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Health information technology generates vast amounts of electronic data in our hospital information systems. Information overload, however, hinders our efforts to use these data to address patient safety issues. This study describes an application of Business Intelligence (BI), a method for leveraging enterprise data, in analyzing clinical data for gaining knowledge about our methods of blood glucose testing at Duke University Hospital. We extracted glucose readings from our data warehouse using a web-based BI tool. We then compared two instruments used to measure blood glucose concentration in neonates, the point-of-care-testing (POCT) device and the gold standard laboratory analyzer. Our results indicate significant variance between the two instruments, suggesting an increased risk of under-diagnosing neonatal hypoglycemia. Hematocrit and hypoglycemia were found to be factors in this variance. We recommend further evaluation of POCT devices, leveraging clinical data, borrowing data management strategies from other industries, and fostering education in medical informatics.

Headings:

Medical Informatics – Technological innovations

Medical records – Data processing

Medicine/Databases

Medicine

Evidence-based medicine

VARIANCE BETWEEN LABORATORY AND POINT-OF-CARE TESTING OF  
BLOOD GLUCOSE: BUSINESS INTELLIGENCE TOOLS FOR PATIENT SAFETY

by  
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## **Introduction**

In recent years, hospitals have embraced the goal of improving patient safety and clinical effectiveness.<sup>1</sup> The Institute of Medicine reports and their focus on evidence based care<sup>2,3</sup> have inspired health care leaders to systematically improve their care delivery systems rather than attribute errors to the individuals who operate within them.<sup>4</sup> Advances in safety policy have accumulated at a rapid rate,<sup>5</sup> and health systems often struggle to keep up with the growing body of patient safety recommendations. The promise of electronic health records, clinical decision support, and health analytics have prompted significant excitement among health systems engaged in quality improvement initiatives.<sup>6</sup> Numerous studies demonstrate the potential of medical informatics implementations in addressing diverse patient safety issues.<sup>7-10</sup> Physicians' increasing use of health information technology, however, continues to face obstacles for effective application to safety and quality of health care, and experts call for research in this area.<sup>11</sup>

One such obstacle is the sheer volume of information that clinicians confront. Not only do they inundate themselves with the information retrieval necessary for evidence based clinical practice,<sup>12</sup> they also do so inadvertently through all the data collected as a byproduct of care.<sup>13</sup> Many hospitals have implemented electronic health records, computerized physician order entry (CPOE), and clinical laboratory systems that all contribute to terabytes of data amassing in clinical data silos. The full-fledged adoption of electronic health records and advances in genomic medicine promise to

increase both the rate and complexity of data accumulation. This unwieldy accumulation is fertile ground for research, and the information yielded could promote greater health system efficiency, increased patient safety, and accelerated knowledge discovery. The secondary use of health data – the use of health data outside of direct patient care – is already becoming an important priority in our nation’s healthcare agenda.<sup>14</sup> However, our comprehension of this data is not keeping pace with its accumulation.<sup>15</sup> An active investment in data governance, data warehousing, and health analytics is necessary to harness the potential of our burgeoning data stores.

Other industries faced with similar obstacles have developed and refined Business Intelligence (BI) technology, the aim of which is to transform an organization’s data into useful, informed actions. BI encompasses the methodologies, analytical tools, applications, and databases that allow for this important transformation.<sup>16-18</sup> While different implementations of BI vary in their emphases on reporting, analytics, and data warehousing/storage, the broad goal is to support interactive access to an organization’s data for decision making and to provide a holistic and accurate view of the business.<sup>16-18</sup> Since the introduction of BI in the 1980s, industries such as finance, automotive, energy, and e-commerce have recognized that the ability to transform data into informed actions is a necessary strategic advantage.<sup>16-18</sup> In an environment of increasing global competition, organizations without the quick ability to retrieve and analyze their own data for identifying errors and monitoring performance are at a considerable disadvantage.<sup>19</sup> Just as these other industries use BI tools to leverage data for performance improvement and seeking profits in competitive markets, so can hospitals do the same for seeking increased patient safety and quality of care.

The purpose of this study is to demonstrate the value of Business Intelligence in the clinical realm by investigating the precision and accuracy of point-of-care glucose testing in the neonatal population at Duke University Hospital. We respond to two questions: Is point-of-care testing (POCT) accurate when compared to our gold standard laboratory measurement? How can we employ BI tools to clinical data and patient safety questions?

In this investigation, we focus on a single facet of BI: the hypothesis-driven querying and reporting. This method of analyzing data with specific questions in mind is distinct from - but complementary to - other BI applications such as data mining, which is automated and discovers hidden patterns in data. We demonstrate that clinically relevant information can be gained by retrieving and analyzing a large set of clinical data from our enterprise data warehouse known as the decision support repository (DSR).

## **Background**

### **Business Intelligence**

The term Business Intelligence was coined by H. P. Luhn in 1958 when – suggesting that progress in any human endeavor depends on the efficient communication of information – he described a hypothetical system designed to deliver timely, actionable information to the hands of decision-makers.<sup>20</sup> The necessity for businesses to have access to timely, accurate, and actionable information has grown since then, and the widespread use of commercial BI tools was observed by the mid-1990s.<sup>16</sup> BI tools are needed because they facilitate the use of data stored in an organization's electronic information systems - data that otherwise would have been stored and forgotten, possibly

in unusable or incompatible formats. For businesses to leverage their electronic data, they use BI tools to place the data in a meaningful context (yielding “information”), and then discern relationships in the information (gaining “knowledge”).<sup>21</sup> BI tools are designed to transform data into *actionable knowledge*. Here is an example of this pathway. Unorganized numbers in the rows and columns of a database are meaningless unless they are transformed to the context of financial figures to *inform* about financial gains and losses. Understanding relationships between these gains and losses, and their relationships to business policies, indicates *knowledge* about how policies affect business performance. If this knowledge can be gained in a timely fashion, it is *actionable*, and decision-makers can use it to guide the direction of the business’s future ventures.

Central to all BI implementations is the Data Warehouse (DW), a specialized repository of data optimized for querying and analysis. Sustaining this warehouse is an Extract, Transform, Load (ETL) process to gather data from across an organization's transactional systems and load them into the DW (Figure 1). Using this aggregate data, three main classes of investigation are typically supported through BI applications: (i) querying, reporting, and hypothesis-driven analysis; (ii) data mining and knowledge discovery; and (iii) business performance management (BPM).<sup>16</sup> In the first application, users create *ad hoc* reports and analyze data to understand relationships. Data mining is a sophisticated technique facilitating the discovery of novel or hidden patterns in data. BPM is commonly utilized by business executives using the balanced scorecard, a methodology for monitoring business performance with a well-rounded set of metrics.<sup>22</sup> These powerful capabilities lead to the popular impression of BI tools for providing access to the right information at the right time in the right place.<sup>16</sup>

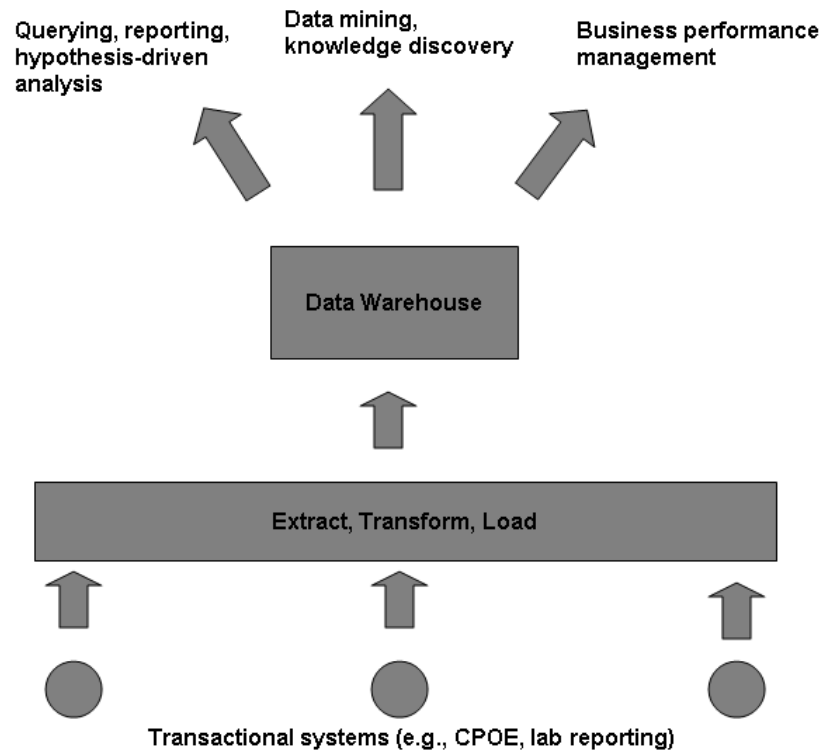


Figure 1. The BI process and functionalities

The real-world application of BI tools is exemplified by businesses such as Toyota, Overstock.com, and Coca-Cola, who use BI to correct errors and inefficiencies, view real-time performance, and outperform their competitors.<sup>16</sup> It is common for successful businesses to have developed BI implementations when facing difficulties with organizational data.<sup>16-18</sup> Toyota, for example, developed its BI system in response to numerous problems including error-ridden data, strong competition, difficulty sharing information, and lack of access to information needed for quick decision-making.<sup>16</sup>

In healthcare systems, BI tools are ever more important for strategic management, applied to administrative data and used primarily by health executives.<sup>23-26</sup> St. Francis Physician Hospital Organization, a 650-physician group in Hartford, Connecticut, has successfully used a BI system to determine where to expand their business in terms of

specialties and locations.<sup>27</sup> They were also able to determine how to market their physicians more effectively after discovering that many of their patients were looking outside of the organization for care in particular specialties.<sup>27</sup> Brigham and Women's Hospital in Boston has used a BI tool with a scorecard methodology to manage 10,000 patient satisfaction surveys per year and to help increase satisfaction scores for obstetric nursing from the 50th percentile to the 90th percentile.<sup>27</sup>

Increasingly, healthcare systems are showing an interest in developing more clinically-themed warehouses of health data.<sup>28</sup> Several investigations highlight the value of leveraging such repositories for data mining, a non-hypothesis-driven technique for the undirected discovery of new associations. Prather et al.<sup>29</sup> described a technique for data mining using factor analysis in a large clinical database to discover factors associated with preterm birth. Harrison<sup>30</sup> described the value of "well-standardized and well-characterized data" in clinical laboratory databases - in combination with other clinical data - for research and discovery of interactions between genotype, phenotype, and disease in populations. Mullins et al.<sup>31</sup> also demonstrated the potential of mining a large clinical database for the identification of previously well-known and novel disease associations. Clinical data warehouses prove invaluable in these studies because data collection is far easier than if the data had to be extracted anew from multiple operational systems.<sup>28</sup>

At Duke University Hospital we have demonstrated the use of our clinical data warehouse and business intelligence tools in a few cases. We created dynamic safety reports of adverse drug events by aggregating data from several clinical databases.<sup>32</sup> In another example, we determined the economic impact on total hospital costs of

Methicillin-resistant *Staphylococcus aureus* infection control policies in the neonatal intensive care unit.<sup>33</sup> With the encouraging success of data mining and our recent endeavors, we seek to apply the clinical data warehouse and its associated BI tools for investigation into more clinical scenarios, in this case, POCT for blood glucose. Our techniques complement the prior research in data mining, and we aim to fill a gap in hypothesis-driven analysis of a large clinical data warehouse.

### **Neonatal hypoglycemia and the importance of point of care testing**

Maintaining adequate levels of blood glucose is essential to normal neural function and development in newborns.<sup>34</sup> Neurological dysfunction has been associated with neonatal hypoglycemia which manifests both acute<sup>35</sup> and long-term<sup>36-38</sup> effects. Clear associations have not been established between specific blood glucose values and neurological injuries. Even the identification of clinically significant hypoglycemia is a difficult task, with little consensus surrounding its definition, diagnosis, significance, and outcome.<sup>34,39-41</sup> Empirical evidence to inform clinical practice regarding neurodevelopmental outcomes and neonatal hypoglycemia is sparse,<sup>42</sup> and past research has shown inconsistent study designs, questionable accuracy of glucose measurements, and heterogeneous patient characteristics. To practically address these uncertainties, operational thresholds for neonatal hypoglycemia interventions have been suggested,<sup>39</sup> and others call for tailoring diagnosis and management to each patient, while holding a low threshold for diagnosis and attentively taking frequent blood glucose measurements.<sup>41</sup>

The most reliable and accurate testing method is in the clinical laboratory, but drawbacks include the relatively large volume of blood needed for analysis as well as the amount of time to run results. Point-of-care testing with a bedside glucometer is advantageous, requiring a smaller volume of blood and quickly informing the clinician. The glucometer was originally designed in the context of the adult diabetic, where self-screening for hyperglycemia is the priority, and detection of hypoglycemia is assisted by the patient's own recognition of symptomatology. These devices are increasingly being used to monitor the glycemic status of neonates in the NICU, and anecdotal evidence from our institution indicates that clinicians rely on them heavily for decision-making. There are concerns about the use of these instruments in the neonatal population.<sup>43</sup> For example, while a difference of 10 mg/dL in blood glucose concentration is not likely to change the management of a hyperglycemic adult diabetic, such an error in a newborn has important implications for intervention, stressing the need for confirmatory testing in the laboratory.<sup>44</sup>

Numerous studies have investigated the accuracy of POCT devices in neonates and other populations, and no consensus has been reached regarding accuracy. The International Organization for Standardization (ISO) has recommended that 95% of measurements should be within 15 mg/dL for blood glucose concentrations  $\leq 75$  mg/dL, and  $\pm 20\%$  for glucose concentrations  $> 75$  mg/dL.<sup>45</sup> While some studies report satisfactory accuracy and recommend the use of specific POCT devices,<sup>46,47</sup> others have found even the same instruments to be inconsistent and unsuitable.<sup>48-50</sup> Operator error is likely a reason for inconsistency in measurements.<sup>51</sup> Other contributing factors include greater fluctuations of blood glucose levels in newborns compared to older children<sup>52</sup> and

differences in glucose concentration between plasma and blood. Some discrepancies may also be attributable to errors in laboratory reference methods.<sup>53</sup> Additionally, the time delay associated with sending samples to the laboratory can account for glycolytic decreases in glucose concentration, as can increased levels hematocrit.<sup>54</sup>

There is a need for continued evaluation of blood glucose POCT performance. The unique needs and risks of the NICU add to our urgency to address this gap in understanding our clinical procedures.

### **Materials and methods**

This investigation was IRB exempt as it did not constitute human subjects research as defined under federal regulations [45 CFR 46.102 (d or f) and 21 CFR 56.102(c)(e)(1)].

#### **Study design**

A retrospective analysis was performed on data contained in the Duke University Health System Decision Support Repository, its enterprise data warehouse. Blood glucose concentration readings were extracted for a population of infants under one year of age who had a POCT glucose measurement taken within 15 minutes of a gold standard lab glucose measurement. Values analyzed by POCT devices were compared with values analyzed by laboratory instruments. Comparisons were made between these two readings on the same patient. Two analyses were conducted. In the first, we examined the variance between POCT and laboratory values as a function of the gold standard

laboratory value. Secondly, we evaluated the influence of hematocrit on laboratory and POCT blood glucose values.

### **Materials**

Duke University Health System has implemented a COGNOS (Armonk, NY) BI tool to access data collected in the Decision Support Repository.<sup>32,55</sup> The reporting tool is foundational to Duke's online query system, known as the Duke Enterprise Data Unified Content Explorer (DEDUCE) (Figure 2), and enables users to extract data from the warehouse. The tool is designed to assist researchers with varying levels of computer expertise to access the data warehouse.<sup>32,55</sup> DEDUCE uses a simple interface for constructing queries and viewing results. Neither knowledge of Structured Query Language (SQL) nor familiarity with database design is necessary to use DEDUCE, as the system guides the user through a step-by-step process of constructing a query. DEDUCE allows users to retrieve datasets by patient demographics and through five subject areas: diagnoses, procedures, labs, CPOE orders, and medication orders.

The underlying Decision Support Repository is run on an Oracle 9.2 (Redwood Shores, CA) database. Using an ETL application, this data warehouse is updated daily with laboratory data from operational systems for inpatient and outpatient services throughout Duke's health system.

Data for blood glucose values were obtained from both laboratory and POCT devices. Laboratory analysis was performed with either the Beckman Coulter UniCel DxC 800 (Fullerton, CA) or Danaher Radiometer ABL 835 (Washington, DC). POCT samples tested before May 2007 were analyzed with the Abbott PCx (Abbott Park, IL),

and samples drawn after June 2007 were analyzed with the Roche ACCU-CHEK (Basel, Switzerland). It is important to note that we combined data collected from different models of POCT devices. However, a preliminary investigation at our institution indicated no significant difference in variance when data from the two models are evaluated independently.

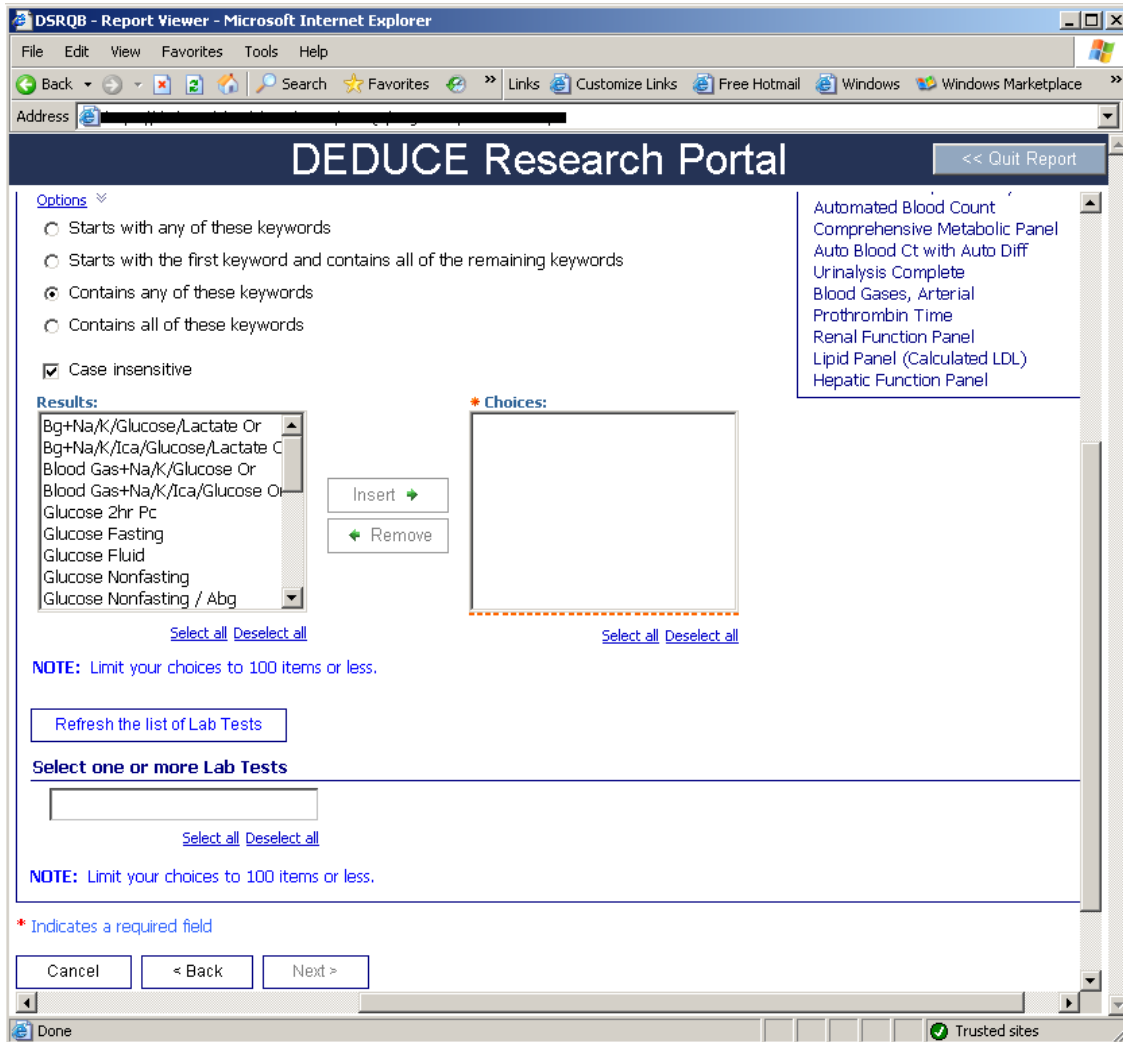


Figure 2. Screenshot of DEDUCE

### **Data extraction and analysis**

DEDUCE was used to retrieve blood glucose data for pediatric patients who were less than one year of age at the time when blood was drawn for routine patient care between June 2001 and March 2009. Blood glucose values for POCT were included if they were obtained within 15 minutes (before or after) of the report of a laboratory-tested blood glucose value. Hematocrit values were also obtained for the patient on the day of the blood glucose testing.

To minimize error from glycemic changes occurring during processing time and in the interval between the POCT and laboratory tests, we only analyzed blood glucose data pairs within a narrow fifteen minute window. Medical interventions - such as infusion of glucose or insulin - during these intervals could complicate the paired readings. However, the fifteen minute window allows little time for interventions to be initiated, and insulin is rarely used in our NICU.

The dataset was exported for analysis in JMP statistical software (Cary, NC). A POCT value for blood glucose was matched to a corresponding laboratory value through a unique patient key. If the two values fell within the “15-minute-prior” or “15-minute-post” window, a data pair was generated for inclusion in the study. Values for hematocrit were matched to the glucose values if they were obtained on the same day. The difference between blood glucose values in each pair was calculated to yield the variance ([POCT value] – [laboratory value]).

The variance was plotted against the corresponding laboratory value to determine changes in variance according to the laboratory-tested glucose values. To determine the effect of hematocrit on variance, blood glucose values from POCT and laboratory

methods were each plotted against matched hematocrit values. Linear regression analysis was performed to yield a line of best fit for each plot.

## **Results**

A total of 3,692 patients with laboratory tests between June 2001 and March 2009 were studied. All patients were under the age of 1 year at the time of blood sampling. Among the 22,416 laboratory glucose results and 18,507 POCT results, there were 17,222 paired readings, averaging 4.67 pairs per patient.

The blood glucose values measured by POCT ranged from 15 mg/dL to 591 mg/dL, with a mean of 133.40 mg/dL (std dev 67.11) and median of 116.00 mg/dL. Laboratory test values ranged from 10 mg/dL to 1998 mg/dL, with a mean of 123.30 mg/dL (std dev 71.39) and median of 104.00 mg/dL. Daily mean hematocrit values (n=26,714) ranged from 19% to 73% (mean 37.10%, std dev 7.54%, median 36.00%).

### **Variance between POCT and laboratory testing**

The variances in blood glucose values (calculated as [POCT value] – [laboratory value]) were mostly in the positive range (mean 19.12 mg/dL, std dev 34.30, median 19.00, range -918.0 to 499.0). However, 2.5% of the variance was -26 mg/dL or below, indicating that the very negative values in the stated range were outliers.

Linear regression analysis was conducted to evaluate the relationship between variance in the readings to the laboratory values. There was a negative linear relationship between the two variables with variance decreasing with higher laboratory values ( $R^2 = 0.0493$ ,  $p < 0.0001$ ) (Figure 3).

The average positive variance indicates that POCT devices are typically overestimating blood glucose levels compared to temporally associated laboratory results. There was a greater positive variance at lower levels of blood glucose indicating that this overestimation is more pronounced in hypoglycemic patients.

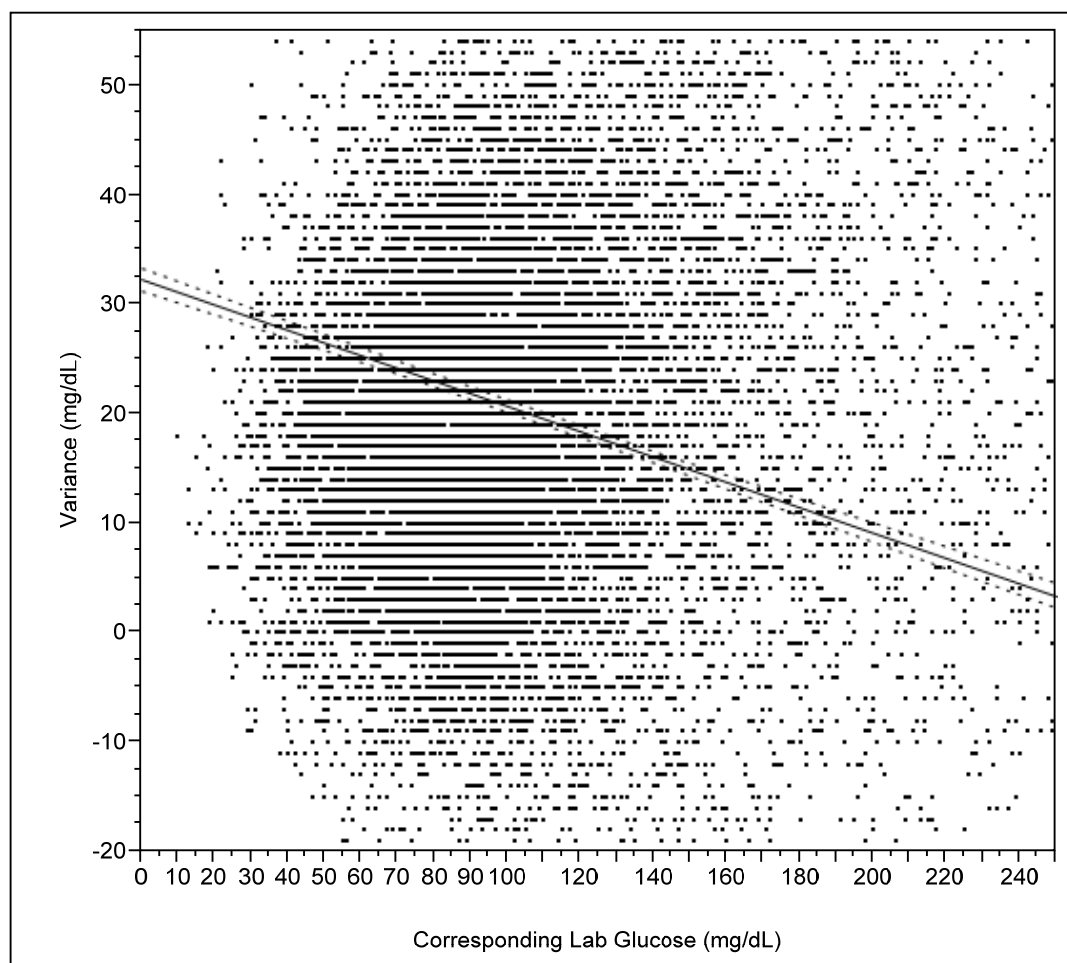


Figure 3. Variance ([POCT value] – [laboratory value]) versus corresponding laboratory glucose value

### **Effect of hematocrit**

Regression analysis demonstrated a negative relationship between blood glucose value and hematocrit for both instruments (laboratory values  $R^2=0.0187$ ,  $p<0.0001$ ; POCT values  $R^2=0.0466$ ,  $p<0.0001$ ) (Figure 4). On average, blood glucose values decrease with increasing hematocrit for both POCT and laboratory tests.

The slope of the line of best fit for POCT ( $m=-198.56$ ) was more negative than that for the laboratory ( $m=-138.75$ ). POCT devices showed greater variation across hematocrit levels, while the laboratory results were relatively more stable.

The regression lines intersect at a hematocrit level of approximately 66%. At this level of hematocrit, both instruments show similar readings. This indicates that for anemic patients, hematocrit levels could explain variance between the devices – and for polycythemic patients, variance between the devices was less accounted for by hematocrit.

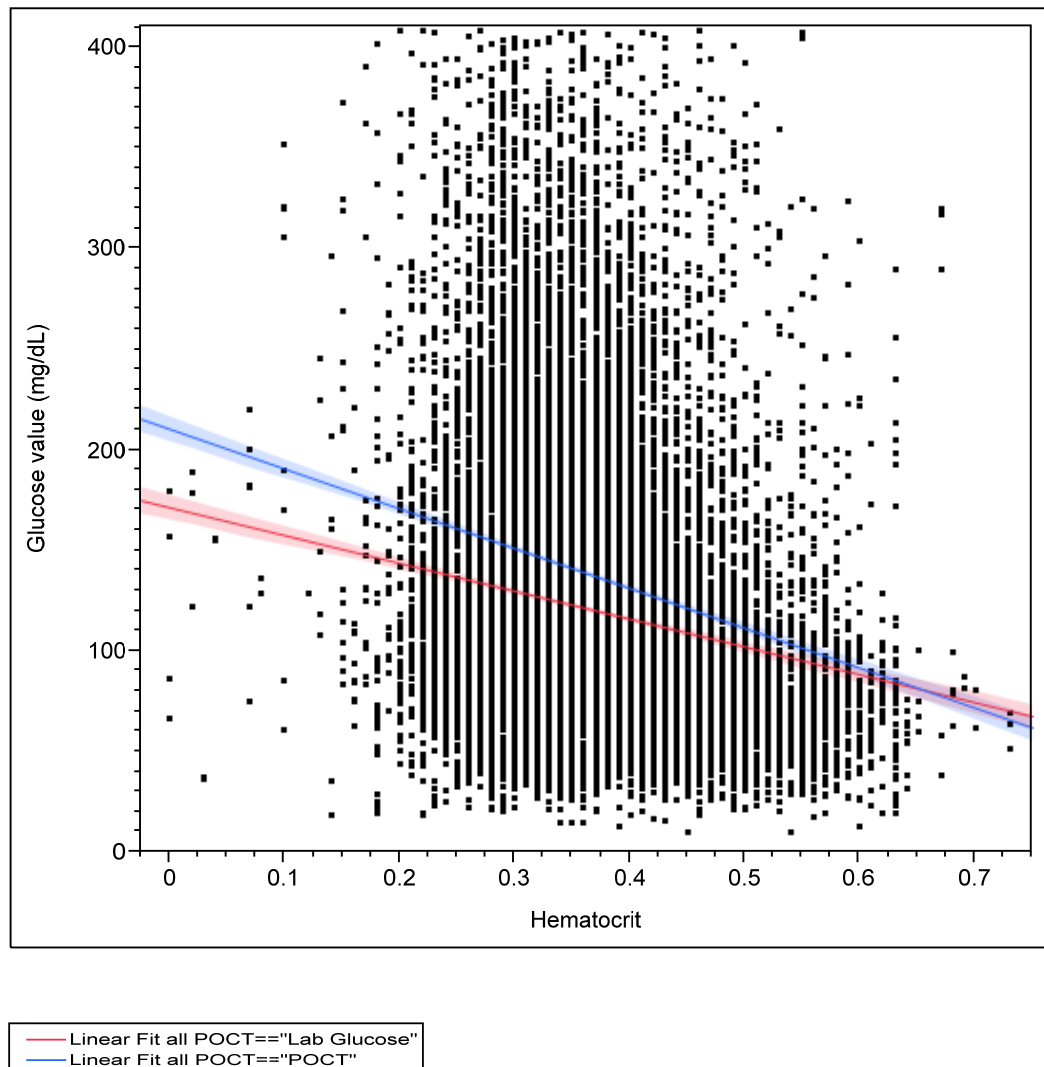


Figure 4. Glucose values versus hematocrit

### **Efficiency of Business Intelligence in this case**

By using Business Intelligence tools, it took less than fifteen minutes to construct the query for data extraction. The automated extraction from the data warehouse took 16 minutes and 35 seconds, rather than the several months a manual chart review would likely have required. The resulting csv data file was compatible with JMP software,

facilitating immediate statistical analysis. Because of the guided query development function of DEDUCE, queries could be written without technical database expertise.

The use of business intelligence tools contrasts with traditional methods of retrospective analysis, which would have involved a time-intensive procedure of manual data extraction by technical personnel. The traditional method would require extensive communication among experts in different fields with possibly several iterations of back-and-forth query refinement before a satisfactory dataset could be obtained. Similarly, a prospective analysis might require much greater numbers of staff and possibly several months to years to complete. By using BI technology in this retrospective analysis for data querying and extraction, this study could be completed in less time and with less staff than other methodologies.

## **Discussion**

### **Variance between POCT and laboratory testing and the effect of hematocrit**

We found significant variance between POCT blood glucose values and gold standard laboratory values in our study sample. According to our linear regression analysis, the variance was greatest in the hypoglycemic range and decreased with higher laboratory blood glucose values.

While the precise risk of neurodevelopmental injury due to neonatal hypoglycemia has not been firmly established, this pattern of variance is still concerning. When laboratory testing recorded blood glucose levels in the hypoglycemic range, many POCT devices were reading values in the euglycemic range. This discrepancy could lead clinicians to under-diagnose and subsequently under-treat neonatal hypoglycemia.

A widely accepted medical decision point is 40 mg/dL – if blood glucose falls below this level, clinicians will initiate medical intervention to increase blood glucose concentration. Interpolating from our regression lines, a laboratory reading of 40 mg/dL corresponds to a POCT reading of approximately 68 mg/dL. With a positive variance of approximately 30 mg/dL indicated by the regression, this may mean a neonate's blood glucose level might fall below 10 mg/dL before the POCT reading would indicate that intervention is necessary.

However, a concern that arises is that the variation we saw could be attributed to time-dependent decreases in glucose concentration that occur between the blood sample drawing and its clinical laboratory analysis. This phenomenon may contribute to lower blood glucose concentrations reported by the laboratory. In this investigation, the timestamp of the laboratory value is the time at which hospital staff drew the patient's blood before sending it to the laboratory. During busy periods, increased processing times by the clinical laboratory could lead to glycolytic decreases in blood samples. However, we expect this problem is mitigated at our institution because of the dedicated pediatric laboratory in close proximity to the NICU and pediatric wards.

In our second analysis, lower hematocrit levels were associated with higher levels of blood glucose for both measurement methods. Also, low hematocrit may be a factor behind the increased variance between the two measurement methods, while higher levels of hematocrit had a less pronounced association with variance. We saw that blood samples from anemic patients demonstrated higher blood glucose levels as measured by POCT. These observations are consistent with other studies,<sup>56-58</sup> so considerations of hematocrit should be taken in further studies of glucose testing performance. This is a

particular concern for critically ill patients whose clinical scenarios are complicated by anemia.

As a tool originally designed for maintaining glycemic control in adult diabetics, the portable glucometer has great value in accurately reading levels of hyperglycemia. However, the use of glucometers has become routine in the NICU for detecting hypoglycemia, which is not the original intention of the device. Although the devices have become indispensable in maintaining tight glycemic control, their use in intensive care units is increasingly under scrutiny for risks of hypoglycemia and possibly increased mortality.<sup>59</sup> Our results showed that POCT devices could under-diagnose hypoglycemia and cautions that their unevaluated use for neonatal patients may not be ideal.

#### **Suggestion #1 – Continued, rigorous evaluation of clinical tools and systems**

POCT devices for glucose measurement are commonly used, but they are not fully tested for the neonatal intensive care population. Our data indicate a potential risk to this population if POCT devices are relied upon as the sole means for decision making in glycemic control. Confirmatory testing by the laboratory is indeed a common - and necessary - occurrence for NICU patients, but POCT devices are nevertheless heavily relied upon. This reliance has spread without the benefit of rigorous evaluation to ensure that the devices deliver accurate results.<sup>60</sup>

This may be a symptom of what Wachter calls the “unforeseen consequences of computerization”<sup>61</sup> in our hospitals. The acceleration of health information technology is furthering the guidelines, rules, decision support, and other systemic practices that control clinicians’ behavior. When safely implemented, these practices have the potential to do

much good; on the other hand, if they are not rigorously evaluated, they could cause problems across the healthcare field. The significant variation we saw in POCT and gold standard laboratory testing indicates a need for evaluating and bolstering our systems for safe blood glucose monitoring.

### **Suggestion #2 - Leveraging our data stores**

The medical profession generates an enormous amount of clinical care data. A clinician may retrieve a patient's blood glucose value, use it for treatment decision making, and then leave it stored and possibly forgotten in the archives of a clinical information system. It is possible for a health system to see terabytes of clinical data neglected in this manner. But the utility and value of these data extend beyond a single use. Data retain their value after the patient leaves the hospital, and achieve greater value when shared and analyzed – they are an organizational asset.<sup>62,63</sup> With data accessible for analysis, experts from diverse fields – for instance, medicine, epidemiology, and computer science - could study them and uncover novel relationships to yield more actionable knowledge. Data warehouses and BI tools facilitate this data-sharing and analysis to the benefit of the health system. We should aim to extract the greatest value from the data that we already have.

### **Suggestion #3 - Learning from other industries**

Fostering positive change and overcoming the inertia of established practices are difficult tasks for any industry - and when one sector has a good idea, it is recommended that all take the opportunity to learn from one another.<sup>64</sup> Two business paradigms for

change are taking hold in medical practice and management. There is the “systems” view of errors<sup>4</sup> - addressing faulty systems rather than holding individuals responsible - and the six sigma methodology,<sup>65</sup> an approach to quality improvement adapted from high-efficiency and high-quality industries such as consumer electronics manufacturing. Data warehouses and BI have proven successful in other industries. Just as businesses have embraced information technology innovations to adapt to pressures of international competition, health care systems could intensify applications of informatics to meet the growing demand for increased patient safety and quality of care, which has been made a priority in our national agenda. BI tools contribute to those efforts, help medical decision-makers understand their environments more thoroughly, and provide information critical for continued improvement.

#### **Suggestion #4 – Cultivating informatics skills in medical training**

Applied medical informatics has demonstrated its success for improving the quality and safety of health care.<sup>10</sup> Informatics skills could be an integral part of patient safety training, so it would be beneficial to cultivate this skill set during the early stages of a physician’s education. The AMIA 10x10 Program<sup>66</sup> provides an excellent opportunity for providing medical informatics training to a wide audience. However, medical informatics appears to be a field largely unexplored by many medical students. Given the growing impact of health information technology and its potential for improving patient safety, cultivating medical informatics skills is important to the future of the health professions.

This study was facilitated in part by an innovative dual degree MD/MSIS program between the Duke University School of Medicine and the School of Information and Library Science at the University of North Carolina at Chapel Hill, which combines graduate education in Information Science within a traditional medical curriculum. We hope this study demonstrates the utility of such interdisciplinary education and how the novel application of information science practices to clinical data can contribute to patient safety discoveries.

### **Limitations**

This study was performed at a large academic medical center, and the results may be difficult to generalize beyond this setting. Ideally, the analysis would have included a larger dataset with more than 8 years of data; however, this analysis was limited to the data available in our data warehouse, which was a relatively recent addition to the Duke University Health System. Obviously, a prospective study is the ideal method by which researchers could determine the precision and accuracy of POCT devices. However, conducting a prospective study with this number of patients – or greater – would be extremely difficult, and it was more feasible to rely on retrospective analyses for their statistical power.

### **Conclusion**

The proliferation of health information technology in our hospitals creates opportunities for Business Intelligence tools to leverage clinical data for patient safety and quality of care improvements. In this study, we used BI tools to identify a significant

variance between POCT devices and laboratory analysis for measuring blood glucose values among pediatric patients. Factors contributing to this variance include hypoglycemia and anemia. Clinicians should evaluate their POCT devices and guidelines to ensure that clinical decisions are based on accurate data. We suggest further studies to be conducted with larger datasets to evaluate the accuracy of blood glucose testing for more patient populations. This research was greatly facilitated by BI tools and we suggest that healthcare leaders consider the potential of this technology for maximizing the value of their institutional data.

### **Acknowledgments**

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