MODELING DISPARITIES IN PROVIDER-ORDERED TEST RESULTS

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CERTIFICATE OF APPROVAL

This is to certify that the Master's Capstone Project of

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"*Modeling Disparities in Provider-Ordered Tests Results*"

Has been approved

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ABSTRACT

Introduction

Health care providers place a variety of orders in many clinical contexts: ambulatory, inpatient, emergency department, and beyond. Laboratory tests are a ubiquitous and sometimes costly aspect of medical care. Providers may order laboratory tests to assist with diagnosis, based on antiquated training, reflexively to mitigate liability, as a pre-requisite to pharmacologic therapy, or automatically as a part of an order set. Providers have little, if any, assistance from electronic health records (EHRs) to guide their understanding of trends in their own normal or abnormal lab results.

The project aim was to develop a framework to visualize analytics and disparities in laboratory test results ordered by providers. Laboratory tests are the focus of the investigation given the relative ease of data analysis of numerical values. The conceptual principle may, however, be extended to a wide array of orders (e.g., radiology results, cardiac testing, or pathology results). The visualization framework is intended to provide information to providers at the point of order entry to identify their historical rates of abnormal (or normal, depending on context) results. Such data visualization is intended to exist as a contextually-based infobutton rather than a mandatory clinical decision support (CDS) alert. Contextual information (e.g., diagnoses) is considered along with correlation to colleagues' historical data and patient outcomes.

Methods

Data utilized in the study were prospectively collected on patients admitted to the Cleveland Clinic main campus medical intensive care unit between April 2010 and December 2013. Data elements available included demographics (gender, age), order-specific details (attending physician, order date and time, and order status), and lab results (result date and time, result, abnormally low or high, and normal laboratory values). Additional data were obtained from a business intelligence system, which included International Classification of Diseases, Ninth Revision, Clinical Modification diagnosis codes.

Results

The resulting visualization framework consists of components allowing data analysis, as desired by the user, in a variety of fashions. Each order's constituent components are analyzed separately. Histograms allow the provider to review data compared to colleagues when focusing on normal, abnormal, or all values. The limits of normal are adjustable, depending on the provider's preferences and possibly clinical context. For each order, the diagnoses most frequently associated with the order and odds ratios are listed in descending order, by the provider along with colleagues for comparison. Finally, to avoid overwhelming providers in anticipation of using the framework in a clinical environment, brief summarized notes of diagnosis-based context specific data are provided. The notes alone could be used in an eventual production environment to help providers change ordering behavior.

Conclusion

Health care providers, limited by time and accessibility of clinical data through EHRs, need opportunities to determine appropriateness of clinical orders. This work demonstrates the potential infobutton-type approach to allowing providers an opportunity to evaluate their own performance in comparison to colleagues in a patient-specific contextual fashion. While constant alerts and reminders provide limited benefit due to fatigue, personalized data should be made available to interested providers to help make meaningful and informed patient care decisions.

INTRODUCTION

Health care providers place a variety of orders related to patient care in many clinical contexts: ambulatory, inpatient, emergency department, and beyond. Laboratory tests, a frequently placed order type, are a ubiquitous and sometimes costly aspect of medical care. Providers may order laboratory tests to assist with diagnosis, based on antiquated training, reflexively to mitigate liability, as a pre-requisite to pharmacologic therapy, or automatically as a part of an existing order set. Providers have little, if any, assistance from electronic health records (EHRs) to guide their understanding of trends in their own normal or abnormal lab results.

Overuse and inappropriate laboratory testing is a problem recognized for many years. Strategies focused on educating providers on appropriate laboratory testing involve guidelines, protocols, decision support systems, and feedback with mixed results [1 2]. Unnecessary laboratory testing still occurs and can be a very costly part of medical care [3 4]. Unfortunately, simply displaying order costs or providing summary tables to providers does not alter ordering behavior [5 6]. Incentives and report cards have also fallen short [7-9]. Process- or team-based approaches, including expert systems integrating consensus guidelines systematically, emerged as the more likely methods to curtail unnecessary laboratory testing [2 10-13]. Not all laboratory tests, however, have consensus guidelines and the ability to systematically restrict orders cannot be applied universally. Integrated educational support systems have shown promise [14].

Efficacy of Laboratory Tests

Laboratory tests range in cost and potential for morbidity. Typically, commonplace high volume laboratory tests are inexpensive and introduce limited immediate risk in patient care (e.g., introducing blood stream infections, localized hematomas, etc.). Laboratory results, however, can sometimes misdirect or prolong medical care unnecessarily. Eliminating or reducing unnecessary, costly, or risky laboratory testing has been a long-standing and important topic in health care [13 15 16]. As technology advances, a focus on eliminating overuse of new tests, which are typically costly, is also important [17].

Laboratory tests may altogether be unnecessary [3 16]. For example, pre-operative coagulation studies are a historical practice (some might argue relic) in medicine, but often provide little, if any, appreciable value [18 19]. Neuhauser and Lweicki demonstrated the sixth stool guaiac was not cost effective in screening for colon cancer [3]. Finding systematic ways and EHR-based tools to help providers identify historical disparities and unnecessary testing are needed.

A variety of interventions have focused on altering ordering behavior. Examples include consensus-based alerts and prospective constraints [20], incorporation of practice guidelines [21], restricting orders [22], and educational intervention along with test unbundling [23]. Such studies typically demonstrate reductions in order frequency with corresponding cost savings. Endpoints such as clinical outcome and applicability of laboratory results are rarely measured or discussed. I argue that, in addition to reducing the volume of unnecessary laboratory tests, health care providers should focus on increasing the frequency of orders that result in meaningful normal or abnormal tests

results, depending on the clinical context (e.g., desired diagnostic sensitivity or specificity). For example, automatically ordering or confirming a known normal sodium value often adds little to patient care; however, identifying an abnormal sodium value with the right index of suspicion (e.g., suspected volume depletion) can add significant value to help guide treatment decisions.

Health care providers are not necessarily to blame in ordering unnecessary studies, including, but not limited to, laboratory tests. Discrete, contextual, and personalized data are necessary to help a provider understand the likelihood a laboratory test may or may not provide meaningful data in a patient's care. Those data can then be interpreted by the provider or EHR to determine if they have meaning to the patient under consideration.

Order Sets and Computerized Provider Order Entry (CPOE)

As EHRs have become integral parts of medical care, computerized provider order entry (CPOE) implementation is widespread. As a convenience and safeguard afforded by CPOE, a variety of order sets typically accompany CPOE for an array of providers in a variety of patient contexts. A negative byproduct of order sets is the default behavior selecting potentially unnecessary orders, sometimes in perpetuity (e.g., daily indefinitely), such as laboratory tests. Such behavior can result in unnecessary costs, wasted time, and patient complications as a result of inaction, additional diagnostic interventions, or delay in continuity of care.

Mekhjian et al. evaluated the hypothesis that order sets might decrease unnecessary laboratory testing [24]. The group compared the frequency of laboratory

orders prior to CPOE implementation using paper orders and following CPOE implementation. Regardless of the disease, they found that the number of laboratory orders increased approximately 50% over a two year period. The majority of increases were in medical diagnosis-related groups (DRGs), whereas surgical DRGs saw a decrease in orders. The group concluded that computerized order sets increases laboratory utilization. The impact on unnecessary spending, misdirected card, and clinical outcome is uncertain.

Informaticians have investigated the option of peer-derived consensus alerts focused on discontinuing pre-determined and prevention of unnecessary or redundant orders [20]. Despite the promise in improving byproduct orders from order sets, alert fatigue and non-compliance, unfortunately, may result in such an intervention having unilateral, sustainable affects.

Infobuttons

Infobuttons are often used in clinical decision support (CDS) applications [25-42]. The use of infobuttons is commonly helpful in the context of offering providers details regarding medication administration [43]. Infobuttons have also been used in laboratory analysis [31]. A guiding principle of infobuttons is to provide context-specific links to separate systems that provide information in an anticipatory fashion [29].

The literature provides examples of a variety of context-dependent infobuttons [43 44]. The context of an infobutton has a wide array of interpretations, ranging from gender-specificity to diagnostic-specificity and beyond. There are, however, sparse examples of infobuttons (or similar) that illustrate on-demand provider-dependent data to

help guide clinical decision making. Contextually appropriate and anticipated information appropriate to the provider and situation are important for success [35]. The infobutton paradigm is fitting in the application of visualizing historical order data to identify disparities in provider's historical laboratory results.

Aim

The project aim was to develop a framework to visualize analytics and disparities in laboratory test results ordered by providers. Laboratory tests are the focus of the investigation given the relative ease of data analysis of numerical values. The conceptual principle may, however, be extended to a wide array of orders (e.g., radiology results, cardiac testing, or pathology results). The visualization framework is intended to provide information to providers at the point of order entry to identify their historical rates of abnormal (or normal, depending on context) results. Such data visualization is intended to exist as a contextually-based infobutton rather than a mandatory CDS alert. Contextual information (e.g., diagnoses) is considered along with correlation to colleagues' historical data and patient outcomes.

Hypothesis

When ordering tests, providers have a difficult time quantifying the patient's and their own pre-test probability of an abnormal test result. The diagnostic utility of a laboratory test is likely highly variable depending on the ordering provider (i.e., his or her historical trend) and patient context. I hypothesize that the rate of abnormal test results varies dramatically among providers, resulting in disparities in diagnostic utility.

Visualizing such abnormalities in a framework will educate providers, uncover disparities, and potentially impact ordering behavior.

The proposed research seeks to:

1) Quantify the rates of abnormal test results ordered by providers
2) Identify disparities in frequency of tests ordered or abnormal results obtained by providers
3) Develop visualization tools intended to provide an overview for providers useable at the point of order entry as an infobutton (and beyond)
4) Seek to determine if clinically-relevant contextual distinction can be created and visualized

MATERIALS AND METHODS

Data Acquisition

Data were collected on patients admitted to the Cleveland Clinic main campus medical intensive care unit (MICU) between April 2010 and December 2013. Patients were included if they were assigned to a bed in one of four MICU locations: G60, G61, G62, or G91. Data were collected prospectively under Cleveland Clinic Institutional Review Board (IRB) Registry 11-524 ("Medical Intensive and Respiratory Special Care Unit Outcomes Registry"). For the current study, the data were ascertained and reviewed in a retrospective fashion.

Data elements collected included demographics (gender, age), order-specific details (attending physician, order date and time, and order status), and lab results (result

date and time, result, abnormally low or high, and normal laboratory values). Additional data were obtained from a business intelligence system, EPSi (Allscripts, Chicago, IL) and merged to the MICU registry by medical record number and date. EPSi data included International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) diagnosis codes).

Approval to conduct the retrospective medical records review was obtained from Cleveland Clinic IRB (14-032) and Oregon Health and Science University IRB (IRB00010365) by way of waived oversight.

Data Analysis and Visualization

Data were stored and analyzed using a commodity 64-bit server running Ubuntu Linux 12.04.3 LTS with an AMD FX^{TM}-4100 Quad-Core Processor, 4 GB of RAM, and 2 TB RAID 0 hard disk array. Software employed included a MySQL 5.5.34 database (Oracle Corporation, Redwood City, California), Apache 2.2.22 Web server (Apache Software Foundation, Forest Hill, Maryland), and PHP: Hypertext Preprocessor 5.3.10 scripting language (The PHP Group). Data display was accomplished using HyperText Markup Language (HTML) 4.01 Transitional.

Statistical analyses were performed using custom-written PHP functions along with functions from a standard PHP class *PECL stats* (e.g., stats_cdf_chisquare). Student's t-test for continuous variables and chi-squared test for categorical variables were used to evaluate for statistical significance. Odds ratios using 95% confidence intervals were also calculated. A p-value of 0.05 was used to determine statistical significance.

RESULTS

Demographics

Between April 2010 and December 2013, 10,160 patients were admitted to the Cleveland Clinic main campus MICU. Those patients were present in the MICU for 12,413 episodes of care. 3,883 different named orders were placed for a total of 4,074,440 orders. 1,557 providers ordered tests on patients during the timeframe. Given the large data set and the prototype nature of the work, I focused explicitly on the following most common orders with their respective component results: ACTIVATED PTT, BASIC METABOLIC PNL, CBC + AUTO DIFF, CBC + PLT, CK TOTAL AND CK-MB, COMP METABOLIC PANEL, MAGNESIUM BLD, MAGNESIUM BLD., PHOSPHORUS INORGANIC, PROTHROMBIN TIME/PT, TROPONIN T, URINALYSIS WITH MICROSCOPIC. For brevity, only a selected subset of the orders are presented in this work to illustrate the visualization framework.

Visualization Framework

The goal of developing the framework was to provide a variety of tools that a provider could use to analyze his or her historical laboratory ordering practices and results. Each is described below.

Order Components

A single laboratory order often represents a variety of constituent components. The first step in the framework is an interface to allow users the ability to view results, by

order component, as desired. A production tool could be programmed to show, hide, or sort the components based on local or user-defined preferences. Figure 1 illustrates an example of the component values when a user reviews data for a CK TOTAL AND CK-MB order. The user has the ability to review his or her historical rate of normal and abnormal results. In addition, the aggregated historical results of all providers at the institution are displayed for comparison. This view contains significant amounts of data that may be overwhelming in a production environment. Nevertheless, it can be made available if a user selects "view more data," or analogous, in a production environment.

Frequency Histograms

Histograms allow the provider to review his or her data compared to colleagues' when focusing on normal, abnormal, or all values. Figure 2 illustrates a histogram of all laboratory values for a TROPONIN T order. The limits of normal are adjustable, depending on the provider's preferences and possibly clinical context. A production environment could tailor the limits based on a variety of clinical conditions and the laboratory result (e.g., principal diagnosis, multiple repeated orders of the same test, etc.). The histograms provide a way for users to quickly visualize how frequently their laboratory results are normal (or abnormal) and if there are disparities between themselves and colleagues.

Diagnosis-based Context Specificity

Analysis of laboratory results must occur in a context-sensitive fashion. Figure 3 illustrates, given the presence of a selected diagnosis, the odds of having an abnormal test

result. The list is ordered by decreasing odds ratios, with odds less than one at the bottom of the list. Such a list can help providers understand how they utilize laboratory orders in the context of the diagnoses associated with patients. Similarly, Figure 4 illustrates a list of diagnoses sorted by the frequency with which they are present in association with a laboratory order. Comparison between a selected provider and colleagues is available.

The present work utilized retrospective review of data coded after discharge. A production environment could compare a working list of available diagnosis codes—perhaps even just the principal diagnosis—to the historical data. Highlighting where the diagnoses lie on the sorted list of odds ratios could help frame a provider's understanding of his or her historical utilization practices and whether proceeding with the desired order would be meaningful. The opportunity to create designated, appropriate, or expected diagnoses for a laboratory order or component would help highlight if the laboratory test is used appropriately. A list, such as complied in Figure 3, would be a possible place for a clinical guidelines committee to start.

Provider-specific Notes

Finally, to summarize the diagnosis-specific comparisons in a simple manner usable by providers, I created a notes section. Figure 5 illustrates some of the notes for a TROPONIN T order, highlighting differences (or similarities) between the selected provider an all colleagues. The notes provide a personalized, dashboard-type review of historical behavior that can help a provider understand his or her trends and possibly influence or change ordering behavior.

DISCUSSION

By individual provider or as a whole, there are numerous disparities in how and why providers utilize laboratory testing, as measured by the frequency of abnormal or normal results. The disparities may be due to clinical variation in patients, incorrect use of laboratory orders, antiquated training, clinical policy, or to mitigate liability. A very likely explanation is the increased use of CPOE order sets. A complex discussion, however, is beyond the scope of the current project. This work sought to provide ways to analyze individual orders, by provider, in order to identify and suggest correctable reasons for such disparities.

Giving a provider information that identifies he or she orders the test for a certain associated diagnosis more or less than colleagues is intended to help the provider understand if his or her historical ordering practices are sensible. In addition, reviewing one's own historical tendencies for the odds of an abnormal test result associated with a diagnosis may help shape a provider's understanding of his or her ordering efficiency. The project's goal was to construct visualization tools to help providers answer the questions: "Have I historically been ordering this laboratory test appropriately and effectively?" and "How do I compare to my colleagues using this laboratory test?" I feel this framework can help providers answer those questions.

In completing the project, I realized that it would be helpful to devise a standard or ontology that would classify the appropriate diagnoses (e.g., by ICD-9-CM codes) for each laboratory test to maximize sensitivity or specificity, depending on the desired diagnostic utility. For example, if a Troponin test is ordered to identify cardiac strain or damage, what are the diagnoses for which such a test is expected and appropriate? Such

a list of diagnoses would change if the goal of the test, in the individual circumstance or perhaps always, varied based on the desire to rule out a diagnosis (sensitivity) or rule in a diagnosis (specificity). The ability to systematically and objectively determine such a list may be challenging, but will be an important topic for informaticians to consider in the future. Just like laboratories determine normal limits based on reviewing frequency distributions, so too could such a list of diagnoses be determined.

Limitations

At times, MICU patients are boarded in locations outside of the designated MICU typically due to limited bed availability or a multi-disciplinary team care. In those cases, the patient would not have been included in the data for this study. Given that the study's goals were to provide a visualization framework, incomplete data were tolerable.

Demographic data were incompletely available on the patients in the data set (8,894 or 88%). In addition, ICD-9-CM codes were linked for 8,366 of the patients in the data set (82%). The data were also reviewed in a retrospective fashion. ICD-9-CM codes were formally assigned after discharge, which is not reflective of a production clinical environment. Assignment of ICD-9-CM codes during hospitalization does occur and could be used to compare the current patient to historical data. In addition, certain behavior may have been driven by residents, fellows, protocols, or order sets. Capturing those differences in a retrospective review—and perhaps in a clinical production environment—is challenging.

Providing context- and provider-specific results dynamically in an EHR may be challenging given the large amount of data to be processed, particularly for high

frequency orders. The intended clinical use of the data does not mandate frequent data refreshes and could therefore be processed *a priori* in batch, if significant processing limitations were encountered.

SUMMARY AND CONCLUSIONS

Health care providers, limited by time and accessibility of clinical data through EHRs, need opportunities to determine appropriateness of clinical orders. This work demonstrates the potential infobutton-type approach to allowing providers an opportunity to evaluate their own performance in comparison to colleagues in a patient-specific contextual fashion. While constant alerts and reminders provide limited benefit due to fatigue, personalized data should be made available to interested providers to help make meaningful patient care decisions.

EHRs and CPOE provide an excellent avenue by which many, if not soon to be all, providers enter orders and review results. A multi-faceted approach to curtail unnecessary ordering, particularly of laboratory tests, will likely prevail to provide the most positive results. CDS, consensus-based alerts, restricting ordering, collegial pressure, and context- and provider-specific historical data are all methods that can be employed to achieve the task. Important to the goal is ensuring clinical care delivery is not compromised.

Simple, uncomplicated, provider- and context-specific notes for a laboratory test may provide meaningful feedback to modify ordering behavior. Such notes and feedback are intended to be and would likely function the most effectively in an infobutton approach. Alert fatigue with mandatory alerts or notes is not intended. Future directions

beyond this work include implementation of the framework in a live EHR and CPOE system to measure the impact it might have on changing ordering behavior. Implementation was beyond the scope of this project.

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FIGURES

ORDER: CK TOTAL AND CK-MB

Component	Analysis	Ordered	Patient Encounters	Valid Numbers	Low Values	High Values	Mean	Median	Histograms
CK U/L diagnoses odds	Physician ID 1201198140	605	208	588 [97.2%]	189 [31.2%] ↓	89 [14.7%] ↓	468	1,502	» all values
	Colleagues (excluding ID 0)	16,388	4,963	15,877 [96.9%]	4,492 [27.4%]	2,995 [18.3%]	445	292	» normal values » abnormal values » abnormal (low) values
	Statistical Difference?			No (p 0.757)	**Yes (p 0.043)**	**Yes (p 0.029)**	No (p 0.847)		» abnormal (high) values
CK MB % % diagnoses odds	Physician ID 1201198140	603	208	160 [26.5%] ↓	0	26 [4.3%] ↓	0.7 ↓	1.8	» all values
	Colleagues (excluding ID 0)	16,344	4,961	5,681 [34.8%]	0	1,232 [7.5%]	1.1	19.4	» normal values » abnormal values
	Statistical Difference?			**Yes (p < 0.0001)**		**Yes (p 0.004)**	**Yes (p < 0.0001)**		» abnormal (high) values
MB ng/mL diagnoses odds	Physician ID 1201198140	603	208	603 [100.0%]	0	69 [11.4%]	6.9	2.3	» all values
	Colleagues (excluding ID 0)	16,349	4,961	16,272 [99.5%]	0	2,001 [12.2%]	6.2	2.8	» normal values » abnormal values
	Statistical Difference?			No (p 0.167)		No (p 0.601)	No (p 0.506)		» abnormal (high) values

Figure 1. Physician-specific analysis of laboratory results of components on order for CK TOTAL AND CK-MB. Emphasis is on comparing the selected physician's performance to that of his or her colleagues'. Highlighted cells draw the user to physician vs. colleague comparisons that are statistically different. Hyperlinks allow users to view more data about associated diagnoses, odds ratios, or histograms.

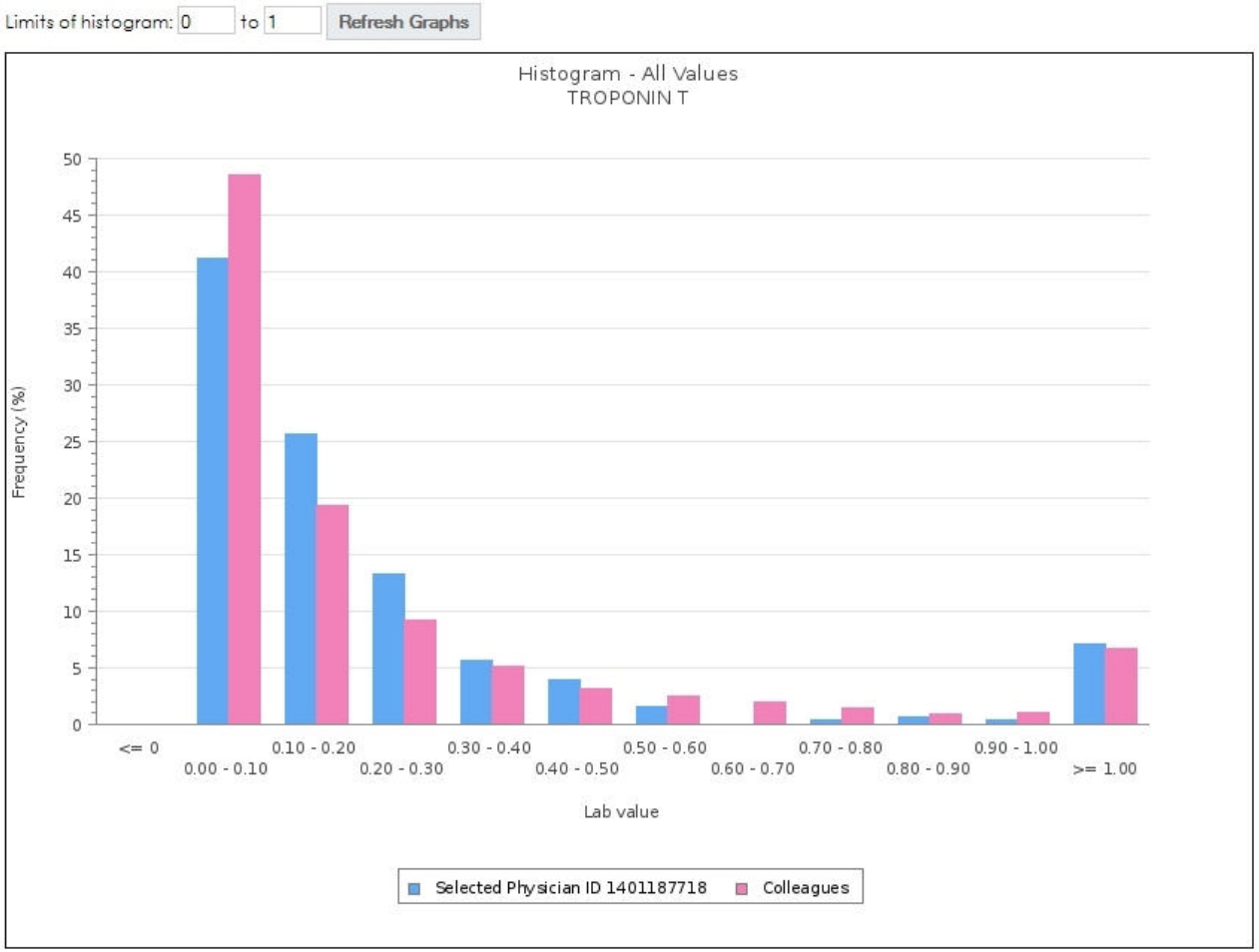

Figure 2. Frequency histogram of laboratory results for TROPONIN T order. Based on the laboratory specified limits of normal, histograms are available for normal, abnormal, or all values. The user can also change the limits of the histogram to review a region of interest. Emphasis is on comparing the selected physician's performance to that of his or her colleagues'.

To be included, each diagnosis must have at least 5 % of total order count. TOTAL: 31,341, CURRENT INCLUSION THRESHOLD: 1,567

Refresh Data

TROPONIN T normal range 0 to 0.1 used to calculate odds [Reference range: 0 - 0.1]

TROPONIN T

If patient has the diagnosis, odds of having an abnormal test result

Highlighted rows are ICD-9 codes "expected" or "appropriate" for **TROPONIN T** (work in progress)

Row	ICD-9	Description	Total Count	OR (95% CI)	p value
1	40391	Hypertensive chronic kidney disease, unspecified, with chronic kidney disease stage V or end stage renal disease [403.91]	3,643 (11.6%)	10.1 (9.3 - 10.9)	< 0.0001
2	41071	Subendocardial infarction, initial episode of care [410.71]	2,602 (8.3%)	8.9 (8.1 - 9.8)	< 0.0001
3	V4511	Renal dialysis status [V45.11]	3,326 (10.6%)	8.6 (7.9 - 9.3)	< 0.0001
4	5856	End stage renal disease [585.6]	4,386 (14.0%)	8.5 (7.9 - 9.1)	< 0.0001
5	28521	Anemia in chronic kidney disease [285.21]	3,303 (10.5%)	5.5 (5.1 - 6.0)	< 0.0001
6	4148	Other specified forms of chronic ischemic heart disease [414.8]	2,005 (6.4%)	3.4 (3.1 - 3.7)	< 0.0001
7	4275	Cardiac arrest [427.5]	3,394 (10.8%)	3.3 (3.0 - 3.5)	< 0.0001
8	70723	Pressure ulcer, stage III [707.23]	2,186 (7.0%)	3.0 (2.8 - 3.3)	< 0.0001
9	70703	Pressure ulcer, lower back [707.03]	5,550 (17.7%)	2.8 (2.7 - 3.0)	< 0.0001
10	2753	Disorders of phosphorus metabolism [275.3]	8,027 (25.6%)	2.6 (2.5 - 2.7)	< 0.0001
11	70725	Pressure ulcer, unstageable [707.25]	2,105 (6.7%)	2.5 (2.3 - 2.6)	< 0.0001
12	2763	Alkalosis [276.3]	5,070 (16.2%)	2.5 (2.4 - 2.7)	< 0.0001
13	34831	Metabolic encephalopathy [348.31]	2,405 (7.7%)	2.4 (2.2 - 2.6)	< 0.0001
14	570	Acute and subacute necrosis of liver [570]	2,140 (6.8%)	2.4 (2.2 - 2.6)	< 0.0001
15	78552	Septic shock [785.52]	8,168 (26.1%)	2.3 (2.2 - 2.4)	< 0.0001
16	2767	Hyperpotassemia [276.7]	6,123 (23.9%)	2.3 (2.2 - 2.4)	< 0.0001
17	78559	Other shock without mention of trauma [785.59]	4,323 (13.8%)	2.1 (2.0 - 2.3)	< 0.0001
18	2869	Other and unspecified coagulation defects [286.9]	2,555 (8.2%)	2.1 (2.0 - 2.3)	< 0.0001
19	3572	Polyneuropathy in diabetes [357.2]	1,996 (6.4%)	2.1 (1.9 - 2.3)	< 0.0001

Figure 3. If a patient has the diagnosis, odds of having an abnormal test result for a TROPONIN T order. The list is sorted by decreasing odds of the diagnosis resulting in an abnormal test result. Highlighted rows were manually selected as diagnoses expected or likely to result in abnormal test results. Default inclusion criteria are that a diagnosis must be present for 5% of the total order count. Default laboratory limits of normal are provided. The user may adjust the inclusion criteria percentage and default limits of normal. CI = confidence interval; OR = odds ratio.

TROPONIN T

Row	ICD-9	Description	Colleague Count	Total Principal Diagnosis Count	Provider Count (1401187718)
1	51881	Acute respiratory failure [518.81]	14,285 (45.6%)	2,123 (6.8%)	251 (37.3%)
2	V1582	Personal history of tobacco use [V15.82]	13,402 (42.8%)	0	227 (33.7%)
3	4280	Congestive heart failure, unspecified [428.0]	11,583 (37.0%)	80 (0.3%)	229 (34.0%)
4	4019	Unspecified essential hypertension [401.9]	11,197 (35.7%)	72 (0.2%)	128 (19.0%)
5	42731	Atrial fibrillation [427.31]	10,975 (35.0%)	163 (0.5%)	141 (21.0%)
6	5849	Acute kidney failure, unspecified [584.9]	10,851 (34.6%)	384 (1.2%)	221 (32.8%)
7	2762	Acidosis [276.2]	10,321 (32.9%)	3 (0.0%)	190 (28.2%)
8	2724	Other and unspecified hyperlipidemia [272.4]	10,282 (32.8%)	0	252 (37.4%)
9	99592	Severe sepsis [995.92]	9,517 (30.4%)	2 (0.0%)	158 (23.5%)
10	2768	Hypopotassemia [276.8]	8,808 (28.1%)	32 (0.1%)	152 (22.6%)
11	78552	Septic shock [785.52]	8,018 (25.6%)	0	150 (22.3%)
12	2767	Hyperpotassemia [276.7]	7,946 (25.4%)	55 (0.2%)	177 (26.3%)
13	2753	Disorders of phosphorus metabolism [275.3]	7,817 (24.9%)	0	210 (31.2%)
14	V5866	Long-term (current) use of aspirin [V58.66]	7,803 (24.9%)	0	165 (24.5%)
15	5990	Urinary tract infection, site not specified [599.0]	7,352 (23.5%)	71 (0.2%)	79 (11.7%)
16	V4986	Do not resuscitate status [V49.86]	7,189 (22.9%)	0	146 (21.7%)
17	41401	Coronary atherosclerosis of native coronary artery [414.01]	7,058 (22.5%)	6 (0.0%)	100 (14.9%)
18	0389	Unspecified septicemia [038.9]	6,996 (22.3%)	2,616 (8.3%)	74 (11.0%)
19	2761	Hyposmolality and/or hyponatremia [276.1]	6,860 (21.9%)	58 (0.2%)	109 (16.2%)
20	25000	Diabetes mellitus without mention of complication, type II or unspecified type, not stated as uncontrolled [250.00]	6,590 (21.0%)	0	92 (13.7%)
21	2851	Acute posthemorrhagic anemia [285.1]	6,425 (20.5%)	53 (0.2%)	83 (12.3%)
22	2760	Hyperosmolality and/or hypernatremia [276.0]	6,335 (20.2%)	23 (0.1%)	135 (20.1%)
23	4168	Other chronic pulmonary heart diseases [416.8]	6,155 (19.6%)	139 (0.4%)	110 (16.3%)
24	42789	Other specified cardiac dysrhythmias [427.89]	5,886 (18.8%)	41 (0.1%)	123 (18.3%)
25	53081	Esophageal reflux [530.81]	5,856 (18.7%)	5 (0.0%)	129 (19.2%)
26	486	Pneumonia, organism unspecified [486]	5,792 (18.5%)	663 (2.1%)	156 (23.2%)

Figure 4. Diagnoses most frequently encountered for a TROPONIN T order. The list is sorted by decreasing diagnosis frequency encountered by colleagues. The frequency for the selected provider is also available in order to compare the provider to colleagues. Highlighted rows were manually selected as diagnoses expected or likely to result in abnormal test results.

ORDER: TROPONIN T

Component	Notes
TROPONIN T *ng/mL* diagnoses odds	• Colleagues' most common associated diagnosis: **Acute respiratory failure [518.81]** at 87% vs. your 37% • Your most common associated diagnosis: **Other and unspecified hyperlipidemia [272.4]** at 37% vs. colleagues' 63% 3 diagnoses with highest odds of abnormal **TROPONIN T**:

OR	95% CI	p value	Diagnosis
10.1	9.3 - 10.9	< 0.0001	Hypertensive chronic kidney disease, unspecified, with chronic kidney disease stage V or end stage renal disease [403.91]
8.9	8.1 - 9.8	< 0.0001	Subendocardial infarction, initial episode of care [410.71]
8.6	7.9 - 9.3	< 0.0001	Renal dialysis status [V45.11]

Figure 5. Notes for analysis of laboratory results of components on order for TROPONIN T. CI = confidence interval; OR = odds ratio.