USING MEDICATION LIST – PROBLEM LIST MISMATCHES AS MARKERS OF POTENTIAL ERROR

- A FEASIBILITY STUDY -

by

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CERTIFICATE OF APPROVAL

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ABSTRACT

The goal of this project is to specify and develop an algorithm that will check for drug and problem list mismatches in an electronic medical record (EMR). The algorithm is based on the premise that a patient's problem list and medication list should be in agreement, and mismatches in the two lists may be indicative of medication error. Successful development of this system could mean detection of some errors, such as medication orders entered into a wrong patient record, or drug therapy omissions, that are not otherwise detected via automated means. Additionally, mismatches may serve to identify opportunities to improve the integrity of a working problem list.

To assess the feasibility of this concept, this study compared medications listed in a pharmacy information system with items in an online nursing adult admission assessment, serving as a proxy for the problem list. Where drug and problem list mismatches were discovered, examination of the patient record by a clinician identified the nature of the mismatch, and any potential causes. Use of the algorithm to detect mismatches in diabetes treatment indicates that it successfully detects both potential medication error and opportunities to improve problem list completeness and accuracy. After development and initial testing, 251 mismatches were detected in 2,221 records to which the algorithm was applied over a two-month period. Of these, 134 mismatches were clinically significant opportunities to detect either medication error or improve the problem list, 92 mismatches were found to be not clinically significant, and 23 mismatches were a result of algorithm failures. The online nursing assessment proved a useful proxy in lieu of a formal coded problem list. This algorithm, once fully developed and deployed, could prove a valuable way to improve the patient problem list, and could decrease the risk of medication error.

Its scalability to include other disease states and their associated drugs makes this a basis for a myriad of exciting future research work.

INTRODUCTION

Background and Significance

A study by Ernst and Grizzle in the Journal of the American Pharmaceutical Association indicates that drug misuse costs the economy more than $177 billion a year [1]. In fact, the costs associated with drug-related problems exceed the costs of medications themselves. Heightened concern about medication error has also resulted from the Institute of Medicine report, *To Err is Human* [2], and its follow up report, *Crossing the Quality Chasm* [3].

Medication errors are defined by the United States Pharmacopoeia (National Coordinating Council for Medication Error Reporting and Prevention) as "Any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the health care professional, patient, or consumer. Such events may be related to professional practice, health care products, procedures, and systems, including prescribing; order communication; product labeling, packaging, and nomenclature; compounding; dispensing; distribution; administration; education; monitoring; and use [4]." Hepler and Strand concluded that medication errors typically fall into one of eight categories: untreated indications, improper drug selection, sub-therapeutic dosage, failure to receive drugs, over-dosage, adverse drug reactions, drug interactions, and drug use without indication [5].

A host of advantages of clinician computerized order entry for the prescribing of drugs have been described [6,7,8,9,10]. Alert and reminder systems to help identify drug interactions, therapeutic duplications, and drug-allergy contraindications have proven to have value in reducing medication error [7]. However, automated systems that check for untreated indications, failure to administer drugs and use of drug without an appropriate indication are not common.

In spite of the benefits of computerized order entry, the possibility exists that new, unanticipated error types may be precipitated by the use of this technology [11]. Errors due to automation may include adjacency errors (selecting an incorrect drug or patient because they are adjacent in a list), errors due to automation fatigue (too many notices given that are not relevant to a patient's care, causing a failure to acknowledge a relevant notice), and errors due to automation complacency (over-reliance on an automated system).

Qualitative research work on physician order entry (POE) by Ash's Physician Order Entry Team (POET) at Oregon Health & Sciences University has identified a recurring problem in clinician order entry environments: the possibility of inadvertent entry of patient orders for the wrong patient [12]. Other studies have also identified this potential source of error in the clinician ordering process [11,13,14,15]. Visual cues ordinarily encountered with the paper record (such as chart thickness, location, handwriting recognition, and other situational cues) are eliminated in POE environments, and the wrong-patient entry problem can be insidious. The problem may be recognized and corrected either at the time of order entry, later by the ordering clinician or other clinicians involved in the patient's care, or it may go entirely unrecognized, potentially causing serious patient harm.

The "wrong patient" error may occur when the ordering clinician fails to:

- change to a new patient record after work is completed on a prior patient
- recognize a difference in similar names
- recognize selection of the wrong patient in adjoining beds or rooms, or adjacent in an alphabetized list
- recognize the deletion or addition of digits when entering a patient record by account or medical record number.

Implementation of pop-up alerting dialogues requesting clinician verification of a patient's identity may help to circumvent this error type. While this alerting scheme may help to arrest errors such as selecting a patient with a similar name or a patient in an adjacent bed or room, other wrong-patient errors can persist. This error may also be a result of *not* changing to a new patient record when work on a particular patient is completed, causing orders for the second patient to be entered into the record of the first. In this circumstance, the pop-up alert requesting verification of identity will *not* be deployed and will not help to arrest the error.

Bar Code Medication Administration, a technology whereby medications are scanned and matched with a patient's bar-coded wristband prior to their administration, has also been proposed as a way of preventing medication error [11], including inadvertent medication administration to the wrong patient. However, this technology will fail to stop a medication being given to the wrong patient *if the ordering clinician enters medication orders into an EMR for the wrong patient.* The result will be that the wrong drug will be given to the "right" patient.

In addition to errors of commission already described (wrong patient, wrong drug errors), other error types escape detection by currently implemented decision support modalities. Medication errors such as failure to discontinue a drug that is no longer needed, and errors of omission, either at the prescribing or transcription steps of the medication use process, also have the potential to cause patient harm.

Little data exist to quantify the rate at which these errors take place. Bates, et.al. [16] refer to "substitution errors" as errors that result in the wrong drug being given, or a wrong patient receiving a drug. Errors reported in the Bates study include prescribing, transcription, dispensing, and administration errors. During the study's baseline period (immediately preceding the

implementation of physician order entry), 5% of all medication errors were substitution errors, and 2.9% of all medication errors reported were inappropriate drug errors (which include inappropriate drug selection based on patient variables, interactions, incorrect dose, dosage form, route, frequency, concentration, dilution, and rate of administration). Omission errors were not reported in isolation, but were conglomerated with "dose errors" which accounted for 33.5% of all medication errors reported during this baseline period.

Wrong drug, wrong patient, and omission errors are also reported elsewhere in the literature (see Table 1).

Table 1. Error Rates by Study Author and Type (% of all reported medication errors)

	Omission	Wrong Drug / Wrong Patient
Barker, et al.[17]*	33.3% & 41.2%	30.5% & 20.1%
Shannon, et al.[18]*	6.5% & 3.1%	22.4% & 20.1%
Barker, et al.[19]*	25.9% & 23.9%	5% & 4.2%
Phillips, et al.[20]	0.5%	18.9%
Cavell, et al.[21]	4.7%	33%

* Note: results from studies by Barker, et al., Shannon, et al., and Barker, et al., indicate two different figures because the results represent performance of two different detection and reporting methods.

While these specific sources of error vary in terms of their contribution to all medication errors in these studies, the argument can be made that this is an area that bears closer scrutiny.

Current Detection of Wrong Patient Orders

Wrong-patient order entry errors already occur with existing (non-POE) computerized medication management systems. Orders may be handwritten by a physician or nurse into the incorrect chart (see Figure 1), triplicate forms or other copies of orders may be mislabeled by nursing or clerical staff, pharmacy staff may transcribe the paper order copy into the wrong computerized patient record (see Figure 2), or improper labeling may be placed on medications by the pharmacy prior to their delivery to the patient bedside. However, many of these errors are detected in

environments lacking POE because order transcription from the paper chart to the pharmacy system, and ultimately to the Medication Administration Record (MAR), is double-checked by nursing and pharmacy personnel. These double-checks are done prior to administration of a new drug, and during once-daily review and verification of MAR contents with written orders. When mismatches are detected, they are negotiated and resolved by the pharmacist, nurse, and physician working cooperatively.

Figure 1. Verbal Order Transcribed into the Wrong Patient Chart.

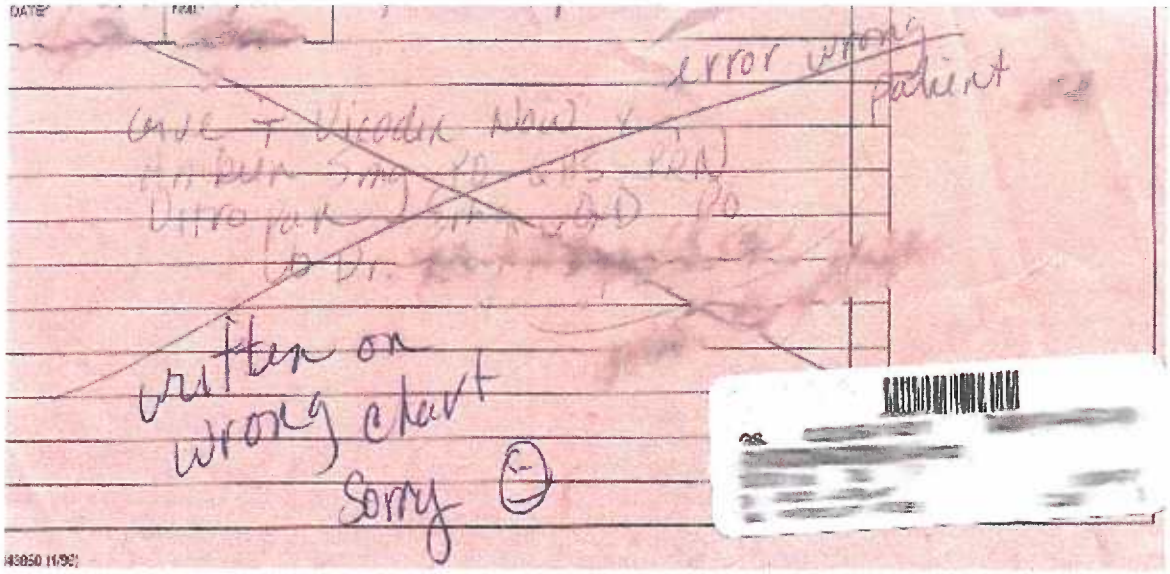
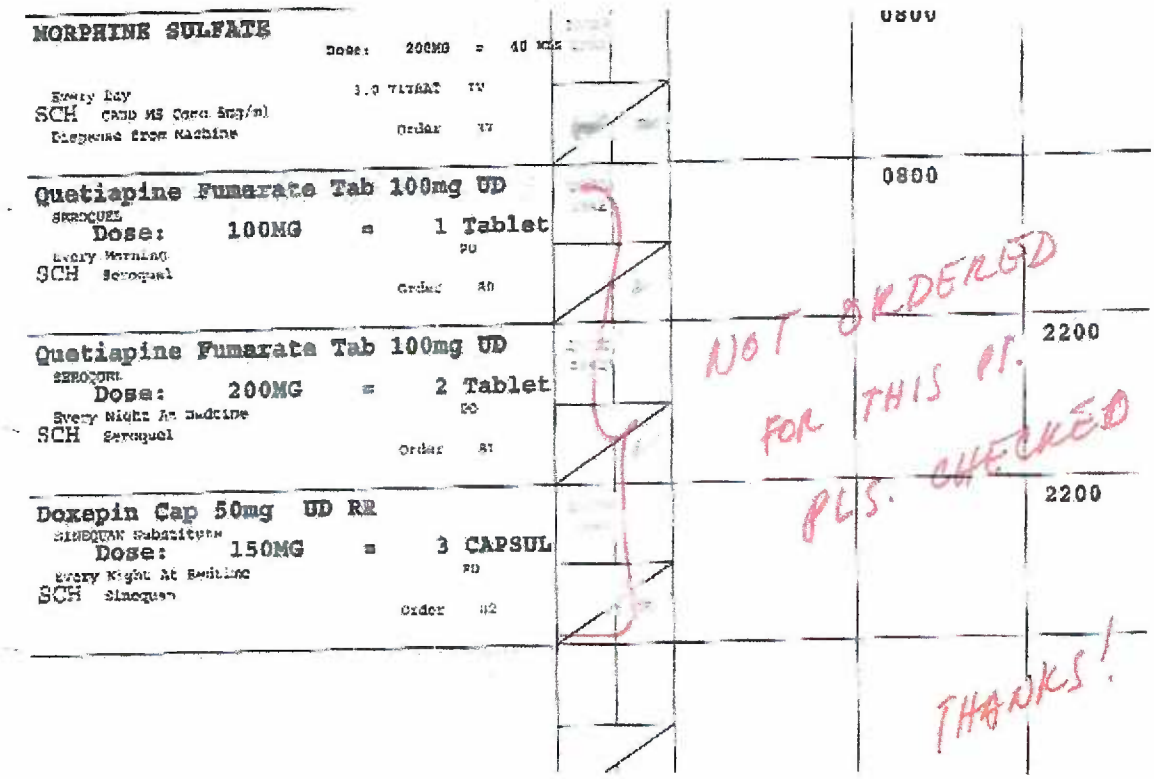


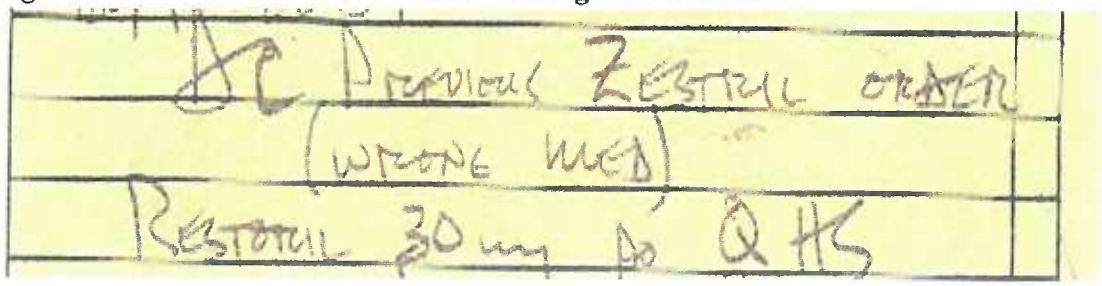
Figure 2. Medication Administration Record with Multiple Wrong Patient Entries.



It must be stressed, however, that in POE environments, it is unclear what role the nurse or other agent will play in verification of orders after they have been entered by the physician [22]. The wrong-patient order entry problem may be more difficult to detect in these settings. There may be few, if any, other information sources to double-check an order as to patient identity before the nurse administers a POE-entered drug in good faith.

Drug name confusion (for drugs with "sound alike" names, or names with a similar appearance) can also be a source of inappropriate drug use in an inpatient care environment (see Figure 3). Again, clinician diligence is relied upon to detect such errors.

Figure 3. Clinician Detected Sound-Alike Drug Name Error.



Within the course of practice, clinical pharmacists also attempt to identify wrong patient, wrong drug, and inappropriate drug errors. One of the methods pharmacists may use to optimize treatment regimens is by performing an assessment of a patient's acute and chronic problems and drug therapy needs [23,24]. During this assessment process, a conscious attempt is made to assure that all drug therapies are being given for correct indications, and that all assessed problems are being treated appropriately.

A Proposed Intervention

The patient medication list can be viewed as a snapshot of a patient's condition to the trained eye; a snapshot that should match with a patient's problem list, where such a problem list exists and is current. Automated means of detecting medication list – problem list mismatches using an EMR-based query tool may therefore serve as a helpful way to identify errors that are not currently detected via by computerized decision support functionalities. Interestingly, use of a tool to identify these medication list – problem list mismatches may also prove an effective way to verify the integrity of a working problem list.

Implications

By utilizing the existence of a drug treatment as reason to search for a corresponding problem within a patient record, and, alternatively, using the existence of a problem as reason to search for a corresponding drug treatment, it is proposed that several medication error types and problem list deficiencies may be revealed. An analytic framework for medication and problem list disagreements or "mismatches" may best demonstrate the types of problems that might be detected and the circumstances leading to their detection (See Table 2).

Table 2. Analytic Framework: Mismatch Type vs. True Disease Status

	True Disease Status	
	Patient has Disease	**Patient does not have Disease**
Drug (+) **Problem List (–)**	cause: • problem list incomplete • problem list not done	cause: • order entered for the wrong patient • drug being used for inappropriate indication • failure to discontinue the drug (condition no longer exists)
Drug (–) **Problem List (+)**	cause: • error of omission • accidental discontinuation • problem being managed by other interventions	cause: • problem no longer exists and should be deleted from the list • problem list is inaccurate

Matching problem lists and drug indications may be particularly helpful in an inpatient setting. Inpatient medical and intensive care wards are extraordinarily busy environments. Care may be administered by teams who may not initially be familiar with the patient and their ongoing treatment needs. Economic pressures continue to shorten patient lengths of stay, placing additional pressures on clinicians to become rapidly familiar with patients in their care. Additionally, care in these environments is round-the-clock, and all participants in medication administration may be fatigued or under stress. Current acute shortages of professionals such as nurses and pharmacists should also be recognized. It should also be noted that nearly 10,000 new

drug entities have entered the healthcare marketplace in the last 15 years, placing additional cognitive burden on busy clinicians [25].

Drug – Disease Interactions

Functionality exists within some currently implemented order entry systems to detect "drug – disease interactions." These are best described as drug – disease *precautions* or *contraindications*. Examples include detecting relative contraindications such as use of nephrotoxic drugs in patients with renal failure, the use of sympathomimetic decongestants in patients with hypertension, use of beta-blockers in asthmatic patients, and the use of anticholinergic drugs in patients with benign prostatic hyperplasia. While valuable to patient safety, this functionality is not intended nor currently deployed as a mechanism by which drug therapy omissions, or drug use without indication might be detected.

Purpose and Rationale

This feasibility study will develop and evaluate a simple means of detecting mismatches in drug lists and problem lists. Where mismatches are detected, follow-up with the patient record by a clinician will describe the nature of each mismatch, any medication errors that are revealed, and any opportunities to improve problem list and record integrity that are discovered. Initial evaluation will be limited to a relatively small domain, that of diabetes care. If successful, further work my be warranted to fully develop and deploy all of the working components necessary to comprehensively handle all problems, drugs, and drug indications in medical therapeutics.

Two hypotheses were developed and explored:

- Automated matching of a patient's medication list and problem list will prove a useful way to discover medication errors.

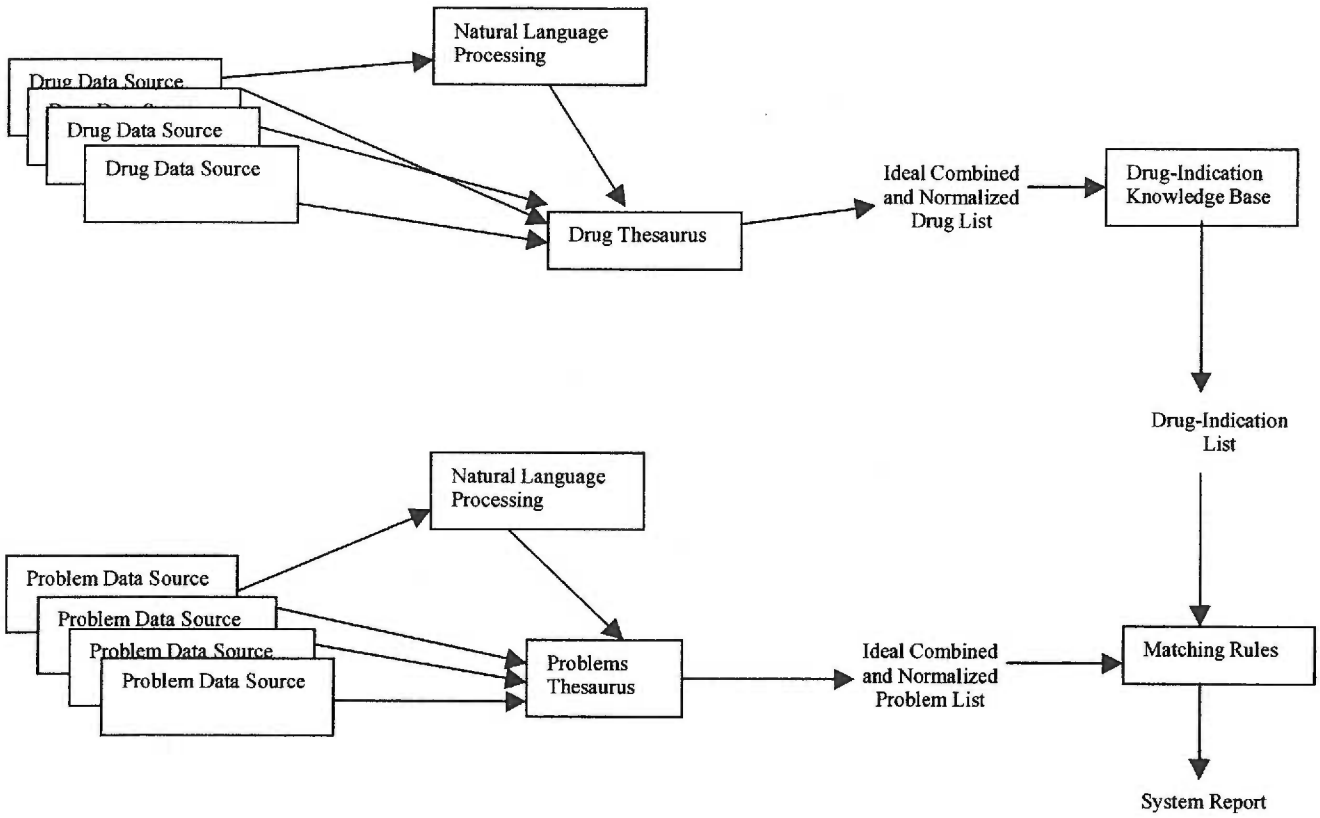
- This check will aid in the discovery of problems of medical record integrity (opportunities to improve incomplete or inaccurate problem lists).

METHODS

A Theoretical Model

An idealized system that will check for mismatches in problem lists and medication lists requires a number of components (see Figure 4).

Figure 4. Theoretical Model: Medication List – Problem List Matching System



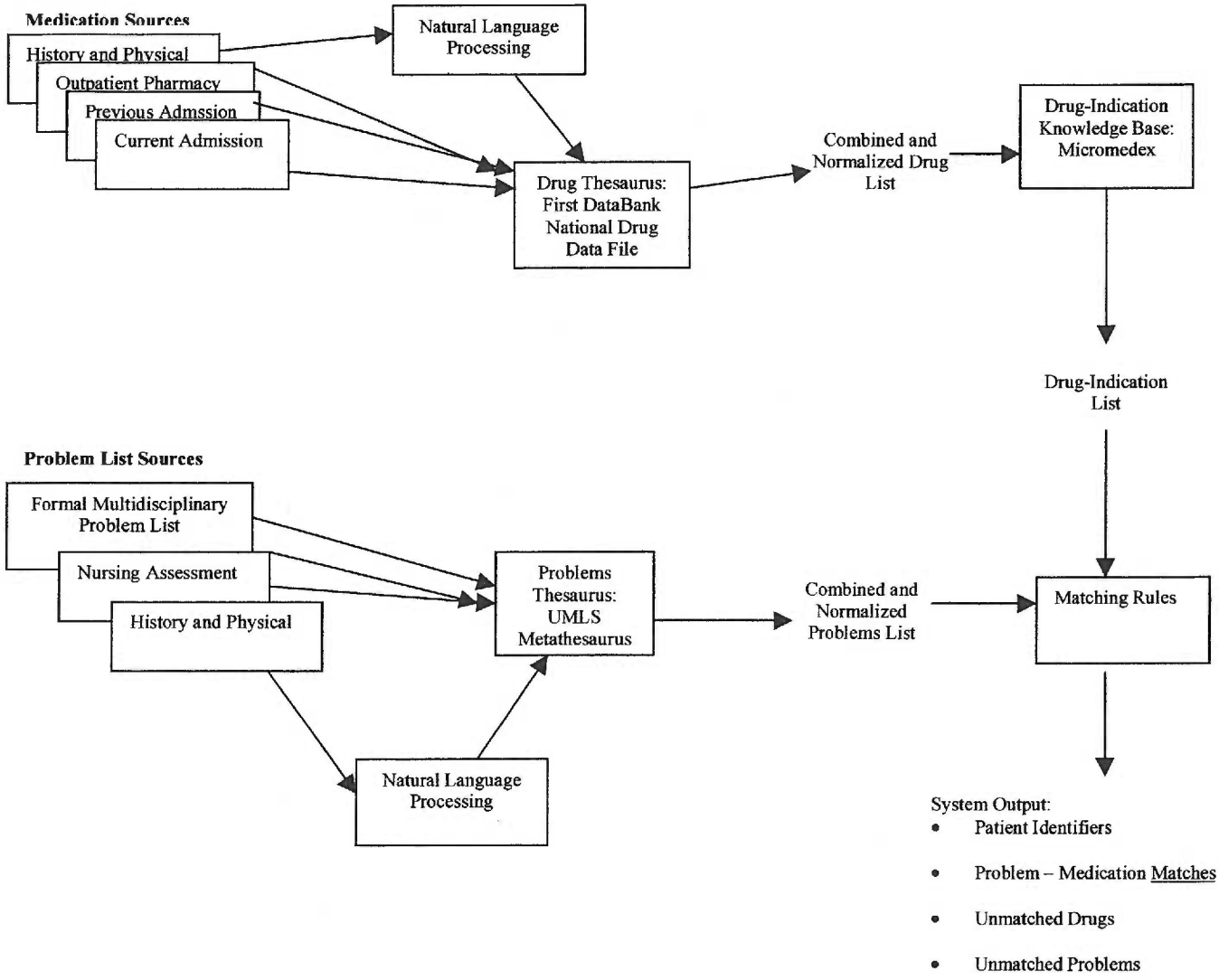
The ideal system would glean drug data and problem list data from all available sources, including inpatient and outpatient data sources, formalized lists within the record, and text within the clinical narrative (to be preprocessed by a natural language processing system). These data would then be submitted to their component drug and problem thesauri. For drugs, the thesaurus

would detect duplicate drugs that may have different brand names but share the same generic name, and convert them to a shared drug data coding scheme. Similarly, for problems, term synonymy (such as "hypertension" and "high blood pressure") could be normalized and all terms placed in a shared consistent problems language. The combined drug list would then have to undergo an extra step. Each generic drug would have to be assigned its list of therapeutic uses, including Food and Drug Administration (FDA)-approved and non-approved indications. The indications list would enumerate all problems that a patient's drug list might implicate.

The drug-indicated list of problems and the problem list are then submitted to the system rules. Where one of the drug's indications is found in the problem list, a match would exist. Where none of the drug's indications matches with a problem in the problem list, or none of the problems listed matches with the list of patient drugs and their possible indications, a mismatch would exist. Where mismatches occur, either because a problem exists for which there is no matching drug, or because a drug exists for which there is no matching problem, the system would provide an indication of the detected mismatches in the form of a report.

As an example, the hypothetical system in Figure 5 shows a working system and how its components might be implemented:

Figure 5. Hypothetical Medication List – Problem List Matching System



One of the strengths of a system as proposed above is the normalization of drug and problem list data sources to a summary "best list" of both data types. The matching algorithm's value is in its ability to point out obvious areas where one or both lists require reconciliation and where clinician scrutiny might be beneficial.

Potential Algorithm Components

Medication Data Elements

A number of uncoded and coded pieces of patient medication information are available in an inpatient setting (see Table 3).

Table 3. Potential Medication Data Sources in a Typical Inpatient Environment

Uncoded Sources	Coded Sources
• Verbal cues from the patient • Patient's own typed or handwritten medication list • Handwritten physician orders • Progress notes • History and physical • Discharge Summaries • Emergency department records • Other clinical narratives • Nursing Kardex • Nursing admission assessments • Medication Administration Record • Outpatient prescription records (in some settings)	• EMR's Pharmacy management system (entries by pharmacist or other clinician) • Online Medication Administration Record (in some settings) • Outpatient prescription records (in some settings) • Online Nursing admission assessments

Increasingly, the EMR's pharmacy management system is relied upon for comprehensive recording of medication orders in the inpatient setting. Upon patient admission, medication orders are either written into the paper chart for transcription by the pharmacist into the pharmacy system, or, in POE environments, are entered directly into the EMR by a clinician. Unfortunately, communication between inpatient and outpatient medication management systems is not common. Automatic continuation of a patient's outpatient orders on admission to an inpatient setting is rare, necessitating manual transcription of drug treatments from written or electronic sources to the inpatient record. This process can be a source of frustration and may also contribute to medication errors.

Problem List Data Elements

One of the recommendations of the Institute of Medicine is the implementation of an EMR-based problem list [26]. Potential benefits of EMR-based problem lists include advanced functions such as guided data entry, linkages of problems and charges, disease management functions, and automated decision support [27]. It is proposed that use of the problem list can help to prevent errors, improve interdisciplinary communication, help orient the clinician to the patient, and aid in student and resident education [28]. Problem lists may employ a controlled clinical terminology [29] or a combination of clinical terminologies [30].

Whereas computerized medication order entry serves as a unifying repository for medication information in most settings, there may be no similar unifying home for problem list information in the EMR. Problem lists may be found in a number of different places both within and outside of the medical record. None of these problem lists, in isolation, describe the definitive or "best" problem list (see Table 4).

Table 4. Potential Problem List Data Sources in a Typical Inpatient Environment

Uncoded Sources	Coded Sources
• Verbal cues from the patient • Patient's own typed or handwritten problem list • Handwritten admission notes • Progress notes • History and physical • Discharge Summaries • Emergency department records • Other clinical narratives • Outpatient records • Nursing Kardex • Nursing admission assessments	• Formal coded problem lists (where available) • ICD-9 codes • Online Nursing Admission Assessments • Outpatient problem lists

While no single source is seen as being *the* definitive problem list, problem lists in the clinical narrative, such as the within the History and Physical, Admission Summary, and Discharge Summary tend to be more formalized instantiations. Clinicians from all disciplines jointly contributing to a problem list's construction and maintenance, using all information from both outpatient and inpatient information sources, may best compose the "ideal" problem list. As with medication list data, use of all available sources of problem list information may be the best way for a clinician or automated quality improvement system to negotiate the ideal problem list.

It is important to note that ICD-9 codes, while a rich source of coded problem list information, are not assigned by coding personnel until patient discharge at most health systems. This renders prospective use of this data *during* a patient admission for decision support or quality improvement functions impossible.

Nursing assessments also contain an abstraction of problem list information. Nursing assessment is defined as "a systematic, dynamic process by which the nurse, through interaction with the client, significant others, and health care providers, collects and analyzes data about the client [31]." Nursing assessment tasks are ongoing throughout a patient's admission, and include assessment of a patient's medical history, physical, and social function within the context of the patient's current condition and care.

By comparison, completion of an *Admission* Assessment by the admitting nurse is a required function, usually completed within a few hours of admission. The admission assessment is done only once, and the data for a single admission are not updated once the assessment is completed. Nurses identify both chronic and acute disease issues during this assessment process. Admission assessments may be recorded on paper data sheets or done directly in the EMR in coded electronic format. "Online charting" of nursing assessments directly into the EMR is done in

some settings. Use of an EMR functionality to record nurse admission assessment data makes this coded data accessible and potentially valuable to a computer-based decision support or quality control function very early in a patient's stay.

Knowledge base and ontology

Drugs, their indications, and the hierarchical drug classes to which they are assigned can be fluid. It is imperative that a working system used to detect drug and problem list mismatches communicates with drug and problem list data via a robust and validated domain ontology and knowledge base. The knowledge base would be used to assign both FDA approved and non-FDA approved indications to drug entities. Knowledge base updates would also have to keep pace with potential addition and deletion of drug indications, and addition or removal of drug entities from the market.

Rules

The rules employed must determine whether the combination of medication and problem list data passed to it represent a matching or mismatching state. The algorithm's rules structure must be flexible and robust to keep pace with changing medical knowledge and understanding. Refinement of the rules should eliminate output that is not clinically useful or does not have an impact on patient care. Changes to the rules structure must be done with care, as efforts to improve the systems output usefulness must not be too costly to the system's sensitivity.

Site of Development and Deployment

The algorithm was development and deployed at Legacy Good Samaritan Hospital (GSH), a single tertiary care hospital within the Legacy Health System, which encompasses four hospitals in the Portland, Oregon metropolitan area. Patient populations at GSH include general medical, general surgery, cardiology, cardiac surgery, neurology, rehabilitation, and psychiatry. The

average daily patient census during the study period was 170 patients. The Investigational Review Boards at both Oregon Health & Science University and Legacy Health Systems reviewed and approved the research protocol before work began.

The IDX LastWord System (IDX Systems, Burlington, VT) is the EMR currently employed at all Legacy Health System Portland hospitals. The LastWord product tightly integrates pharmacy, nursing, laboratory, clinical documentation, and other applications.

Use of the EMR at GSH has not eliminated utilization of a paper record. The comprehensive patient record depends upon data recorded in *both* EMR and paper chart components. The paper chart continues to serve as a repository for a number of important data elements, such as:

- original handwritten orders
- handwritten multidisciplinary progress notes
- handwritten nursing physical assessments and shift assessments
- surgical and procedural intervention records
- advance directives and "code blue" intervention records
- emergency room records

The EMR at GSH contains data from a patient's current and previous admissions, including:

- patient demographic data
- patient allergies
- nursing data:
  - admission assessment data
  - vitals
  - inputs and outputs
  - nursing goals
  - patient teaching documentation
- all laboratory data

- clinical narratives
  - history and physical
  - preadmission summaries
  - consultation notes
  - discharge summaries
  - operative notes
  - transfer summaries
- inpatient medication data

Medication errors at GSH are reported through use of incident report forms and a newly implemented online reporting mechanism called "Dr. Quality." Documented medication errors may have occurred at the prescribing, transcription, dispensing, or administration steps of the medication use process. During the first quarter of Fiscal Year 2002, 141 medication errors were reported at GSH. Omission, wrong drug, and wrong patient errors accounted for 51% of all medication errors reported at GSH during the period. These errors, in particular, deserve attention. They are not currently detected by decision support functions in the EMR at GSH, and are the focus of this work.

Omission errors (which include failure to prescribe or transcribe an order, and missed-dose errors) were 28% of all reported medication errors during the reporting period mentioned. 23% of all medication errors during the same period were either wrong drug or wrong patient errors. Clinicians remain a vital safety net in the medication use process. Many of these errors are detected and arrested by clinicians involved in patient care (primarily nurses and pharmacists) before medications were actually administered.

The algorithm will do little to prevent omission errors such as single missed-dose errors that occur at the dispensing or administration steps, or wrong-patient or wrong-drug errors that are made at the time of administration. However, therapy omission errors, wrong-patient or wrong-

drug errors made during prescribing or transcription, and drugs used for inappropriate indications will be potentially detectable, and are the focus of this work.

Model Design and Algorithm Development in IDX LastWord

The proposed algorithm therefore requires coded medication list data, coded problem list data, and a knowledge base to assign appropriate indications to drug entities, and a rules base to perform medication list – problem list matching.

Domain Selection

For this feasibility study, the algorithm was developed for application to a single disease state. Diabetes was chosen as the single disease domain for a number of reasons:

- the prevalence of diabetes is estimated at 6.2% of the US population [32]
- the costs of diabetes in the US are estimated at $98 billion per year [32]
- diabetes is the sixth leading cause of death, and is a frequent source of comorbidity in deaths caused by other conditions [32]
- complications due to diabetes include heart disease, stroke, hypertension, blindness, kidney disease, neuropathies, and peripheral vascular disease [32]
- medications used in the treatment of diabetes are easily enumerated
- the list of indications for medications used in the treatment of diabetes is short
- the risks of receiving treatment in error are very significant
- the risks of not receiving treatment when it is needed are also significant

The decision to implement the algorithm in the area of a single disease state was also a practical one. Diabetes drugs are used to treat or prevent hyperglycemia or maintain glycemic control, and are not commonly used in the treatment of other conditions. This fact simplified development of

the algorithm for this proof-of-concept study. It obviated the need to implement a knowledge base that maps drugs to their indications. The rules base could therefore detect matches or mismatches in the problem list and drug list simply by implementing a simple query to compare known problem list codes and known medication list codes, and report when mismatches are detected.

Selection of Drug Data Element

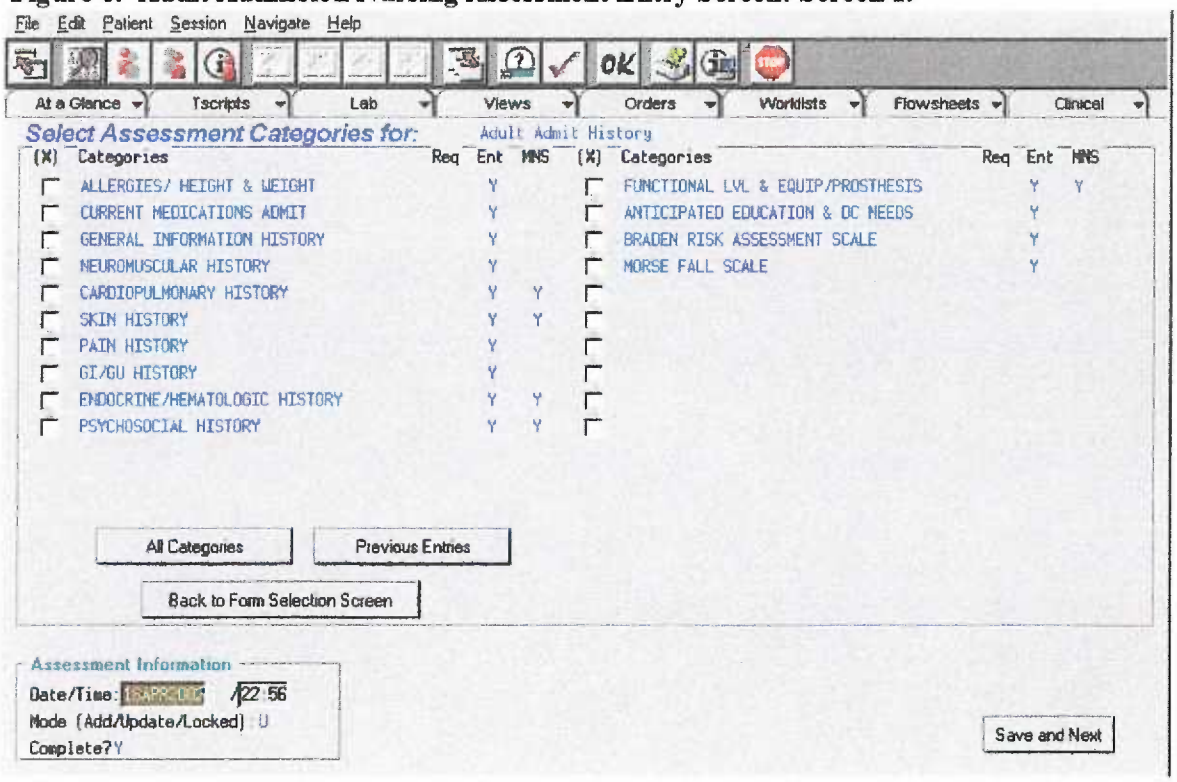
At GSH, the pharmacy staff enters all handwritten physician orders for medications into the EMR. Drug entities within the LastWord system share a single hierarchical framework, the Hierarchical Ingredient Code List, or "HICL" system of classification. HICL classification is a type of descriptive information in the "National Drug Data File" by First DataBank (San Bruno, CA). Drugs within this framework are delineated such that all drugs within a single therapeutic category (e.g. all antidiabetic drugs) share a common prefix within the hierarchy, and are therefore identifiable as a class. Within the hierarchy, all diabetic drugs are coded as "C4**" (where ** indicates final 2-4 digits/letters of the HICL code for a specific drug). All drugs used in the treatment of diabetes share the C4 prefix. The HICL coding scheme itself is a knowledge-structure that implements a hierarchy or taxonomy to categorize drugs into their component physiologic systems and conditions for which they are intended. The existence of this knowledge structure can be capitalized upon in the development of this project. See Addendum I for a list of all drugs sharing the C4 HICL prefix.

Selection of Problem List Data Element

Isolation of candidate coded problem list data was not as obvious. Assignment of ICD-9 codes at GSH is not done until patient discharge, making prospective use of this data for decision support or quality improvement functions impossible. Implementation of a formal coded problem list is being considered, but is not currently employed within Legacy Health System hospitals.

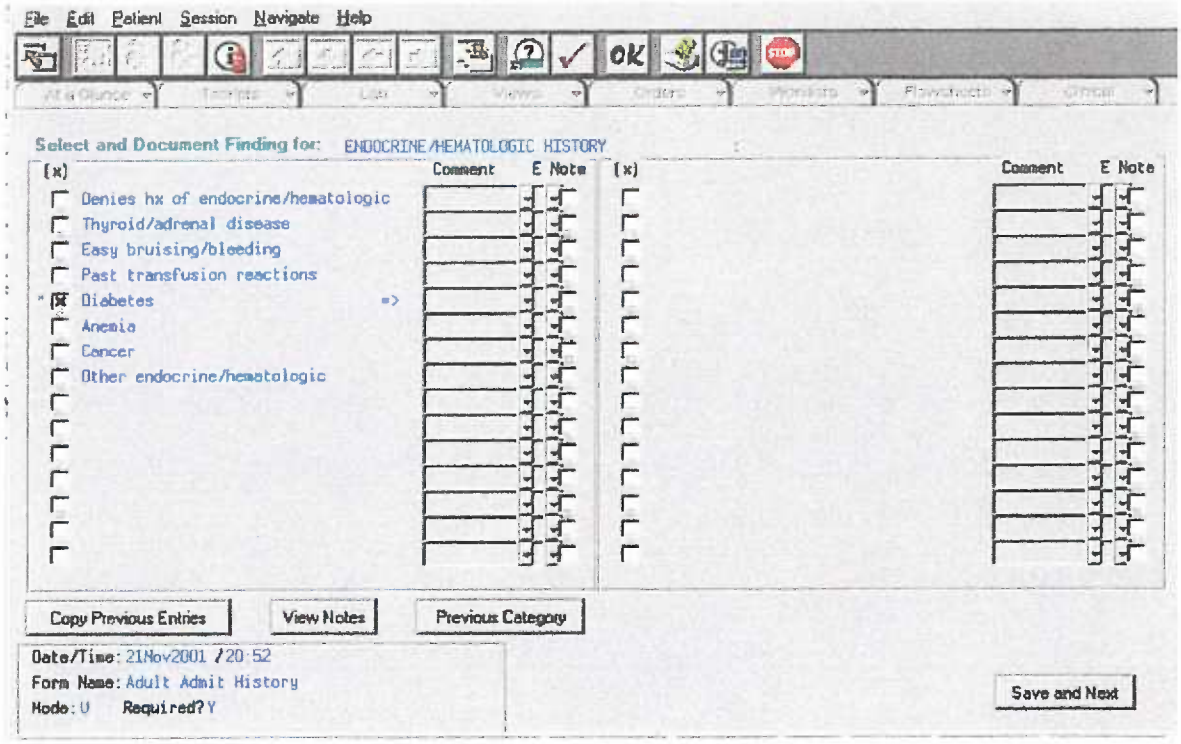
According to Legacy Health System patient care policy, a nurse caring for a patient must conduct a "complete initial biopsychosocial nursing assessment within approximately four hours of admission." The admission assessment is an inventory of a patient's acute and chronic problems, and could therefore serve as a source of problem list information. Adult Admission Nursing Assessments are done in electronic format for all patients admitted to GSH, except for patients admitted directly to the Intensive Care Unit, where they are still completed in paper form. The Adult Admission Nursing Assessment is done only once, and the data are not updated during a patient admission. Entry of nurse assessment data is done using a series of forms within the LastWord product (see Figure 6). Finding codes are embedded in the assessment forms, and are consistently assigned to problems that are selected during the assessment process.

Figure 6. Adult Admission Nursing Assessment Entry Screen: Screen 1.



Within the online assessment structure, selection of a particular category, such as endocrine and hematologic history, then expands to allow documentation of distinct disease states (thyroid disease, bleeding disorders, diabetes, anemias, and cancers) using a simple check box (see Figure 7). The form also permits the recording of free-text comments and notes if desired. A consistent findings code is recorded whenever the assessing nurse selects the check box for a disease finding. The nurse assessment forms within the LastWord product do not utilize a single controlled terminology. A combination of terms from NANDA (North American Nursing Diagnosis Association), NIC (Nursing Interventions Classification), NOC (Nursing Outcomes Classification), and ICD-9 codes are employed

Figure 7. Adult Admission Nursing Assessment: Endocrine / Hematologic Detail



Because data recorded in the online nurse assessment forms is coded using consistent finding codes that are entered into the patient record, and are entered into the record in a timely fashion

that allows use of the data during the admission, this data was used as a proxy for the problem list.

Specification of Rules

The LastWord EMR utilizes a networked system of Tandem® computers running on a proprietary operating system called GUARDIAN. Matching of drug HICL codes embedded in medication entries, and nurse assessment codes from nursing admission assessments, was accomplished within the EMR's database structure using a query language called ENFORM.

The conceptual model for the rules is straightforward. If a HICL code for a diabetes drug exists within a patient record, that record is checked to see if a corresponding nursing assessment exists indicating the presence of diabetes. If the nursing assessment does not indicate that the patient has diabetes, a mismatch state exists which may be indicative of either an issue of problem list integrity or potential medication error. Similarly, if a nursing assessment indicating diabetes exists, but there are no drugs used for the treatment of diabetes, a mismatch state exists

The algorithm for this study was designed as follows: a query is made on patient data from the EMR on a per-patient admission basis and the following are reported:

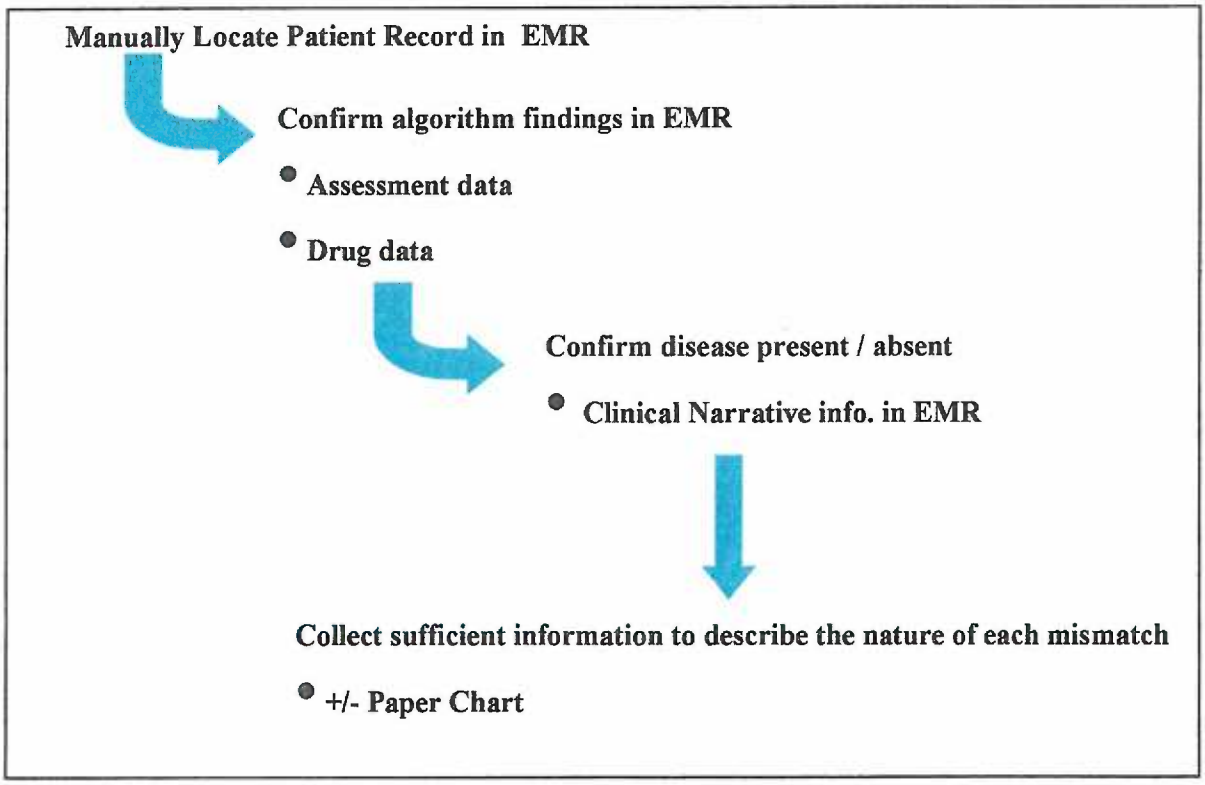
- account number
- medical record number
- presence or absence of a HICL code indicative of diabetes treatment
- presence or absence of a finding code indicative of an assessment for diabetes
- date of birth
- date of patient discharge
- drug data

- generic name
- HICL code
- drug start date
- drug end date

The actual code used for the query is included as Appendix IV.

After the data are reported, the report is examined to identify medical records with drug and assessment mismatches, and investigation of the patient record followed (see Figure 8). Collection of information from the medical record was manually performed by the investigator for each mismatch detected, and conclusions were made as the cause of the mismatch using a prescribed step-wise approach (see Appendix II and Appendix III). Patient records with detected mismatches were not always examined in their entirety. The electronic record contains much of

Figure 8. Data Collection Steps for Patient Records with Mismatches

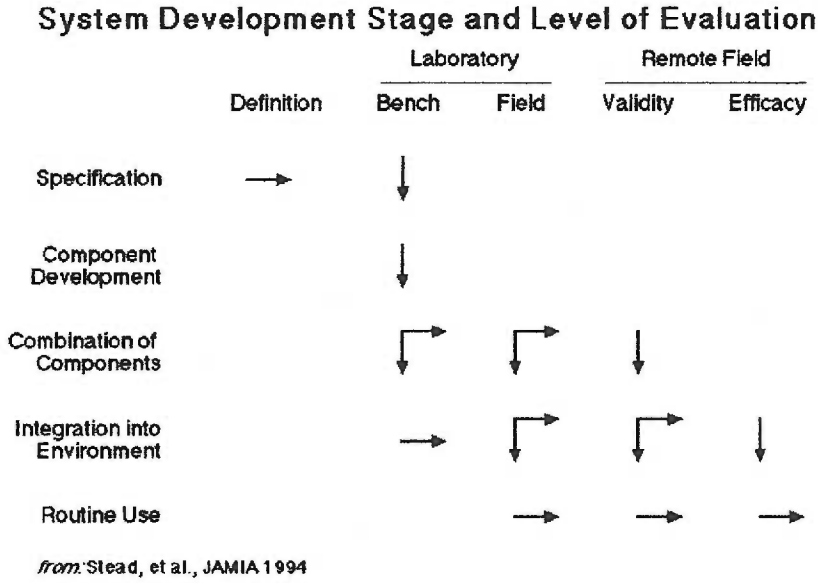


the clinical narrative information, and often contained sufficient information to permit conclusions as to the nature of the mismatch to be made. When adequate conclusions could not be made using data in the electronic record, the paper chart was obtained from medical records and examined.

Testing and Evaluation

In a paper by Stead, et al. [33], a framework for the evaluation of medical informatics research projects is described. They argue that medical informatics projects are not always amenable to the evaluation methods commonly employed in studies in the natural and social sciences, and assert that it is vital to match the evaluation method with the stage of system development. Five levels of system development (specification, component development, combination of components into a system, integration of system into an environment, and routine use), and five levels of evaluation (definition, bench, field, validity, and efficacy) are described (see figure 9).

Figure 9. Stead, et al. Framework for Evaluation of Medical Informatics Projects (arrows indicate appropriate next step(s) in evaluation process)



from Stead, et al., JAMIA 1994

This project will attempt to traverse the first three levels of development: system specification, component development, and preliminary combination of components into a system. In accordance with the framework, evaluation of this tool followed two distinct testing phases:

Bench Testing and Evaluation

Use of a small number of actual patient cases for rapid prototyping is the preferred method to evaluate the component development stage [33]. After initial specification and development, the algorithm scanned the records of all patients discharged on a single day to verify that it was performing as designed. Of the records scanned, the first five drug-positive / problem list-positive matches and first five drug-negative / problem list-negative matches were examined in detail. Additionally, a detailed examination of all *mis*matches revealed in that day's data was done.

Data were collected and analyzed by the researcher in the manner described. Any modifications required to improve algorithm performance would cause a re-test against these test cases to occur. When additional algorithm modifications appeared unnecessary, the next step in the algorithm's evaluation began.

Field Testing and Evaluation

The preferred method of evaluation of a system at the third level of development (combination of components into a system) is early field trials under the direction of the investigator [33]. This phase of evaluation should determine if the system performs adequately in a realistic environment.

During the second phase of evaluation, all patients discharged from GSH during two consecutive months were retrospectively queried for drugs and nursing assessments indicative of diabetes.

The investigator personally examined the patient records for all mismatching cases following the protocols described in Appendices II and III.

The investigator did not examine patient records where *matches* were detected during the field-testing phase for several reasons. The purpose of the bench-testing phase was to examine whether or not the algorithm was performing as designed, including examination of matching patient records. By comparison, the intent of the field testing phase was to evaluate the clinical significance of the algorithm's output as it would be used in a real clinical environment: follow-up of identified patient records with detected mismatches. Additionally, exhaustive review of all 2,221 patient records to which the algorithm was applied was not practical for this feasibility study. Data collection and analysis for patient records with mismatches during this phase proceeded in a manner identical to the bench-testing phase. During this phase of evaluation, mismatches were classified into a taxonomy that grew organically as additional mismatch causes were identified.

RESULTS

Algorithm Development and Bench Testing

During the initial study, the algorithm analyzed the records of all 35 patients discharged from GSH on October 25th, 2001. Four mismatches were detected. Of the 31 *matching* records, 26 matched because neither a diabetes drug, nor an assessment indicative of diabetes, was detected. The remaining five matches were diabetes drug-positive / diabetes assessment-positive matches (see Table 5).

Table 5. Summary of Bench Testing Results

Mismatches (by type)	
Drug (+) / Assessment (-)	2
Drug (-) / Assessment (+)	2
Matches (by type)	
Drug (-) / Assessment (-)	26
Drug (+) / Assessment (+)	5
Total Patients	**35**

The patient records of all four mismatches, all five drug-positive / assessment-positive matches, and the first five drug-negative / assessment-negative matches encountered were then examined in detail to evaluate the algorithm's performance.

Of the four *mis*matches detected, there were two drug-positive / assessment-negative mismatches. Of these, one mismatch resulted because a patient with drug-treated diabetes had an assessment that did not indicate diabetes and was obviously incomplete. The second drug-positive /

assessment-negative mismatch resulted when a patient with treated diabetes had no assessment done at all (see Table 6).

Table 6. Bench Testing: Detail of Mismatch Causes

Drug (+) / Assessment (-)	
Assessment Incomplete	1
No Assessment Done	1
Drug (-) / Assessment (+)	
Diet-Controlled Disease	1
Patient Not Diabetic	1
Total Mismatches	**4**

The remaining two mismatches were drug-negative / assessment-positive mismatches. In one of these cases, the patient had gestational diabetes that was adequately controlled by diet alone. The second case was more interesting. The assessment indicated diabetes with "borderline" indicated within the free-text comment line. However, exhaustive review of the patient record revealed neither evidence of diabetes in this patient, nor any written drug treatment orders.

Follow up by a clinician of all four mismatches detected, even in this small data set, could have meant improvement of at least three problem lists that were either incomplete, potentially inaccurate, or not done at all.

Examination of the five drug-positive / assessment-positive *matching* records confirmed that both drugs and assessments detected by the algorithm were matched accurately. Similarly, the five drug-negative / assessment-negative records selected were matched accurately. None of these records contained a drug or assessment that the algorithm failed to detect.

The benchmarking study was significant for four true-positive mismatches, and ten true-negative matches. No false positive or false negative mismatches were found. Since this phase of the evaluation did not demonstrate any algorithm failures, and the algorithm performed as expected using this small set of actual patient records, the second evaluation phase was conducted.

Field Testing and Evaluation

To evaluate its performance in an actual patient care environment and the clinical significance of its output, the algorithm retrospectively queried the records of all patients discharged from GSH during October and November of 2001. A total of 2,221 patient records representing 10,360 patient-days of data were queried. During the period, a total of 440 patients (19.81%) were discharged with diabetes as a primary or secondary diagnosis. To accurately verify the nature of each mismatch, the investigator personally reviewed the medical records of all patients in whom mismatches were detected. Drug – assessment mismatches were detected in 251 records (11.3%) during this period, equivalent to 4.11 mismatches per day within this single disease state. Of these, 162 were mismatches that resulted because a patient had a drug treatment for which there was no corresponding problem, and the remaining 89 were mismatches where the nursing assessment indicated a problem for which there was no corresponding drug treatment (see Table 7).

Table 7. Summary of Field Testing Results

Mismatches (by type)	
Drug (+) / Assessment (-)	162
Drug (-) / Assessment (+)	89
Total Mismatches	**251**

Exhaustive review of all 2,221 patient records to which the algorithm was applied was not done in this feasibility study. Therefore description of detected *matches* that were true matches (true-negative results), and incorrect matches (false-negative results) are not enumerated. Of 251 total mismatches detected, 226 (90%) mismatches detected were true mismatches (true-positives), and twenty-three (9.2%) mismatches resulted due to algorithm failures (false-positives) (see Table 8). Conclusions could not be made for two patient records with mismatches: the paper charts for these patient records were not available for review, and absolute conclusions as to the reasons for those mismatches could therefore not be made.

Table 8. 2 X 2 Table Summarizing Field Testing Results

		True Mismatch Status		
		Positive (+)	**Negative (-)**	
Drug / Assessment Mismatch	**Positive (+)** 251	226†	23	Predictive value (+) = 0.9003
	Negative (-) 1970	False Negatives (not examined)	True Negatives (not examined)	Predictive value (-) (not calculated)
		Sensitivity (not calculated)	Specificity (not calculated)	Prevalence = 0.103

†: 2 patient records could not be examined fully and were lost to follow-up.

Clinically Significant Mismatches

134 mismatches (52.3%) were potentially clinically significant, equivalent to a rate of 2.16 per day. A clinically significant mismatch is defined as a mismatch that, if detected, could have had a potential impact on current or future care to that patient. Of these, 12 were potential medication errors. The remaining 122 mismatches represented identified opportunities to improve the problem list (see Table 9).

Table 9. Potential Clinically Significant Mismatches

Medication Errors (by type)	
Order entered for the wrong patient	2
Potential error of omission – no order written to continue treatment	1
Error of omission – order written – pharmacy failed to enter	9
Identified Opportunities to improve problem lists (by type)	
Assessment incomplete	50
No assessment done	55
New onset diabetes (during admission or newly detected)	12
Nursing assessment indicates diabetes in a non-diabetic patient	5
Total	**134**

"Incomplete assessments" are those assessments that do not indicate diabetes, but where the record clearly shows that the patient is diabetic. A "no assessment" result indicates that an adult admission nursing assessment for a patient was never completed in electronic format

Clinically Insignificant Mismatches

The remaining 92 mismatches represented clinically insignificant mismatches detected by the algorithm, or assessment entry artifact. Clinically insignificant mismatches are those mismatches that, if detected, would likely *not* have had a potential impact on current or future care to that patient (see Table 10).

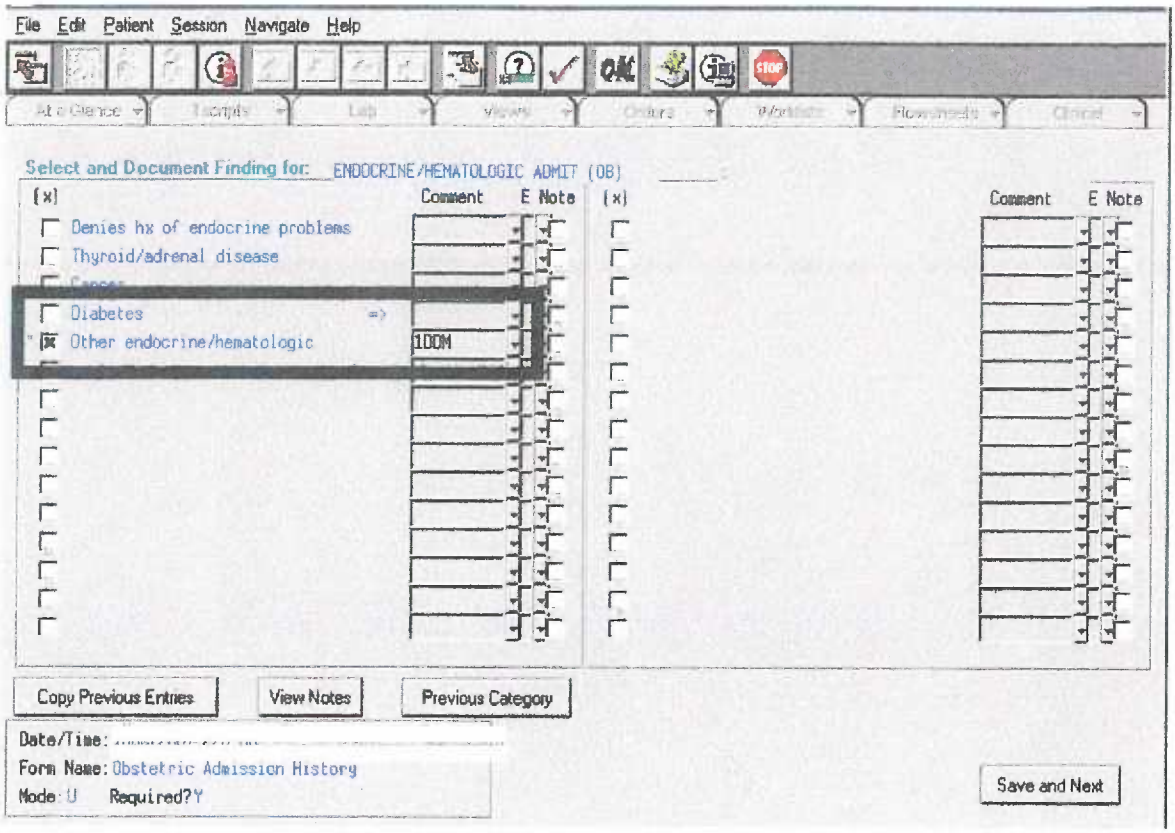
Table 10. Clinically Insignificant Mismatches

	Totals
Assessment Entry Artifact	
Ambiguous Assessment Entry	27
Appropriate Use of Drug in Non-Diabetics	
Total Parenteral Nutrition-induced hyperglycemia	11
Steroid-induced hyperglycemia	9
Peri-operative insulin use	13
Stress-induced hyperglycemia	1
Hyperkalemia	2
True Diabetics – Treatment Withheld	
Problem being managed by other interventions	23
Short stay – no drugs administered	4
All oral medications being held	2
Total	**92**

Assessment Entry Artifact

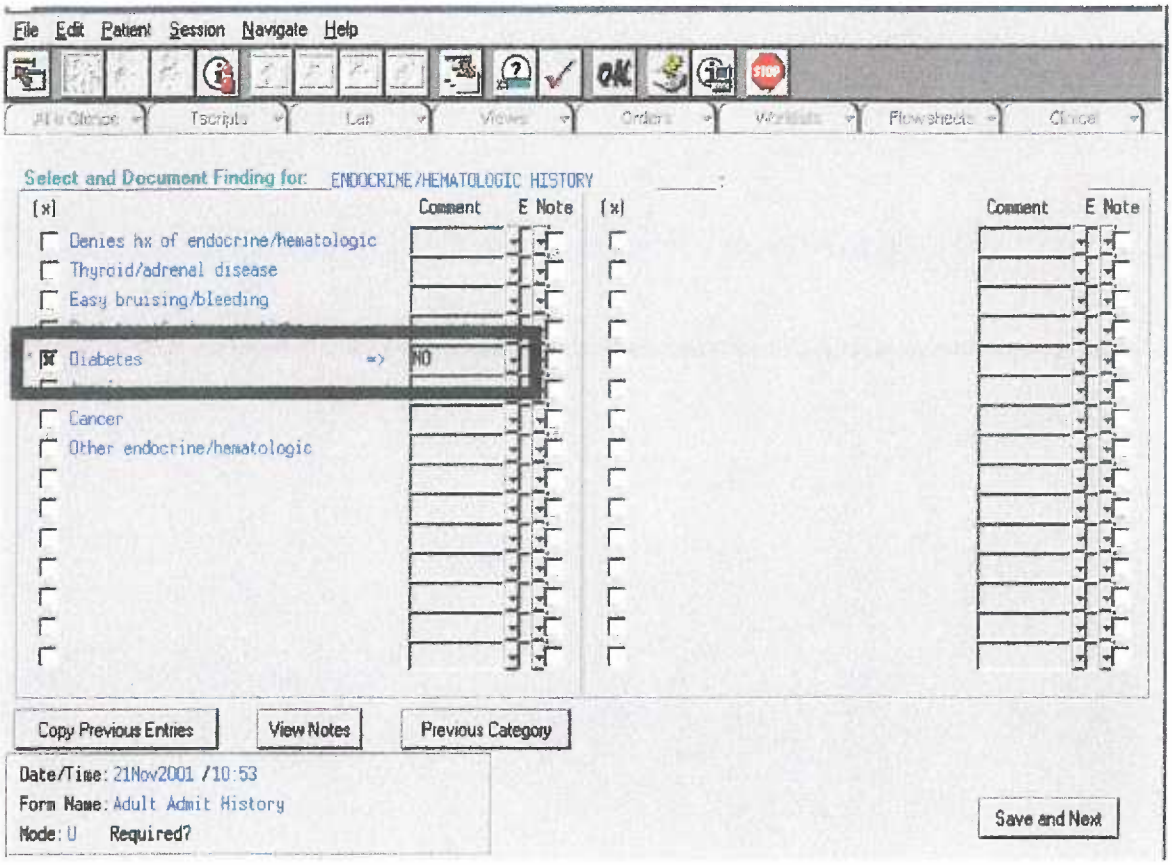
Some assessments were recorded in a manner that, while clear to the human user, was ambiguous to the algorithm. For example, in some cases the check box for diabetes was *not* checked but "IDDM" (Insulin Dependent Diabetes Mellitus) "type2" (Type 2 diabetes) or "yes" was placed in the comment line (see example: Figure 10).

Figure 10. Ambiguous Assessment Entry: Diabetes not Selected



On other occasions the check box for diabetes had been selected and "NO", "NONE", or "denies" placed in the comment line (see example: Figure 11).

Figure 11. Ambiguous Assessment Entry: Diabetes Selected and Negated



There were 40 cases where non-diabetic patients were treated appropriately with drugs used to reduce blood glucose. In patients treated for "Total Parenteral Nutrition - induced" and "Steroid – induced" hyperglycemia, the patient was not diabetic according to the record, but insulin was being utilized to treat hyperglycemia or maintain glycemic control in patients receiving these therapies. Use of insulin to maintain tight glucose control in stressful environments such as surgery and intensive care, and use of insulin to treat hyperkalemia were similarly judged appropriate uses in non-diabetic patients. Four of these mismatches were deemed clinically significant. In these four cases, insulin was being used for either steroid- or total parenteral nutrition-induced hyperglycemia, but the mismatch meant the discovery of four records for which no assessment had been done, and were clinically valuable data.

Patients with diabetes but in whom drug treatments were appropriately being withheld also had clinically insignificant mismatching records detected. "Problem being managed by other intervention" included patients with either a history of gestational diabetes, disease adequately controlled through diet or exercise, patients with a history of diabetes exacerbated by steroid use but are no longer on steroids, and "borderline" diabetics with no current medication needs. Mismatches may have also occurred in patients with very short inpatient stays, or patients (especially pre- and post-surgical patients) in whom all medications to be given by mouth were being withheld.

Query Failures

There were 23 query failures or errors (false positives). The algorithm failed to detect the drug in 19 of these cases. The 4 remaining were instances where the algorithm failed to detect an existing and accurate assessment.

The type of mismatch relative to the patient's true disease status has distinct implications as to the meaning of that detected mismatch. Application of the analytic framework described in Table 1 to the data to the may best illustrate the results (see Table 11).

Table 11. Analytic Framework with Results (Note: clinically significant mismatches are **BOLDED,** clinically insignificant mismatches are *italicized,* and query failures are in plain text)

	True Disease Status			
	Patient has Diabetes		**Patient does not have Diabetes**	
	cause:	totals	cause:	totals
Drug (+) for Diabetes **Problem List (–) for Diabetes**	**Problem list incomplete**	**50**	**Order entered for the wrong patient**	**2**
	No assessment done	**51**		
			Drug being used for inappropriate indication	**0**
	New onset DM (during admission or newly detected)	**12**		
			Failure to discontinue the drug (condition no longer exists)	**0**
	Assessment entry artifact (assessment for DM not checked but comment line includes "IDDM", etc.)	*1*		
			TPN coverage only	*11*
			TPN coverage and no assessment done	**3**
	Assessment not detected	4		
			Peri-operative insulin	*13*
			Coverage for steroid use	*9*
			Coverage for steroid use and no assessment done	**1**
			Treatment for hyperkalemia	*2*
			ICU-induced stress	*1*
Drug (–) for Diabetes **Problem List (+) for Diabetes**	cause:		cause:	
	Potential error of omission – no order written	**1**	**Problem no longer exists and should be deleted from the list**	*0*
	Error of omission – order written-pharmacy failed to enter	**9**	**Nursing assessment indicates patient diabetic but they are not**	*5*
	Accidental discontinuation	**0**	*Assessment entry artifact (assessment entered as Diabetes: "NO" or "denies" or "denies diabetes")*	*26*
	Problem being managed by other interventions	*23*		
	Short stay – no drugs administered	*4*		
	Medication being held – pt. is NPO	*2*		
	Query failed to detect drug	19		

DISCUSSION

This proof-of-concept study successfully demonstrates that using a matching algorithm to compare a patient's medication list and problem list in an electronic medical record is a potentially valuable way to identify medication errors and improve the integrity of a working problem list. While identification and use of HICL codes as the medication data entity was straightforward, selection of a candidate problem list data entity was not. The use of coded online nurse assessment data as a proxy for a formal problem list was not without some problems, but it proved an effective solution in a setting where a formal coded problem list is not one of the EMR's current features. Because these data were coded and available to the algorithm at the time of its development and implementation, use of these data as a practicality permitted validation of the medication list – problem list matching concept to proceed.

The primary motivation in developing this tool was to uncover wrong-patient medication order entry and other medication errors. While the algorithm demonstrated an ability to uncover medication errors, a somewhat unexpected result was its value as a way to improve the problem list.

Groups of Results

Many of the types of mismatches discovered were unexpected. As outlined in Table 2, ten "cases" or mismatch types were anticipated (six medication error types and three problem list deficiencies). During field-testing using two months of patient data, 25 different mismatch types were found. Fourteen potentially clinically significant mismatch types were discovered (6 medication error types and 8 problem list deficiency types), eight mismatch types were deemed true mismatches but not clinically significant, and there were two mismatch types that resulted

due to query failures. Although some mismatch types were only subtly different, consideration of all potential mismatch types is important to ongoing development of a robust system.

Clinically Significant Mismatches

Wrong Patient Medication Errors:

The algorithm proved useful in detecting orders entered for an incorrect patient (the original impetus for creating the algorithm). While only two such errors were found, detection of this error type is significant. Wrong-patient drug administration, especially with drugs used in diabetes treatment, is a potentially devastating error. The implications of this error are two-fold. The person who is administered a drug to lower blood glucose levels in error is put at tremendous risk of harm. Sequelae of profound hypoglycemia include coma, permanent neurologic deficits, cardiac dysrythmias, and death. By corollary, a patient who fails to receive a needed drug because the order has been entered into, or assigned to, another patient's record, is also at risk of harm.

A method to detect and prevent this type of error warrants exploration. Detection of two wrong-patient errors during this two-month study period may imply this error takes place twelve times annually within diabetic patients alone at GSH. It is reasonable to expect that similar wrong-patient order entry errors take place within other disease domains at similar rates, and also have the potential to cause significant patient harm.

Neither wrong-patient order entry case detected resulted in drug actually being administered to a patient. Nursing staff detected and arrested both errors prior to their administration. Again, it must be stressed that the role of nurses or other clinical staff in verifying order entry in POE environments is unclear, and may make detection of these errors more difficult, and perpetuation

of these errors potentially more likely. This algorithm might prove a valuable intervention to detect these error types in an inpatient setting with implemented POE.

One wrong patient mismatch resulted because a medication order was entered for the wrong patient during pharmacy transcription. In the second case, an insulin vial was removed from an automated medication dispensing machine on the floor by nursing personnel. There was no pharmacy transcription error in this case. When a medication is removed from an automated dispensing machine, a charge to the patient results that is detectable by the algorithm. This is an interesting unanticipated benefit of the algorithm: it can detect medication errors that result when drugs are used in "floor stock" settings, or situations where the traditional medication administration cycle might be abbreviated or out of normal sequence.

It is interesting to note that one of the cases of wrong-patient order entry was detected because an assessment had never been done. The obvious implication might have been to conclude that the mismatch resulted because no assessment had been done. However, the data collection process consistently used throughout the study required verification of disease (or lack thereof) in each patient in whom a mismatch was detected. Examination of the medical record made it clear that the patient did not have diabetes, and review of actual written orders for this patient revealed that no order had ever been written for insulin.

The case of wrong-patient medication use where insulin was removed from an automated dispensing device was detected and recorded by the traditional GSH medication error reporting system. The other wrong patient order entry error found in this study was not otherwise detected by GSH medication error reporting mechanisms.

Other errors of commission that were potentially detectable by this check, such as drugs used for an inappropriate indication and failure to discontinue a drug for a condition that no longer exists were not found in this study.

Medication Omission Errors

Medication omission errors also proved to be detectable using this tool. Omission errors may result because a physician failed to write an order for a needed drug, or because a written order was never transcribed into the pharmacy system. Though transcription tasks in the medication administration cycle will likely be minimized in POE environments, they will likely not be totally eliminated. Verbal orders taken by nurses and other clinicians will still require transcription into an EMR. Pharmacy order changes precipitated by a need to change drug formulations to make an order "right" with current inventories will also involve a transcription step. Any transcription processes will remain potential opportunities for error.

There was a single case detected where a patient's usual outpatient medication regimen was not continued on admission to the inpatient setting. While it is not clear that this drug was omitted in error, the patient's labs did indicate that clinically significant hyperglycemia resulted (for which no treatment was given) during the patient's third and fourth day of admission.

Nine omission errors resulted because of a failure to transcribe written medication orders into the EMR. In one case, follow-up with the patient record revealed that pharmacy staff never transcribed a written order for sliding-scale insulin. The interesting implication in this case was that investigation of this mismatch would likely have made obvious that the patient was also on the antidiabetic drugs glyburide, metformin, and rosiglitazone as an outpatient. Again, while it was not clear whether the absence of these drugs was the result of oversight or was intentional

during this admission, the tool could have signaled an opportunity to intervene that may have become clinically important.

In another case, the written order "[patient] may use his usual dose of insulin if eating normally" was also never transcribed by pharmacy. While there are obvious clarity issues with the manner in which this order was composed, the nurses were aware of this order and did administer NPH insulin twice and record the administration of drug on the administration record. Similarly, a written order "may take her usual dose of insulin if eating" was also never transcribed into the electronic record or MAR. In this case, no insulin was given or charted on MAR. It was not clear whether both pharmacy and nursing staff missed this order, or if insulin therapy was, in fact, never required in this patient and therefore never administered. Investigation of these mismatch cases would have resolved this somewhat ambiguous order and strengthened the medication list.

None of the ten omission errors found during this study were detected by traditional medication error reporting mechanisms at GSH.

Overall, the tool did show promise as a way to detect medication errors. It should be noted that many errors reported by traditional medication error reporting mechanisms are dispensing and administration errors. Such errors may be reported in isolation. For example, for a patient who misses one dose of a four-times-a-day dosing schedule, this missed dose would constitute *one* medication error. The error types detected by this algorithm (prescribing and transcription errors), if left undetected, may have more significant results. A single error of this type would also be recorded as *one* medication error. However, for the same hypothetical four-times-a-day dosing schedule, a total of four potential wrong patient or omission errors could occur *per day* because of a single prescribing or transcription error.

Problem List Deficiencies:

The preponderance of mismatches detected by this algorithm were issues of problem list integrity; either incomplete assessments or assessments that were not done at all. This finding has interesting implications for health systems that either already have formal coded problem lists in their EMR's, or are considering their use. To be truly useful for decision support, interdisciplinary communication, and potential financial uses, problem lists must be evolving entities. Verification of the problem list using the medication list as an internal crosschecking mechanism may prove a useful method to ensure their completeness and accuracy.

Incomplete Problem Lists

Fifty mismatches resulted because of incomplete nursing assessments. Incomplete assessments were those where the patient record showed an obvious documented history of diabetes, but the assessment form's check box for diabetes was not selected by the nurse completing the assessment. Whether this was oversight on the part of the nurse completing the admission assessment, reflected an admission assessment that a nurse intended to complete but never did, or reflected some artifact of the assessment entry process (i.e. the nurse believed an assessment was properly saved but it was not), was not clear. As an example, in one case, a diabetic patient with "diabetes and cellulitis" listed as the reason for admission did not have diabetes checked off in the admission assessment.

Several cases existed where two admission assessments were completed during a single admission. On occasion, a nurse, having run out of time during his/her shift, might ask the nurse assuming responsibility for a patient to finish the admission assessment. The second nurse might instead initiate and complete a new assessment, leaving the previous incomplete admission assessment in place in the EMR as well. This circumstance had interesting results. In one of the cases, two admission assessments were done for a single patient; one at the time of admission and

one about 48 hours after admission. The more recent assessment indicated that the patient was diabetic. However in this case the *newer* assessment appeared to be inaccurate and the patient, in fact, had no evidence to verify the presence of diabetes in the record.

Some artifacts of the way the admission assessment forms are completed may have accounted for a portion of patients with incomplete assessments. Patients who, during their admission, develop diabetes or are newly diagnosed diabetics, may have been assessed at admission as non-diabetics. This is technically not an incorrect assessment *at the time of admission.* It is an interesting finding in that it points out not only potential challenges to maintaining a dynamic and up-to-date record of patient problems, but also the potential value of the algorithm in assuring an up-to-date problem list exists, even *within* a single admission.

Fifty-one patients had no nursing admission assessment done in electronic form. Adult admission assessments for patients admitted directly to the Intensive Care Unit (ICU) are still done in paper format, and are never entered as online computerized assessments. During the study period there were 254 patients admitted directly into the ICU. Data regarding the number of *diabetics* admitted directly into the ICU was not available. However, 18.84% of patients discharged from GSH during the study period had diabetes as a primary or secondary diagnosis. Using this percentage, we can roughly estimate that 47.8 direct ICU admissions were diabetic patients during the period. So the case can be made that direct ICU admissions represented a significant proportion of the patients with no online admission assessment. The admission assessment may otherwise have been overlooked or neglected in the remainder.

Five mismatches resulted because the assessment indicated that a patient was diabetic, but no evidence existed within the clinical record to confirm diabetes. The nursing assessment relies, in part, on a patient interview. The patient may have indicated during the assessment interview that

they thought themselves diabetic or perhaps "borderline" diabetic, but may not have been. The other obvious explanation is an incomplete medical history existed in the clinical narrative, which made the investigator's conclusion of absence of disease inaccurate.

Such inconsistencies, while discoverable and made correctable by the algorithm, are also an obvious liability and a potential source of false negative results. For example, cases where patients were listed as diabetic and were not could potentially render medications entered in error undetectable. Similarly, cases where the assessment failed to list diabetes, and orders were *not* written for diabetic medications when they were needed would also go undetected.

Clinically Insignificant Mismatches

Some mismatches resulted for reasons other than problem list deficiencies or medication errors. These clinically insignificant mismatches resulted due to either an artifact in the assessment entry process, appropriate use of diabetes drugs for non-diabetics, and cases where treatment was being judiciously withheld in true diabetics. These cases serve to underscore the importance of the cognitive work of a clinician to assess the importance of each reported mismatch, and point to areas where the algorithm rules might be modified to make the tool's output more useful.

Twenty-seven admission assessments, although perhaps perfectly clear to a human user, were entered in a way that was ambiguous to the algorithm. In most cases nurses used the admission assessment forms as intended: where disease exists the appropriate check box was selected. However, it appeared the assessment form was being used as a checklist-like device by some users. Assessment forms in these cases included checks in *each* box, whether disease existed or not, and the comment line described the presence or absence of disease for each checked box. The comment line adjacent to the diabetes check box allows free text entry of a small amount of text, and provides for four pre-formatted drop-down selections (Type I, Type II, Diet,

Gestational). While the meaning of the recorded form was decipherable to a human user, the result was ambiguous to the algorithm.

There was a single case where the assessment check box within the form was not marked for diabetes, but "1DDM" was entered into a free-text comment line adjacent to the "OTHER ENDOCRINE/HEMATOLOGIC" selection. Directly above this selection line is the dialog for "DIABETES." Despite taking time to convey information in the form of this free-text entry, this simple selection had been ignored (see Figure 10). And though the intent of this entry was obviously "Insulin Dependent Diabetes Mellitus", even with a natural language processing functionality to glean data from the free-text comment line, the meaning of this entry might still have been lost. There were 26 cases where the check box for diabetes was selected within the assessment and descriptors such as "NO", "denies", or "denies diabetes" entered into the free-text comment line. These entries were made in a manner that was obviously intuitive to the person entering the data, and in a way that preserved meaning for the person that might subsequently read and use the data. Rather than indicting the manner in which the users recorded data in these cases, these ambiguous entry findings might, more importantly, point to the need for an improved user interface for the recording of this information.

Glucose lowering agents are sometimes used appropriately in non-diabetic patients. Non-diabetic patients may experience hyperglycemia when being treated with total parenteral nutrition [34], and steroid therapies [35]. Insulin is also beneficial in non-diabetics in stressful situations such as in intensive care settings [36], post-myocardial infarction [37], and during and after surgical procedures [38]. Insulin is sometimes used to treat acute hyperkalemia as well [39]. There were 36 cases in this study where glucose-lowering drugs were used appropriately in non-diabetics.

Finally, 29 clinically insignificant mismatches existed where a patient's disease is being managed by other interventions (e.g. diet and exercise), in patients who did not receive injectable or oral treatment because their inpatient stay was very short, or patients for whom drugs administered by mouth were being held (e.g. before or after a diagnostic procedure).

These instances underscore the challenges to developing and maintaining system components to stay current with guidelines, hospital policy, and circumstances peculiar to a particular setting. Continued work to refine the algorithm's rule base may eliminate some of these mismatch types, though outright elimination of these mismatches from the algorithm's output would require careful consideration. Ongoing evaluation work would be required to show that changes to system components to minimize or eliminate clinically insignificant output do not adversely affect the algorithm's performance.

Not all medical problems require therapy, and pharmacotherapy may be only one of many potential treatment options. The system could be expanded to include detection of non-drug therapeutic interventions, where appropriate. Additionally, drugs and their associated indications are always evolving. These factors further emphasize the need for a dynamic knowledge base, and system rules. But the system will remain only an adjunct to quality improvement. The systems output will always require human expert review.

Query Failures

There were 23 query failures (false positive mismatches) detected during evaluation. These failures reflect the algorithm's dependence on EMR data elements that do have some limitations. All detected failures are correctable. The majority of these (19) were caused by the algorithm's failure to detect a drug that was correctly entered into the EMR. As designed, the algorithm detects drugs via drug charges to the patient account. Where an order was entered for a drug but

no charge accrued (e.g. drug never used and credited after discharge, patient's own medications used, or an insulin vial never removed from automated dispensing machine), a no-charge entry resulted. These entries were rendered undetectable by the query. In these cases, a mismatch resulted for patients who should have had drug-positive / assessment-positive matches.

Four query failures were the result of admission assessments that were not detected. A peculiarity of a single assessment type (Behavioral Health Adult Admission Assessment used for patients admitted to the psychiatric ward) and the finding code employed explains this finding. A single assessment finding code, 2083 (diabetes), was shared by the standard Adult Admission Assessment, the Rehabilitation Admission Assessment, and the Obstetrics and Gynecology Admission Assessment. The Behavioral Health Assessment used a different synonymous finding code, 3021 (diabetes), and was thus rendered undetectable. Inclusion of this finding code in the system's rules would be easily accomplished.

Relationship with Other Published Studies

It is difficult to draw parallels to other study results. While the importance of accurate and complete medication lists and problem lists is acknowledged, attempts to use a patient medication list and problem list matching methodology to confirm or identify problems with these lists are not reported in the literature. Additionally, medication errors reported in this study were detected within a single disease state, and only pertain to errors made during the prescribing and transcription process alone, including omission errors (including failure to treat, and errors due to mental lapses) and commission errors (wrong patient, wrong drug, and inappropriate use errors). The algorithm is not designed to detect dose, route, frequency, or preparation errors, nor does it attempt to discover drug-drug or drug-allergy interactions, which are reported in other medication error studies.

In the study by Bates, et al. [16], substitution errors were defined as occasions where a wrong drug was given or a wrong patient received a drug. The rate of substitution errors reported was 7 per 1,000 patient-days. This medication list – problem list matching algorithm was only implemented in a single disease state. However, if one considers that there were 440 patients discharged with diabetes either as a primary or secondary diagnosis during the study period (19.81% of patients), and that there were 10,360 patient-days during the period, there was a potential 2052 *diabetic patient* patient-days during the study period. Two wrong-patient errors in 2052 *diabetic* patient days equates to roughly one (0.975) wrong-patient error per 1000 patient-days. While this comparison may be a tenuous one, especially since this study did not detect dispensing and administration errors, a comparison of rates is still somewhat valuable in lending some amount of external validity to this study's findings.

Study Limitations

This study's conclusions and generalizability are limited by a number of factors. This work examined mismatches only over a two-month study period, using patient data from a single hospital, and only sought mismatching states within a single disease and therapeutic domain. The data collection processes outlined in Appendix II and Appendix III were not validated. Because patient records where drug / assessment *matches* were detected were not examined during the larger field testing evaluation phase, and mismatching patient records were not examined in their entirety, there is no gold standard on which to base these conclusions. Both appropriate and inappropriate mismatches may have existed that remained undetected. Additionally, the validity of the use of nurse assessments, specifically nurse assessments for diabetes, as a proxy for problem list data, was never established.

It should be noted that the C4 HICL coded drugs list (see Appendix I), in addition to being inclusive of all drugs used in the treatment of diabetes, also includes several drugs *not* used in the treatment of diabetes (Vitamin B Complex, Brewers Yeast, Guar Gum, and Herbal Drugs). While the investigator is not aware of any algorithm failures that resulted due to any of these drug entities, their existence may have caused algorithm output artifact (e.g. resulting in detected matches where there should have been none detected). The impact of these drug entities on the study's results is not known.

Future work

A number of opportunities exist for future research and development efforts. The most obvious first step is elimination of known query failures. These query failures resulted because either a drug HICL code or problem list code was not detected. Until such time as a true coded problem list is implemented, and the algorithm continues to rely on the nurse assessment for problem list data, the findings codes for *all* diabetes assessments should be included within the algorithm's rule-base. Since dependence on charges for query performance also proved a liability and significant source of false-positive results, the potential to change the code to examine medication order entities in addition to drug charges should be pursued. Correction of these two known query failures should pose no significant design hurdles.

A more in-depth, intensive examination of all patient records submitted to the algorithm should be the next research priority for this system. Iterative refinement of the algorithm with repeated exposure to the same test-set of patients would be an ideal way to rapidly improve the system. This should be undertaken to detect more conclusively not only true- and false-positive results, but also determine conclusively all true- and false-negative results during the field testing evaluation phase (ignored in this study), to enable a gold standard to be established. In the present

feasibility study, true- and false-negative results were not determined during field evaluation, as exhaustive review of 2,221 records would have been impractical.

During the field testing level of evaluation, matching records were not investigated. This level of evaluation was undertaken to examine the clinical significance of the algorithm's findings, so follow-up of even a sample of matching patient records would not have simulated the way the data would be used in actual practice. Ignoring *matching* records did have some potential consequences. For patients with diabetes:

- potential omissions were not detected in untreated diabetics with either no assessment or an incomplete assessment
- opportunities to improve the problem list were not detected in treated diabetics when the drug was not detected and the problem list was either not done or inaccurate.

and for non-diabetic patients:

- where drug was not detected due to query failure, mismatches were not detected in non-diabetics receiving treatment in error
- where the assessment was checked for diabetes with "NO" in the comment line, a patient receiving treatment in error would not have been detected
- where the problem list indicated diabetes and the patient was receiving treatment in error, mismatches were not detected.

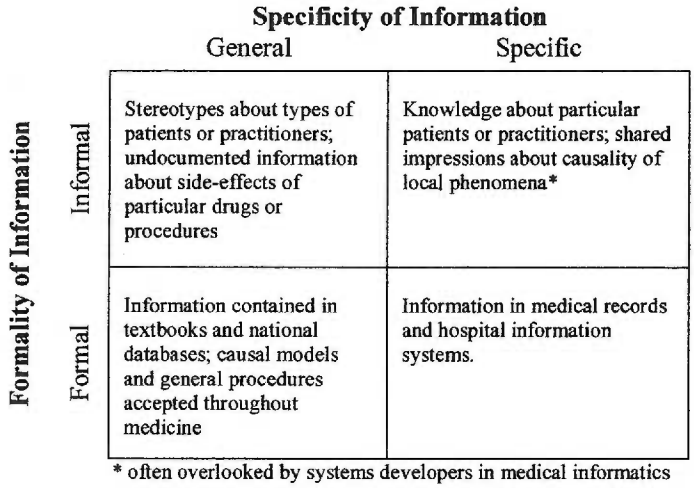
Use of an intermediate number of actual patient records, or an available test-set of patient records about which everything is known, would permit more reliable conclusions about the algorithm's current performance to be drawn, and point out areas needing improvement with greater certainty. For example, if 200 patient records were selected for full evaluation, since mismatches were detected in 11.4% of patient records, 22 mismatches would likely be detected. A more in-depth

look at the algorithm's performance for both mismatching and matching patient records could be accomplished with this intermediate test set, while still permitting full review of all patient records.

Refinement and ongoing maintenance of this tool will likely be more difficult than its initial development. Refining the system's rules could minimize the number of clinically insignificant results. In the short term, turning "off" mismatches that resulted because an assessment was not done, or perhaps routing these results only to nursing staff might be a way to minimize the time required to investigate these "no assessment" mismatches. In the longer term, obvious avenues worth exploring include leveraging laboratory data, medication information from previous admissions, and medication information from the current admission (e.g. the existence of total parenteral nutrition or steroid therapy) as a means of eliminating clinically insignificant mismatches. Medication list data from other sources (such as the outpatient record or medications from a previous admission) might also be considered by a mature system. Similarly, other problem list sources, such as those found in the clinical narrative, might be included. Refinement of algorithm output to minimize insignificant results would have to be weighed carefully with the possibility of causing increased false-negative results, and the potential clinical consequences of missing clinically significant mismatches.

Forsythe, et al. [40] suggest that formally coded information that is generalizable to all health settings is only one of four principal types of information critical to the practice of medicine and that should be considered by developers of automated systems to support clinical practice. In addition to formalized globally applicable information, developers should also consider informal generalizable information, and both informal and formally codified local knowledge (see Figure 12).

Figure 12. Forsythe, et al. Information Types Framework (with examples of each type).



from Forsythe, et al. 1990

In accordance with this framework, this system was initially built upon a foundation of generalized formal knowledge (considering only drugs used in the treatment of diabetes and a corresponding nursing assessment finding). Later inclusion of formal (policies and procedures, pharmacy and therapeutics committee recommendations) and informal (recognition of practice patterns) *local* knowledge sources would strengthen the system and the clinical usefulness of its output.

Receiver operating characteristic (ROC) curves are a useful way to examine the trade-off between false positive and false negative results as the number of facts considered by a system are changed [41]. Clearly, with a system such as the one proposed, the risk of eliminating clinically significant results in an effort to limit the amount of clinically insignificant output would have to be carefully weighed. Plotting of system performance using ROC curves might be useful as the number of input items considered by the algorithm (e.g. coexistence of laboratory, other medication, and other problem list data) is varied or different knowledge bases, thesauri, and reporting structures are utilized.

This query tool will not initially be employed as a real-time alert at the time of order entry. Such an alerting mechanism might prove too disruptive to the order entry task at this early stage of development. However, if properly integrated into the work process of a physician, nurse, or pharmacist, this application might eventually prove valuable as a real-time alert. The vision for the tool in the shorter term is that it would create a report of mismatches discovered for all hospital inpatients on a once-daily basis. The results of the report would be available for review, either by the prescriber or other clinician (e.g. pharmacist or nurse), for follow up at the earliest opportunity. Additionally, implementing the algorithm to run its report on a daily basis, rather than on a per-admission basis as was done in this retrospective study, may impact results and clinical value of the system. Potential implications include detecting any omitted orders soon after an in-house patient transfer, identifying treatment and problem list issues with newly diagnosed disease, attention to omitted orders in a more timely fashion, and detecting instances of accidental or wrong patient order discontinuation. These error types could not have been detected in this current study, as any orders entered into the EMR (no matter how briefly) during the admission would be detected causing a *matching* state to exist if the patient is diabetic. If implemented on a per-day basis with this disease state (4.11 mismatches per day were detected in this study) and the addition of three additional disease states (e.g. depression, hypercholesterolemia, and hypertension), we might anticipate the need to investigate as many as 16 records per day (approximately four mismatches per day anticipated in four disease states) in this population. If once daily mismatch reporting is to be considered, some method by which mismatches that have been already investigated and rejected could be "turned off" or verified could be chosen, though this would have to be done with care.

Findings from this system would hopefully be used to validate or augment existing medication error reporting schemes and any quality indicators already in use for nurse assessments. Also,

using this system and medication information as a means of providing 'prompts' to assist in initial building of any current or future problem list entity could have interesting implications. The medication list is a highly granular indication of a patient's current problems, and could be used as a source of prompts or decision points for the clinician to use when taking an initial inventory of a patient's acute and chronic problems. The algorithm might also prove an effective aid to current reimbursement strategies thorough validation of existing reimbursement coding lists, and pointing out coding opportunities that had not already been considered.

Although this system was tested to find only mismatches in the area of diabetes treatment, note that a mismatch of a single drug may precipitate investigation and discovery of a host of order entry errors. Ultimately, such a system might be scaled to also search for mismatches in other chronic disease states, such as hypertension, depression, seizure disorder, hypothyroidism, congestive heart failure, hyperlipidemia, and infectious diseases.

CONCLUSION

This proof-of-concept study successfully demonstrated that a novel matching algorithm that compares a patient's medication list and problem list in an electronic medical record can be developed and be used in a way to benefit patient care. The matching algorithm is a valuable way to identify clinically significant mismatches, such as those arising due to medication error or deficiencies in the integrity of a patient's problem list. The medication error types that are detectable by this check are not otherwise detected by commonly employed medication decision support functions. Clinically insignificant mismatches, resulting from artifacts in the way assessments are entered, appropriate use of glucose-lowering drugs in non-diabetic patients, and diabetics in whom pharmacotherapeutic treatments were being withheld, were also detected. These mismatches point out opportunities to improve the system's output to make it more clinically useful. This work also demonstrated the potential value of using nursing assessment data, a data source that may already be in place in many settings, as a source of actionable problem list information in an EMR. Exploration of the system's usefulness in construction and validation of dynamic problem lists in an EMR, and its scalability to detect medication errors in other disease states and therapeutic categories make this a concept on which a myriad of future research work might be based.

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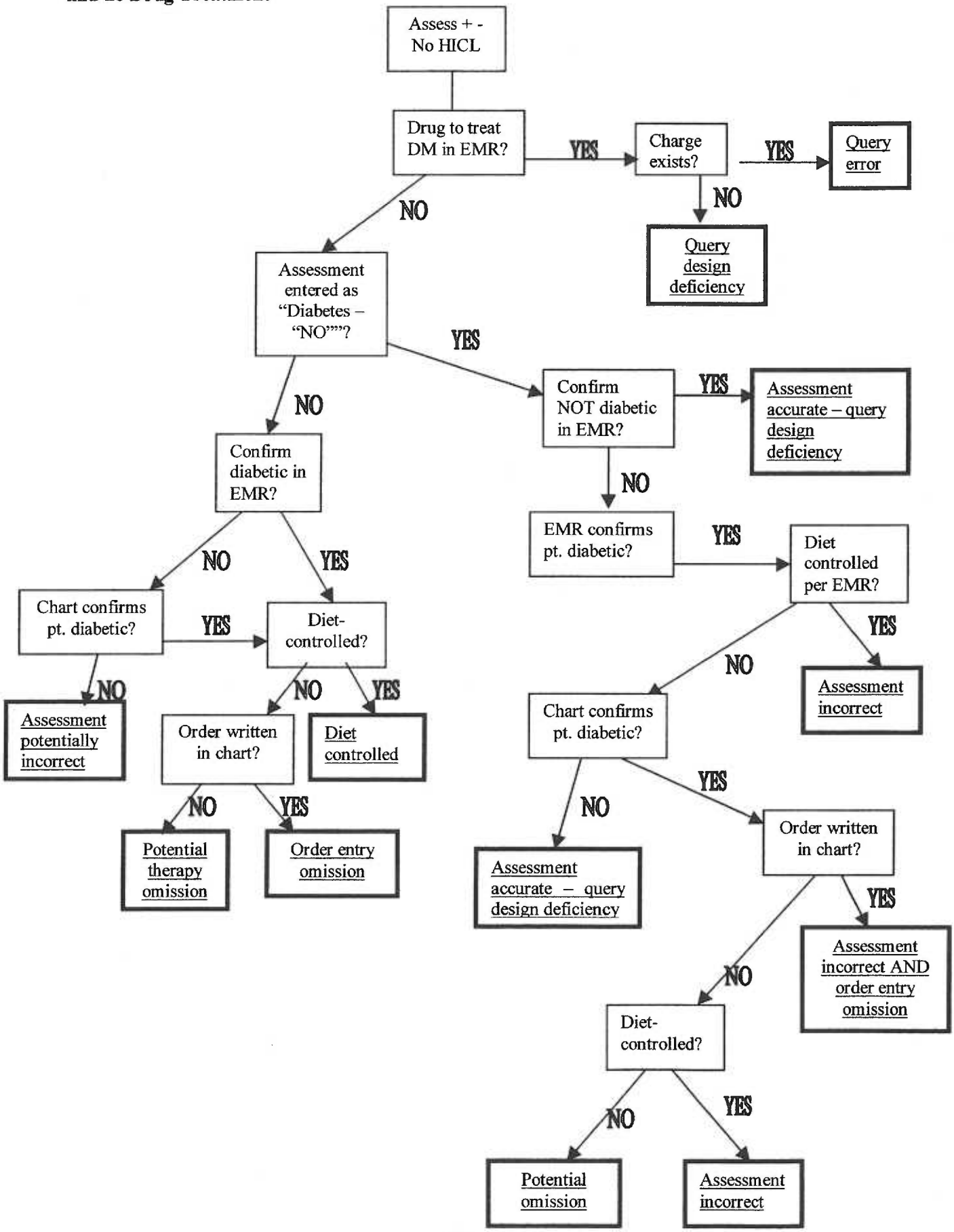
Appendix I. Drugs Sharing the C4 HICL Code Prefix.

GENERIC NAME	HICL CODE
ACARBOSE	C4MA
ACETOHEXAMIDE	C4KA
BREWERS YEAST	C4LAO4
CARBUTAMIDE	C4KI
CHLORPROPAMIDE	C4KC
GLIBORNURIDE	C4KK
GLICLAZIDE	C4KG
GLIMEPIRIDE	C4KJ
GLIPIZIDE	C4KF
GLIQUIDONE	C4KH
GLYBUR I DE	C4KE
GLYBURIDE, MICRONIZED	C4KEMC
GUAR GUM	C4OAOI
HERBAL DRUGS	C4PAOI
HYPOGLYCEMICS	C4
HYPOGLYCEMICS, ABSORPTION MODIFIER,	C40
HYPOGLYCEMICS, ALPHA-GLUCOSIDASE INH	C4M
HYPOGLYCEMICS, BIGUANIDE TYPE (NON-S	C4L
HYPOGLYCEMICS, COMBINATION	C4Q
HYPOGLYCEMICS, INSULIN-RELEASE STIMU	C4K
HYPOGLYCEMICS, INSULIN-RESPONSE ENHA	C4N
HYPOGLYCEMICS, UNSPECIFIED MECHANISM	C4P
INS ISP SOR,SOH (OBSOLETE)	C4GYHR
INSUL ISP 50% REG (OBSOLETE)	C4GY
INSUL PRT ZN (OBSOLETE)	C4GBHU
INSULIN ASPART	C4GJ
INSULIN BEEF PURIFIED	C4GABP
INSULIN BEEF, CRYSTALLIZED	C4GABJ
INSULIN GLARGINE	C4GK
INSULIN GLOBIN ZINC	C4GG
INSULIN GLOBIN ZINC HUMAN	C4GGHU
INSULIN ISOPHANE NPH	C4GC
INSULIN ISOPHANE NPH,BF-PK	C4GCBK
INSULIN ISOPHANE, BEEF	C4GCBF
INSULIN ISOPHANE,BEEF PURE	C4GCBP
INSULIN ISOPHANE, PORK	C4GCPK
INSULIN ISOPHANE,PORK PURE	C4GCPF
INSULIN LISPRO (NPL)	C4GI
INSULIN LISPRO,HUMAN REC.ANLOG	C4GH
INSULIN LOW ZINC	C4GALZ
INSULIN NPH HUMAN RECOM	C4GCHR
INSULIN NPH HUMAN SEMI-SYN	C4GCHS
INSULIN PORK, AMORPHOUS, INSUL PK,AMOR	C4GAAV
INSULIN PROTAMINE ZINC	C4GB
INSULIN PROTAMINE ZINC BEEF PURIFIED	C4GBBP
INSULIN PROTAMINE ZINC PORK PURIFIED	C4GBPF
INSULIN PROTAMINE ZINC,BEEF	C4GBBF
INSULIN PROTAMINE ZINC,PORK	C4GBPK
INSULIN PROTAMINE ZN HUM S-S	C4GBHS
INSULIN PROTAMINE ZN,BF-PK	C4GBBK
INSULIN REG HUMAN SEMI-SYN	C4GAHS
INSULIN REG, HUM S-S BUFF	C4GABH
INSULIN REG,HUM REC BUFF	C4GAHT
INSULIN REGULAR	C4GA
INSULIN REGULAR HUMAN REC	C4GAHR
INSULIN REGULAR, BEEF-PORK	C4GABK
INSULIN SULFATED BEEF	C4GASU

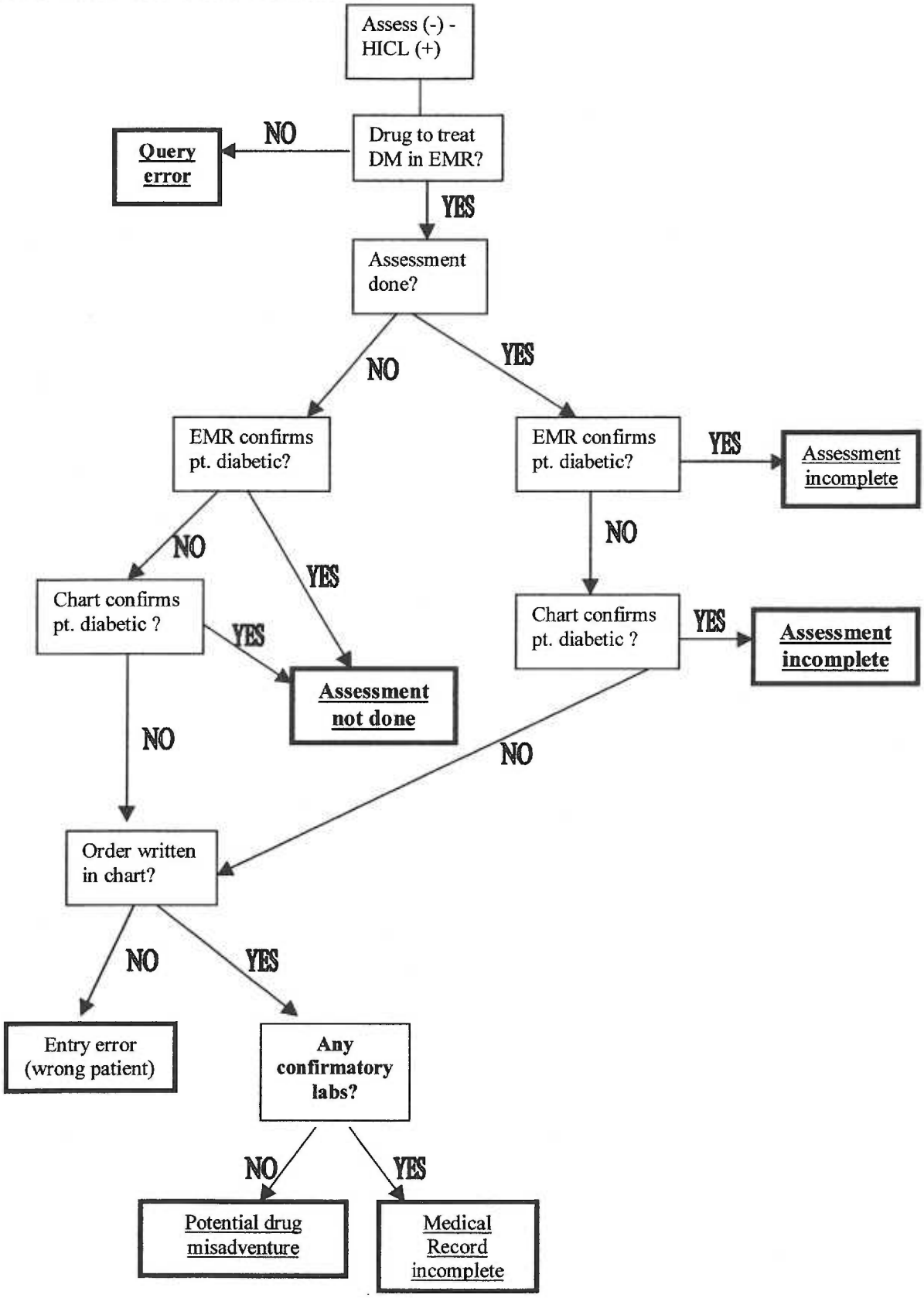
Appendix I. Drugs Sharing the C4 HICL Code Prefix (cont.).

GENERIC NAME	HICL CODE
INSULIN ZINC	C4GD
INSULIN ZINC BEEF	C4GDBF
INSULIN ZINC EXTEND HUMAN REC	C4GEHR
INSULIN ZINC EXTENDED	C4GE
INSULIN ZINC EXTENDED BEEF PURIFIED	C4GEBP
INSULIN ZINC EXTENDED, BEEF	C4GEBF
INSULIN ZINC EXTENDED, BF-PK	C4GEBK
INSULIN ZINC HUMAN REC	C4GDHR
INSULIN ZINC HUMAN SEMI-SYN	C4GDHS
INSULIN ZINC PROMPT	C4GF
INSULIN ZINC PROMPT HUMAN	C4GFHU
INSULIN ZINC PROMPT, BEEF	C4GFBF
INSULIN ZINC PROMPT,BEEF PURE	C4GFBP
INSULIN ZINC PROMPT, BF-PK	C4GFBK
INSULIN ZINC PROMPT, PORK	C4GFPK
INSULIN ZINC PROMPT,PORK PURE	C4GFPF
INSULIN ZINC,BEEF PURIFIED	C4GDBP
INSULIN ZINC, BEEF-PORK	C4GDBK
INSULIN ZINC,PORK	C4GDPK
INSULIN ZINC,PORK PURIFIED	C4GDPF
INSULIN, GLARGINE	C4GKIK
INSULIN, BEEF	C4GABF
INSULIN, PORK	C4GAPK
INSULIN, PORK PURIFIED	C4GAPF
INSULIN,PORK REG CONCENTRATE	C4GARC
INSULINS	C4G
METFORMIN	C4LB
METFORMIN CH- PHENOXYACETATE	C4LBCX
METFORMIN EMBONATE	C4LBEB
METFORMIN HCL	C4LBHC
MIGLITOL	C4MB
NATEGLINIDE	C4KN
ORAL HYPOGLYCEMICS, NON-SULFONYLUREA	C4L
ORAL HYPOGLYCEMICS, SULFONYLUREAS	C4K
PHENFORMIN	C4LA
PHENFORMIN HCL	C4LAHC
PIOGLITAZONE	C4NC
PIOGLITAZONE HCL	C4NCHC
REPAGLINIDE	C4KM
ROSIGLITAZONE	C4NB
ROS IGLITAZONE MALEATE	C4NBMA
TOLAZAMIDE	C4KD
TOLBUTAMIDE	C4KB
TOLBUTAMIDE SODIUM	C4KBNA
TROGLITAZONE	C4NA
VITAMIN B COMPLEX	C4LAO3

Appendix II. Evaluation Steps for Patient Records with Assessments Indicative of Diabetes and no Drug Treatment



Appendix III. Evaluation Steps for Patient Records with Drug Treatment Indicative of Diabetes and no Assessment for Diabetes.



Appendix IV: ENFORM Code for Medication List – Problem List Matching

```
!section xxwlr.wl955ed
!       Retrospective Drug-Nurse Assessment Survey:  Linked Diabetes
all sites

 set @margin 6

 open disch-report;
 open prmord-rec;
 open prmmi-rec;
 open ippev-rec;
 open reg-report;
 open acct-report;
 open phdict-med-report;
 open nasfind-rec;
 open comment-rec;
 open phdict-fac-report;

!link optional required for admits without admit comments
 link acct-report.acct-chief-complaint to optional comment-rec.ts;

 list
 by   disch-report.fac                          noprint form
 by   disch-report.acct-num                     noprint
      tab 54
!by   phdict-finding.finding-text               as a60  heading "Admit
Finding"
!by   nasfind-rec.nasfind-note-value            as a10  heading "Note"

      count(nasfind-rec.nasfind-ncp-finding over disch-report.acct-num
            where nasfind-rec.nasfind-ncp-finding      = 2083)
                                                as i5   heading
"Admit/Note"
      count(nasfind-rec.nasfind-ncp-finding over disch-report.acct-num
            where nasfind-rec.nasfind-ncp-finding      =  537)
                                                as i5   heading "Ed/Note"
      count(prmmi-rec.prmt-mi-subject       over disch-report.acct-num
            where phdict-med-report.med-ingred-num-p12 = "C4")
                                                as i5   heading "C4 HICL"
 where
      disch-report.ddate                        ge report-date
 and  disch-report.ddate                        le report-date2
 and  disch-report.disch-delete-date            eq 0
 and  disch-report.disch-ptptr                  gt 10
 and  disch-report.fac                          eq report-fac
!and  disch-report.adm-type                     eq "I" or "A" or "V"

 and  disch-report.disch-ptptr                   = reg-report.key
 and  disch-report.disch-key.acct-num            = acct-report.acct-num
 and  disch-report.acct-num                      = nasfind-rec.nasfind-
ncp-acct
 and  disch-report.acct-num                      = ippev-rec.ev-acct
 and  ippev-rec.ordact-permanent-key             =
        prmord-rec.order-patnum-orig-num-key
```

```
 and  prmord-rec.perm-order-pri-key            =
      prmmi-rec.perm-order-pri-key
 and (prmmi-rec.prmt-mi-gen-subj-1 + 858849280)=
        phdict-med-report.dict-int-key
 and (disch-report.fac       + 808583168)      =
        phdict-fac-report.dict-int-key

 title
 phdict-fac-report.fac as a30                   skip
 "Inpatient Diabetes Assessment-Drug Survey for Discharges "
     (report-date  + PDO) as date *             "  Thru  "
     (report-date2 + PDO) as date *             skip 2 center

 after change on  disch-report.acct-num print
      reg-report.patient-display-name          as a24  "  Acct: "
      disch-report.acct-num                    as i9   "  "
      reg-report.long-mrn-num                  as i12  "  "
      reg-report.sex                           as a1   "/"
     (reg-report.dob + PDO)       as Date "DB2MA3Y4"  "  "
      comment-rec.ctext                        as a40

before change on  disch-report.acct-num print skip

 footing //
 "Diabetes Assessment-Drug Survey Run "
    @date as date *  space 3 @time as time *  space  7 "Page " @pageno
;
```