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RESEARCH ARTICLE

The Health-Economic Impact of a Prospectively Validated Severity of Illness Predictor for Adult Critical Care

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ABSTRACT

Background: The ViSIG system, a clinical decision support system for adult intensive care units, was previously shown to be associated with significant reductions in length of stay, readmissions, and duration of mechanical ventilation. However, the health-economic benefits of ViSIG have yet to be fully understood. Infections and acute kidney injury are two measures of clinical significance with key financial implications, and their reduction could further strengthen the published association of ViSIG use with improved outcomes. Further, it is important to demonstrate the economic benefit of ViSIG for its widespread adoption by ICUs.

Objective: To investigate the potential health-economic benefits associated with using a previously validated clinical decision support system, ViSIG.

Study Design and Methods: In this study, we analyzed data from a previous analysis of ViSIG. The study cohort consisted of six ICUs at two hospitals, with a total of 2,256 admissions in the 'Blinded' Phase and 1,890 admissions in the 'Visible' Phase. We compared the frequency of new infections and Acute Kidney Injury (AKI) between the two phases and used multivariable mixed models to adjust for each patient's severity of illness. To estimate the economic benefit of ViSIG, we calculated the mean total charges per patient for each phase and the change in patient throughput to arrive at a net gain/loss annual total charges per bed.

Results: In the Visible Phase, infections declined by 40.5% ($p<0.001$). When adjusted for patient severity of illness, the Visible Phase had an odds ratio of 0.52 (95% confidence interval = 0.43, 0.62). There was a 24.5% relative decrease in the occurrence of AKI ($p<0.001$) and a 35% adjusted decrease from Blinded to Visible Phase ($p<0.001$). The mean total charges were $59,886 and $55,821 for the Blinded and Visible Phases, respectively. However, due to a reduced ICULOS in the Visible Phase, there was a 14.2% increase in admissions during the 90-day period. This resulted in an estimated mean increased revenue of $3,872 per patient at ICUs using ViSIG.

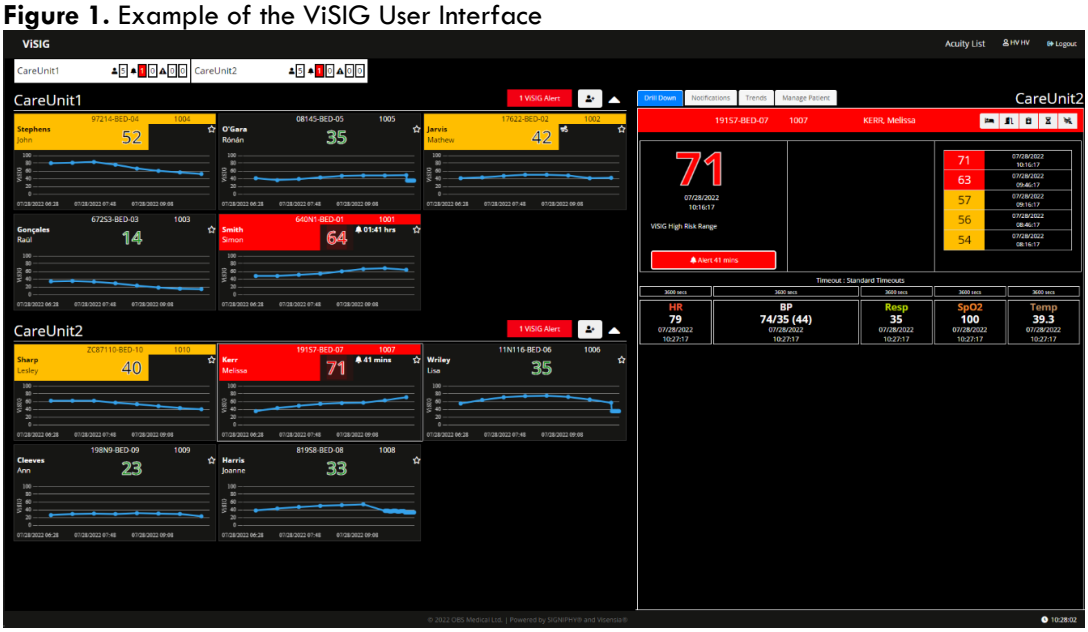
Conclusion: ViSIG was associated with a reduction in two major clinical events: new infections and progression to AKI. This lessened clinical burden may be associated with reduced ICULOS, which resulted in increased patient throughput and, thus, increased revenues. Future studies need to measure specific clinician actions to characterize a cause-and-effect relationship.

Introduction

Severity of illness predictors are utilized in clinical practice to predict mortality, estimate length of stay, and many other adverse outcomes.[1] Many of these predictors were developed and validated using a retrospective analysis of a previously existing database. However, a noticeable shift has occurred from developing retrospective predictive models in critical care to creating predictive models based on real-time prospective data.[1] The desire for actionable information has driven this shift clinicians can use at the bedside.[2] Despite the desire for prospective predictive models, almost all these clinical decision support system models have used retrospective data for their evaluation and have yet to test their effectiveness in real-time clinical settings.[3] A novel analytics tool called "ViSIG" was shown to be predictive of adverse outcomes using live, real-time data in adult intensive care units (ICUs).[4-5] This model development and testing type is rare for critical care analytical tools.

ViSIG continuously collects information on vital signs and whether a patient is receiving mechanical ventilation. A dedicated server at each hospital collects vital sign information on each patient admitted to an Intensive Care Unit (ICU) in real-time. Information on when a patient received mechanical ventilation was established by a respiratory rate reading with a "VENT" tag" attached to its HL7 message. Within seconds of data capture, the patterns in those elements are weighted to produce a severity score highly predictive of adverse outcomes. This score, called the ViSIG Score (ViS), ranges from 0 to 100 and is updated every 30 minutes. The ViS is displayed via a user interface (Figure 1) from a web application. A previous study[4] established ICU mortality risk ranges for the ViS that corresponds to a low, medium, and high mortality risk: 0-38 was colored green for low-risk, 39-57 was colored yellow for moderate-risk, and 58 -100 was colored red for high-risk. This was further enhanced by a patient's score in the high-risk range continually flashing until disabled by a clinician. Also visible was an arrow indicating the direction and amount of change in the ViS during the preceding two hours.

Figure 1. Example of the ViSIG User Interface



Five ICUs at Robert Wood Johnson-Barnabas Hospital (RWJ) and one ICU at Stamford Hospital (STM) participated. This information was acquired for all patients at the participating ICUs between two distinct periods: from November 1, 2021, through February 28, 2022, and March 1, 2022, through May 31, 2022. In the first period (Blinded Phase), the ViS for each patient was calculated every 30 minutes but not displayed to clinicians. In the second period (Visible Phase), information identical to that in the Blinded Phase was obtained. However, each patient's 30-minute ViS and its trend were made visible to clinicians through a web application; an example of the user interface is shown in Figure 1.

The rationale for ViSIG is that it allows earlier interventions to minimize the impact of complications in patients who are physiologically beginning to deteriorate but have not manifested this downward trajectory clinically. A published clinical study in which the ViSIG user interface was turned off for three months, followed by a three-month period in which the user interface was visible to clinicians, suggested that ViSIG might contribute to significantly lower intensive care unit (ICU) outcomes.[5]After adjusting for patient severity of illness, the outcomes of ICU length of stay (LOS), % readmissions, and duration of mechanical ventilation were significantly reduced when ViSIG was made visible to clinicians. Still, to fully explain the value of a real-time severity of illness prediction tool, finding out if clinical factors correlated with the earlier-obtained results also declined while using ViSIG is incumbent.

There are two areas where the utility of a real-time predictive model could be evaluated to provide a comprehensive assessment of the potential for adoption. First, to strengthen the associations between predictive models and decreased clinical outcomes, it is beneficial to determine if such models led to changes in measurable clinical events. Second, demonstrating an economic

benefit when integrating a clinical decision support system into the clinical workflow would lower the resistance to incorporating a new product into hospitals' electronic medical records systems. This study aims to extend the abovementioned clinical study[5] to determine if there are health-economic benefits associated with ViSIG use.

Methods

This study used data from a previously published prospective clinical study[5] that had received IRB approval (Western IRB consortium, now called WCG IRB, on 10/10/2019) and waiver of the need for consent. We retrospectively collected additional information on key clinical events from the six ICUs using Medical Decision Network's (Charlottesville, VA) Phoenix ICU Database, which was active at both hospitals. This included:

1. Evidence that a patient experienced an infection (urinary tract infection, pneumonia, sepsis) by having an ICD-10 code of either: N39.0, N99.528, T83.518, T83.593 (urinary tract); B84.5, B96.0, J09.X, J10.X, J11.X, J12.X, J13.X, J14.X, J15.X, J16.X, J17.X, J18.X, J85.1, J85.9, T81.44 (pneumonia); and A02.1, A22.7, A24.1, A26.7, A32.7, A39.4, A40.X, A41.X, A42.7, A54.8, B00.7, B37.7, J95.0, N08.0, N16.0, O85, R65.1, T88.0, R57.2, A09.0, J20.0, I33.0, L09.4, J02.0 L02.9, L03.0, L03.1, T81.1 (sepsis); "X" is a placeholder for any character {0-9}.
2. An ICD-10 code of N17.0, N17.1, N17.2, N17.8, N17.9, designated a diagnosis of Acute Kidney Injury (AKI);
3. Total charge for a patient's stay in the ICU

We targeted infections and AKI as outcomes of interest because these clinical scenarios were likely to be affected by hypervigilant monitoring of the severity of illness. There is a known association between infection and AKI and subsequent poor outcomes in the ICU.[6-7] Further, infections and AKI have been reported to result in higher ICU costs.[8-9].

We examined the frequency of events by the risk range corresponding to a patient's maximum ViS (low, moderate, high) for the Blinded and Visible Phases. Crosstab tables were evaluated for the occurrence of an infection and the presence of AKI by ViSIG risk ranges for each Phase. We then conducted a multivariate analysis of each outcome (infection, AKI) using each admission's maximum ViS risk range and Phase (Blinded or Visible) as predictor variables. To partially address the confounding issue due to an admission's severity of illness, the APACHE IV's Acute Physiology Score (APS)[10] and time between hospital and ICU admissions (prelos) were also included in the multivariable models. The APS accounted for 66% of the prognostic power of a model for predicting hospital mortality, thus making it an excellent severity of illness adjuster. A mixed-effects generalized linear model with a logit link function and ICUs modeled as a random effect was evaluated. The odds ratio for Phase, its 95% confidence interval, and p-value were obtained.

To measure the economic impact of information from ViSIG, we retrospectively evaluated how the change in total charges and patient throughput between phases could financially impact an ICU. We obtained each Phase's least-squares mean for log (total charges) using the abovementioned multivariate methods and then converted the numbers back to their original scale (exp^{lsm}). Next, we set a 90-day fixed period starting with the Phase's first admission to determine the patient throughput. We did that as the Blinded Phase lasted one month longer than the Visible Phase. For each Phase, we obtained the number of admissions during the 90-day time frame. Formula 1, shown below, was used to estimate the difference in total charges for each Phase:

Formula 1. $\delta = (\#\ admissions_{VISIBLE} * exp\ (LSM_{VISIBLE})) - (\#\ admissions_{BLINDED} * exp\ (LSM_{BLINDED}))$.

where δ =is the difference in total charges between Visible and Blinded Phases for the 90-day period; # admissions is the number of admissions per 90-day period for each Phase; and LSM is the least square means of log(charges) for each Phase.

The difference in total charges δ was then divided by the number of beds in the six ICUs to determine the gain or loss from implementing ViSIG for a single bed.
All analyses were carried out using SAS V9.4 (Cary, NC).

Results

There were 1,895 admissions to RWJ and 361 admissions to STM in the Blinded Phase. Similar proportions of admissions occurred in the Visible Phase (p>0.10): 1,577 admissions to RWJ and 313 admissions to STM. Table 1 shows the characteristics for admissions in both Phases.

Table 1. Characteristics and outcomes for admissionns by study Phase

Characteristics	**Blinded Phase:** (ViSIG score blinded to clinicians)	**Visible Phase:** (ViSIG score visible to clinicians)	*P*-value
Number of admissions	2,256	1,890	
Sex = Female	41.4%	40.8%	> 0.10
Age: median [intra-quartile range]	66 [56, 77]	67 [55, 67]	> 0.10
Race = White	52.8%	54.7%	> 0.10
Diagnosis			0.02
Cardiovascular	22.9%	31.0%	
GI	7.0%	4.0%	
Neurologic	17.8%	19.8%	
Respiratory	23.7%	15.9%	
Sepsis	11.2%	11.1%	

Characteristics	**Blinded Phase:** (ViSIG score blinded to clinicians)	**Visible Phase:** (ViSIG score visible to clinicians)	*P*-value
Trauma	10.6%	10.9%	
Other	7.0%	7.4%	
Acute Physiology Score[1]: median [IQR]	42.0 [31.0, 61.0]	39.5 [29.0, 56.0]	< 0.001
Previous length of stay[2](prelos)	0.30 [0.08, 1.63]	0.26 [0.07, 1.18]	0.04
% Receiving mechanical ventilation	24.2%	20.0%	0.001
% Having a Do Not Resuscitate order	19.6%	13.7%	< 0.001
Maximum ViSIG Score: median [IQR]	38.0 [28.0, 53.0]	38.0 [28.0, 50.0]	> 0.10
ICU Mortality	12.4%	9.5%	0.003
ICU Length of Stay: mean (stderr)	4.06 (0.12)	3.50 (0.10)	< 0.001
Duration of mechanical ventilation	3.12 (0.17)	2.51 (0.16)	<0.001
Readmissions	7.9%	4.9%	< 0.001
Infections	4.5%	2.8%	0.005
Acute Kidney Injury	3.8%	1.9%	<0.001
Total charges	$89,048	$78,131	<0.001

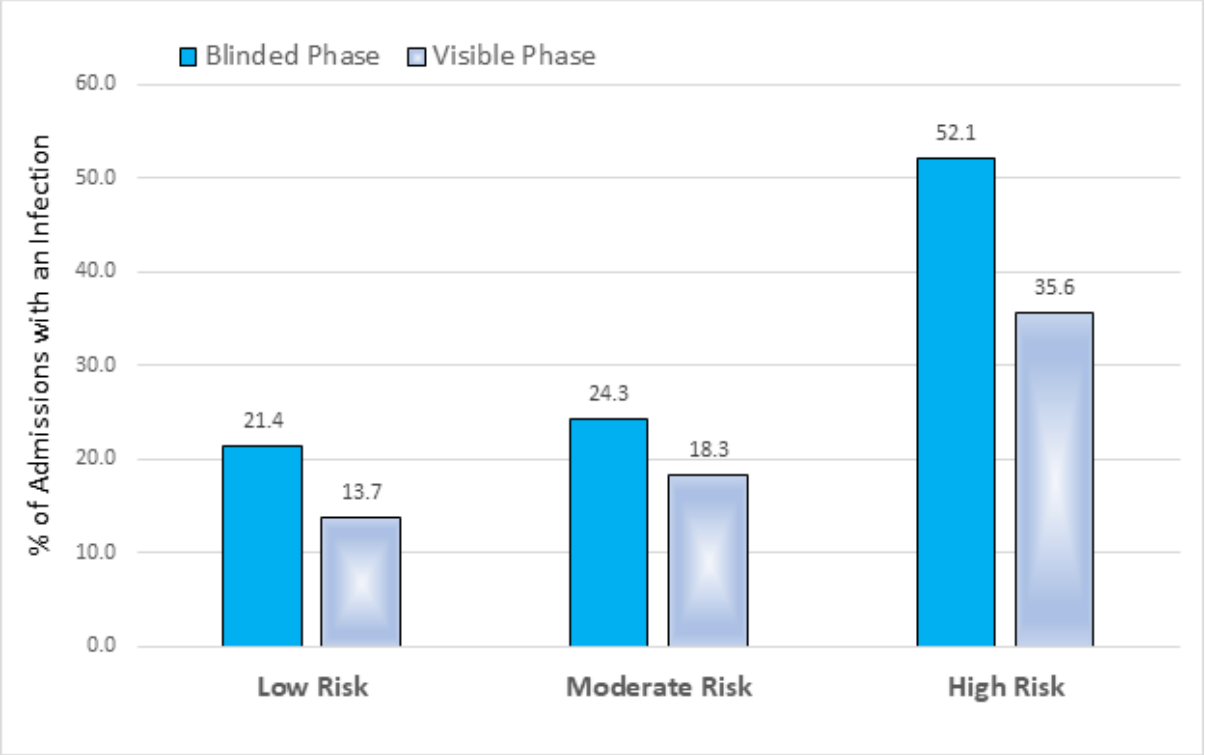
[1] The Acute Physiology Score is the component of the Acute Physiology, Age, and Chronic Health Evaluators (APACHE) IV score that measures physiologic derangement

[2] Duration from hospital admission until intensive care unit admission

There were virtually no differences between the two Phases in age, sex, gender, or maximum ViS. The Unblinded Phase had a higher percentage of respiratory diagnoses, while the Visible Phase had a higher percentage of cardiovascular diagnoses. Admissions in the Blinded Phase had a significantly higher severity of illness than admissions in the Visible Phase: Blinded Phase admissions had a higher ICU mortality, ICULOS, duration of mechanical ventilation, and percentage of readmissions.

In the Blinded Phase, 28.9% of admissions had an infection, which decreased to 19.5% in the Visible Phase, a decrease of 40.5% (p<0.001). Figure 2 shows the frequency of infections by Phase and ViS mortality risk group.

Figure 2. Percentage of Admissions Acquiring a New Infection by Phase and ViSIG Risk Group



The frequencies of patients with infections from Low- to Moderate- to High-Risk groups increased monotonically (p<0.001). When going from the Blinded Phase to the Visible Phase, there were absolute decreases in new infections for all groups, but the largest reduction was in the high-risk group. In the multivariable model, when adjusting for the ViS risk group, APS, and prelos. Phase was highly significant (p<0.001) with an odds ratio of 0.52 (95% confidence interval = 0.43, 0.62). The infection rate in the high-risk group was statistically greater (p<0.001) than in the low-risk group, but the rates in the moderate and low-risk groups were roughly the same.

For AKI, 24.8% of admissions in the Blinded Phase were affected, while 18.0% of Visible Phase admissions were found to have developed AKI, a relative decrease of 24.5% (p<0.001). Figure 3 shows the frequency of AKI by Phase and ViS mortality risk group.

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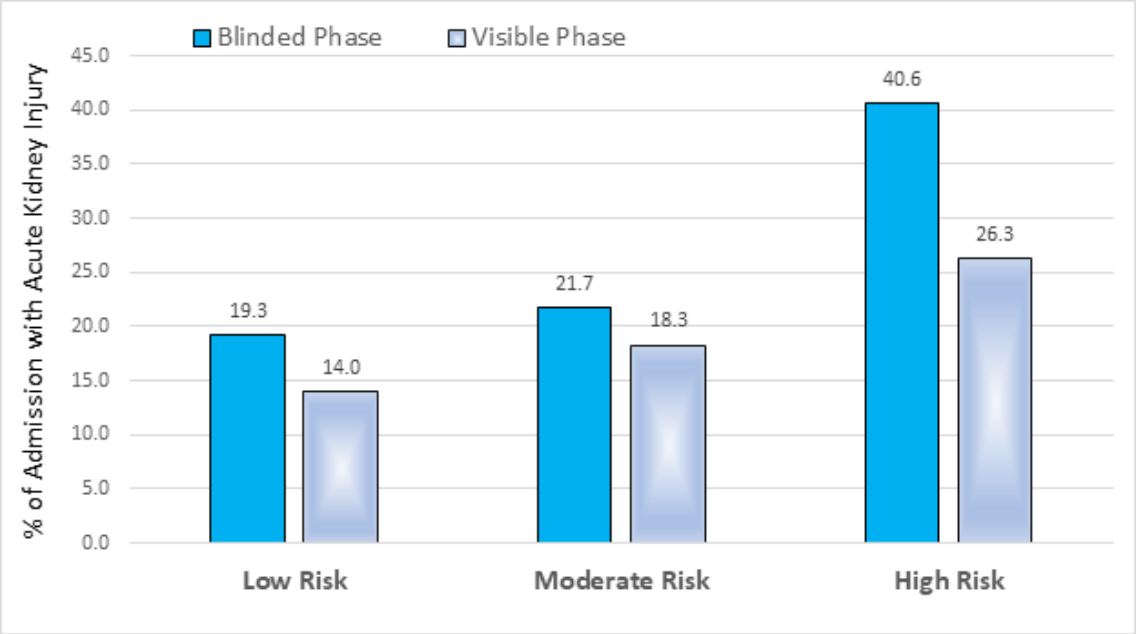
Figure 3. Percentage of Admissions Progressing to AKI by Phase and ViSIG Risk Group



When going from the Blinded to Visible Phase, there were small decreases in AKI for the Low- and Moderate-risk groups. However, in the high-risk group, reported AKI dropped a relative 35.3% from the Blinded to the Visible Phase, which was highly significant ($p<0.001$). In the multivariable model, there was a 35% (23%, 46%) overall decrease from the Blinded to the Visible Phase ($p<0.001$). The rates for AKI in the three risk groups were not statistically different from each other.

Information on total charges was available for 54% of the admissions. This was due to two ICUs having sent over charges for only 3% of their admissions; the other four ICUs sent relevant charge information for 83% of their admissions. Thus, we removed the two ICUs that were missing charge information for the financial analysis. Table 2 shows the results of the calculations of total charges.

The multivariable model's least square means for log (total charges) was 11.00 for the Blinded Phase and 10.93 for the Visible Phase. When transformed back to their original units, these charges were $59,886 for the Blinded Phase and $55,821 for the Visible Phase, a decrease of 6.8% ($p=0.10$). There were 1,083 and 1,257 admissions during the 90-day period for the Blinded and Visible Phases, respectively. This amounts to a 14.2% increase in patients throughout. The estimated charges (reverting log (charges) back to its original scale) were $59,886 for the Blinded Phase and $55,821 for the Visible Phase, a decrease of 6.8% ($p=0.10$). However, the number of admissions during the 90-day period in the Visible Phase was 14.2% higher than in the Blinded Phase. When taking this into account, total revenues for the Visible Phase were estimated to be higher by $4,193,357. This equates to an increased revenue of $3,872 per admission.

Table 2. Tabulation of the Total Charges for All Patients Adjusted for Patient Severity of Illness for Each Phase

Phase	Least Square Means	Adjusted Back to Original Units	# Admissions During 90-Day Period	Estimated Total Charges
Blinded	11.00	$59,886	1,083	$64.9M
Visible	10.93	$55,821	1,237	$69.1M

Discussion

This is the first study to report on a prospective health-economic assessment of a real-time decision support system in the ICU. While the reduction in deleterious outcomes from using ViSIG was statistically significant in a previous study,[5] potential reasons for the reduction were not firmly established. In this study, we showed that ViSIG use might be associated with reductions in AKI and infections, two clinical conditions with a major impact on ICU outcomes. Along with the increased throughput brought about by a significant decrease in ICULOS, an ICU using ViSIG could experience increased revenues annually per admission.

There are reasons why using a clinical decision support system may reduce poor outcomes and costs. In our study, we measured the incidence of two drivers of increased patient burden and cost: development of AKI and acquiring infections. AKI is often seen in the ICU, occurring in approximately 40% of ICU admissions].[6] It is costly, with an incremental cost of $10,000-$80,000 per event, and when severe, requires extensive treatment such as dialysis or extra-corporeal filtration. Similarly, new infections for ICU patients are common, with 30% of hospital-acquired infections happening in the ICU[7-8] and an additional $30,000 per case.[9] Clinician action that prophylactically addresses those conditions and ameliorates their morbidity could result in lower costs and ICULOS.

Studies estimating overall ICU costs1[11-12] have utilized national databases such as the Hospital Cost Report

Information System (HCRIS). One of the goals was to develop a national estimate of ICU costs in the United States. However, we used total patient-level charges for admissions in our study. This information came from ICD-10 charge codes collected from each ICU's electronic medical record system. The advantage of this method is that we could have a precise dollar figure for total charges by Phase for each patient. Other studies have reported cost estimates of approximately 1/3rd of charges.[13] Our estimates of per-patient cost ($26,000 - $29,700) are modestly higher than that found in other studies that had an actual cost per patient],[14-16] probably due to the rising cost of healthcare from the time of their data collection (2013, 2002, 2012-2016) to when our data were collected (2022). Additionally, the majority of our data came from an urban hospital (RWJ). These hospitals may have higher-cost patients due to being referred from a lesser-tier facility, having a longer ICU LOS, and being more likely to need mechanical ventilation]. [17] These characteristics are likely to result in an increased ICULOS and, therefore, cost. [18-20]

While we have associated ViSIG's clinical benefits with a corresponding financial value, we could not ascertain precisely which clinical actions were responsible. It will be incumbent to show an action and response linkage to connect changes in outcomes with changes in clinical practice. To that end, future studies of ViSIG should add the recording of specific treatments, such as intravenous antibiotic administration, the addition of vasopressors, or the application of the KDIGO bundle.[21] The timing of these actions relative to a high-risk alert being generated would be of enormous value.

There are limitations to our study. First, our clinical outcome assessment of infections and AKI was limited to ICD10 codes, likely to be under-enumerated. We could not use other criteria for determining infection or AKI because these data were inaccessible. Since the times of infection and AKI first being documented were unavailable, a VIS indicating a high-risk patient might have occurred after these outcomes. Second, two ICUs at RWJ were missing charges. Thus, they were removed from the analysis of that outcome. Third, there were only six ICUs at two hospitals. Therefore, our results may not be extensible to other ICUs.

Conclusion

This study showed that a decision-support system in the ICU might decrease adverse events, specifically new infections and progression to AKI. This lessened clinical burden may be associated with reduced ICULOS. We also demonstrated how a decline in ICULOS could lead to increased revenue due to increased patient turnover. Future studies need to measure specific clinician actions to characterize a cause-and-effect relationship.

Conflicts of Interest Statement: Dr. Kramer holds a patent on part of the VSIG predictor tool. Ms. Maurer works for Medical Decision Network, whose ICU database Phoenix was utilized in this study.
Funding information: Self-funded study.

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