

Usefulness of Pharmacy Claims for Medication Reconciliation in Primary Care

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Medication reconciliation is “the process of comparing a patient’s medication orders to all of the medications that the patient has been taking.”¹ Strong evidence supports the value of reconciliation in inpatient settings² and at transitions of care,^{3,4} leading to The Joint Commission requirement for medication reconciliation at hospital admission and discharge.¹ However, the benefit of medication reconciliation may have the most impact in ambulatory settings, where discrepancies frequently occur between physician medication orders in the electronic health record (EHR) and what the patient is actually taking.⁵⁻⁸ Given that 3 of 4 physician office visits yield at least 1 new prescription,⁹ such discrepancies likely contribute to the estimated 3.3 million serious preventable outpatient medication errors^{10,11} and 1.9 million adverse drug event-related visits annually in the United States.¹² As a result, national programs including Meaningful Use and the National Committee for Quality Assurance Medical Home Certification now require more frequent and systematic medication reconciliation in primary care practice.^{13,14}

Despite its recognized importance, medication reconciliation is challenging.¹⁵ Physicians cite lack of time as a barrier, and most practices do not have access to resources such as clinical pharmacists to support reconciliation.^{8,16,17} Improvements in health information technology may facilitate accurate medication reconciliation in real time,¹⁸ and federal incentives have increased the adoption of electronic prescribing (e-prescribing).¹⁹ These platforms often make aggregated pharmacy claims available to providers, frequently within the native EHR. Claims data are a proven source for medication reconciliation,^{20,21} but few practices outside of large managed care organizations have access to these data.²²

The purpose of this study was to evaluate aggregated pharmacy claims available through the EHR of a large primary care network as a source for estimating the prevalence and identifying the predictors of medication discrepancies

ABSTRACT

Objectives: Methods for efficient medication reconciliation are increasingly important in primary care. Aggregated pharmacy data within the native electronic health record (EHR) may create a new opportunity for efficient and systematic medication reconciliation in practice. Our objective was to identify the prevalence and predictors of medication discrepancies between pharmacy claims data and the medication list in a primary care EHR.

Study Design: Retrospective cohort study.

Methods: We conducted a retrospective cohort study of patients prescribed a new antihypertensive in a large primary care practice network between January 2011 and September 2012. We compared patients’ active medications recorded in the practice EHR with those listed in pharmacy claims data available through the EHR. The primary outcome was the presence of a medication discrepancy.

Results: Of 609 patients, 468 (76.9%) had at least 1 medication discrepancy. Significant predictors of discrepancies included the total medication count (odds ratio [OR], 2.18; 95% CI, 1.85-2.57) and having a recent emergency department visit (OR, 2.58; 95% CI, 1.03-6.45). The identified discrepancies included 171 patients (28.1%) with 229 controlled substance discrepancies.

Conclusions: Our study revealed a high rate of discrepancies between pharmacy claims data and the provider medication list. Aggregated pharmacy claims data available through the EHR may be an important tool to facilitate medication reconciliation in primary care.

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between claims data and the medication list in the primary care EHR. Our secondary aim was to determine the factors associated with discrepancies involving high-risk medications, including controlled substances. Our findings will provide a first step toward identifying the potential benefit of using aggregated claims data as a platform for improving the efficiency and quality of medication reconciliation in primary care.

Take-Away Points

- Aggregated pharmacy claims data are increasingly available within a provider electronic health record.
- Our study suggests that this data may provide a foundation for assessing medication adherence and conducting medication reconciliation.
- Optimizing the accessibility and function of this data should be a high priority as the primary care information technology infrastructure expands.

METHODS

Design Overview

We conducted a retrospective cohort study of established patients who were prescribed a new antihypertensive during a primary care office visit. We compared medications listed in the practice EHR with those identified from pharmacy claims data available through the EHR. We identified and characterized discrepancies between the 2 lists, simulating medication reconciliation at the time of the new prescription. The study was approved by the Christiana Care Institutional Review Board.

Setting and Data Sources

We conducted this study in a large multi-specialty medical practice, which includes 14 primary care sites providing care for over 100,000 people in northern Delaware and the surrounding communities. These practices share an EHR (Centricity from GE Healthcare) used for all clinical encounters. All prescriptions in the multi-specialty practices are generated through the EHR, and e-prescribing has been available since 2010.

Providers can request aggregated pharmacy claims data in real time within the EHR. Patients must provide consent, which was incorporated into the patient registration process. Surescripts provides the pharmacy data, including claims from retail and mail-order pharmacies, and from pharmacy benefit managers for private and public insurers.

Study Population

We identified established patients within the practices who were prescribed a new antihypertensive medication at an office visit between January 2011 and September 2012. We required a diagnosis of hypertension (*International Classification of Diseases, Ninth Revision, Clinical Modification* [ICD-9-CM] code 401.xx) or elevated blood pressure (ICD-9-CM code 796.2) in the EHR at the time of prescription. We required patients to have had at least 1 primary care visit recorded in the EHR in the 18 months prior to

the index visit in order to eliminate patients who were new to the practice or whose practices were transitioning from paper records to electronic. To avoid medication changes as a result of formulary requirements, we only included prescriptions for a new drug class. Only the first qualifying prescription per patient was considered.

We included patients with a pharmacy claim history imported to the EHR on or after the index visit in order to capture all claims prior to the index visit. We required evidence of at least 1 claim in the pharmacy claim history to minimize mislabeling medications as missing for patients whose claim history was not available in the data source.

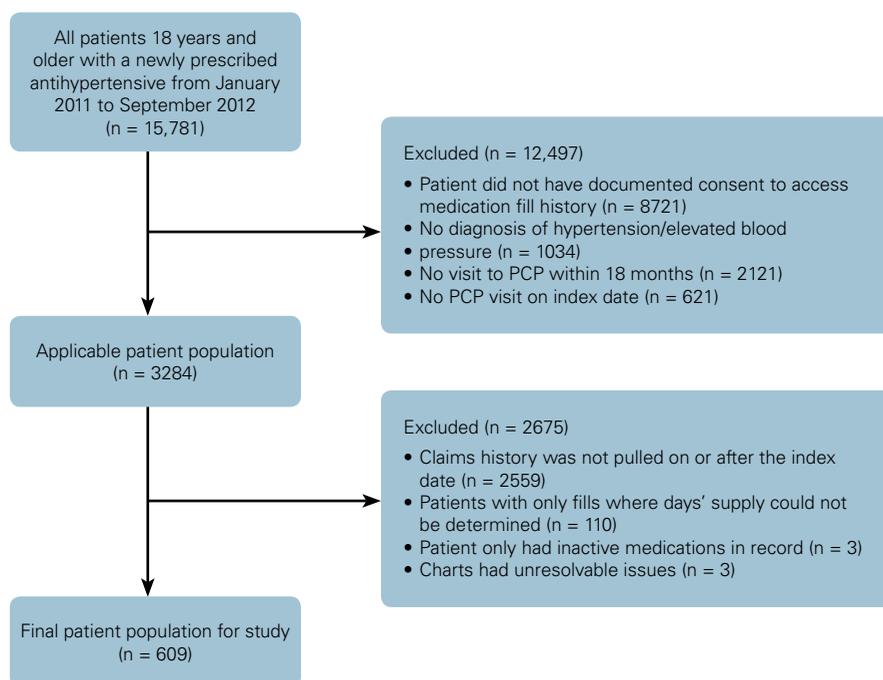
Study Definitions

To identify medication discrepancies, we generated separate lists of active medications at the time of the index visit for the provider's EHR and the pharmacy claims. We excluded medications for which the days' supply could not be calculated (ie, over-the-counter, insulin, and ophthalmics). We collapsed medications by generic name regardless of dose or frequency. Active medications from the provider's EHR were those with a start date in the EHR prior to the index date, and the stop date, if present, was on or after the index visit. We did not require evidence of a prior prescription from the EHR, as providers routinely document medications prescribed by other providers.

From the pharmacy claims history, we identified all medication claims within the 120 days prior to the index visit. We calculated the end date for the most recent fill for each medication as the days' supply plus a 15-day grace period to account for adherence variability and oversupply. We considered medications active if the calculated end date fell on or after the index visit. One author (DC) classified all medications. When validating a random 10% sample, a second pharmacist identified 6 errors among 977 medications—an error rate of 0.61%—which we considered acceptable.

After finalizing each medication list, we manually compared them to simulate medication reconciliation. Our primary outcome was the presence of a medication discrepancy, defined as a medication present in only 1 source. This interpretation aligns with previous defini-

■ **Figure.** Patient Flow Chart



PCP indicates primary care provider.

tions of unintentional medication discrepancies,²³ which have been associated with higher rates of potential adverse drug events.^{2,24}

Key Covariates

Demographic variables from the EHR at the index visit included patient age, gender, race, and primary insurance. We included clinical variables such as the total number of medications from both the EHR and claims data. We also included the number of active antihypertensive medications and blood pressure at the index visit. We measured patient comorbidity using the Elixhauser index, and classified these as either cardiovascular (CV)-related or unrelated comorbidities.^{25,26} We included previous healthcare utilization, including counts and timing of hospitalizations, emergency department (ED) visits, and primary care visits at our institution.

Statistical Analysis

We used χ^2 and *t* tests to determine the association of discrepancies with covariates. We then developed multivariate logistic and log-linear regression models. Variables included in the final models include those statistically significant in the univariate model and those deemed clinically relevant.

As total medication count at index visit was a strong predictor, we generated versions of both models with and without this variable. The results of the logistic and log-linear regression models were very similar; we present only the results of the logistic regression models. We separately developed similar models for controlled substance discrepancies. We conducted sensitivity analyses excluding antibiotics and antifungals, but these did not change our models significantly so they are not reported. All analyses were done with SAS version 9.3 (SAS Institute, Cary, North Carolina).

RESULTS

The **Figure** shows the development of our cohort. Of 15,781 patients who had a new prescription generated for an antihypertensive medication during the study period, 3284 met our initial patient criteria. Of these, 2675 did not have a medication refill history that met criteria. Our final study population included 609 patients; the patients included in our final cohort had a larger proportion of blacks (*P* = .01) and females (*P* = .05), but were similar to the previous 3284 in regard to other demographic characteristics.

The 609 patients in our study cohort accounted for 2947 medications meeting study definition. Of these, 1401

■ **Table 1.** Study Demographics

Variable	Whole Population	No Discrepancy	≥1 Discrepancy	P
	n/mean (%/SD) n = 609	n/mean (%/SD) n = 141	n/mean (%/SD) n = 468	
Age	56.07 (14.1)	55.62 (14.8)	56.21 (13.9)	.670
Female	373 (61.3%)	75 (53.2%)	298 (63.7%)	.025
Race				.814
White	329 (54.0%)	75 (53.2%)	254 (54.3%)	
African American/black	148 (24.3%)	37 (26.2%)	111 (23.7%)	
Other/undetermined	132 (21.7%)	29 (20.6%)	103 (22.0%)	
Insurance type				.016
Private	345 (56.7%)	89 (63.1%)	256 (54.7%)	
Medicare	186 (30.5%)	32 (22.7%)	154 (32.9%)	
Medicaid	65 (10.7%)	14 (9.9%)	51 (10.9%)	
Self-pay/other	13 (2.1%)	6 (4.3%)	7 (1.5%)	
Number of hypertension medications prescribed previous to index visit^a				.033
0	195 (32.0%)	45 (31.9%)	150 (32.1%)	
1	228 (37.4%)	64 (45.4%)	164 (35.0%)	
≥2	186 (30.5%)	32 (22.7%)	154 (32.9%)	
PCP visits within previous year				.371
0	22 (3.6%)	7 (5.0%)	15 (3.2%)	
1-3	368 (60.4%)	89 (63.1%)	279 (59.6%)	
≥4	219 (36.0%)	45 (31.9%)	174 (37.2%)	
Days to last PCP visit				.885
≤30	196 (32.2%)	44 (31.2%)	152 (32.5%)	
31-90	180 (29.6%)	44 (31.2%)	136 (29.1%)	
≥91	233 (38.3%)	53 (37.6%)	180 (38.5%)	
≥1 ED visits in past year	146 (24.0%)	22 (15.6%)	124 (26.5%)	.008
≤90 days to last ED visit	76 (12.5%)	8 (5.7%)	68 (14.5%)	.005
≥1 hospitalizations in past year	127 (20.9%)	15 (10.6%)	112 (23.9%)	.001
≤90 days to last hospitalization	59 (9.7%)	3 (2.1%)	56 (12.0%)	.001
Systolic blood pressure^b	148.9 (18.8)	150.5 (17.2)	148.5 (19.2)	.282
Diastolic blood pressure^c	88.1 (11.9)	90.1 (9.5)	87.5 (12.5)	.010
Non-CV-related comorbidities	1.4 (1.3)	1.1 (1.1)	1.5 (1.4)	<.001
CV-related comorbidities^d	0.4 (0.7)	0.3 (0.6)	0.4 (0.7)	.039
Total medication count^e	4.8 (3.4)	2.4 (1.7)	5.6 (3.5)	<.0001

CV indicates cardiovascular; ED, emergency department; PCP, primary care provider.

^aAs listed in the electronic health record (EHR).

^bn = 589.

^cn = 587.

^dExcludes hypertension.

^eTotal of unique medications from EHR and fill history.

"n/mean" indicates that either the n or mean of the variable is provided, depending on whether the item is categorical or continuous.

(47.5%) were identified as discrepancies, 831 (59.3%) appeared only in the EHR, and 570 (40.7%) only in the pharmacy claims.

The majority of patients (468 of 609; 76.8%) had at least 1 medication discrepancy (mean ± SD = 2.3 + 2.4). Charac-

teristics of patients with and without a discrepancy appear in **Table 1**. Patients with a discrepancy were more likely to have a hospitalization in the past year (23.9% vs 10.6%; $P = .001$), noncardiovascular comorbidities (1.4% vs 1.1%; $P < .001$), and a higher total medication count (5.6 ± 3.5 vs

Table 2. Univariate and Multivariate Models for Risk Probability of Medication Discrepancy

Variable	Univariate Analysis OR (95% CI)	Multivariate Analysis OR (95% CI)
Age	1.00 (0.99-1.02)	0.98 (0.96-1.00)
Female	1.54 (1.05-2.26)	1.63 (1.03-2.58)
African American/black ^a	0.89 (0.56-1.39)	0.84 (0.48-1.47)
Medicare ^b	1.67 (1.07-2.63)	
1 antihypertensive ^c	0.77 (0.50-1.20)	
≥2 antihypertensives ^c	1.44 (0.87-2.39)	
ED visit within 90 days	2.82 (1.32-6.02)	2.58 (1.03-6.45)
≥1 hospitalizations in past year	2.64 (1.49-4.70)	1.57 (0.78-3.16)
Systolic blood pressure	0.99 (0.98-1.01)	
Diastolic blood pressure	0.98 (0.97-1.00)	
CV-related comorbidities (count)	1.37 (0.99-1.89)	
Non-CV-related comorbidities (count)	1.34 (1.11-1.54)	0.81 (0.65-1.01)
No PCP visits in past year ^d	0.68 (0.27-1.73)	0.89 (0.31-2.53)
≥4 PCP visits in past year ^d	2.00 (0.74-5.42)	0.57 (0.34-0.94)
Total medication count	1.95 (1.69-2.25)	2.18 (1.85-2.57)

CV indicates cardiovascular; ED, emergency department; OR, odds ratio; PCP, primary care provider.
^aReference is white.
^bReference is private insurance.
^cReference is 0 antihypertensives.
^dReference is 1-3 PCP visits.

2.4 ± 1.7; *P* < .001). Among patients with discrepancies, 116 of 468 (24.8%) had medications in the provider list but not in the fill history, 186 (39.7%) in the fill history but not the provider list, and 166 (35.5%) had discrepancies from both the provider list and fill history.

Table 2 shows the multivariate logistic regression model for having at least 1 medication discrepancy; total medication count was strongly associated with the presence of a discrepancy (odds ratio [OR], 2.18; 95% CI, 1.85-2.57). Other significant covariates included being female (OR, 1.54; 95% CI, 1.05-2.26) and count of noncardiovascular comorbidities (OR, 1.34; 95% CI, 1.11-1.54). When we excluded total medication count from the model, being female, having a recent ED visit, or experiencing a hospitalization in the past year were all associated with increased odds of discrepancy.

We identified 229 discrepancies involving a controlled substance among 171 patients (28.1%); 139 (60.1%) were in the EHR without a corresponding fill and 90 (39.9%) were filled without appearing in the EHR. **Table 3** shows the multivariate analysis predicting 1 or more controlled substance discrepancies. Total medication count (OR, 1.27; 95% CI, 1.19-1.36) and female gender (OR, 1.66; 95% CI,

1.10-2.49) were significant covariates associated with increased risk. When we excluded total medication count from the model, an ED visit in the past 90 days was significantly associated with a controlled substance discrepancy.

DISCUSSION

Recent policy changes including Meaningful Use and the Medical Home Certification process increasingly emphasize medication reconciliation in primary care, prioritizing methods for efficient and systematic medication reconciliation in routine practice. We used aggregated pharmacy fill data available through a provider EHR to simulate reconciliation between the provider medication list and pharmacy fill history in a cohort of patients prescribed a new antihypertensive medication. In our cohort, more than 75% of patients had at least 1 discrepancy, involving nearly half of all medications. Patients with higher medication counts and higher previous healthcare utilization were at increased risk of discrepancies.

Our findings are consistent with previous literature, which, using various methodologies, has identified discrepancy rates in the outpatient setting from 26% to

■ **Table 3.** Predictive Model for Controlled Substance Medication Discrepancies

Variable	Univariate Model OR (95% CI)	Multivariate Model OR (95% CI)
Age	0.99 (0.98-1.00)	0.98 (0.96-0.99)
Female	1.60 (1.01-2.33)	1.66 (1.10-2.49)
African American/black	0.96 (0.62-1.48)	
Medicare ^a	0.95 (0.64-1.42)	
1 antihypertensive ^b	0.79 (0.51-1.20)	
≥2 antihypertensives ^b	0.81 (0.52-1.26)	
ED visit within 90 days	2.34 (1.43-3.83)	1.61 (0.92-2.81)
≥1 hospitalizations in past year	1.62 (1.07-2.46)	
Systolic blood pressure	1.00 (0.99-1.01)	
Diastolic blood pressure	1.01 (0.99-1.02)	
CV-related comorbidities (count)	0.86 (0.65-1.14)	
Non-CV-related comorbidities (count)	1.16 (1.02-1.32)	0.88 (0.75-1.03)
1-3 PCP visits in past year ^c	1.36 (0.49-3.77)	
≥4 PCP visits in past year ^c	1.53 (0.53-4.43)	
Total medication count	1.22 (1.16-1.29)	1.27 (1.19-1.36)

CV indicates cardiovascular; ED, emergency department; OR, odds ratio; PCP, primary care provider.
^aReference is private insurance.
^bReference is 0 antihypertensives.
^cReference is 0 PCP visits.

97%.^{6,7,27,28} Importantly, we identified only discrepancies based on drug name and not on differences in dose and frequency; had we considered these additional factors, the number of discrepancies likely would be greater. While our high discrepancy rate may reflect incomplete data in our source, 40% of the discrepancies in our sample involved medications appearing in the claims history but not recorded in the EHR, suggesting that even if incomplete, pharmacy fill data provide valuable information.

This high rate of discrepancies is alarming, particularly given the association of discrepancies with adverse events.²⁹ Consistent with prior research, discrepancies in our cohort occurred in patients with markers of increased comorbidity and utilization. Patients with a higher total medication count, a recognized surrogate for medical complexity,³⁰ are more likely to have discrepancies. Patients with multiple medications and comorbidities frequently see many providers,³¹ making reconciliation within primary care particularly challenging. We anticipated that frequent primary care office visits would provide opportunity to conduct medication reconciliation, minimizing discrepancies, but did not see this association.

Importantly, we identified that nearly a third of our patients had a discrepancy involving controlled substances. This is an area of increasing emphasis owing to concerns about diversion or misuse. Taken together, our find-

ings provide strong evidence that claims data available through the EHR contain meaningful information while further underscoring the importance of medication reconciliation among patients with high comorbidity burden, particularly following ED or hospital visits, as emphasized in Stage 2 of Meaningful Use.¹³

Limitations

Before considering the implications of our findings, it is important to recognize several limitations. First, we used aggregated pharmacy data that may be incomplete, and our findings may overestimate the proportion of medications that are prescribed in the EHR but not filled. Second, slightly fewer than 20% of patients in our applicable patient population met study criteria, often resulting from unavailable pharmacy records, suggesting that providers were not routinely accessing these data in practice. Patients in our final cohort had a greater proportion of black and female patients, perhaps indicating selection bias in the patients or practices in which this data is accessed in clinical practice. Finally, physicians may be more likely to conduct medication reconciliation at the time of a new prescription, so the medication lists we are comparing may have already been adjusted by physicians. In that case, our findings could represent a “best case scenario.”

Despite these limitations, our findings provide insight into the potential for improved access to pharmacy claims data through an expanding health information technology infrastructure to facilitate medication reconciliation. Previous research suggests that claims data can improve the completeness²⁰ and accuracy²¹ of medication reconciliation, and we have demonstrated that aggregated pharmacy fill data can be used to identify medication discrepancies at the individual patient level in a multi-payer primary care network.

Implications

Our study has important implications for the use of aggregated pharmacy fill data. First, this information could be used to help providers identify medications prescribed by other providers, potentially minimizing drug interactions or duplication. This is particularly important for narcotic prescriptions, where tracking and monitoring for diversion and misuse are well-recognized goals for providers. Secondly, this information could help providers identify medication nonadherence. Previous literature suggests that providers have limited ability to reliably assess adherence in clinical practice,³² and claims data can provide objective information to inform decision making. Finally, given the significant demands on primary care practices, our results suggest that these data may have the most potential for benefit in patients at higher risk for adverse events, such as those with higher rates of comorbidity or healthcare utilization.

There are barriers to overcome if these data are to impact clinical care. First, the aggregated data must be complete. In terms of narcotics, many states have drug monitoring programs for complete tracking of narcotic fills, regardless of source, and the exchange of these data within the EHR is being considered for Stage 3 of Meaningful Use.³³ Joining these data with aggregated pharmacy data would have the potential to provide more complete data to providers. Secondly, the EHR platform should provide an efficient mechanism to identify and prompt clinicians about discrepancies in real time. Despite available data, few providers in our system accessed pharmacy claims through the EHR, suggesting that future efforts to use this information meaningfully will require making it readily available and actionable. Finding methods to provide the data objectively, such as automated assessments of discrepancy counts and validated adherence estimates,³⁴ will be necessary for optimal incorporation of this information in practice. Third, the EHR should provide an easy mechanism to incorporate identified medications automatically into the medication list, allowing

providers to take advantage of the EHR functionality to identify interactions.

CONCLUSIONS

Medication reconciliation is increasingly important but challenging to conduct in primary care. Our findings suggest that aggregated pharmacy claims data available within the provider EHR can be used to identify discrepancies at the individual level in a multi-payer setting. Availability of this information in real time should be made a priority for health information technology efforts, as aggregated pharmacy claims may provide an optimal foundation for efficient and high-quality medication reconciliation.

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REFERENCES

1. Sentinel event alert: using medication reconciliation to prevent errors. The Joint Commission website. http://www.jointcommission.org/assets/1/18/SEA_35.pdf. Updated February 9, 2006. Accessed July 16, 2013.
2. Pippins JR, Gandhi TK, Hamann C, et al. Classifying and predicting errors of inpatient medication reconciliation. *J Gen Intern Med*. 2008;23(9):1414-1422.
3. Delate T, Chester EA, Stubbings TW, Barnes CA. Clinical outcomes of a home-based medication reconciliation program after discharge from a skilled nursing facility. *Pharmacotherapy*. 2008;28(4):444-452. doi:10.1592/phco.28.4.444.
4. Boockvar KS, Carlson LaCorte H, Giambanco V, Fridman B, Siu A. Medication reconciliation for reducing drug-discrepancy adverse events. *Am J Geriatr Pharmacother*. 2006;4(3):236-243.
5. Orrico KB. Sources and types of discrepancies between electronic medical records and actual outpatient medication use. *J Manag Care Pharm*. 2008;14(7):626-631.
6. Varkey P, Cunningham J, Bisping S. Improving medication

- reconciliation in the outpatient setting. *Jt Comm J Qual Saf*. 2007;33(5):286-292.
7. Nassaralla CL, Naessens JM, Hunt VL, et al. Medication reconciliation in ambulatory care: attempts at improvement. *Qual Saf Health Care*. 2009;18(5):402-7. doi:10.1136/qshc.2007.024513.
 8. Schnipper JL, Kirwin JL, Cotugno MC, et al. Role of pharmacist counseling in preventing adverse drug events after hospitalization. *Arch Intern Med*. 2006;166(5):565-571.
 9. National Ambulatory Medical Care Survey. CDC website. <http://www.cdc.gov/nchs/fastats/drug-use-therapeutic.htm>. Published February 2012. Accessed December 27, 2013.
 10. Center of Information Technology Leadership. The value of computerized provider order entry in ambulatory settings. Partners Healthcare website. http://www.partners.org/cird/pdfs/CITL_ACPOE_Full.pdf. Published 2007. Accessed April 24, 2014.
 11. National Priorities Partnership. Preventing medication errors: a \$21 billion opportunity. National Quality Forum website. https://www.qualityforum.org/NPP/docs/Preventing_Medication_Error_CAB.aspx. Published December 2010. Accessed March 3, 2014.
 12. Sarkar U, López A, Maselli JH, Gonzales R. Adverse drug events in U.S. adult ambulatory medical care. *Health Serv Res*. 2011;46(5):1517-1533.
 13. Stage 2 Eligible Professional Meaningful Use Core Measures: measure 14 of 17. CMS website. http://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/downloads/Stage2_EP_Core_14_MedicationReconciliation.pdf. Published October 2012. Accessed April 25, 2014.
 14. NCOA's patient-centered medical home (PCMH) 2011. National Committee for Quality Assurance website. https://www.ncqa.org/Portals/0/Programs/Recognition/PCMH_2011_Overview_5.2.pdf. Published January 31, 2011. Accessed April 24, 2014.
 15. Bayoumi I, Howard M, Holbrook AM, Schabert I. Interventions to improve medication reconciliation in primary care. *Ann Pharmacother*. 2009;43(10):1667-1675. doi:10.1345/aph.1M059.
 16. The Joint Commission. Meeting The Joint Commission's 2013 National Patient Safety Goals. 2012:1-4. http://www.jcrinc.com/assets/1/14/EBMNP3G13_Sample_Pages.pdf. Accessed July 16, 2013.
 17. Lesselroth BJ, Holahan PJ, Adams K, et al. Primary care provider perceptions and use of a novel medication reconciliation technology. *Inform Prim Care*. 2011;19(2):105-118.
 18. Bassi J, Lau F, Bardal S. Use of information technology in medication reconciliation: a scoping review. *Ann Pharmacother*. 2010;44(5):885-897.
 19. United States Office of the National Coordinator for Health Information Technology. Update on the adoption of health information technology and related efforts to facilitate the electronic use and exchange of health information. http://docs.ismgcorp.com/files/external/ONC_report_to_Congress_062713.pdf. Published June 2013. Accessed July 15, 2013.
 20. Warholak TL, McCulloch M, Baumgart A, Smith M, Fink W, Fritz W. An exploratory comparison of medication lists at hospital admission with administrative database records. *J Manag Care Pharm*. 2009;15(9):751-758.
 21. Smith M, Giuliano MR, Starkowski MP. In Connecticut: improving patient medication management in primary care. *Health Aff (Millwood)*. 2011;30(4):646-654.
 22. Ho PM, Bryson CL, Rumsfeld JS. Medication adherence: its importance in cardiovascular outcomes. *Circulation*. 2009;119(23):3028-3035. doi:10.1161/CIRCULATIONAHA.108.768986.
 23. Schnipper JL, Liang CL, Hamann C, et al. Development of a tool within the electronic medical record to facilitate medication reconciliation after hospital discharge. *J Am Med Inform Assoc*. 2011;18(3):309-313.
 24. Schnipper JL, Hamann C, Ndumele CD, et al. Effect of an electronic medication reconciliation application and process redesign on potential adverse drug events: a cluster-randomized trial. *Arch Intern Med*. 2009;169(8):771-780. doi:10.1001/archinternmed.2009.51.
 25. Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. *Med Care*. 1998;36(1):8-27.
 26. Turner BJ, Hollenbeak CS, Weiner M, Ten Have T, Tang SS. Effect of unrelated comorbid conditions on hypertension management. *Ann Intern Med*. 2008;148(8):578-586.
 27. Stephens M, Fox B, Kukulka G, Bellamy J. Medication, allergy, and adverse drug event discrepancies in ambulatory care. *Fam Med*. 2008;40(2):107-110.
 28. Manley HJ, Drayer DK, McClaran M, Bender W, Muther RS. Drug record discrepancies in an outpatient electronic medical record: frequency, type, and potential impact on patient care at a hemodialysis center. *Pharmacotherapy*. 2003;23(2):231-239.
 29. Boockvar KS, Liu S, Goldstein N, Nebeker J, Siu A, Fried T. Prescribing discrepancies likely to cause adverse drug events after patient transfer. *Qual Saf Health Care*. 2009;18(1):32-36. doi:10.1136/qshc.2007.025957.
 30. Steinman MA, Hanlon JT. Managing medications in clinically complex elders: "there's got to be a happy medium." *JAMA*. 2010;304(14):1592-1601. doi:10.1001/jama.2010.1482.
 31. Pham HH, Schrag D, O'Malley AS, Wu B, Bach PB. Care patterns in Medicare and their implications for pay for performance. *N Engl J Med*. 2007;356(11):1130-1139.
 32. Medication Adherence Time Tool: improving health outcomes. American College of Preventive Medicine website. http://www.acpm.org/?MedAdherTT_ClinRef. Published 2011. Accessed May 21, 2014.
 33. Tang P, Hripacsak G. Draft recommendations Meaningful Use Stage 3. HealthIT.gov website. http://www.healthit.gov/facas/sites/faca/files/muwg_stage3_draft_rec_07_aug_13_v3.pdf. Published 2013. Accessed March 5, 2014.
 34. Karve S, Cleves MA, Helm M, Hudson TJ, West DS, Martin BC. Prospective validation of eight different adherence measures for use with administrative claims data among patients with schizophrenia. *Value Health*. 2009;12(6):989-995. doi:10.1111/j.1524-4733.2009.00543.x. ■

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