxin 0.125 MG</td><td>ca ly</td><td>05/28/13</td></tr> </table> <p style="text-align: center;">MORE</p>	MetFORMIN HCl 500 MG	two ti	02/25/13	Losartan Potassium 100	ca ly	06/27/13	Eplerenone 50 MG	ca ly	05/28/13	Lasix 40 MG	once d	05/03/13	Toprol XL 50 MG	two ti	06/24/13	CloNIDine HCl 0.1 MG	as nee	05/28/13	Pravachol 40 MG	ca ly	12/31/12	Coumadin 5 MG	CC 15	07/09/13	Citracal + D 315-200 MG-	ca ly	02/21/06	Daily Multiple Vitamins	ca ly	02/21/06	Ep Pen 2-Pak 0.3 MG/0.3	pm	06/08/11	Ipratropium Bromide 0.0	n each	06/27/13	Lanoxin 0.125 MG	ca ly	05/28/13	<p style="text-align: center;">Goals</p> <p>Goal not met: LDL >70 Goal met: BMI < 30 Goal met: BP < 130/80 Goal met: A1c < 7.0% Goal Met: Nonsmoker</p>
MetFORMIN HCl 500 MG	two ti	02/25/13																																						
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Daily Multiple Vitamins	ca ly	02/21/06																																						
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Ipratropium Bromide 0.0	n each	06/27/13																																						
Lanoxin 0.125 MG	ca ly	05/28/13																																						
<p style="text-align: center;">Labs</p> <table style="width: 100%; border-collapse: collapse;"> <tr><td>Trig</td><td>120 mg/dl</td><td>5/06/13</td></tr> <tr><td>Chol</td><td>212 mg/dl</td><td>5/06/13</td></tr> <tr><td>LDL</td><td>121 Calc</td><td>5/06/13</td></tr> <tr><td>HDL</td><td>67 mg/dl</td><td>5/06/13</td></tr> <tr><td>Glucose Fasting</td><td></td><td></td></tr> </table>	Trig	120 mg/dl	5/06/13	Chol	212 mg/dl	5/06/13	LDL	121 Calc	5/06/13	HDL	67 mg/dl	5/06/13	Glucose Fasting			<p style="text-align: center;">Action Items</p> <table style="width: 100%; border-collapse: collapse;"> <tr><td>Document last Bone Mineral Density test (DXA), if applicable</td><td style="text-align: right;">PREV</td></tr> <tr><td colspan="2"><hr/></td></tr> <tr><td>DOC Document or perform Diabetic Foot Exam</td><td style="text-align: right;">DM</td></tr> <tr><td>***Medication Adherence Alert: ARB therapy Rx has not been dispensed per medication fulfillment history</td><td style="text-align: right;">RX</td></tr> <tr><td>MED Change / titrate Lp c lowering med* due to LDL goal not met</td><td style="text-align: right;">CAD</td></tr> <tr><td>LAB: Order Digoxin Level Last Digoxin level > 12 mos prior.</td><td style="text-align: right;">HF</td></tr> <tr><td>PROC Order or Discuss obtaining Bone Mineral Density test (DXA) (q 2 yrs) for Osteoporosis Dx or Osteoporosis Risk, unless documented today</td><td style="text-align: right;">PREV</td></tr> <tr><td>VAC: Consider Zoster vaccination, unless contraindicated</td><td style="text-align: right;">PREV</td></tr> <tr><td>REFER: Consider referral for Diabetic Education (rec q 3 yrs)</td><td style="text-align: right;">DM</td></tr> <tr><td>REFER: Perform / Refer to Ophthalmology for Diabetic Eye Exam (yearly)</td><td style="text-align: right;">DM</td></tr> </table>	Document last Bone Mineral Density test (DXA), if applicable	PREV	<hr/>		DOC Document or perform Diabetic Foot Exam	DM	***Medication Adherence Alert: ARB therapy Rx has not been dispensed per medication fulfillment history	RX	MED Change / titrate Lp c lowering med* due to LDL goal not met	CAD	LAB: Order Digoxin Level Last Digoxin level > 12 mos prior.	HF	PROC Order or Discuss obtaining Bone Mineral Density test (DXA) (q 2 yrs) for Osteoporosis Dx or Osteoporosis Risk, unless documented today	PREV	VAC: Consider Zoster vaccination, unless contraindicated	PREV	REFER: Consider referral for Diabetic Education (rec q 3 yrs)	DM	REFER: Perform / Refer to Ophthalmology for Diabetic Eye Exam (yearly)	DM				
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Figure 9: Sample pre-visit decision support report showing alert for potential medication non-adherence to ARB anti-hypertensive therapy (yellow highlight added for display).

Tables

Table 1: Key definitions used in data queries.

Cohort Name	ICD9-CM Codes
Hypertension	401.xx-404.xx
Dyslipidemia	272.xx
Depression	296.2, 296.3, 296.9, 300.4, 311

Table 2: Medi-Span GPI-4 and GPI-8 codes used to define medication classes.

Antihypertensive medications									
Drug Subclass	GPI-4 code(s)	Agent	GPI-8 code(s)	Drug Subclass	GPI-4 code(s)	Agent	GPI-8 code(s)		
Beta-Blockers (nonselective)	3310	Carteolol	33100005	Angiotensin Receptor Blockers	3615	Candesartan	36150020		
		Nadolol	33100010			Eprosartan	36150024		
		Penbutolol	33100025			Irbesartan	36150030		
		Pindolol	33100030			Losartan	36150040		
		Propranolol	33100040			Olmesartan	36150055		
		Sotalol	33100045			Telmisartan	36150070		
		Timolol	33100050			Valsartan	36150080		
Beta-Blockers (cardioselective)	3320	Acebutalol	33200010	Diuretics (CAI, Loop, Ksparing, thiazide)	3710	Acetazolamide	37100010		
		Atenolol	33200020			Dichlorphenamide	37100020		
		Betaxolol	33200021			Methazolamide	37100030		
		Bisoprolol	33200022			Bumetanide	37200010		
		Metoprolol	33200030			Ethacrynic Acid	37200020		
						Furosemide	37200030		
Alpha-Beta Blockers	3330	Carvedilol	33300007			Torsemide	37200080		
		Labetalol	33300010			Amiloride	37500010		
						Spironolactone	37500020		
Calcium Channel Blockers	3400	Amlodipine	34000003			Triamterene	37500030		
		Bepidil	34000005			Bendroflumethiazide	37600010		
		Diltiazem	34000010			Chlorothiazide	37600020		
		Felodipine	34000013			Chlorthalidone	37600025		
		Isradapine	34000015			Hydrochlorothiazide	37600040		
		Mibefradil	34000017			Indapamide	37600050		
		Nicardipine	34000018			Methclothiazide	37600055		
		Nifedipine	34000020			Metolazone	37600060		
		Nimodipine	34000022			Polythiazide	37600065		
		Nisoldipine	34000024			Trichlormethiazide	37600075		
		Verapamil	34000030						
						Combination Products?		Not included in protocol (various GPI)	
		ACE Inhibitors	3610	Benazepril	36100005				
Captopril	36100010								
Enalapril	36100020								
Fosinopril	36100027								
Lisinopril	36100030								
Moexipril	36100033								
Perindopril	36100035								
Quinapril	36100040								
Ramipril	36100050								
Trandolapril	36100060								

HMG Co-A reductase inhibitors				Antidepressant Medications			
Drug Subclass	GPI-4 code(s)	Agent	GPI-8 code(s)	Drug Subclass	GPI-4 code(s)	Agent	GPI-8 code(s)
Statins	3940	Atorvastatin	39400010	SSRI	5816	citalopram	58160020
		Cerivastatin	39400020			escitalopram	58160034
		Fluvastatin	39400030			fluoxetine	58160040
		Lovastatin	39400050			fluvoxamine	58160045
		Rosuvastatin	39400060			paroxetine	58160060
		Pravastatin	39400065			sertraline	58160070
		Simvastatin	39400075				
				SNRI	5818	duloxetine	58180025
Combination Products (statin/other)		Not included in protocol (various GPI)				venlafaxine	58180090
Bile Acid Sequestrants?		Not included in protocol (GPI-4 = 3910)					
Fibrates?		Not included in protocol (GPI-4 = 3920)		Aypical/Other A	5803	Nefazodone	58120050
Ezetimibe?		Not included in protocol (GPI-4 = 3930)			5812	Trazodone	58120080
					5830	Bupropion	58300040
						Mirtazapine	58300050
						Maprotilene	58300010
				MAOI?		Not included in protocol (GPI-4 = 5810)	
				TCA?		Not included in protocol (GPI-4 = 5820)	

Table 3: Basic demographic descriptive measures for study populations using the final data extraction provided by DARTNet Institute personnel.

		Patients (N)	%F	Age (mean)	Age(median)	Encounters (N)
7/1/2009-2/1/2014	All	132,171	62.3%	54.1	55	853,288
	Hypertension cohort	36,354	54.7%	65.0	66	233,135
	Dylipidemia cohort	29,172	51.7%	65.3	66	187,443
	Depression cohort	15,063	73.0%	55.8	56	94,763
	Hypertension & Dyslipidemia	19,631	50.6%	67.2	68	
	Hypertension & Depression	6,785	68.8%	63	63	
	Dyslipidemia & Depression	5,747	67.5%	63.6	64	
	All three diseases	3,940	65.8%	65.4	65	
11/1/2012-10/31/2013	All	81,627	62.4%	55.8	57	120,301
	Hypertension cohort	29,258	55.4%	64.7	66	42,939
	Dylipidemia cohort	24,349	52.0%	65.2	66	36,135
	Depression cohort	12,084	73.5%	56.3	57	17,428
	Hypertension & Dyslipidemia	16,677	50.9%	67.0	67	
	Hypertension & Depression	5,783	69.4%	62.7	63	
	Dyslipidemia & Depression	5,000	67.9%	63.3	64	
	All three diseases	3,456	66.2%	65.0	65	

Table 4: Medication prescription records by medication class by cohort. Diagonals (in gray) represent patients and medications from the same disease cohort/class. Off-diagonals represent patients with a diagnosis receiving medication prescriptions from a different medication class.

7/1/2009-2/1/2014	cohort↓ / medication class→	All	Anihypertensive medications	HMG Co-A reductase inhibitors	Antidepressant Medications
	All patients	2,140,613	261,591	113,859	94,869
Hypertension cohort	1,274,098	243,701	81,500	45,753	
Dyslipidemia cohort	1,083,497	165,287	111,583	40,649	
Depression cohort	651,091	60,749	25,754	61,746	
11/1/2012-7/30/2013	cohort↓ / medication class→	All	Anihypertensive medications	HMG Co-A reductase inhibitors	Antidepressant Medications
	All patients	443,858	53,004	23,163	18,738
	Hypertension cohort	256,909	49,206	16,372	8,863
	Dyslipidemia cohort	219,714	33,209	22,764	7,963
	Depression cohort	131,466	12,158	5,100	12,079

Table 5: Medication fulfillment records by medication class by cohort. Diagonals (in gray) represent patients and medications from the same disease cohort/class. Off-diagonals represent patients with a diagnosis receiving medication prescriptions from a different medication class.

7/1/2009-11/2/2013	cohort↓ / medication class→	All	Anihypertensive medications	HMG Co-A reductase inhibitors	Antidepressant Medications
	All patients	1,859,613	259,126	105,782	113,291
	Hypertension cohort	976,871	199,525	64,547	48,244
	Dyslipidemia cohort	795,525	132,512	83,708	41,099
	Depression cohort	429,855	46,474	18,957	53,055
11/1/2012-10/31/2013	cohort↓ / medication class→	All	Anihypertensive medications	HMG Co-A reductase inhibitors	Antidepressant Medications
	All patients	1,216,354	172,186	71,332	73,314
	Hypertension cohort	685,161	139,154	46,132	33,797
	Dyslipidemia cohort	556,292	94,106	59,467	29,110
	Depression cohort	302,456	33,149	13,696	36,646

