

Using Length of Stay to Understand Patient Flow for Pediatric Inpatients

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Abstract

Objectives: Develop and test a new metric to assess meaningful variability in inpatient flow. **Methods:** Using the pediatric administrative dataset, Pediatric Health Information System, that quantifies the length of stay (LOS) in hours, all inpatient and observation encounters with 21 common diagnoses were included from the calendar year 2013 in 38 pediatric hospitals. Two mutually exclusive composite groups based on diagnosis and presence or absence of an ICU hospitalization termed Acute Care Composite (ACC) and ICU Composite (ICUC), respectively, were created. These composites consisted of an observed-to-expected (O/E) LOS as well as an excess LOS percentage (ie, the percent of day beyond expected). Seven-day all-cause risk-adjusted rehospitalizations was used as a balancing measure. The combination of the ACC, the ICUC, and the rehospitalization measures forms this new metric. **Results:** The diagnosis groups in the ACC and the ICUC included 113,768 and 38,400 hospitalizations, respectively. The ACC had a median O/E LOS of 1.0, a median excess LOS percentage of 23.9% and a rehospitalization rate of 1.7%. The ICUC had a median O/E LOS of 1.1, a median excess LOS percentage of 32.3%, and rehospitalization rate of 4.9%. There was no relationship of O/E LOS and rehospitalization for either ACC or ICUC. **Conclusions:** This metric shows variation among hospitals and could allow a pediatric hospital to assess the performance of inpatient flow. (*Pediatr Qual Saf* 2018;2:e050; doi: 10.1097/pq9.000000000000050; Published online December 18, 2017.)

Optimal patient care “can only be delivered when the right patient is in the right place with the right provider and the right information at the right time” Institute for Healthcare Improvement¹

INTRODUCTION

The time a patient spends in an inpatient environment depends on the patient’s disease and severity of illness as well as being directly impacted by the efficiency and effectiveness of care. Patient flow, or the management and movement of patients in a healthcare setting, links efficiency

and effectiveness of care with a patient’s length of stay (LOS). As inferred in the Institute for Healthcare Improvement quote above, these factors need to be aligned for optimal patient care to occur. Poor management of patient flow may lead to ineffective coordination of treatments, tests, and other interventions that can prolong diagnosis and/or recovery.

Inpatient settings are often the focus of efforts to improve patient flow as inefficiencies can lead to strains on capacity, contributing to nonoptimal treatments, processes, and outcomes. Although increasing inpatient bed capacity may be necessary at times, the expense of doing so can only be justified



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if systems are already running efficiently. Consequences of inefficient patient flow include patient dissatisfaction, delays between admission decision and hospitalization, delayed or even cancelled elective hospitalizations for surgical procedures or medical evaluations, increased lengths of stay, poor quality of care, and decreased revenue for the organization.¹⁻³ Thus, assessment of patient flow is critical, and the design (or redesign) of systems and processes should consider the whole continuum of the patient experience to achieve high-quality outcomes.⁴⁻⁸

One key step in improving patient flow is understanding the sources of variation in system-wide processes. Additionally, system capacity may appear to be adequate for demand, but because of variation in the timing of patient arrivals and the ability to absorb that demand, there may be times when capacity is not adequate and then “waits, delays, and cancellations” result.¹ Queuing theory holds that once utilization increases above a certain threshold level, commonly understood to be 80%-90% of capacity, wait times will exponentially increase.^{9,10} Industry research also shows that a nonoptimized hospital can obtain a 15–20% increase in bed and service capacity via a redesign of patient flow processes.¹¹ If resources can be appropriately allocated, “patient outcomes, staff morale and retention, healthcare costs, and the quality of life for both patients and caregivers” can improve.¹

Despite its importance to the management of patient care, measuring patient flow has proven quite challenging. Administrative coding is typically used to average lengths of stay (LOS) of inpatient encounters. These administrative datasets have limitations as some are infrequently updated and most LOS are recoded in days (ie, the number of midnights crossed) rather than something more granular like hours. Given the challenges in assessing patient flow, various groups have proposed detailed plans for measuring it, such as with composite scores.⁴ Although these may offer benefits to individual hospitals to measure the process, outcome and balancing measures, such an approach does not lend itself to cross-hospital benchmarking.

To better quantify, understand, and benchmark pediatric inpatient flow, we propose the following pediatric-specific measure, PedsLOS. PedsLOS uses selected high-volume medical and surgical diagnostic administrative codes and associated LOS for both acute and critical care patients to obtain a representative view of patient flow. We also utilize rehospitalization rates (inclusive of admission and observations) for these codes as a balancing measure. If there is variation among hospitals, these metrics can be used to benchmark one organization’s LOS performance with that of others. Once benchmarked and gaps identified, standard improvement work can begin to assess the causes of variation and opportunities to enhance specific bottlenecks.

HOSPITAL VIGNETTE

Fictitious Hospital 16 is concerned about inefficiencies of care, but it is not yet clear where those inefficiencies

manifest. Therefore, the Patient Flow team at Hospital 16 plans to use PedsLOS. They note that the Heat Map of the Acute Care Composite (Fig. 3) may yield the most insights since their performance on the ICU composite (ICUC) shows good overall performance. They find that their overall performance on the Acute Care Composite is poor. Because the Acute Care Composite is broadly based into surgical and medical composites, they assess both to determine if there are differing results. Interestingly, their performance on the Medical Composite scores well. However, their performance on the Surgical Composite scores poorly, specifically in the APR-DRGs involving tonsillectomies/adenoidectomies as well as shoulder/arm surgeries.

This finding resonates with the Patient Flow team. They have understood for a few years that some inefficiencies of care may exist in both of those areas but had not had data to support this suspicion. The Patient Flow team knows that their best next steps are to involve the experts in these cases and invite surgeons, relevant nursing staff, quality improvement professionals, and others to explore the possible areas of inefficiencies. Once identified, the Patient Flow team collaborates with all involved to begin standard quality improvement work. In 3–6 months, these efforts have been completed, and the team plans to reassess their performance on PedsLOS. They anticipate that with their investigations and interventions that they will see positive results.

METHODS

Data Source

Data for this retrospective cohort study were obtained from the Pediatric Health Information System (PHIS), a national administrative database containing resource utilization data from tertiary care children’s hospitals affiliated with the Children’s Hospital Association (Lenexa, Kans.). For external benchmarking, participating hospitals ($n = 49$) provide discharge data, including patient demographic characteristics, diagnoses, procedures, charges, and LOS. Thirty-eight of these hospitals provide hospitalization hour and discharge hour so that LOS can be calculated in hours. Thus, they were included in this study.

The protocol for the conduct of this study was reviewed and approved by Children’s National Health System (Washington, D. C.) with a waiver of informed consent.

Patients

Children were included in the study if they were (1) hospitalized as an inpatient or observation status; (2) were discharged from one of the 38 hospitals submitting hourly LOS data to PHIS for the 2013 calendar year; and (3) were classified into one of the 23 selected all-patient refined diagnosis-related groups [APR-DRG, version 25 (3M-Corp, Minneapolis, Minn.)]. In PHIS, the APR-DRG

group and severity of illness level are assigned at discharge using the patient demographics, diagnoses, and procedures that occur during the encounter.¹² These APR-DRGs were selected because they make up a representative portion of total hospital discharges reported at PHIS hospitals, namely 20% of total hospitalizations for the group. Beyond this, top 20% of hospitalizations, comparisons across hospitals became increasingly difficult due to differences in hospitals and their patients. We collected 2 sets of APR-DRGs representing these common diagnoses within the acute care population and those with a critical care stay. Therefore, 2 mutually exclusive populations were created: medical and surgical patients with acute care stays only (Acute Care Composite, Fig. 1A) and those whose hospitalization included any time in an intensive care unit (ICUC, Fig. 1B). Hospitalizations were excluded if the patient died in the hospital, was seen in a Neonatal Intensive Care Unit, or had a complex chronic condition (CCC).¹³ The patients with a CCC were excluded since the variability of their complexity would likely complicate comparison across hospitals. Hospitalizations were classified as an ICU stay and therefore included in the ICUC if they had any of the following: critical care APR-DRGs (Fig. 1B), major/extreme severity of illness or were in either APR-DRG 139 (Pneumonia) or APR-DRG 53 (Seizure) and were hospitalized in an ICU.

Outcomes

We measured hospitals at the various composite levels with the Acute Care Composite and the ICUC, using 2 primary outcomes: observed-to-expected LOS (O/E LOS) and excess LOS. As a balancing measure, hospitals were

also measured on 7-day all-cause risk-adjusted rehospitalization rates. We used rehospitalization as a balancing measure to LOS, as there is at least theoretical concern that hospital stays that are too short may increase the risk of rehospitalization; a very short LOS may raise the risk of a return to the hospital. Conversely, several studies have not found a relationship between LOS and rehospitalization, though that may be because transition services were improved and/or observed LOS was not reduced to unsafe levels.¹⁴⁻¹⁷

Study Definitions

The LOS is the total time in hours that a patient spends in the hospital. O/E LOS uses actual LOS divided by an expected benchmark, based on diagnosis (ie, APR-DRG) and 4 severity of illness levels, stratified into minor (level 1), moderate (level 2), major (level 3), or extreme (level 4) and is determined using demographic and diagnostic data and comorbidities.¹² A patient staying as long as expected would have an O/E LOS of 1; values less than 1 indicate a patient is staying a shorter duration than expected, whereas values greater than 1 indicate a patient is staying longer than expected. Patient flow refers to the management and movement of patients in a health care facility; when viewed at the hospital level, it is the aggregation of many flow steps and processes including value-added activities and wait times. Throughput reflects how long it takes, on average, for each patient to be served, so understanding how long it takes to care for a patient is important to identifying improvement opportunities and understanding total throughput capabilities and opportunities for a hospital.¹⁸

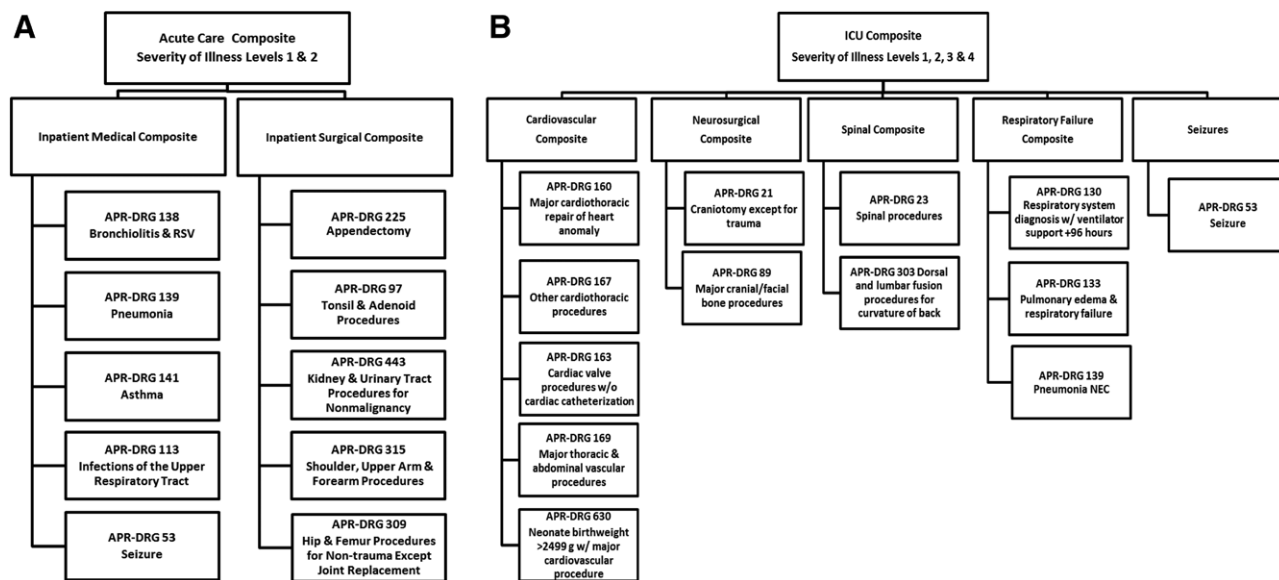


Fig. 1. A, Acute Care Composite components. Excluded from this composite are neonatal intensive care unit patients, patients who have died while inpatient, children with CCCs, any patient with an invalid discharge hour, any patient who has had a critical care stay during the recorded hospitalization. B, ICUC components. Excluded from this composite are neonatal intensive care unit patients, patients who have died while inpatient, children with CCCs, any patient with an invalid discharge hour, any patient who has had a critical care stay during the recorded hospitalization. Neonatal patients admitted to a pediatric ICU or cardiac ICU are included in this population.

We calculated O/E LOS for each APR-DRG by summing the actual LOS for hospitalizations that met the inclusion criteria and divided by the sum of the expected LOS for each of the included hospitalizations. Since O/E LOS may have bimodal distributions at both the long and short stays at a particular hospital and therefore mask possible beneficial results of many short LOS patients, we included an additional view of LOS, termed the excess LOS. At the discharge level, excess LOS was calculated as the difference between the actual LOS and the expected LOS for each hospitalization. If this difference was less than zero, we set the excess LOS to zero. The excess LOS was then expressed as a percentage of the hospital's actual total LOS. To create the composite ratio measures, we summed the observed and expected lengths of stay from the individual APR-DRGs within each category and divided the resulting sums. The 7-day all-cause rehospitalization rate for each hospital was risk-adjusted using the APR-DRG severity of illness score.

Expected LOS was determined for each APR-DRG at each level of severity by calculating the 10% Winsorized mean LOS across all hospitals.¹⁹ Winsorized means attempt to reduce the influence of outliers by setting the lowest 5% of observations at the fifth percentile and the highest 5% of observations at the 95th percentile.

Heat Maps

To graphically display the issue areas for the respective diagnoses at each hospital, we created heat maps showing each the Acute Care Composite and ICUC. For the Acute Care Composite, the overall performance is presented graphically in the first column and sorted overall by performance in this column. Then the medical and surgical composites respective subgroup performance is displayed. Similarly, for the ICUC, the overall performance is presented graphically in the first column and sorted overall by performance in this column. The subgroups of the ICUC are also graphically displayed. For both heat maps, cells colored red indicate conditions for which the hospital has an O/E LOS ratio () significantly > 1 (ie, the lower limit of the 95% CI for the O/E LOS > 1.0). Cells colored green indicated conditions for which the hospital has an O/E LOS significantly < 1 (ie, the upper limit of the 95% CI for the O/E LOS < 1.0). Cells colored yellow are conditions for which the hospital has an O/E LOS not significantly different than 1. Sorted by frequency of O/E LOS significantly > 1 cells.

Statistical Analysis

Categorical variables were described using frequencies and percentages, whereas continuous variables were described using medians and interquartile range (IQR) values. Hospitals were determined to be outliers if the 95% CI for their O/E LOS ratio did not include 1.0. All correlations were assessed using Spearman's correlation.

All statistical analyses were performed using SAS statistical software, version 9.3 (SAS Institute, Cary, N.C.), and P values < 0.05 were considered statistically significant.

RESULTS

Acute Care Composite

During the study period, 113,768 (20.5%) of the PHIS inpatient discharges were flagged with one of the identified acute care APR-DRG groups. The representative percentage for the Acute Care Composite cases within each institution varied by hospital, with a median of 21.0% (IQR, 17.6–24.5%). The cohort of patients who met criteria for the Acute Care Composite is shown in Table 1. The median O/E LOS ratio across hospitals was 1.0 (IQR, 0.9–1.1), with a median excess LOS% of 23.9% (IQR, 20.9–27.2%). In general, the use of excess LOS% allowed for greater spread among hospitals and correlated highly with the O/E ratio ($\rho = 0.88$; $P < 0.001$). The median 7-day all-cause risk-adjusted rehospitalization rate was 1.7% (IQR, 1.3–2.1%) without a clear relationship between O/E LOS and rehospitalization rates ($\rho = -0.05$; $P = 0.770$; Fig. 2A). On an individual institutional level, we observed variability between medical and surgical acute care composites—that is, the O/E LOS were not necessarily consistently in the same direction for both composites (Fig. 3).

ICUC

For acute care hospitalizations with an ICU stay, 31,400 (28.6%) of the PHIS discharges were flagged with one of the identified ICUC APR-DRG groups. The representative percentage of ICU cases within each institution also varied with a median of 28.1% (IQR, 22.5–33.5). The cohort of patients who met criteria for the ICUC is also shown in Table 1.

Table 1. Patient Characteristics of Hospital Discharges Meeting Acute Care Composite and Acute Care with ICUC Criteria

Patient Characteristics	Acute Care Composite, n (%)	ICUC, n (%)
N Discharges	113,768	31,400
Gender		
Male	66,179 (58.2)	16,406 (52.3)
Female	47,582 (41.8)	14,991 (47.7)
Race		
Non-Hispanic White	49,454 (43.5)	17,785 (56.6)
Non-Hispanic Black	26,014 (22.9)	4,532 (14.4)
Hispanic	25,978 (22.8)	5,177 (16.5)
Asian	2,812 (2.5)	1,059 (3.4)
Other	9,510 (8.4)	2,847 (9.1)
Payer		
Government	67,401 (59.2)	16,041 (51.1)
Private	40,080 (35.2)	13,483 (42.9)
Other	6,287 (5.5)	1,876 (6)
Age (y)		
< 1	23,906 (21)	9,644 (30.7)
1–4	42,998 (37.8)	7,028 (22.4)
5–9	25,301 (22.2)	4,526 (14.4)
10–14	15,463 (13.6)	5,464 (17.4)
15+	6,100 (5.4)	4,738 (15.1)

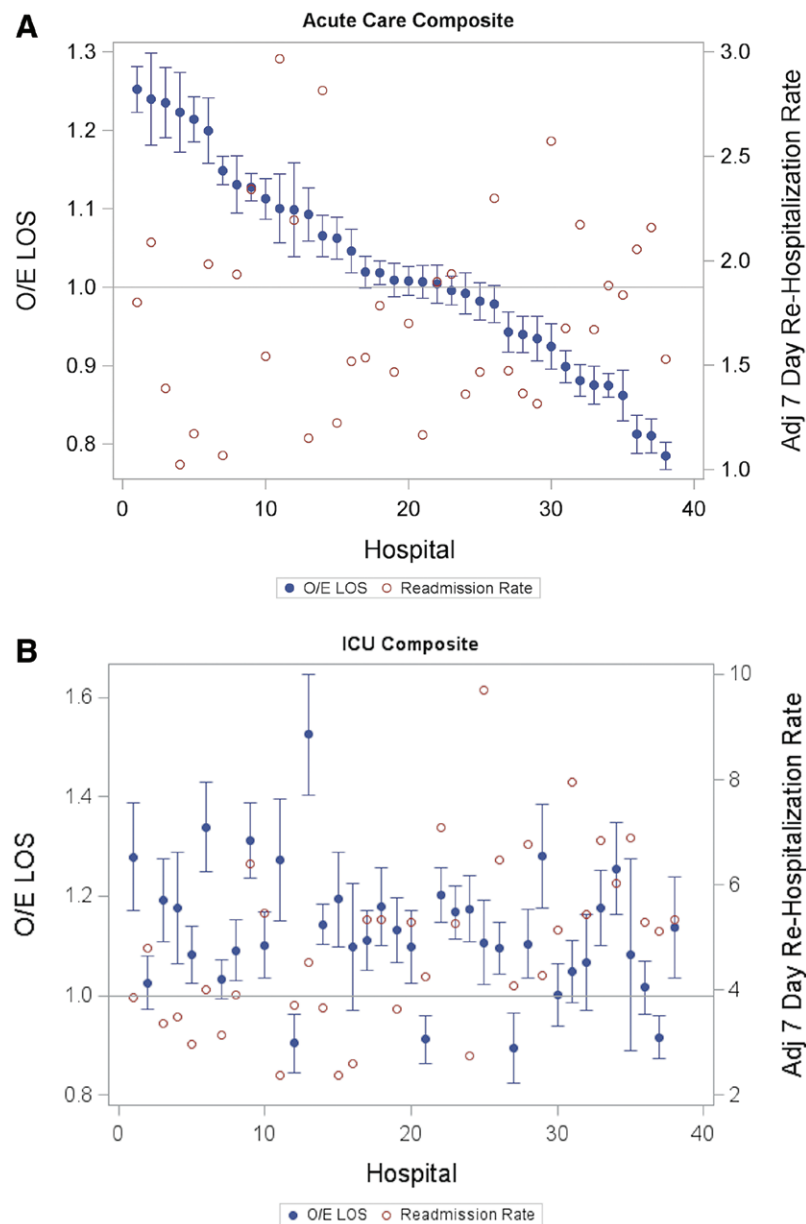


Fig. 2. A, Acute Care Composite with the adjusted 7-day rehospitalization rate with each hospital's O/E LOS ratio. Error bars represent 95% CIs. B, ICUC with adjusted 7-day rehospitalization rate with each hospital's O/E LOS ratio. Error bars represent 95% CIs.

The O/E LOS across hospitals for the ICUC had a median of 1.1 (IQR, 1.0–1.2) with a median excess LOS% of 32.3% (IQR, 28.7–35.4%). Similar to the Acute Care Composite, the use of excess LOS% allowed for greater spread among hospitals and correlated highly with the O/E ratio ($\rho = 0.85$; $P < 0.001$). The 7-day all-cause risk-adjusted rehospitalization rate was higher for the ICUC, with a median of 4.9% (IQR, 3.6–5.5%). Like the Acute Care Composite, we could not identify a clear relationship between O/E LOS and rehospitalization rates ($\rho = 0.03$; $P = 0.874$; Fig. 2B). Subgroups for the ICUC and the individual performance is shown in Figure 4.

DISCUSSION

The goals of understanding patient flow are to improve both the patient's experience of care and the efficiency of care. These goals are well aligned to enhance performance and, if improvement efforts are conducted thoughtfully, should not be counterproductive. Measuring LOS using a comparative database such as PHIS can help hospitals understand their performance not only against their past performance but also against that of their peers (see Vignette). PedsLOS will help hospitals understand this performance for common conditions, ultimately providing insights into where improvement work should be focused. By using the PHIS dataset and importantly

Hospital	Acute Care Composite												
	Overall	Medical Composite						Surgical Composite					
		Overall	Bronch & RSV	Pneum	Asthma	URI	Seizure	Overall	Appy	T&A	Kidney, Urinary	Shoulder, Arm	Hip, Femur
1	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
2	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
3	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
4	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
5	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
6	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
7	Red	Red	Green	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
8	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
9	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
10	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
11	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
12	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
13	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
14	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
15	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
16	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
17	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
18	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
19	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
20	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
21	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
22	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
23	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
24	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
25	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
26	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
27	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
28	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
29	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
30	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
31	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
32	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
33	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
34	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
35	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
36	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
37	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red
38	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red	Red

Fig. 3. Heat Map of Acute Care Composite performance by hospital. Cells colored red indicate conditions for which the hospital has an O/E LOS ratio (O/E LOS) significantly > 1. Cells colored green indicated conditions for which the hospital has an O/E LOS significantly < 1. Cells colored yellow are conditions for which the hospital has an O/E LOS not significantly different than 1. Sorted by frequency of O/E LOS significantly > 1 cells.

without additional data collection by the hospital, PedsLOS shows notable variation of both the Acute Care and ICUC, allowing for performance assessments and differences between and within institutions to be explored.

Existing benchmarking available from other administrative datasets uses the APR-DRG O/E LOS based on midnight crossings and excludes observation-status stays. In contrast, the PHIS and PedsLOS approach utilizes hourly data (reflecting the commonly shorter LOS) and include observation-status stays.²⁰⁻²² This enhanced level of detail may also lead to better acceptability for use as an outcome measure since the data more accurately represents the patient’s experience regarding LOS. Another improvement over other datasets is that PHIS is available with quarterly updates to the data only a few months in arrears. Therefore, improvement efforts can be tracked over time with more representative data.

Exploring patient flow variation will hopefully lead to improved performance as best practices are learned and

improvement methods spread across organizations. Since we used 2 novel measures and 1 balancing measure to improve our understanding of patient flow, organizations have multiple lenses to view this complex problem. Using only 1 of these measures to assess patient flow does not adequately portray performance, as excellent performance in only 1 of these measures may not represent desirable care.

PedsLOS does have limitations. As with any measure based on administrative coding, there are challenges as to the accuracy of this coding. For example, the severity of illness assignment depends on the accuracy of physician documentation and the accuracy of the discharge coding. However, since these metrics mostly rely on diagnosis codes, hospitalization, and discharge dates and times, these limitations should be minimal. Also, since the PHIS dataset is proprietary data and therefore not publically available, the spread of this information may be limited. However, the approach could be replicated for more general use should hourly data as well as observation stays be included in other datasets.

Hospital	ICU Composite					
	Overall	Cardiovascular Composite	Neurosurgical Composite	Respiratory Failure Composite	Seizures	Spinal Composite
1	Red	Red	Red	Red	Red	Red
22	Red	Red	Yellow	Red	Red	Red
2	Red	Red	Red	Red	Red	Yellow
11	Red	Yellow	Red	Red	Red	Red
33	Red	Red	Yellow	Red	Red	Yellow
23	Red	Red	Red	Red	Red	Yellow
29	Red	Red	Red	Red	Red	Red
13	Red	Red	Green	Red	Red	Red
6	Red	Green	Red	Red	Red	Red
24	Red	Red	Red	Red	Yellow	Red
20	Red	Yellow	Red	Red	Red	Red
9	Red	Red	Red	Red	Red	Red
18	Red	Red	Red	Red	Yellow	Red
26	Red	Red	Red	Red	Red	Red
15	Red	Red	Red	Red	Red	Red
7	Red	Red	Red	Red	Red	Red
19	Red	Red	Red	Red	Red	Yellow
25	Red	Yellow	Red	Red	Red	Red
12	Red	Red	Red	Red	Red	Red
5	Red	Red	Red	Red	Red	Red
27	Red	Red	Red	Red	Red	Red
3	Red	Red	Red	Red	Red	Red
8	Red	Red	Red	Red	Red	Red
10	Red	Red	Red	Red	Red	Red
36	Red	Red	Red	Red	Red	Red
37	Red	Red	Red	Red	Red	Red
4	Yellow	Red	Red	Red	Red	Green
32	Yellow	Red	Red	Green	Red	Red
38	Yellow	Red	Green	Red	Red	Red
14	Yellow	Red	Red	Red	Red	Red
28	Yellow	Red	Red	Red	Red	Red
30	Yellow	Red	Red	Green	Red	Red
16	Yellow	Red	Red	Red	Green	Green
31	Yellow	Red	Red	Red	Red	Red
21	Green	Red	Green	Red	Red	Green
17	Green	Green	Red	Red	Red	Red
35	Green	Red	Red	Red	Red	Green
34	Green	Yellow	Green	Green	Red	Red

Fig. 4. Heat Map of ICUC performance by hospital. Cells colored red indicate conditions for which the hospital has an O/E LOS ratio (O/E LOS) significantly > 1. Cells colored green indicated conditions for which the hospital has an O/E LOS significantly < 1. Cells colored yellow are conditions for which the hospital has an O/E LOS not significantly different than 1. Sorted by frequency of O/E LOS significantly > 1 cells.

This metric also only reports final outcomes—overall LOS—involving a very complex process and does not specifically provide information about the many important and multidisciplinary steps involved in patient care and patient flow. Thus, it can serve only as an indicator to where issues may exist and therefore help target how a hospital may improve inpatient flow. However, further investigations into why performance does not align with that of a hospital’s peers will need to be explored. For example, if the discharge of a medical hospitalization such as an asthma patient is delayed due to the requirement of care team rounding times, this may negatively impact a local hospital’s average LOS for that diagnosis. Therefore, the local team may explore inefficiencies to

address these hindrances. Lastly, it is not clear that the ideal LOS are the lowest LOSs. Assuming that the low LOS are the desirable, LOS assumes that there is waste that is eradicable. While that is likely the case, given the intrinsic inefficiencies in health care, this is not proven for each of the included diagnoses. Our goal in presenting the rehospitalizations balancing measure was to help alleviate this ambiguity. Hospitals should feel reasonably confident that if they have a low LOS compared with their peers and their respective rehospitalizations are at a desirable rate that the care is not overly inefficient. An additional balancing measure to consider for future work would be unplanned returns to the Emergency Department for the same condition as this would possibly negatively impact

the patient as well. Also as administrative datasets such as PHIS incorporate ICD-10 coding, modifications would need to be made to reflect the similar diagnoses codes used from ICD-9. Lastly, the included APR-DRGs do not represent a consistent proportion of total encounters across the 38 hospitals. Therefore, some may be overemphasized in the roll-up portion of the metric.

Despite these limitations, the findings support the use of this metric as a method to identify diagnosis-based variation in patient flow. Improving patient flow is a goal at many hospitals, but measuring the multidimensional aspects of flow and their impact on quality is difficult. Our hope is that by providing a framework to hospitals within the PHIS dataset as well as those that obtain their administrative data elsewhere for assessing patient flow across hospitals. Measurement is crucial to identifying and mitigating variation, and the need for an improved method to assess patient flow is critical. Importantly, this metric represents an enhanced understanding over currently available benchmarking data. We would hope in the future that some high performing hospitals, those with low O/E LOS as well as excess LOS and 7-day readmissions, would utilize quartile rank of these metrics and even decile level rank to enhance further their understanding of their performance rather than simply a mean. Use of these metrics to assess patient flow performance will allow an organization to appropriately identify their efficiencies or inefficiencies of care and therefore highlight areas in need of optimization.

DISCLOSURE

The authors have no financial interest to declare in relation to the content of this article.

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