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Medication Reconciliation during Transitions of Care Across Institutions: A Quantitative Analysis of Challenges and Opportunities

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Abstract

Objective Medication discrepancies between clinical systems may pose a patient safety hazard. In this paper, we identify challenges and quantify medication discrepancies across transitions of care.

Methods We used structured clinical data and free-text hospital discharge summaries to compare active medications' lists at four time points: preadmission (outpatient), at-admission (inpatient), at-discharge (inpatient), and postdischarge (outpatient). Medication lists were normalized to RxNorm. RxNorm identifiers were further processed using the RxNav API to identify the ingredient. The specific drugs and ingredients from inpatient and outpatient medication lists were compared.

Results Using RxNorm drugs, the median percentage intersection when comparing active medication lists within the same electronic health record system ranged between 94.1 and 100% indicating substantial overlap. Similarly, when using RxNorm ingredients the median percentage intersection was 94.1 to 100%. In contrast, the median percentage intersection when comparing active medication lists across EHR systems was significantly lower (RxNorm drugs: 6.1–7.1%; RxNorm ingredients: 29.4–35.0%) indicating that the active medication lists were significantly less similar ($p < 0.05$).

Keywords
- medical records' systems
- computerized
- medication reconciliation
- patient safety

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Medication lists in the same EHR system are more similar to each other (fewer discrepancies) than medication lists in different EHR systems when comparing specific RxNorm drug and the more general RxNorm ingredients at transitions of care. Transitions of care that require interoperability between two EHR systems are associated with more discrepancies than transitions where medication changes are expected (e.g., at-admission vs. at-discharge). Challenges included lack of access to structured, standardized medication data across systems, and difficulty distinguishing medications from orderable supplies such as lancets and diabetic test strips.

Conclusion Despite the challenges to medication normalization, there are opportunities to identify and assist with medication reconciliation across transitions of care between institutions.

Background and Significance

Transitions of care, defined as "movement of a patient from one setting of care to another",[1] are high-risk events. Important clinical information may be lost as the patient transitions from one setting or provider to another.[2,3] Although adverse events may occur for many reasons, adverse drug events (ADEs) are a common cause of morbidity and even mortality.[4] Unfortunately, medication discrepancies across care transitions are common.[5] To the extent that care transitions require that each medication must be accurately entered, verified, represcribed, stopped, or changed, discrepancies are more likely when there are multiple medications (polypharmacy) and when there are changes in medications.[6,7] Care transitions related to hospital admission and discharge are associated with a high risk of inadvertent medication discontinuation—in both intensive care unit (ICU) and non-ICU admissions.[8] Such errors of omission could increase risk of adverse events such as emergency department visits, hospitalization, and death.[9]

Accurate and accessible medication records are required for safe clinical decision-making. For example, Nirmatrelvir/Ritonavir (Paxlovid) for COVID-19 must be prescribed within at most 5 days from the onset of symptoms but interacts with many commonly prescribed drugs. Thus, to safely prescribe Paxlovid, the clinician must know the patient's current medications. Medication reconciliation has been shown to reduce medication discrepancies and ADEs,[10] and is required by various quality metrics and government programs.[11,12]

Ideally, medication lists that reflect medications that are active at a particular point in time should match between institutions. Consider four medication lists: (1) preadmission (outpatient), (2) at-admission (inpatient), (3) at-discharge (inpatient), and (4) first posthospital visit (outpatient) list. Theoretically, the preadmission and the at-admission medication lists should be similar, though discrepancies can occur for a variety of reasons. For example, the patient could have seen a specialist at a different institution between the last outpatient visit and admission. Similarly, we expect the at-discharge list to be similar to the medication list at the first follow-up visit; barring changes between these events. For example, the patient may have completed a course of antibiotics prescribed at discharge. In contrast, we do not expect the at-admission list to match the at-discharge list due to medication changes that are likely to occur during hospitalization.

Previous studies have shown that discrepancies are highly prevalent among populations of hypertensive patients.[13,14] We hypothesized that this kind of medication discrepancy is prevalent regardless of disease type.

Objectives

Regardless of whether discrepancies are caused by errors, by health system fragmentation, or other reasons, discrepancies between medication lists may increase ADE risk in multiple ways. For example, errors of omission may occur if necessary medications are inadvertently not continued and errors of commission may occur if unnecessary medications are prescribed.[15] Therefore, we analyzed medication data across inpatient/outpatient care transitions to quantify the discrepancies between medication records across care transitions and across EHR systems.

Methods

We used data from two institutions in the southern United States that share patients but are administratively separate with separate EHR systems. One institution, the University of Texas Health Science Center at Houston (UTHSC-H) is an academic medical center with an Epic EHR implementation that operates a network of outpatient clinics but does not operate an inpatient facility (hospital). The second institution, Memorial Hermann Hospital System is a Cerner site that is affiliated with the academic medical center and operates both inpatient outpatient facilities. Patients often transition between the two institutions. In this study, we analyzed inpatient admissions of patients from the academic medical center to the hospital and their subsequent discharge back to the outpatient clinics. This study has been approved by the Committee for the Protection of Human Subjects (the UTHSC-H Institutional Review Board [IRB]) under protocol HSC-SBMI-13-0549.

We focused on the discrepancies in medication information between the two systems. Specifically, we calculated the intersection (i.e., number of medications in common) and the

discrepancies between two lists. Discrepancies were calculated as follows:

$$\text{Discrepancies} = (\text{no. of Medications on List A}) + (\text{no. of Medications on List B}) - 2 \times (\text{no. of Medications on both List A and B})$$

For example, suppose list A contained aspirin, lisinopril, gabapentin and list B contained lisinopril, gabapentin, tadalafil. The number of discrepancies would be: $3 + 3 - 2 \times 2 = 2$.

We used outpatient EHR data to identify adult patients (>18 years old) with an identified primary care physician at the academic medical center who were seen in the outpatient setting, admitted to hospital, and subsequently discharged home between January 1, 2022 and March 31, 2023. Patients with no primary care physician at the academic medical center, who died, or who were transferred to other facilities, such as skilled nursing facilities or acute rehabilitation, were excluded. ►Fig. 1 provides an overview of our study.

We refer to discharges from the hospital as "discharge events" (DEs). DEs were the unit of analysis because some patients were admitted more than once during the study period. Active medications were assumed to be the medications that the patient was taking at a particular point in time. Medication adherence (compliance) was outside the scope of this study.

We used partially structured discharge summaries that were completed by the discharging inpatient clinician (or designee) because structured medication data from the inpatient facility were not available. The discharge summaries contained a partially structured "discharge medications" section. The discharge medication section was further structured into four categories of medications.

1. *Unchanged*: medications that were active both at-admission and at-discharge.
2. *Changed*: medications where some element was changed, such as dose or route of administration.
3. *New*: medications that were started during the hospitalization and were to remain active postdischarge.

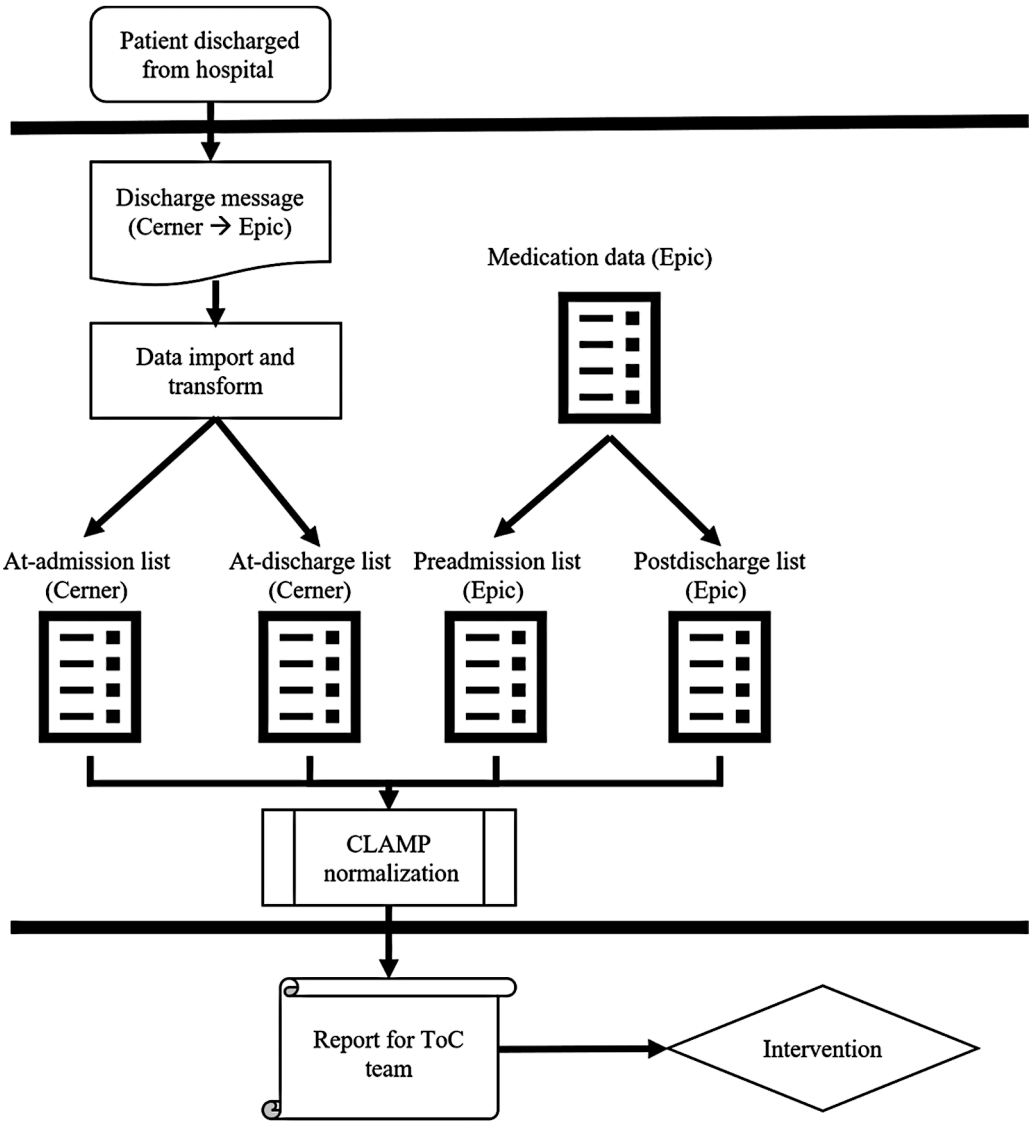

Fig. 1 Overview. ToC, transitions of care.

4. *Discontinued*: medications that were active before the hospitalization that the patient should no longer take after discharge.

We compared the prescription start and end dates to the hospitalization dates to determine the active medications at four specific times: preadmission, at-admission, at-discharge, and at the first postdischarge encounter.

1. *Preadmission*: active medications before the admission date.
2. *At-admission*: all medications listed in the following discharge message categories—changed, unchanged, and discontinued.
3. *At-discharge*: all medications listed in the following discharge message categories—new, changed, and unchanged.
4. *Postdischarge*: encounter medications were defined as the active medications at the first encounter after discharge. An encounter was defined as any recorded event that was not exclusively financial or administrative.

One caveat to this grouping is that the "changed" category does not list what changed in that medication order. The change could have been strength, frequency, or form but that information was not provided in the discharge message.

We used two sections of the outpatient EHR (Epic) to define medication lists. The first section was the active medication list and the second was the discharge summary. The Active Medication list included the medications ordered and marked as active using the metadata: start date, end date, cancel date. The discharge note in the outpatient EHR (Epic) was received from the inpatient EHR (Cerner) and contained patient identifier, discharging physician name, admission date, discharge date, and discharge note text.

To retrieve the discharge medications, the following steps were taken. The discharge summaries were identified in the source inpatient database (Epic Clarity) system using python scripts and inserted into a local database. We validated that the extracted message matched what was seen in the outpatient EHR graphical user interface and in the source inpatient database (Epic Clarity).

Discharge summaries were preprocessed by first identifying the location of the discharge medication section and mediation categories: new, changed, unchanged, and discontinued. These data were then processed using a Clinical Language Annotation, Modeling, and Processing (CLAMP)[16] pipeline. CLAMP can parse clinical text and normalize the text using specific vocabularies. For this project, we used a medication pipeline that identified medications and used the RxNorm ontology for standardization. The output contained specific RxNorm concept unique identifiers (CUIs) when dosage and route were specified and a generic RxNorm CUI that was one level up in the RxNorm hierarchy.

The CLAMP output was processed and loaded into a relational database. After these steps were taken, the active medication lists were imported for those patients who had a DE. Using RxNav API,[17] the medications identified with RxNorm CUIs (we refer to this as RxNorm drug) were further mapped to the ingredient (we refer to this as RxNorm ingredient). For multi-ingredient formulations, all ingredients were compared as if they were separate medications. For example, hydrochlorothiazide/lisinopril combination was treated as two medications: hydrochlorothiazide and lisinopril. After ingredient classification, the four medication lists were assembled using the admission and discharge times to identify medications active before admission and after discharge. Dosages (e.g., 25 vs. 50 mg) and route (e.g., oral vs. sublingual) were considered at the drug level, but not the more general ingredient level. Frequency of administration was ignored. Notably, route and frequency were often missing.

A random sample of 15 DEs were chosen for manual review and compared to the results generated by the automated system. A clinical expert constructed the four lists independently of the automated lists, extracting the medication information from the medication and notes sections of the Epic user interface. The lists created by the clinical expert were compared to the automatically constructed medication lists.

Statistical analysis was performed using Python 3.10 and R version 4.2.2. Descriptive statistics such as mean, standard deviation, median, and interquartiles (Q1 = 25th percentile, Q3 = 75th percentile) were reported. Wilcoxon's signed-rank test was used to compare intersection mean percentage between two time points and *p*-values were reported. All statistical tests were two-sided and statistical significance was defined at $p < 0.05$.

Results

Starting from 26,569 DEs and after applying the exclusion criteria shown in ►Fig. 2, we analyzed 383 DEs. These 383 DEs were attributed to 353 patients (239 female [68%], 114 male [32%]; 211 were aged between 18 and 64 [60%], 142

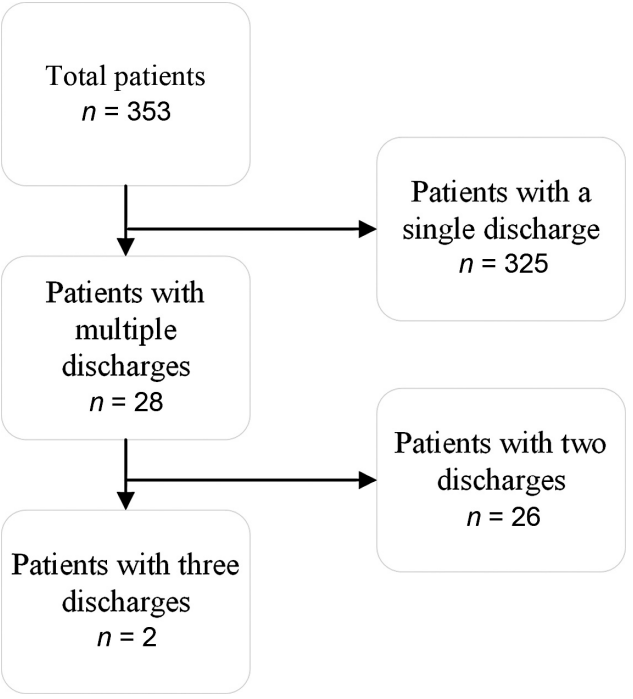

Fig. 2 Number of patients versus discharge events.

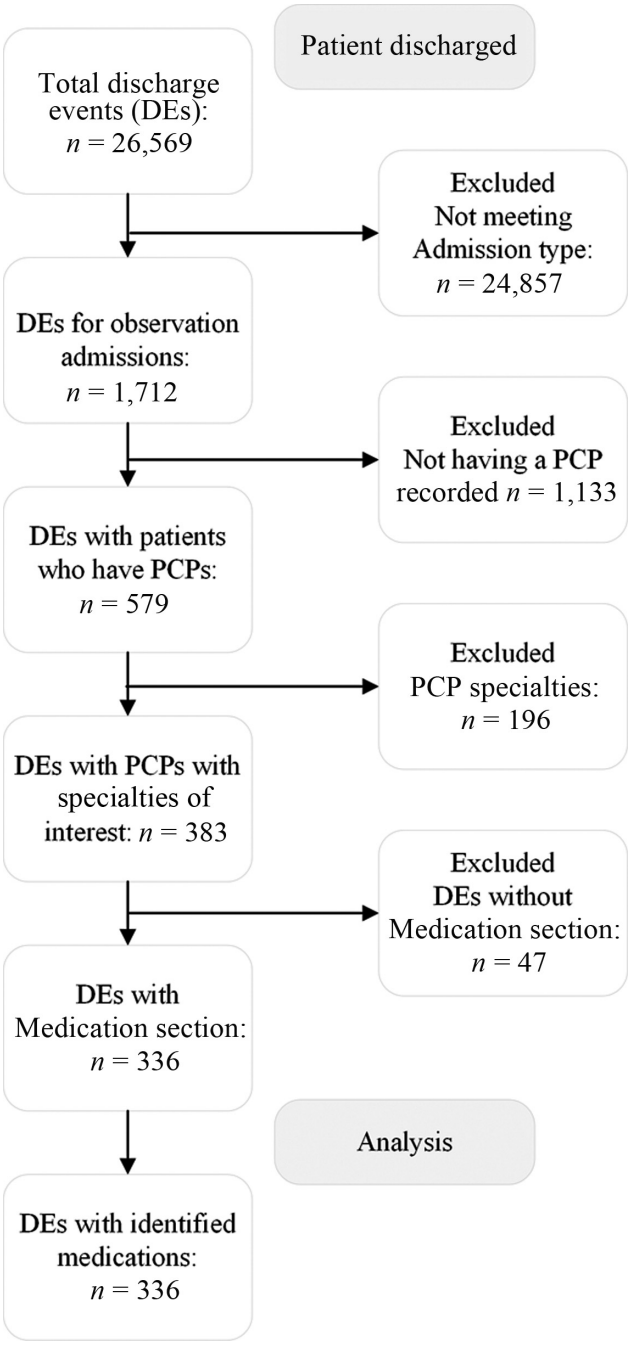

Fig. 3 CONSORT diagram of discharge events. CONSORT, Consolidated Standards of Reporting Trials; DE, discharge event; PCP, primary care physician.

were aged >65 [40%]). ►Fig. 2 shows the breakdown of patients with single and multiple DEs. Notably two patients had three DEs during the study period. ►Fig. 3 shows the process of filtering and identifying DEs.

Term normalization to RxNorm drugs and subsequently to RxNorm ingredients are shown in ►Table 1. As an example, albuterol sulfate is reconciled from four distinct RxNorm concepts to one RxNorm Ingredient concept.

►Table 2 shows the number of medication entries in each of the four lists and in total. The medication list comparison results are shown in ►Table 3 using specific RxNorm drugs and more general RxNorm ingredients. Overall, the intersection between lists from the same EHR system was substantially greater by all measures (mean, median, percent of total medications on list) than the intersection between lists from different EHR systems.

When using RxNorm drugs, the intersection percentages between two different time points were examined using Wilcoxon's signed-rank test and *p*-values were reported in ►Table 4. The intersection percentage difference between the preadmission and at-admission versus at-discharge and postdischarge were not statistically significant difference ($p = 0.79$). However, all other list comparisons were significant.

When using RxNorm ingredients, all comparisons were statistically significant.

Discharge message timeliness was assumed to be important so the time between discharge and receiving the discharge message was also analyzed. We found a mean of 14.4 hours and a maximum of 58 days.

To confirm the accuracy of the automated results, a manual review was done on 15 DEs by an author with no prior knowledge regarding the system output for these 15 DEs. These DEs contained a total of 455 medication records; one DE was not reviewed due to restricted access to the patient record. There were a total of 42 discrepancies (9.2%) between the manual and automated results. Twenty discrepancies (4.4%) were related to nonmedication orderable supplies such as lancets, blood glucose monitoring supplies, or diabetic test strips that had no RxNorm identifier. In 16 cases (3.5%), CLAMP did not identify the text string correctly. Three discrepancies were caused by reviewer error (0.7%). Finally, three (0.7%) had date-related artifacts that caused an incorrect postdischarge encounter, this was associated with one of the fifteen DEs.

Table 1 Drug normalization example

Drug name	Strength	Form	RxNorm drug	RxNorm ingredient
Albuterol sulfate	108	HFA	142153	Albuterol
Albuterol sulfate	108	Puffs	745679	Albuterol
Albuterol sulfate	2.5 mg/3 mL	–	351136	Albuterol
Albuterol (Eqv-ProAir HFA)	90 µg/inh	Puffs	307782	Albuterol

Abbreviations: HFA, hydrofluoroalkane; inh, inhaler.

Table 2 Number of drugs and ingredients in each medication list

List	RxNorm Drug *N* (mean, median, range, standard deviation)	RxNorm Ingredient *N* (mean, median, range, standard deviation)
Preadmission	2,953 (7.71, 6, 0–33, SD = 6.78)	2,704 (7.07, 6, 0–28, SD = 6.11)
At-admission	2,736 (7.14, 5, 0–31, SD = 6.79)	2,254 (5.89, 4, 0–26, SD = 5.68)
At-discharge	2,978 (7.78, 7, 0–32, SD = 6.46)	2,430 (6.34, 5, 0–26, SD = 5.31)
Postdischarge	3,069 (8.01, 7, 0–33, SD = 7.12)	2,787 (7.27, 6, 0–31, SD = 6.36)
Total	11,736	10,175

Abbreviation: SD, standard deviation.

Table 3 Medication list comparison with respect to intersection (drugs in common)

	RxNorm drug (range, SD)	RxNorm ingredient (range, SD)
Preadmission versus at-admission (across EHRs) *N* = 383 DEs		
Intersection mean	1.43 (0–10, 1.92)	2.96 (0–17, 3.52)
Intersection median	1	2
Intersection mean percentage	15.0% (0–100, 20.1)	33.9 (0–100, 34.0)
Intersection median percentage (Q1, Q3)	6.1% (0, 66.7)	29.4% (0.62)
Difference mean	11.99 (0–44, 9.22)	7.03 (0–28, 5.61)
Difference median	9	6
At-admission versus at-discharge (same EHR) *N* = 383 DEs		
Intersection mean	6.33 (0–25, 6.07)	5.22, (0–23, 5.1)
Intersection median	5	4
Intersection percentage	71.3% (0–100, 39.8)	70.0% (0–100, 40.6)
Intersection median percentage (Q1, Q3)	94.1% (50, 100)	94.1% (44.6, 100)
Difference mean	2.26 (0–24, 2.87)	1.80 (0–14, 2.18)
Difference median	1	1
At-discharge versus postdischarge (across EHRs) *N* = 376 DEs		
Intersection mean	1.47, 0–9, 1.93	3.07, 0–17, 3.5
Intersection median	1	2
Intersection percentage	15.5% (0–100, 19.9)	37.2% (0–100, 34.9)
Intersection median percentage (Q1, Q3)	7.1% (0, 25.5)	35% (0, 66.7)
Difference Mean	13.14 (1–47, 9.02)	7.83, (1–30, 5.29)
Difference Median	11	7
Preadmission versus postdischarge (same EHR) *N* = 376 DEs		
Intersection mean	7.41, 0–33, 6.77	6.85, 0–28, 6.11
Intersection median	6	5
Intersection percentage	78.4% (0–100, 39.5)	78.8% (0–100, 39.5)
Intersection median percentage (Q1, Q3)	100% (87.1, 100)	100% (91.3, 100)
Difference mean	1.19, 0–16, 2.15	1.00, 0–28, 1.93
Difference median	0	0

Abbreviation: DE, discharge event.
Q1, 25th percentile; Q3, 75th percentile.

Table 4 *p*-Values of pairwise comparison of intersection percentages between different time points for pairs of medication lists

Time point	Pairwise comparison					
	RxNorm drug			RxNorm ingredient		
Preadmission versus at-admission (across EHRs)	Ref	–	–	Ref	–	–
At-discharge versus postdischarge (across EHRs)	0.7903	Ref	–	0.012	Ref	–
At-admission versus at-discharge (same EHR)	<0.0001	<0.0001	Ref	<0.0001	<0.0001	Ref
Preadmission versus postdischarge (same EHR)	<0.0001	<0.0001	0.002	<0.0001	<0.0001	0.0005

Abbreviation: Ref, reference.

Discussion

We found substantial discrepancies between medication lists associated with transitions of care between outpatient and inpatient settings. These discrepancies were more associated with transitions across EHR systems than clinical changes. For example, the difference between outpatient (preadmission) and at-admission medication lists (different EHR systems) was larger than the difference between at-admission and at-discharge lists (same EHR system).

Strengths of our study included reliance on real-world data from two collaborating institutions. We developed an automated system that allowed us to review over 10,000 individual ingredient entries, more than what would be practical to accomplish manually. Manual validation of the automated system performed without prior knowledge of the automated results increases confidence in the accuracy of the automated system.

At our institution, a group of community health workers and case managers at a transitions of care "hub" review the four lists produced by our system to identify patients at risk for ADEs. Patients deemed at risk such as those with 10 or more medications (polypharmacy), high-risk medications (e.g., diphenhydramine in an elderly patient), or multiple new medications are prioritized for human follow-up by a nurse case manager. Without the medication extraction system, the case manager had to review the semistructured discharge document, the current (postdischarge) medication list, manually reconstruct the preadmission medication list, and then manually compare these lists. Anecdotally, this requires approximately 10 to 20 minutes per case. An added practical benefit is that the system described in this paper integrates information that previously required access to multiple systems including the outpatient EHR and payer portals to identify recently discharged patients.

Our study was limited to two collaborating institutions and reflects the clinical workflow at these institutions. Clinical workflows, including medication reconciliation practices, may be different in different settings and for different care transitions (e.g., discharge to acute rehabilitation). Similarly, we restricted our analysis to a general adult population. Results may be different for other populations such as pediatric, geriatric, or obstetrical populations and in other geographic areas (e.g., rural).

Another limitation is that our data did not allow us to determine whether discrepancies were errors or to attribute clinical consequences to discrepancies. As discussed above, discrepancies could have occurred due to health system fragmentation (e.g., seeing an outside specialist who changed medications between the last outpatient visit and admission) or multiple other factors. Finally, our data did not allow us to assess adherence (compliance). Some discrepancies could have been attributable to discrepancies between prescribed medications and the medications that the patient was actually taking at a particular point in time (e.g., at-admission) or what the patient reported to the admitting clinician.

Previous studies have shown that it is possible to extract knowledge from unstructured data.[16,18,19] Identification of medications from discharge summaries is not a new challenge and we were able to leverage existing tools like CLAMP[16] and RxNorm resources maintained by the National Library of Medicine. A common classification approach is to rely on the main ingredient of a combination.[18,19] A limitation of this approach is that ignoring some ingredients can lead to misclassification.

In our study, discrepancies between automated and manual medication identification accounted for 9.2% of the manually reviewed data with only half of these attributable to the automation; the rest were not related to medications (e.g., diabetic supplies), date errors in the medical record or reviewer error. A substantial proportion of the remaining errors were attributable to incorrect templates used in the notes system, or a missing medication section.

Correct and current medication information is important for clinical performance measures[12] and patient safety[20]; particularly at care transitions. We found substantial discrepancies between medication lists, particularly across EHR systems. This is not a new finding, nearly 20 years ago, researchers noted that most medication lists were not accurate.[21] Our findings are similar to prior studies showing medication list intersections between transitions of care from 30 to 80%.[22,23] Unfortunately, to the extent that discrepancies correlate with inaccuracies, regardless of whether the discrepancy was due to an error or resulted from system-level properties that inhibit routine, automated, and accurate information sharing, progress over the past 20 years has been limited.

We found multiple instances of repeated medications that had different RxNorm drugs in both structured data (outpatient) and discharge notes (inpatient). For example, a list may contain two entries for Lisinopril "1: Lisinopril 10 mg po qd" and "Lisinopril," resulting in two RxNorm drugs. This

accounts for some of the discrepancies in the medication lists using RxNorm drugs. The comparison using RxNorm ingredient combines entities with duplicate medications, brand names, and different formularies between institutions (see ►Table 3), at the cost of abstracting away information about different formulations (e.g., liquid vs. pill form of the same drug). Another advantage of comparing ingredients rather than RxNorm drugs is that supplies that are not likely to cause ADEs, such as insulin syringes, were not identified as medications and thus not considered discrepancies. We recognize that there could have been cases where a patient runs out of supplies and is not able take a necessary medication (e.g., insulin).

Discrepancies in medication lists do not necessarily represent errors by either patient or clinician. For example, a patient could have seen an outside clinician who changed the medication regimen between the last preadmission visit and admission. Similarly, administrative discrepancies such as inpatient formularies and outpatient insurance coverage may require medication changes (e.g., therapeutic substitution[24]). Thus, we did not expect that medication lists between the two institutions would be identical. However, quantifying these discrepancies can inform the design and implementation of systems to support safe clinical decision-making.

Unfortunately, most clinics lack EHR functionality to support automated medication reconciliation.[25] Examples of automated systems that may decrease the manual work required for medication reconciliation include tools to (1) accurately extract medication lists from routinely collected health data, (2) present these lists in an interface that makes comparison simple[26,27] (e.g., displays both lists on the same screen), and (3) highlight discrepancies between lists of medications.[28,29]

Medication lists within the same EHR (e.g., at-admission and at-discharge) tend to be more similar than lists in different EHRs (e.g., preadmission and at-admission). This finding highlights the importance of EHR interoperability for institutions that share patients. Previous studies of interoperability found that implementations of the same vendor tend to be somewhat more interoperable than implementations of products from different vendors.[30] Standardizing representations, such as using the same vocabulary to represent medications in both systems and sharing these as structured data rather than text notes may improve concordance of medication lists across care transitions.

Conclusion

Active medication lists in the same EHR system are similar to each other, but there are many discrepancies between active medication lists in different EHR systems. There is opportunity to improve medication reconciliation. An automated system, such as the one that we developed, implemented, and validated can identify medication list discrepancies to be addressed within a transitions of care program.

Clinical Relevance Statement

Accurate automated identification of medication lists preadmission, at-admission, at-discharge, and at first encounter postdischarge is possible. These lists can support automated clinical decision support (e.g., drug interaction detection), support transitions of care services (e.g., help community health workers and nurse case managers to identify patients at risk of ADEs). Since transitions of care often involve transitions between clinical systems (e.g., different institutional EHRs), interoperability between clinical systems is important for patient safety across care transitions.

Multiple Choice Questions

1. What medication lists were most concordant?
   a) At-admission and at-discharge
   b) Preadmission and at-admission
   c) Preadmission and postdischarge
   d) At-admission and postdischarge

   Correct Answer: The correct answer is option c. The mean intersection was 7.41 (highest) and the median difference was 0 meaning that these two lists were most similar.

2. What standard was used to compare medication lists in this study?
   a) National drug codes
   b) International Classification of Diseases, 10th Revision
   c) RxNorm ingredients
   d) Current Procedural Terminology

   Correct Answer: The correct answer is option c. RxNorm ingredients were used to compared medication lists in this paper. NDC codes were not used because they reflect packaging (e.g., 30 tablet package vs. 90 tablet package) that are not necessarily clinically significant. ICD10 is a controlled vocabulary of diseases/conditions and CPT is a controlled vocabulary of procedures.

Authors' Contributions

All authors participated in the problem formulation and experimental design. A.A. and E.V.B. wrote the initial manuscript. A.A. performed the data analysis. A.A., L.R.T., G.M.F., L.D.H., K.O.H., H.M.H., and E.V.B. revised the manuscript. E.V.B. provided the data. All authors reviewed and approved the manuscript prior to submission.

Human Subjects Protection

This study has been approved by the Committee for the Protection of Human Subjects (the UTHSC-H IRB) under protocol HSC-SBMI-13-0549.

Data Availability

The data underlying this article cannot be shared publicly due to the fact that these data are individually identifiable and represent real-world patients.

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Conflict of Interest
None declared.

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