

Effects of a pharmacy-driven medication history program on patient outcomes



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Purpose: Obtaining an accurate medication history is a vital component of medication reconciliation upon admission to the hospital. Despite the importance of this task, medication histories are often inaccurate and/or incomplete. We evaluated the association of a pharmacy-driven medication history initiative on clinical outcomes of patients admitted to the general medicine service of an academic medical center.

Methods: Comparing patients who received a pharmacy-driven medication history to those who did not, a retrospective stabilized inverse probability treatment weighting propensity score analysis was used to estimate the average treatment effect of the intervention on general medical patients. Fifty-two patient baseline characteristics including demographic, operational, and clinical variables were controlled in the propensity score model. Hospital length of stay, 7-day and 30-day unplanned readmissions, and in-hospital mortality were evaluated.

Results: Among 11,576 eligible general medical patients, 2,234 (19.30%) received a pharmacy-driven medication history and 9,342 (80.70%) patients did not. The estimated average treatment effect of receiving a pharmacy-driven medication history was a shorter length of stay (mean, 5.88 days vs 6.53 days; $P = 0.0002$) and a lower in-hospital mortality rate (2.34% vs 3.72%, $P = 0.001$), after adjustment for differences in patient baseline characteristics. No significant difference was found for 7-day or 30-day all-cause readmission rates.

Conclusion: Pharmacy-driven medication histories reduced length of stay and in-hospital mortality in patients admitted to the general medical service at an academic medical center but did not change 7-day and 30-day all-cause readmission rates. Further research via a large, multisite randomized controlled trial is needed to confirm our findings.

Keywords: length of stay, medication reconciliation, mortality, outcomes, pharmacy, students

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Accurate medication reconciliation is a vital component of safe care for patients admitted to the hospital, with both the Institute of Medicine and the Joint Commission identifying it as a priority.^{1,2} The Institute for Healthcare Improvement defines medication reconciliation as the formal process of collecting and maintaining a complete and accurate list of a patient's current medications (ie, a medication history, or preadmission medication list [PAML])

and comparing that list to the prescribing clinician's admission, transfer, and discharge orders.

Completing an accurate medication history can be time-consuming, averaging up to 45 minutes in some studies.^{3,4} The gold standard for obtaining a medication history is dual-source verification.⁵ Potential sources include the patient, a caregiver, and family interviews; community pharmacy dispense data; skilled nursing

facility or electronic health record (EHR) medication lists; and third-party insurance claim data. Due to the time involved in obtaining medication records from different sources to establish an accurate list, busy clinicians are often not able to complete the task using 2 sources. Up to two-thirds of patients have at least 1 medication error on their PAML on admission to a hospital general medicine ward,⁶⁻⁸ and these errors have the potential to contribute to sub-optimal care, clinical deterioration, or adverse events. Inaccuracies in this list can impact care delivered in the hospital and after discharge.

Despite the vast resource investment and published literature surrounding medication reconciliation interventions over the last decade, there is a relative paucity of studies associating accurate medication reconciliation with measurable improvements in clinical and utilization outcomes. Early studies evaluating the acquisition of medication histories by pharmacy team members versus physicians and nurses demonstrated improved accuracy, with fewer medication discrepancies and omissions.⁹⁻¹⁶ Subsequent work confirmed these findings and highlighted the varying personnel employed (eg, pharmacist, pharmacy technician, pharmacy student/intern).¹⁷⁻¹⁹ Pharmacy student involvement, in particular, reduces cost and increases trust in the accuracy of medication histories.²⁰ Studies of pharmacy-driven interventions, however, are often limited by small sample sizes. In addition, heterogeneity in study designs and chosen measures results in an overall poor-quality body of evidence relating to patient outcomes, medication discrepancies, and healthcare utilization.^{21,22}

We developed a pharmacy-driven medication history program at our institution that effectively reduced clinician burnout and improved the accuracy of the PAML.²³ The objective of the study described here was to evaluate patient outcomes including length of stay (LOS), in-hospital mortality, and 7- and 30-day readmission rates in patients

KEY POINTS

- Accurate medication histories are essential for medication reconciliation.
- Obtaining an accurate medication history is time-consuming for clinicians and increases administrative burden.
- Pharmacy-driven medication histories may reduce length of stay and inpatient mortality in a medically ill population.

who received a pharmacy-driven medication history compared to those who did not.

Methods

Intervention. In September 2018, we launched a quality improvement intervention utilizing pharmacy students, referred to as pharmacy trainees (PTs), to complete medication histories on general medical adult patients admitted to the emergency department boarder service (EDB) at Massachusetts General Hospital (MGH), a 1,000-bed quaternary care referral center that averages approximately 12,000 general medical patient discharges annually. Standard care involved the clinician interviewing the patient or caregiver (if possible) and editing the home medication list in the electronic health record. This service was offered in addition to the standard care provided to patients and not as a replacement to standard care.

PTs in this study were Northeastern University Co-operative students (first through third professional year) on 4-month experiences at MGH. PTs were trained to complete medication histories using dual-source verification, with sources including but not limited to the EHR, patient/family member, pharmacy, and medication fill records. The PTs updated the EHR medication history, placed their findings in a templated note, and sent it to

the emergency department pharmacist for review and cosignature. Pertinent findings that would impact the care of the patient (no longer taking a medication, a change in dose, taking medications not on the original list) were also communicated to the care team. Data about medication history discrepancies were collected by PTs in real time using a Health Insurance Portability and Accountability Act (HIPAA)-compliant data collection tool.

This intervention was undertaken as a quality improvement initiative and per hospital policy was not deemed research by the institutional review board.

Patient population and data sources. All patients over 18 years of age admitted to the EDB service between September 1, 2018, and December 31, 2019, were eligible for inclusion in the pharmacy-driven medication history (intervention) or comparison cohort. There was no washout period, as both the intervention and the control groups were concomitant. Patients were eligible for a pharmacy-driven medication history via one of 2 paths. The first was clinician request. If there were no active clinician requests, then the PT identified patients on the ED boarder service at high risk for readmission (using a proprietary readmission risk score based upon regression analysis of internal variables) to conduct a medication history. We included the most common major diagnosis categories (eTable 1) and excluded categories with few admissions (ie, admissions for burn or HIV care) and categories with non-general medicine admissions (ie, admissions for eye, ear, nose, and mouth diseases or for pregnancy). Other exclusion criteria included discharge against medical advice or to hospice care, not being ultimately sent to general medicine unit after EDB evaluation (ie, the patient was transferred to a surgery unit); discharge after December 31, 2019; and missing data on any covariates used for adjustment (eTable 2).

For patients with multiple admissions during the analysis period, if patients received the intervention any

time during the study, only the first intervention was included, and all other admissions were removed regardless of timing. If a patient did not receive the intervention, the first admission was used, and subsequent ones were excluded from analysis. The data sources to obtain patient baseline characteristics included the HIPAA-compliant data logging tool, internal EHR and quality data, and the Vizient unplanned readmissions and medical comorbidities database. Standard medication histories (for the control group) were documented in the electronic medical record as “reviewed by provider” and were completed by the ED boarder service or its designee.

Adjustment of patient baseline difference between intervention and comparison cohorts. We assessed the impact of the intervention on patient outcomes via inverse probability treatment weighting (IPTW). IPTW is a statistical approach to adjust for confounding in observational studies.^{24,25} The goal of IPTW is to remove baseline differences in patient characteristics between intervention and control cohorts using a propensity

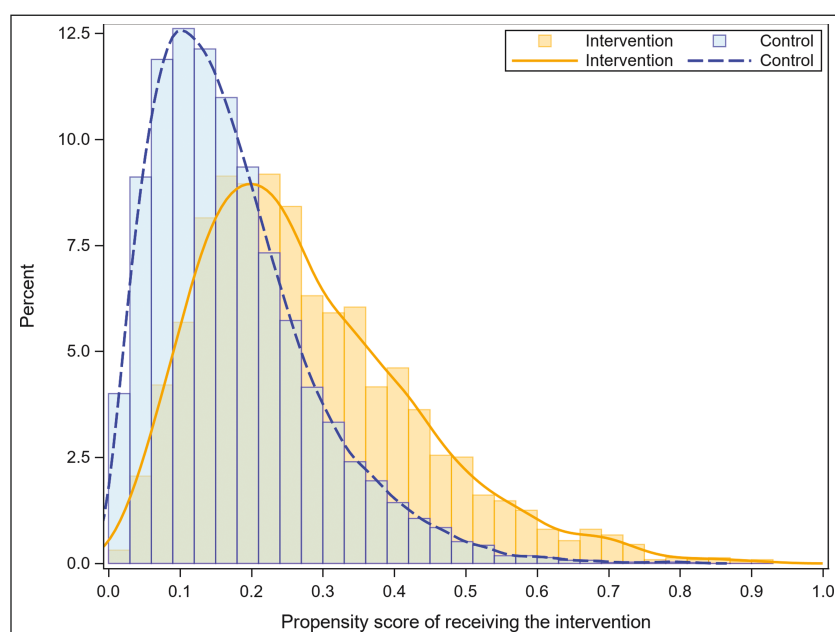
score. First, logistic regression is performed to calculate a propensity score for every patient, representing the probability of their being in the intervention group, conditional on observed baseline characteristics. A total of 52 covariates were included in the model (eTable 2). To assess the model quality and covariate balance, we explored the distribution of propensity scores using the kernel density plot between intervention and comparison cohorts. A sufficient overlap in the range of propensity scores suggested that patients in the 2 cohorts were comparable (Figure 1). Second, weights were calculated for all patients based on their propensity scores. For intervention patients, the weight was an inverse of the conditional probability of receiving the intervention; for comparison patients, the weight was an inverse of 1 minus the conditional probability of receiving the intervention. These weights were further stabilized to improve precision. This weighting assignment created a pseudo population in which patient baseline characteristics were similar across the intervention and comparison groups (similar to the

data created by a random clinical experiment), and this pseudo population was used to compare patient outcomes by including the weights in subsequent regression models. The IPTW removed confounding and yielded an unbiased estimate of the intervention's effect.

Patient outcomes. Patient outcomes assessed were LOS, in-hospital mortality, and 7-day and 30-day unplanned readmissions. All patients were included in the in-hospital mortality analysis; only survivors of hospital admission were included in the LOS analysis. Readmissions included only those patients readmitted to our hospital (data was unavailable for readmissions to other hospitals), and planned readmissions were excluded based on the Centers for Medicare and Medicaid Services definition. Nonsurvivors and patients discharged from the hospital after December 1, 2019, were also excluded because 30-day readmission information was unavailable at the time of analysis.

Statistical analysis. To compare the difference of patient baseline characteristics between the intervention and comparison cohorts before and

Figure 1. Distribution of propensity score and kernel density curves between intervention and comparison patients.



after the use of stabilized IPTW, the absolute standardized difference was used. This approach allowed us to adjust the influence due to the difference in sample size between 2 cohorts. A difference of greater than 0.1 indicated a significant imbalance between the intervention and comparison patients.

Linear regression was used to assess LOS, and logistic regression was used for in-hospital mortality and 7-day and 30-day readmission measures. Both unadjusted and adjusted analyses were performed. In the unadjusted model, only a single variable indicating whether a patient received the intervention was included. In the adjusted model, we added weighting created by IPTW in addition to the intervention indicator. This adjusted model estimated the average treatment effect for the entire population, which was the effect when the entire patient cohort was moved from comparison to intervention.

We constructed bootstrap confidence intervals, which are more

accurate than traditional intervals obtained from a single sample. In this approach, we resampled the original data with replacement to create 500 simulated samples. We fit the multivariate models separately using the new samples and obtained 500 bootstrap estimates. These 500 estimates were ranked from low to high, and values from the 2.5th and 97.5th percentiles were considered as the bootstrap 95% confidence interval.

Two sensitivity analyses were performed: (1) excluding all deaths due to potential errors on medication lists at discharge, and unavailable “meds-to-beds” information for deceased patients; (2) excluding all patients with missing major diagnosis category data.

Statistical analyses were performed using SAS software, version 9.4 (SAS Institute, Inc., Cary, NC).

Results

During the study period, 2,871 patients were admitted to the EDB service

and had a medication history completed by the PTs (intervention cohort), and 16,170 patients were admitted without a medication history completed by the PTs (comparison cohort). After exclusions were applied (Figure 2), a total of 11,576 patients remained in the primary analysis, 2,234 (19.30%) in the intervention cohort and 9,342 (80.70%) in the comparison cohort. Table 1 describes the selected baseline characteristics of intervention and comparison patients. After adjustment with propensity score and stabilized IPTW, all covariates were well balanced between the 2 groups.

Table 2 shows unadjusted and adjusted associations of the intervention with patient outcomes. After adjustment for baseline differences, the average LOS was shorter for intervention patients (5.88 days) than for comparison patients (6.53 days) (coefficient: -0.64 ; 95% CI, -0.98 to -0.30 ; $P = 0.0002$). The adjusted in-hospital mortality rate was 2.34% for the intervention cohort and 3.72% for the comparison cohort (odds

Figure 2. Study population exclusions in intervention and comparison cohorts.

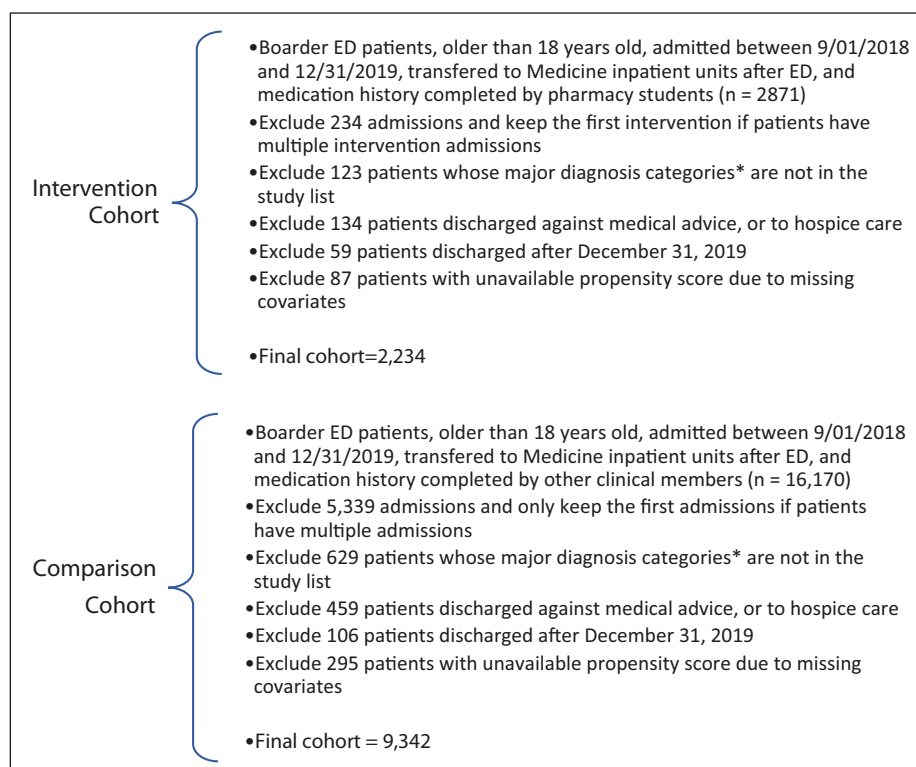


Table 1. Selected Baseline Characteristics of Patients in Intervention and Comparison Cohorts

	Unadjusted data			Adjusted data with use of inverse probability treatment weighting		
	Intervention (n = 2,234), % ^a	Comparison (n = 9,342), % ^a	Standardized difference	Intervention (n = 2,234), % ^a	Comparison (n = 9,342), % ^a	Standardized difference
ED admission year						
2018	14.91	29.52	0.36	28.65	26.82	0.04
2019	85.09	70.48		71.35	73.18	
Demographics						
Age, mean (SD), y	64.19 (18.31)	64.10 (18.35)	0.00	63.95 (18.43)	64.10 (18.27)	0.01
Female	45.66	45.41	0.01	45.98	45.42	0.01
Race						
White	79.19	77.35	0.07	78.01	77.70	0.03
Black	8.24	7.30		7.92	7.53	
Other	12.58	15.35		14.08	14.77	
Marital status						
Married	37.74	44.27	0.16	42.16	42.98	0.02
Unmarried	60.97	53.64		56.00	55.10	
Unknown	1.30	2.09		1.84	1.92	
English language	88.76	87.18	0.05	87.94	87.49	0.01
Medical insurance						
Medicare	57.52	55.39	0.17	55.83	55.76	0.00
Medicaid	20.10	16.24		17.27	17.01	
Commercial	19.02	24.87		23.60	23.72	
Other	3.36	3.50		3.30	3.51	
Clinical variables						
Major diagnosis category						
Diseases of nervous system	4.21	4.10	0.25	4.33	4.13	0.06
Diseases of respiratory system	14.64	13.23		15.10	13.53	

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	Intervention (n = 2,234), % ^a	Comparison (n = 9,342), % ^a	Standardized difference	Intervention (n = 2,234), % ^a	Comparison (n = 9,342), % ^a	Standardized difference
Diseases of circulatory system	19.92	27.62		23.78	26.05	
Diseases of digestive system	9.94	9.63		9.60	9.62	
Diseases of hepatobiliary and pancreas	6.13	5.16		5.44	5.33	
Diseases of musculoskeletal and connective tissue	4.43	3.75		3.85	3.89	
Diseases of skin, subcutaneous tissue and breast	3.72	3.20		3.22	3.29	
Diseases of endocrine, nutritional, and metabolic system	4.61	4.78		5.19	4.76	
Diseases of kidney and urinary tract	7.61	5.67		6.26	6.03	
Diseases of blood, organs and immunology	1.79	1.72		1.53	1.72	
Infectious and parasitic DD	7.34	8.39		8.25	8.27	
Alcohol/drug use or induced mental disorders	3.98	2.68		2.81	2.89	
Injuries, poison, and toxic effect of drugs	2.37	2.74		2.84	2.68	
Data missing	9.31	7.32		7.80	7.80	
ED admission date/time						
Weekend/holiday	18.98	27.73	0.21	26.43	26.02	0.01
7 AM-8 PM admissions	62.94	76.35	0.29	74.75	73.94	0.02
Meds-to-beds enrollment	6.04	3.61	0.11	3.81	4.05	0.01
Risk of readmission score >27	16.11	8.31	0.24	9.17	9.75	0.02
Selected comorbidities						
CHF	17.41	14.12	0.09	15.12	14.81	0.01
Valvular	8.37	8.10	0.01	8.67	8.18	0.02
Pulmonary circulation	1.03	1.05	0.00	1.18	1.05	0.01

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PVD	8.37	7.18	0.04	7.98	7.43	0.02
Hypertension	43.91	39.26	0.09	41.23	40.24	0.02
Paralysis	4.74	3.59	0.06	4.00	3.81	0.01
Neurologic disorder	13.16	11.49	0.05	11.64	11.76	0.00
COPD	25.96	23.54	0.06	25.96	24.06	0.04
Diabetes without complication/comorbidity	7.21	8.35	0.04	8.41	8.18	0.01
Diabetes with complication/comorbidity	20.95	19.17	0.04	18.99	19.56	0.01
Renal	25.11	22.46	0.06	22.28	23.00	0.02
Lymphoma	0.54	1.18	0.07	1.05	1.06	0.00
Metastatic	1.48	2.62	0.08	1.90	2.40	0.03
Alcohol abuse	8.50	6.36	0.08	6.90	6.74	0.01
Drug abuse	6.71	5.07	0.07	5.38	5.38	0.00
Psychoses	10.74	7.27	0.12	8.11	8.02	0.00
Depression	28.20	22.66	0.13	24.67	23.71	0.02
Medications at discharge						
Total No. of medications, mean (SD)	16.47 (8.54)	14.18 (8.09)	0.28	14.93 (7.75)	14.63 (8.33)	0.05
No. of high-risk medications, mean (SD)	1.77 (1.92)	1.67 (1.94)	0.07	1.64 (1.83)	1.70 (1.97)	0.01
High-risk medications						
Antiarrhythmic	10.61	10.96	0.01	10.55	10.87	0.01
Anticoagulant	26.28	26.01	0.01	25.19	26.04	0.02
Anticonvulsant	13.65	10.62	0.09	12.50	11.17	0.04
Antineoplastic	3.00	2.90	0.01	2.62	2.89	0.02

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	Unadjusted data		Adjusted data with use of inverse probability treatment weighting		
	Intervention (n = 2,234), % ^a	Comparison (n = 9,342), % ^a	Standardized difference	Intervention (n = 2,234), % ^a	Comparison (n = 9,342), % ^a
Standardized difference					
Antiplatelet	7.12	9.05	0.07	8.25	8.64
Antiretrovirals	4.07	4.01	0.00	3.90	4.03
Immune suppressant	4.39	4.25	0.01	4.06	4.27
Insulin	16.74	14.76	0.05	15.20	15.23
Oral or SC hypoglycemic	4.57	4.70	0.01	4.64	4.68
Opioid	25.65	22.50	0.07	23.51	23.19
Standardized difference					
0.01					
0.01					
0.01					
0.00					
0.00					
0.01					

Abbreviations: CHF, congestive heart failure; COPD, chronic obstructive pulmonary disease; DD, diseases and disorders; ED, emergency department; PVD, peripheral vascular disease; SC, subcutaneous.
^aData are % of patients unless otherwise indicated

ratio, 0.62; 95% CI, 0.46-0.83, $P = 0.001$). The confidence intervals created by bootstrapping were close to the traditional intervals based on the single-sample data. Neither 30-day nor 7-day unplanned readmissions differed significantly between intervention and comparison patients. Minimal change was found in the 2 sensitivity analyses (eTables 3 and 4).

Discussion

We estimate that the effect of a pharmacy-driven medication history program when applied to the general medical service at our institution would result in a significant reduction in hospital LOS and in-hospital mortality. This analysis represents, to the best of our knowledge, one of the largest to date to assess these outcomes, and our findings support the concept that accurate pharmacy-driven medication histories followed by clinician reconciliation are foundational to promoting safe, effective, and efficient inpatient care delivery.

Six different medication discrepancies between the existing EHR medication history and the pharmacy-driven medication history were evaluated for intervention patients, including medications with wrong dose, wrong route, wrong frequency, and/or wrong directions, missing medications, and medications patients were no longer taking. On average, the number of medication discrepancies was 1.65 (SD, 1.28) per patient in the intervention cohort, with discrepancies most commonly involving medications patients were no longer taking (53.80%), missing medications (49.83%), and medications with wrong dose (30.33%). Only 20.38% of patients ($n = 420$) had no discrepancy on admission; 54.44% of patients ($n = 1,122$) had 1 or 2 discrepancies and 25.18% ($n = 519$) had 3 or more discrepancies. When analyzing discrepancies pertaining to 10 high-risk medications (as defined by the pharmaceutical drug classes in Table 1) for patients who took at least one high-risk medication ($n = 1,125$), the mean number of discrepancies per patient was 0.45 (SD,

Table 2. Unadjusted and Adjusted Effects of Intervention on Health Outcomes in Primary Patient Cohorts

Unadjusted analysis			Adjusted analysis using stabilized inverse probability of treatment weighting				
	Mean (median)	Coefficient (95% CI)	P value	Mean (median)	Coefficient (95% CI from original sample)	P value	95% CI from bootstrap
Length of stay, d ^a							
Intervention	6.17 (4)	−0.27 (−0.61, 0.07)	0.12	5.88 (4)	−0.64 (−0.98, −0.30)	0.0002	(−0.96, −0.31)
Comparison	6.45 (4)	Reference		6.53 (4)	Reference		Reference
Odds of event, %							
	Odds of event, %	Odds ratio (95% CI)	P value	Odds of event, %	Odds ratio (95% CI from original sample)	P value	95% CI from bootstrap
In-hospital mortality							
Intervention	1.84	0.48 (0.34, 0.66)	<0.0001	2.34	0.62 (0.46, 0.83)	0.001	(0.39, 0.90)
Comparison	3.78	Reference		3.72	Reference		Reference
30-day readmission ^b							
Intervention	13.07	1.25 (1.08, 1.44)	0.003	10.96	1.02 (0.87, 1.19)	0.85	(0.83, 1.21)
Comparison	10.76	Reference		10.81	Reference		Reference
7-day readmission							
Intervention	3.64	0.99 (0.77, 1.29)	0.96	3.00	0.81 (0.61, 1.06)	0.13	(0.57, 1.15)
Comparison	3.66	Reference		3.70	Reference		Reference

^aAnalysis of length of stay was restricted to patients who survived inpatient admissions.^bReadmission analysis was restricted to patients who survived inpatient admissions and were discharged prior to December 1, 2019, to allow 30 days follow-up time.

0.74), with 31.64% of patients (n = 356) having discrepancies for 1 or 2 high-risk medications and 1.87% (n = 21) having errors for 3 or more high-risk medications.

The shorter LOS in the intervention cohort may be explained by several mechanisms. First, when the medication history is not performed directly by the admitting clinician, they are able to reclaim the time normally spent on this task to execute other aspects of care delivery for that patient and all other patients on a given census. Second, having an accurate admission medication history reduces delays on discharge when reconciling and reviewing medication changes with the patient. Even with a conservative time estimate of 20 minutes spent per medication history, a clinician admitting 4 patients in a shift would save over an hour of time that could be spent executing other value-added patient care tasks. Third, a reduction in medication reconciliation-related adverse events may result in fewer complications and thus a shorter hospitalization.

While we found a 38% lower odds of adjusted in-hospital mortality in the intervention cohort, we hesitate to attribute this finding solely to our intervention due to the retrospective, observational nature of this analysis, despite our analysis accounting for 52 meaningful covariates. One hypothesis for this finding is the reduction in medication discrepancies and adverse drug events seen in previous studies. While previous studies attempted to address mortality,^{21,22} there are no adequately powered, prospective randomized controlled trials to assess this outcome. Further research is therefore needed to confirm this finding.

Clinically significant adverse drug events stemming from lack of communication during transitions of care are common and may contribute to preventable readmissions.²⁶⁻²⁹ Although we did not find a significant difference in 7- or 30-day readmission rates, it is possible that the intervention was more effective in preventing adverse medication events earlier in the hospital

encounter, therefore reducing LOS but not affecting readmissions.

Our analysis has several limitations. First, the intervention was undertaken as a quality improvement initiative to reduce burnout, and our assessment of outcomes was observational and retrospective. While we attempted to control for differences between cohorts by excluding patients in hospice care or receiving comfort measures only and adjusting for many clinical, operational, and secular covariates, there still exists the possibility of imbalanced, unmeasured confounders that account for the differences in observed outcomes, as well as unconscious selection bias in assignment to the intervention group. Second, only readmissions to MGH were captured and a small percentage of patients in the intervention cohort had covariates missing. Both limitations would have resulted in exclusion of patients from the analysis; however, this percentage is likely small with minimal impact on our findings. Third, our initiative was conducted at a single quaternary care academic medical center that cares for complex medicine patients, and thus the observed results may not be generalizable to other settings.

Conclusion

Patients admitted to the general medicine service who had their medication history obtained by PTs during a pharmacy-driven quality improvement initiative had shorter lengths of stay and lower in-hospital mortality, but the intervention had no significant effect on all-cause 7- and 30-day readmissions. Our findings support the premise that obtaining an accurate medication history on admission is paramount to high-quality, efficient, and safe patient care. Further research via a large, multisite randomized controlled trial is needed to confirm our findings.

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authors have declared no potential conflicts of interest.

References

1. Institute for Healthcare Improvement. Medication reconciliation to prevent adverse drug events. Accessed February 23, 2022. <http://www.ihp.org/Topics/ADEsMedicationReconciliation/Pages/default.aspx>
2. Joint Commission. National Patient Safety Goals 2020. Accessed June 9, 2021. https://www.jointcommission.org/-/media/tjc/documents/standards/national-patient-safety-goals/npsg_chapter_hap_jan2019.pdf
3. Meguerditchian AN, Krotneva S, Reidel K, Huang A, Tamblyn R. Medication reconciliation at admission and discharge: a time and motion study. *BMC Health Serv Res*. 2013;13:485. doi:10.1186/1472-6963-13-485
4. Karaoui LR, Chamoun N, Fakhir J, et al. Impact of pharmacy-led medication reconciliation on admission to internal medicine service: experience in two tertiary care teaching hospitals. *BMC Health Serv Res*. 2019;19(1):493. doi:10.1186/s12913-019-4323-7
5. Action on Patient Safety (High 5s) Initiative, World Health Organization. The High5s Project: standard operating protocol. Assuring medication accuracy at transition in care: medication reconciliation. Version 3. Published September 2014. Accessed May 13, 2022. [https://cdn.who.int/media/docs/default-source/integrated-health-services-\(ihs\)/psf/high5s/h5s-sop.pdf](https://cdn.who.int/media/docs/default-source/integrated-health-services-(ihs)/psf/high5s/h5s-sop.pdf)
6. Lau HS, Florax C, Porsius AJ, de Boer A. The completeness of medication histories in hospital medical records of patients admitted to general internal medicine wards. *Br J Clin Pharmacol*. 2000;49:597-603.
7. Cornish PL, Knowles SR, Marchesano R, et al. Unintended medication discrepancies at the time of hospital admission. *Arch Intern Med*. 2005;165(4):424-429.
8. Armor BL, Wight AJ, Carter SM. Evaluation of adverse drug events and medication discrepancies in transitions of care between hospital discharge and primary care follow-up. *J Pharm Pract*. 2016;29(2):132-137.
9. Sproul A, Goodine C, Moore D, et al. Quality of best possible medication history upon admission to hospital: comparison of nurses and pharmacy students and consideration of national quality indicators. *Can J Hosp Pharm*. 2018;71(2):128-143.
10. Lancaster JW, Grgurich PE. Impact of student pharmacists on the medication reconciliation process in high-risk

- hospitalized general medicine patients. *Am J Pharm Educ*. 2014;78(2):34.
11. Janda M, Acquisto NM, Gashlin LZ, Dodds AE. Increasing the quality of medication histories in the emergency department with pharmacy students. *Am J Emerg Med*. 2018;36(5):901-902.
 12. Hayes BD, Donovan JL, Smith BS, Hartman CA. Pharmacist-conducted medication reconciliation in an emergency department. *Am J Health-Syst Pharm*. 2007;64(16):1720-1723. doi:10.2146/ajhp060436
 13. De Winter S, Spriet I, Indevuyst C, et al. Pharmacist- versus physician-acquired medication history: a prospective study at the emergency department. *Qual Saf Health Care*. 2010;19(5):371-375. doi:10.1136/qshc.2009.035014
 14. Reeder TA, Mutnick A. Pharmacist-versus physician-obtained medication histories. *Am J Health-Syst Pharm*. 2008;65(9):857-860. doi:10.2146/ajhp070292
 15. Lubowski TJ, Cronin LM, Pavelka RW, Briscoe-Dwyer LA, Briceland LL, Hamilton RA. Effectiveness of a medication reconciliation project conducted by PharmD students. *Am J Pharm Educ*. 2007;71(5):94. doi:10.5688/aj710594
 16. Carter MK, Allin DM, Scott LA, Grauer D. Pharmacist-acquired medication histories in a university hospital emergency department. *Am J Health-Syst Pharm*. 2006;63(24):2500-2503. doi:10.2146/ajhp060028
 17. Mekonnen AB, McLachlan AJ, Brien JA. Effectiveness of pharmacist-led medication reconciliation programmes on clinical outcomes at hospital transitions: a systematic review and meta-analysis. *BMJ Open*. 2016;6(2):e010003. doi:10.1136/bmjopen-2015-010003.
 18. Choi YJ, Kim H. Effect of pharmacy-led medication reconciliation in emergency departments: a systematic review and meta-analysis. *J Clin Pharm Ther*. 2019;44(6):932-945. doi:10.1111/jcpt.13019.
 19. Hohl CM, Partovi N, Ghement I, Wickham ME, McGrail K, Reddekopp LN, Sobolev B. Impact of early in-hospital medication review by clinical pharmacists on health services utilization. *PLoS One*. 2017;12(2):e0170495. doi: 10.1371/journal.pone.0170495
 20. Champion HM, Loosen JA, Kennelty KA. Pharmacy students and pharmacy technicians in medication reconciliation: a review of the current literature. *J Pharm Pract*. 2019;32(2):207-218.
 21. Anderson LJ, Schnipper JL, Nuckols TK, Shane R, et al; members of the PHARM-DC group. Effect of medication reconciliation interventions on outcomes: a systematic overview of systematic reviews. *Am J Health-Syst Pharm*. 2019;76(24):2028-2040.
 22. Redmond P, Grimes TC, McDonnell R, Boland F, Hughes C, Fahey T. Impact of medication reconciliation for improving transitions of care. *Cochrane Database Syst Rev*. 2018;8:DC010791.
 23. Hillmann W, Hayes BD, Marshall J, et al. Improving burnout through reducing administrative burden: a pilot of pharmacy-driven medication histories on a hospital medicine service. *J Gen Intern Med*. 2021;36:2511-2513.
 24. Desai RJ, Franklin JM. Alternative approaches for confounding adjustment in observational studies using weighting based on the propensity score: a primer for practitioners. *BMJ*. 2019;367:l5657.
 25. Deb S, Austin PC, Tu JV, et al. A review of propensity-score methods and their use in cardiovascular research. *Can J Cardiol*. 2016;32:256-265.
 26. Bates DW, Cullen DJ, Laird N, et al. Incidence of adverse drug events and potential adverse drug events. Implications for prevention. ADE Prevention Study Group. *JAMA*. 1995;274(1):29-34.
 27. Pintor-Marmol A, Baena MI, Fajardo PC, et al. Terms used in patient safety related to medication: a literature review. *Pharmacoepidemiol Drug Saf*. 2012;21(8):799-809.
 28. Forster AJ, Murff HJ, Peterson JE, Gandhi TK, Bates DW. The incidence and severity of adverse events affecting patients after discharge from the hospital. *Ann Intern Med*. 2003;138(3):161-167.
 29. Rozich JD, Resar RK. Medication safety: one organization's approach to the challenge. *J Clin Outcomes Manag*. 2001;8(10):27-34.