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Automated medication reconciliation and complexity of care transitions

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Abstract

Medication reconciliation is a National Patient Safety Goal (NPSG) from The Joint Commission (TJC) that entails reviewing all medications a patient takes after a health care transition. Medication reconciliation is a resource-intensive, error-prone task, and the resources to accomplish it may not be routinely available. Computer-based methods have the potential to overcome these barriers. We designed and explored a rule-based medication reconciliation algorithm to accomplish this task across different healthcare transitions. We tested our algorithm on a random sample of 94 transitions from the Clinical Data Warehouse at the University of Texas Health Science Center at Houston. We found that the algorithm reconciled, on average, 23.4% of the potentially reconcilable medications. Our study did not have sufficient statistical power to establish whether the kind of transition affects reconcilability. We conclude that automated reconciliation is possible and will help accomplish the NPSG.

Introduction

Complete and accurately reconciled lists of medications, across the entire continuum of care, is a formal requirement set by The Joint Commission (TJC) as its National Patient Safety Goal in 2005 [1]. According to The Joint Commission (TJC), "medication reconciliation is the process of comparing a patient's medication orders to all the medications that the patient has been taking." [2]. The "continuum of care" refers to addressing medication reconciliation through healthcare transitions, which TJC defines as a change in setting, service, practitioner or level of care [1]. In order to fulfill this NPSG, TJC requires institutions to implement medication reconciliation across all healthcare transitions.

Medication reconciliation enhances patient safety by decreasing unintentional medication discrepancies [3,4], the incidence of potential adverse drug events (PADEs) [5], and the relative risk of actual adverse drug events (ADE) [6,7]. However, medication reconciliation is an error prone, resource intensive task that requires qualified personnel [6]. Computer-based approaches can improve medication reconciliation. Automated approaches have advantages over paper-based solutions: they enable automatic comparison of medication lists, and the capability to track medication reconciliation performance to inform further process improvement [5]. Also, computer-based approaches may improve medication reconciliation performance by supporting the knowledge-intensive task of assessing medication appropriateness and making it available in a timely fashion.

As previously mentioned, in order to accomplish TJC's NPSG on medication reconciliation and fulfill its potential impact on healthcare improvement, reconciliation strategies should be evaluated in the context of care transitions. However, transitions of care vary in complexity. Hughes states that "transitions among settings pose even more chances for error, as key information may be lost during transfers from or to clinics, nursing homes, and acute care settings" [7]. We propose that the degree of complexity of the transition drives the difficulty of the medication reconciliation task. We will therefore study the agreement between medication lists before and after healthcare transitions of different degrees of complexity. We expect that pairs of medication lists resulting from higher-complexity transitions of care will be less reconcilable than pairs of medications lists resulting from lower-

complexity transitions. In this study, we introduce an automated medication reconciliation algorithm and measure its performance across care transitions of varying degrees of complexity.

Background

Organizations such as the Institute for Healthcare Improvement (IHI), TJC, and the Office of the National Coordinator for Healthcare Information Technology (ONC), have repeatedly called upon healthcare stakeholders to develop medication reconciliation strategies. Even though this NPSG was established in 2005, medication reconciliation remains challenging. Healthcare organizations have expended significant resources to address medication reconciliation, with discouraging results [8]. TJC has been unable to enforce their medication reconciliation NPSG [1] and has been forced to push the deadline for compliance back repeatedly [8]. According to the consensus statement from The Medication Reconciliation conference held on 2009, considering the complexity of interactions within the healthcare system is crucial to the successful implementation of medication reconciliation [8].

Medication reconciliation is a resource intensive task

A clinical unit that performs many discharges and admissions may require additional resources or even full time reconciliation staff [9]. One cost-effectiveness analysis of a medication reconciliation implementation showed that it takes extra time for pharmacists (22 minutes), nurses (17 minutes) and physicians (5 minutes) to perform reconciliation on each admission [6]. In another study, the duration of this task was variable and took up to 60 minutes per admission [9].

Medication reconciliation can also be assessed from a cognitive perspective. Miller showed that working memory capacity is limited to a certain number of items (or "chunks") of information [10]. This limitation can impede cognitive medication processing; CPOE systems, for example, may produce information overload [11]. As part of the medication reconciliation process, the clinical user must remember medication names, dosing forms, doses, and patient instructions for each medication the patient takes. This may take several "chunks" of working memory for a single medication. Knowledge stored in long-term memory may also be needed. For example, the generic equivalents, brand names, and therapeutic uses of a drug may all be needed to assess its appropriateness. These features make medication reconciliation a cognitively demanding task that places load on working memory. Further, the medication lists that need to be reconciled do not have any intrinsic arrangement, which means that the medications can be listed in any order or even across different screens. This can violate the proximity-compatibility principle [12] and thus increase the cognitive load imposed by the reconciliation task.

Since it is cognitively demanding, it is not surprising that medication reconciliation is also error prone. In one study, even after appropriate education, 63% of medication reconciliation forms were incorrect with a mean of 2.4 errors per patient. The most common errors were omitted prescriptions and incorrect directions [13].

In acute care or critical care units, changes in patient conditions can happen rapidly. Thus, medication information may change from hour to hour. However, medication reconciliation is still a time consuming task and its results may not be available in a timely manner. Therefore, decreasing the time required to reconcile medications may increase its usefulness in acute care scenarios.

Computer-based approaches can facilitate medication reconciliation and have a positive impact on patient safety. Significant positive effects were seen after implementing computerized medication reconciliation program with process redesign An IT application, the Pre-Admission Medication List builder (PAML), decreased the relative risk of adverse drug events by 28% [5].

Methods

Transitions of care refer to the interface between two clinical episodes where there is a change in provider, service, setting or level of care within the healthcare continuum. We measured the degree of complexity of transitions in care using a scale that counts the number of variables that change across the transition. We considered the four variables listed in Table 1. Therefore, the degree of complexity varies from 0 to 4. In the baseline transition, degree 0, there is a different episode of care, which involves the same provider, service, setting and level. For example, a patient sees the same physician in the same clinic twice in succession. In contrast, the most complex transitions (degree 4) involve changes in all of these four variables, meaning that the patient has changed to a different provider, a different service, a different setting, and a different level of care.

Table 1 - Variables used to compute the degree of transition complexity

Variable	Definition	Example
Provider	Different healthcare provider within the same service, setting and level of care.	Attending changes from Dr. X to Dr. Y.
Service	Change in clinical service.	Patient transferred from Internal Medicine to Cardiology.
Setting	Relocation from an outpatient to an inpatient setting.	Patient previously seen in an outpatient clinic is admitted to a hospital.
Level	Change in the complexity of care.	Patient is moved from a general medical bed to a critical care unit.

Problem definition

We adopt the National Institute of Standards and Technology (NIST) model of medication reconciliation. NIST views medication reconciliation as the task of merging two lists of medications [14]. For example, one list may be provided by the patient and another by a medical record, or one may be pre- and another post-care transition. Each element of each list is a prescription, containing a medication name, dose, frequency, and instructions (i.e. "take with every meal"). We assume these two lists are complete and, in order to reduce the cognitive load on the user performing the reconciliation, prescriptions that are common to both lists need to be identified and merged in one single list.

Medication reconciliation algorithm

We built a medication reconciliation algorithm. Its input is a pair of medication lists and its outputs is a set of three lists: a list of merged prescriptions and confidence scores, the prescriptions from the first list that could not be merged automatically, and the prescriptions of the second list that could not be merged automatically. Each list is a newline-separated set of medications as found in the clinical notes. The algorithm reconciled pairs of medications lists with minimal false positives. It is intended to help clinicians performing medication reconciliation, and not as a replacement for clinicians. The code is available at https://github.com/drh-uth/MedRec.

Each list is preprocessed by separating its elements at each newline, turning it into a set of prescriptions. Each prescription is converted to uppercase. Leading and trailing spacing and punctuation are removed. The reconciliation algorithm has four steps. Every medication in one list not yet reconciled is compared to every medication in the other list at every step.

The first step is a string comparison. If two preprocessed prescriptions are identical, one of them is output as a reconciled prescription with a match score of 100%. Since this is a simple string match, any difference between both strings that is not eliminated by preprocessing will result in a non-match at this stage. For example, changes in word order, misspellings, and different representations of the same dose (i.e. 10 mg and 10.0 mg) will not match at this stage. If there is a match, the algorithm adds this string to the reconciled list.

In the second step, the still unreconciled prescriptions are then parsed into five different components: name, dose, units, formulation, and instructions using a set of 384 regular expressions built automatically by combining known physical drug forms (i.e. capsule, lozenge, ampule, etc.) extracted from SNOMED-CT with common administration idioms (i.e. "<number> [form here] twice a day"). Please see the code for the exact regular expressions used. We use the drug name to retrieve a list of ingredients using RxNorm. If the lists of ingredients, formulation and dose of two medications are identical, they are reconciled with a match score of 100%. If 30% or more of the list of ingredients of two medications match (and the formulation and dose are equal), then they are output as reconciled with a match score corresponding to the percentage of matching ingredients.

The third step uses RxNorm to retrieve brand names for each drug. If a drug on one list is a brand name for a drug on another list (and the formulation and dose match) then those two drugs are output as reconciled with a match score of 100%.

The fourth and final step attempts to match drugs by their therapeutic intention. We compute the conditions each drug is known to treat, and compare these conditions instead of the drugs themselves. As we do not have access to a commercial database of common drug uses, we relied instead on TREATS relationships extracted from MEDLINE titles and abstracts using the SEMREP software published by the National Library of Medicine. If there is more than one match, the pair of drugs with the highest match percentage is output as reconciled. As this step intends to compare different drugs, dose and formulation are not used. Match scores for this reconciliation step are arbitrarily capped at 50%.

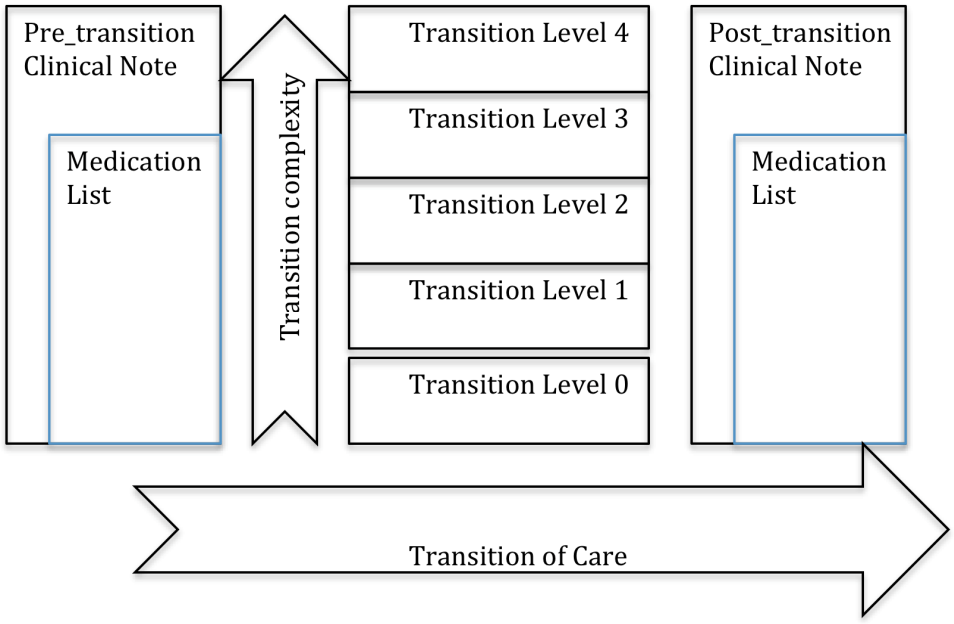
Experimental design

This work qualified for exempt status according to 45 CFR 46.101(b) by the UTHSC-H Committee for the Protection of Human Subjects (UTHSC-H Institutional Review Board).

We obtained a random sample of 495 healthcare transitions (99 each of degrees 0, 1, 2, 3, and 4) that had pre- and post-transition subsequent clinical notes from the UTHealth Clinical Data Warehouse (CDW). CDW staff built a query that retrieved these pairs of clinical notes at random and returned which of the variables (provider, service, setting and level of care), changed from the first note in the pair to the second. The clinical notes could be from any patient, including two different transitions for the same patient. As we were only interested in pairs of notes associated to a healthcare transition, we did not control which patients the notes were pulled from. The results of this query were randomly ordered using the SQL ORDER BY RANDOM() construct. We extracted pairs of notes from the results of this query sequentially until we had 99 of each. Patients who were seen only once, or had no electronic clinical note associated with an encounter, were excluded from the sample. The CDW contains (among other databases) clinical notes from outpatient encounters and billing information for the faculty practice plan. We used the billing database to identify the providers, services, settings, and levels of care where patients received clinical services. We recorded changes in each of the variables in Table 1 to measure the degree of healthcare transition. We then extracted the clinical notes that corresponded to before and after the transition.

As our CDW does not contain inpatient medical records, we were not able to obtain admission or discharge notes, or any inpatient medication lists. Instead, we retrieved the last clinical note available prior to a hospitalization and the first clinical note available after a hospitalization. When a transition in our sample occurred entirely in an outpatient setting, we retrieved the clinical notes that corresponded to the transition itself. Every clinical note in the sample was edited by hand to extract its medication list. The CDW staff edited the lists to ensure that there was only one prescription per line, but made no other modifications. Punctuation, capitalization, spelling, and any apparent omissions and/or obvious errors were left intact. We used only the prescribed medication lists for this experiment. Any information in the note that did not correspond to a prescribed medication (included potentially lists of prior medications) was discarded (Figure 1). Since our purpose was to evaluate a medication reconciliation algorithm, all pairs of medication lists where one or both lists were empty were excluded from the experiment. The medication lists contained no personally identifiable information and were impossible to re-identify without unrestricted access to the CDW.

Figure 1. Experimental design



We passed the pairs of medication lists through the medication reconciliation algorithm previously described. We recorded the degree of healthcare transition, the length of each input medication list, the length of the automatically reconciled list, and the number of prescriptions that could not be reconciled in each list.

Evaluation metrics

We measured how reconcilable the pre- and post-transition medication lists were by looking at how many items in the lists could be automatically reconciled (i.e. how much the lists "agreed" with each other). We measure this by comparing the length of the reconciled list with the length of the unreconciled lists in the output of the algorithm using Hooper's Consistency measure, which is a percentage agreement measure that corrects for the length of the input lists, for each reconciliation operation (Equation 1). Since the most medications that could conceivably be reconciled between two medication lists is the length of the shortest of those lists, we also computed the percentage of potential reconcilability (PPR) achieved, which we define as the length of the reconciled output divided by the length of the shortest input list.

Equation 1 - Hooper's Consistency formula

$$\text{Hooper's} = \frac{\text{Length of reconciled list}}{\text{Length of reconciled list} \; + \; \text{length unreconciled lists}}$$

We performed an Analysis of Variance (ANOVA) using R 2.12.2 (http://www.r-project.org) to determine whether any differences in Hooper's Consistency based on the degree of complexity of the transition were significant.

We also performed a manual review of the output of the algorithm to report on its failures. We reviewed each pair of medication lists and determined the appropriateness of the reconciliation the algorithm performed. False positives were cases in which the algorithm reconciled prescription pairs that, in the authors' opinion, should not have been reconciled. False negatives were cases in which the algorithm failed to reconciled medications that, in the authors' opinion, should have been reconciled. We classified algorithm failures to reconcile medications into four categories:

1. Typo or spelling mistake. The prescription spells the medication name incorrectly (i.e. "Prendisone" instead of Prednisone)
2. Medication name not in RxNorm.
3. Incomplete prescription. Our parsing code requires prescriptions to have a Drug name, dose, presentation, frequency, and an optional route (i.e. "Aspirin 81 mg tablets p.o."). If a component is missing, the prescription will be ignored.
4. Prescription not parsed. The algorithm failed to parse the prescription string in a way not covered by the previous three categories.

Results

Our original sample contained 495 pairs of medication lists. We excluded pairs of medication lists where one or both lists were empty, leaving 94 pairs of lists (Table 2).

Table 2 - Description of data sample.

Degree of transition complexity (0-4)	Number of pairs of medication lists studied	Average length ± standard deviation of length		Range of length (Pre/post transition lists)	
		Pre transition	Post transition	Pre transition	Post transition
0	17	5.3 ± 5.5	5.5 ± 5.2	1-23	1-21
1	31	4.2 ± 4.1	3.4 ± 2.6	1-20	1-11
2	19	3.7 ± 3.4	4.1 ± 3.5	1-11	1-12
3	11	4.4 ± 3.2	3.7 ± 3.2	1-12	1-11
4	16	4.0 ± 4.7	3.8 ± 2.1	1-16	1-9
TOTAL	94	4.3 ± 4.2	4.0 ± 3.4	1-23	1-21

The medication reconciliation algorithm produced a total of 109 reconciled prescriptions for these 94 pairs of medication lists. We present the average and standard deviation of Hooper's consistency and PPR in Table 3. Our ANOVA showed that the differences between groups were not significant (p=0.15). Our algorithm takes a few seconds to reconcile two medication lists on a modern laptop computer.

Our manual review of the output of the algorithm showed that 2 out of 109 (1.8%) of the reconciled prescriptions were incorrectly matched, i.e. were false positives. In both cases, the algorithm misinterpreted frequency descriptions it was not programmed to recognize ("p.r.n." and "twice a day" with no formulation) as "once a day," a simple programming error ("bug") that is easily fixed.

We also reviewed every pair of medication lists manually to detect false negatives. We discovered that 47% of the 94 pairs of lists had at least one false negative. 4% of the 94 pairs had one or more typos; 4% of the pairs had one or more medications that were not in RxNorm; 18% of the pairs had at least one incomplete prescription string; and 28% of the pairs had one or more prescription strings that our code could not parse.

Table 3 - Evaluation results (PPR=Percentage of Potential Reconcilability)

Degree of transition complexity	Average Hooper's Consistency	Standard deviation of Hooper's Consistency	Average PPR	Standard deviation of PPR
0	0.21	0.26	0.32	0.35

1	0.16	0.28	0.23	0.35
2	0.10	0.17	0.17	0.28
3	0.14	0.24	0.36	0.49
4	0.09	0.20	0.16	0.32

Discussion

Previous studies describe medication reconciliation as resource intensive, error prone and potentially unavailable in a timely manner. Automated partial reconciliation of medication lists can decrease the total number of prescriptions that need to be reviewed by clinical staff and focus human efforts on prescriptions that require clinical judgment. We found that an average of 23.4% of prescriptions could be automatically reconciled using a relatively simple algorithm.

We found non-significant differences in the reconcilability of medication lists by the degree of transition in clinical care. We believe that the trend shown in the results, especially the decline in Hooper's consistency and PPR between transitions of degrees 0, 1, and 2 is likely to be real, but our study was underpowered to detect it. The increase in Hooper's consistency between transitions of degree 2 to transitions of degree 3 (which requires a hospitalization, as there is no other way for three or more variables to change simultaneously) suggests that transitions of degree 3 and 4 are different from 0, 1, and 2, and we speculate that the difference was due to the hospitalization. Our CDW contains only outpatient clinical notes. We therefore used outpatient encounters as a proxy for inpatient transitions, which may have affected our results for transition levels 3 and 4. We did not have admission or discharge summaries, or any notes or prescriptions from the hospitalization itself. Therefore, our conclusions may not be equally applicable to all transitions within the care process, but may be stronger for outpatient transitions than inpatient ones.

The main limitation of this study is its small sample size. Unfortunately, we did not expect that a large number of clinical notes (81%) would contain no medications. We chose to discard these notes because it did not make sense to evaluate a medication reconciliation algorithm with no medications. We plan to repeat the study with a larger sample and establish whether the differences we observed were due to random chance or actually dependent on the degree of complexity of the transition in care.

Also, our classification for transition complexity does not consider the time between transitions in care. This may have a considerable effect on the clinical changes that happen to the patient between both encounters. For example, the two encounters in a degree 0 transition may be separated by 10 years. The pair of medication lists of these two events may differ significantly, as new conditions, procedures, and treatments may have happened. Even simple changes in therapeutic guidelines may make two medication lists diverge considerably over years. Therefore, disregarding the temporality of the transitions could have introduced noise in our sample.

A strength of this study is that we used medication lists from real clinical encounters, not synthetic data created or "fixed" for the purpose of this study. This allowed us to study medication reconciliation issues in a realistic context. We also took into account the degree of the transition complexity (to our knowledge, we are the first to consider this).

Our medication reconciliation algorithm performed well. It was able to remove, on average, 23.4% of the potentially removable medications from every transition. It had an error rate of 1.8% due to an easily fixable bug. Even without fixing this bug, the 1,8% error rate was well below the error rates described for human medication reconciliation. We believe that our algorithm is not directly comparable to human medication reconciliation studies, as the tasks are different. Our algorithm is intended to complement a human medication reconciliation process, not replace it. Nevertheless, we think that our results are promising. Peyton et al describe that, after an intervention performed by a specially trained pharmacist, errors of dosing like the ones we found among our output were, on average, 0.1 per patient [13]. Our automated per-patient rate was 0.02, five times lower. Schnipper et al's automated system achieved a rate of 0.32 Potential Adverse Drug Effects (PADEs) per patient. Our reconciliation was partial, and intended to be completed by a human being, but only had 0.02 PADEs per patient [5].

Automated approaches will remove obvious, tedious matches from the reconciliation workflow. Our work will enable clinicians to focus their effort on reconciling medications that require human knowledge, not comparing

identical strings. Automated and semi-automated approaches will enhance availability of medication reconciliation in time-critical scenarios.

We plan a larger study that elucidates whether higher-complexity transitions are correlated with lower automated reconciliation performance. We will also correct the errors detected during this study to improve our algorithm's performance. We will also improve our medication parsing code to take into account the variability we found in our prescriptions. We would also like to study the effect of our semi-automated approach on the cognitive load and overall performance of clinicians on the medication reconciliation task. Finally, we look forward to acquiring medication lists from the inpatient setting in order to study our approach on actual inpatient data.

Conclusion

Automated and semi automated reconciliation approaches will reduce human workload. We presented an automated approach that reconciles medications conservatively to assist clinical users in performing the reconciliation task. We expect that our approach will improve clinical care, compliance with NPSG number 8, and our ability to do so in a timely manner.

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