OurPractice
General Medicine

A hospital-level report for quality care in General Medicine

Background and Indicator Details

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GEMINI

Ontario General Medicine Quality Improvement *Network*

Ontario Health

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Introduction

The Ontario General Medicine Quality Improvement Network (GeMQIN)[1] is a provincial program delivered by Ontario Health, in partnership with the GEMINI data collaborative.[2] GeMQIN is a data-driven community of practice focused on improving the quality of inpatient general medicine care.

GeMQIN uses data from GEMINI to create practice reports at the individual physician level (MyPractice: General Medicine Report[3]), and the hospital level (OurPractice: General Medicine Report[4]). These personalized, confidential reports inform physicians and hospitals about their clinical care patterns and patient outcomes. Quality indicators focus on length of stay, readmission, in-hospital mortality, routine bloodwork, advanced imaging, and appropriate blood transfusions. Hospital-level reports provide risk-adjusted comparisons across the network.

To assist users of these OurPractice: General Medicine Reports, this document provides background information regarding the data sources used, inclusion criteria, indicator selection, contextual interpretation, and specific details for each indicator presented in the OurPractice: General Medicine Report.

Data Collection and Management

The data for this report were collected by GEMINI. Established in 2015, GEMINI is one of Canada's largest hospital data and analytics resources. GEMINI is a hospital research collaborative based out of Unity Health Toronto and currently holds data on over 1.8 million admissions from more than 30 Ontario hospitals. With data for all medical (including general medicine, cardiology, oncology, etc.) and intensive care hospitalizations, GEMINI data covers approximately 60% of all adult medical and intensive care beds across Ontario.

Both administrative and clinical data from hospital information systems are extracted and shared with GEMINI directly from hospitals participating in GeMQIN. Administrative data include defined variables, such as patient demographics, admission and discharge dates, and diagnosis codes standardized for reporting to the Canadian Institute of Health Information (CIHI). Clinical data include variables such as patient vital signs, laboratory test results, imaging, interventions, and medication orders. GEMINI receives hospital data every 3 months and has established analytical processes to handle the volume and range of data collected, along with workflows for de-identification, quality control, standardization, and validation. The methodology for ensuring data quality has been rigorously validated, demonstrating 98% to 100% accuracy across key data elements compared to gold-standard chart review.[5] GEMINI data are collected through research ethics board-approved protocols and are governed by the GEMINI data governance policies.

Inclusion Criteria

OurPractice reports include hospitalizations that meet the following criteria:

1. Discharged during the reporting period
2. Admitted to or discharged from the general medicine department or hospitalist service at a participating hospital

Strategies to attribute patients to General Medicine are tailored and developed in collaboration with each hospital based on their specific model of clinical care.

Patient Diagnoses

The OurPractice: General Medicine reports present data stratified by patient diagnosis groups. We use the Clinical Classifications Software Refined (CCSR)[6] to group Canadian ICD-10-CA[7] codes into clinically meaningful diagnosis groups. These diagnosis groups are based on the most responsible ICD-10-CA discharge diagnosis, as reported in the CIHI Discharge Abstract Database (DAD).[8] The CCSR approach allows us to aggregate more than 70,000 unique ICD-10-CA diagnosis codes into ~540 mutually exclusive categories across 22 body systems. Some diagnosis codes are cross-classified into more than one category because individual ICD-10-CA codes can describe multiple conditions, or a condition and a common symptom/manifestation. We define patient diagnosis based on the default CCSR code. When a proxy most responsible discharge diagnosis is present, that code is used in place of the most responsible discharge diagnosis.

CCSR codes are designed for ICD-10-CM codes. GEMINI has developed an algorithm to reliably map CCSR categories to Canadian ICD-10-CA codes. The algorithm is an open source resource freely available to the public[9] and has been validated by clinical experts.[10]

Indicator Selection

The OurPractice: General Medicine report includes nine indicators that were selected by the GeMQIN Report Development Committee (comprising the program's provincial clinical leads, physicians and interdisciplinary health professionals, hospital administrators, quality improvement experts, and researchers). A focus of GeMQIN in the coming years will be to further develop quality indicators that are relevant to hospital medicine through consultation with an expert Indicator Committee. Feedback and/or participation in future indicator selection is welcome at GeMQIN@OntarioHealth.ca.

Contextual Interpretation

These data are intended to help hospitals understand the quality of general medicine care and inform quality improvement efforts. There are sometimes large differences in quality indicator performance between hospitals. These differences may be due to differences in processes and quality of care, case mix, and/or patient characteristics. Risk adjusted estimates standardize for (i.e., hold constant) differences in case mix and patient severity. This allows any remaining differences between hospitals to be attributed to a hospital's processes and quality of care.

While our risk adjustment demonstrates strong performance, it should be acknowledged that risk adjustment is imperfect and is unable to consider factors that are not included in hospital or administrative health data (e.g., primary care data, outpatient clinic data). Thus, we encourage these data to be interpreted with local context in mind. This context-driven interpretation is especially important given that the COVID-19 pandemic has impacted hospitals in different ways and to varying degrees.

Hospitals in This Report

This OurPractice report includes data from the following hospitals. GeMQIN includes additional hospitals not included in this report because they do not participate in the data collection portion of the program.

- Brampton Civic Hospital – William Osler Health System
- Cortelluci Vaughan Hospital – Mackenzie Health
- Etobicoke General Hospital – William Osler Health System
- Grand River Hospital
- Greater Niagara General Site – Niagara Health
- Hamilton General Hospital – Hamilton Health Sciences
- Humber River Hospital
- Juravinski Hospital – Hamilton Health Sciences
- Kingston General Hospital – Kingston Health Sciences Centre
- Mackenzie Richmond Hill Hospital – Mackenzie Health
- Markham Stouffville Hospital – Oak Valley Health
- Mount Sinai Hospital – Sinai Health
- Michael Garron Hospital – Toronto East Health Network

- North York General Hospital
- Sault Area Hospital
- St. Catharines Site – Niagara Health
- St. Joseph's Health Centre – Unity Health Toronto
- St. Mary's General Hospital
- St. Michael's Hospital – Unity Health Toronto
- Sunnybrook Health Sciences Centre
- Thunder Bay Regional Health Sciences Centre
- University Hospital – London Health Science Centre
- Victoria Hospital – London Health Science Centre
- Welland Hospital Site – Niagara Health

Numbers in this report that rely on network-wide data are not directly comparable to the previous report because this report includes two additional hospitals while not including three hospitals that were included in the previous report. For example, the indicator value at the 25th percentile hospital may not match the previous report. Hospitals included in future reports may also vary depending on the availability of data.

Indicator Details

Table 1: Total Length of Stay

Indicator Name	Total length of stay
Description	The number of days from admission to discharge
Unit of Analysis	Hospitalization
Calculation	Median number of days 1. Identify all hospitalizations discharged during the reporting period 2. Apply exclusions defined below 3. Calculate total length of stay as the difference between date/time of admission and date/time of discharge, in days 4. Sort total length of stay values 5. Select the middle value, representing the 50th percentile total length of stay
Exclusion	Hospitalizations that were transferred in from, or transferred out to, another acute care institution • Coded transfers are based on the DAD fields “Institution From” and “Institution To” Hospitalizations with total length of stay longer than 365 days
Source	Hospital data standardized for reporting to the CIHI DAD
Risk Adjustment	Yes (see Risk Adjustment, below, for details)
Desired Value	No clear desired direction. A shorter length of stay may reflect more efficient use of resources, while a longer length of stay may reflect more thorough care. Interpret in the context of your hospital’s processes of care, case load, and other local clinical context.
Comments	This indicator includes alternate level of care days.

Table 2: Acute Length of Stay

Indicator Name	Acute length of stay
Description	The number of days from admission to discharge, excluding alternate level of care days
Unit of Analysis	Hospitalization
Calculation	Median number of days 1. Identify all hospitalizations discharged during the reporting period 2. Apply exclusions defined below 3. Calculate total length of stay as the difference between date/time of admission and date/time of discharge, in days 4. Subtract alternate level of care days from total length of stay 5. Sort acute length of stay values 6. Select the middle value, representing the 50th percentile acute length of stay
Exclusion	Hospitalizations that were transferred in from, or transferred out to, another acute care institution • Coded transfers are based on the DAD fields "Institution From" and "Institution To" Hospitalizations with total length of stay longer than 365 days. Hospitalizations with entire total length of stay on an alternate level of care service
Source	Hospital data standardized for reporting to the CIHI DAD
Risk Adjustment	Yes (see Risk Adjustment, below, for details)
Desired Value	No clear desired direction. A shorter length of stay may reflect more efficient use of resources, while a longer length of stay may reflect more thorough care. Interpret in the context of your hospital's processes of care, case load, and other local clinical context.
Comments	This indicator excludes alternate level of care days. Alternate level of care days are coded as integers. As a result, all hospitalizations involving alternate level of care will have at least one coded alternate level of care day. In the rare situation where a hospitalization involves ALC and has total length of stay less than 1 day, this hospitalization is assigned no acute inpatient days and is excluded from acute length of stay calculations.

Table 3: Alternate Level of Care Days

Indicator Name	Alternate level of care days (ALC days)
Description	ALC Days ÷ Total Days: the percentage of total inpatient days that were spent on an alternate level of care service ALC Days Per ALC Patient: the median number of days spent on an alternate level of care service, among patients with at least one alternate level of care day
Unit of Analysis	Hospitalization
Calculation	ALC Days ÷ Total Days 1. Identify all hospitalizations discharged during the reporting period 2. Apply exclusion defined below 3. Calculate total length of stay as the difference between date/time of admission and date/time of discharge, in days 4. Calculate the total number of alternate level of care days (sum) 5. Calculate the total number inpatient days (sum) 6. Divide the total number of alternate level of care days by the total number of inpatient days ALC Days Per ALC Patient 1. Identify all hospitalizations discharged during the reporting period 2. Apply exclusion defined below 3. Exclude patients with no ALC days 4. Sort number of ALC days 5. Select the middle value, representing the 50th percentile number of ALC days
Exclusion	Hospitalizations with total length of stay longer than 365 days
Data Source	Hospital data standardized for reporting to the CIHI DAD
Risk Adjustment	None
Desired Value	Fewer alternate level of care days is desirable
Comments	This indicator requires two separate calculations. ALC days ÷ Total Days describes the percentage of total inpatient days that were designated as alternate level of care. ALC Days Per ALC Patient describes the median number of days that patients remain in alternate level of care, among patients with at least one alternate level of care day. Alternate level of care days are coded as integers.

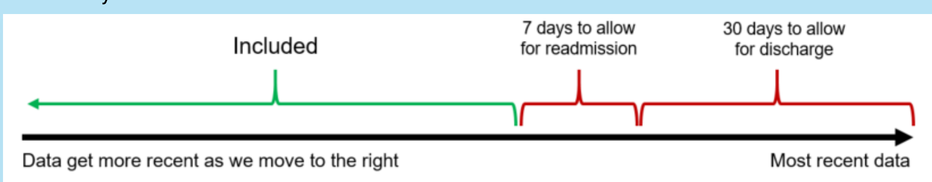
Table 4: 7-Day Readmission

Indicator Name	7-day readmission
Description	Readmission to any medical or intensive care service at a GeMQIN hospital within 7 days of discharge
Unit of Analysis	Episode of Care An episode of care includes all contiguous inpatient hospitalizations admitted to any medical or intensive care service within GeMQIN. Episodes involving interfacility transfers are linked regardless of diagnosis. An acute care transfer is assumed to have occurred if either of the following criteria are met: • An admission to a medical or intensive care service at a GeMQIN hospital occurs within 7 hours after discharge from another GeMQIN hospital, regardless of whether the transfer is coded • An admission to a medical or intensive care service at a GeMQIN hospital occurs 7–12 hours after discharge from another GeMQIN hospital, and at least one hospital has coded the transfer o Coded transfers are based on the DAD fields “Institution From” and “Institution To” For episodes of care involving acute care transfers, readmissions are attributed to the last hospital from which the patient was discharged before readmission.
Calculation	Rate: numerator ÷ denominator (calculation equivalent to arithmetic mean)
Exclusions	Episodes with an invalid health card number

Denominator	Total number of episodes of care discharged during the reporting period
	Exclusions from the denominator:
	• Episodes with discharge as death
	    o DAD discharge disposition codes 07, 72, 73, 74
	• Episodes with at least one record for palliative care
	    o ICD-10-CA code Z51.5 as diagnosis type M
	• Episodes with at least one record for mental health
	    o CIHI major clinical category 17 as diagnosis type M
	• Episodes where the last record is a self sign-out
	    o DAD discharge disposition codes: 06, 61, 62, 65, 66, 67
	• Episodes where the last hospital has coded a transfer out to a non-GeMQIN acute care institution
	    o This indicates that the patient was transferred to a hospital outside of GeMQIN; in which case, readmission cannot be attributed to a GeMQIN hospital
	    o Coded transfers out are based on the DAD field “Institution To”

Numerator	Total number of episodes of care that were followed by readmission to any medical or intensive care service at a GeMQIN hospital within 7 days of discharge during the reporting period
	Exclusions from the numerator:
	• Episodes where the first record is elective admission
	    o DAD admission category code L
	• Episodes with at least one record for chemotherapy for neoplasm
	    o ICD-10-CA code Z51.1 as diagnosis types M, 1, W, X, Y

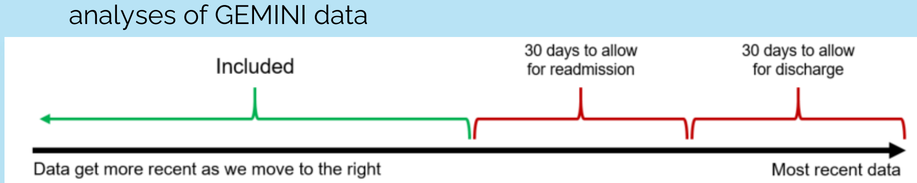
	• Episodes with at least one record for palliative care
	  ○ ICD-10-CA code Z51.5 as diagnosis type M
	• Episodes with at least one record for mental health
	  ○ CIHI major clinical category 17 as diagnosis type M
	• Episodes with at least one record for obstetric delivery
	  ○ ICD-10-CA codes O10–O16, O21–O29, O30–O37, O40–O46, O48, O60–O69, O70–O75, O85–O89, O90–O92, O95, O98, O99 with a sixth digit of 1 or 2, or Z37 recorded in any diagnosis field
	• Medical assistance in dying
	  ○ After April 2018: DAD discharge disposition code 73
	Before April 2018: discharge disposition code 7 and all three Canadian Classification of Health Intervention codes: 1.ZZ.35.HA-P7, 1.ZZ.35.HA-P1, 1.ZZ.35.HA-N3

Data Source	Hospital data standardized for reporting to CIHI DAD
Risk Adjustment	Yes (see Risk Adjustment, below, for details)
Desired Value	Lower 7-day readmission rates are desirable
Comments	This indicator does not capture readmissions to hospitals outside of GeMQIN. In rare cases, an episode of care may be mistakenly identified as two separate episodes. For example, when a patient is transferred from a GeMQIN hospital to a non-GeMQIN hospital and then back to a GeMQIN hospital. The following scenario only applies to hospitals where the data provided to GEMINI does not go beyond the reporting period of the OurPractice report at the time of the development. GEMINI receives data after the inpatient has been discharged from hospital. If a patient is still hospitalized at the time of data extraction, that information will not be provided to GEMINI until the hospitalization has ended. If this particular hospitalization is a readmission, this would result in an underestimation of readmission rates because this hospitalization has not yet been counted by GEMINI. To minimize this bias, 7-day readmission rates exclude the most recent 37 days collected from each hospital. The rationale is as follows: • 7 days must have passed to allow for 7-day readmission to occur • > 95% of hospital admissions will be discharged within 30 days based on analyses of GEMINI data 

Sources: Discharge Abstract Database,[8] GEMINI data,[2] MyPractice: General Medicine,[3] ICD-10-CA codes and classifications.[7]

Table 5: 30-Day Readmission

<table>
<tr><th>Indicator Name</th><th>30-day readmission</th></tr>
<tr><td>Description</td><td>Readmission to any medical or intensive care service at a GeMQIN hospital within 30 days of discharge</td></tr>
<tr><td>Unit of Analysis</td><td>Episode of Care
An episode of care includes all contiguous inpatient hospitalizations admitted to any medical or intensive care service within GeMQIN. Episodes involving interfacility transfers are linked regardless of diagnosis. An acute care transfer is assumed to have occurred if either of the following criteria are met:
An admission to a medical or intensive care service at a GeMQIN hospital occurs within 7 hours after discharge from another GeMQIN hospital, regardless of whether the transfer is coded
An admission to a medical or intensive care service at a GeMQIN hospital occurs 7–12 hours after discharge from another GeMQIN hospital, and at least one hospital has coded the transfer
Coded transfers are based on the DAD fields “Institution From” and “Institution To”
For episodes of care involving acute care transfers, readmissions are attributed to the last hospital from which the patient was discharged before readmission.</td></tr>
<tr><td>Calculation</td><td>Rate: numerator ÷ denominator (calculation equivalent to arithmetic mean)</td></tr>
<tr><td>Exclusions</td><td>Episodes with an invalid health card number</td></tr>
<tr><td>Denominator</td><td>Total number of episodes of care discharged during the reporting period
Exclusions from the denominator:
Episodes with discharge as death
DAD discharge disposition codes 07, 72, 73, 74
Episodes with at least one record for palliative care
ICD-10-CA code Z51.5 as diagnosis type M
Episodes with at least one record for mental health
CIHI major clinical category 17 as diagnosis type = M
Episodes where the last record is a self sign-out
DAD discharge disposition codes 06, 61, 62, 65, 66, 67
Episodes where the last hospital has coded a transfer out to a non-GeMQIN acute care institution
This indicates that the patient was transferred to a hospital outside of GeMQIN; in which, case readmission cannot be attributed to a GeMQIN hospital
Coded transfers out are based on the DAD field “Institution To”</td></tr>
<tr><td>Numerator</td><td>Total number of episodes of care that were followed by readmission to any medical or intensive care service at a GeMQIN hospital within 30 days of discharge during the reporting period
Exclusions from the numerator:
Episodes where the first record is elective admission
DAD admission category code L
Episodes with at least one record for chemotherapy for neoplasm</td></tr>
</table>

	ICD-10-CA code Z51.1 as diagnosis type M, 1, W, X, Y • Episodes with at least one record for palliative care ICD-10-CA code Z51.5 as diagnosis type M • Episodes with at least one record for mental health CIHI major clinical category 17 as diagnosis type M • Episodes with at least one record for obstetric delivery ICD-10-CA codes O10–O16, O21–O29, O30–O37, O40–O46, O48, O60–O69, O70–O75, O85–O89, O90–O92, O95, O98, O99 with a sixth digit of 1 or 2, or Z37 recorded in any diagnosis field • Medical assistance in dying After April 2018: DAD discharge disposition code 73 Before April 2018: discharge disposition code 7 and all three Canadian Classification of Health Intervention codes: 1.ZZ.35.HA-P7, 1.ZZ.35.HA-P1, 1.ZZ.35.HA-N3
Data Source	Hospital data standardized for reporting to CIHI DAD
Risk Adjustment	Yes, see Risk Adjustment, below, for details
Desired Value	Lower 30-day readmission rates desirable.
Comments	This indicator does not capture readmissions to hospitals outside of GeMQIN. In rare cases, an episode of care may be mistakenly identified as two separate episodes. For example, when a patient is transferred from a GeMQIN hospital to a non-GeMQIN hospital and then back to a GeMQIN hospital. The following scenario only applies to hospitals where the data provided to GEMINI does not go beyond the reporting period of the OurPractice report at the time of the development. GEMINI receives data after the inpatient has been discharged from hospital. If a patient is still hospitalized at the time of data extraction, that information will not be provided to GEMINI until the hospitalization has ended. If this particular hospitalization is a readmission, this would result in an underestimation of readmission rates because this hospitalization has not yet been counted by GEMINI. To minimize this bias, 30-day readmission rates exclude the most recent 60 days collected from each hospital. The rationale is as follows: • 30 days must have passed to allow for 30-day readmission to occur • > 95% of hospital admissions will be discharged within 30 days based on analyses of GEMINI data 

Sources: Discharge Abstract Database,[8] GEMINI data,[9] MyPractice: General Medicine,[3] ICD-10-CA codes and classifications.[7]

Table 6: In-Hospital Mortality

Indicator Name	In-hospital mortality
Description	Death occurring in hospital
Unit of Analysis	Hospitalization
Calculation	Rate: numerator ÷ denominator (calculation equivalent to arithmetic mean)
Exclusions	Hospitalizations with total length of stay longer than 365 days Age greater than 120 years Hospitalizations with palliative care as the most responsible discharge diagnosis ○ ICD-10-CA code Z51.5 as diagnosis type M Medical assistance in dying ○ After April 2018: DAD discharge disposition code 73 ○ Before April 2018: discharge disposition code 7 and all three Canadian Classification of Health Intervention codes: 1.ZZ.35.HA-P7, 1.ZZ.35.HA-P1, 1.ZZ.35.HA-N3
Denominator	Total number of hospitalizations discharged during the reporting period
Numerator	Total number of deaths in hospitalizations discharged during the reporting period. Death defined by DAD discharge disposition code 7, 72, 73, or 74
Data Source	Hospital data standardized for reporting to CIHI DAD
Risk Adjustment	Yes (see Risk Adjustment, below, for details)
Desired Value	Lower in-hospital mortality rates are desirable
Comments	Consistent with CIHI's Hospital Standardized Mortality Ratio calculation, risk adjusted quality indicator performance for mortality is limited to diagnosis groups accounting for 80% of in-hospital deaths in GeMQIN participating hospitals. The default setting of the in-hospital mortality indicator page is to exclude hospitalizations with palliative care as the most responsible discharge diagnosis when determining these diagnosis groups. To include palliative care as a most responsible discharge diagnosis, set the "Exclude" filter on the top left of the indicator page to "Nothing"

Table 7: Advanced Imaging Tests

Indicator Name	Advanced imaging tests
Description	The number of advanced imaging tests per hospitalization. Advanced imaging tests include computed tomography, magnetic resonance imaging, and ultrasound
Unit of Analysis	Hospitalization
Calculation	Rate: numerator ÷ denominator (calculation equivalent to arithmetic mean)
Exclusions	Hospitalizations with total length of stay longer than 365 days
Denominator	Total number of hospitalizations discharged during the reporting period
Numerator	Total number of advanced imaging tests in hospitalizations discharged during the reporting period
Data Source	Data extracted from hospital electronic patient records and standardized by subject matter experts
Risk Adjustment	Yes (see Risk Adjustment, below, for details)
Desired Value	No clear desired value. Fewer advanced imaging tests may reflect more efficient use of resources, while more advanced imaging tests may reflect more thorough care. Interpret in the context of your hospital's processes of care, case load, and other local clinical context
Comments	Interventional radiology is not included. Multiple imaging measurements from the same imaging order are treated as a single imaging test

Table 8: Routine Bloodwork Tests

Indicator Name	Routine bloodwork tests
Description	The number of routine bloodwork tests per hospitalization. Routine bloodwork tests are defined as electrolyte tests and complete blood count tests
Unit of Analysis	Hospitalization
Calculation	Rate: numerator ÷ denominator (calculation equivalent to arithmetic mean)
Exclusions	Hospitalizations with total length of stay longer than 365 days
Denominator	Total number of hospitalizations discharged during the reporting period
Numerator	Total number of routine bloodwork tests in hospitalizations discharged during the reporting period
Data Source	Data extracted from hospital electronic patient records and standardized by subject matter experts
Risk Adjustment	Yes (see Risk Adjustment, below, for details)
Desired Value	No clear desired value. Fewer routine blood tests may reflect more efficient use of resources, while more routine blood tests may reflect more thorough care. Interpret in the context of your hospital's processes of care, case load, and other local clinical context
Comments	None

Table 9: Appropriate Red Blood Cell Transfusion

Indicator Name	Appropriate red blood cell transfusion
Description	The rate of appropriate red blood cell transfusion among all red blood cell transfusions in hospitalizations during the reporting period
Unit of Analysis	Blood transfusion
Calculation	Rate: numerator ÷ denominator (calculation equivalent to arithmetic mean)
Exclusions	Red blood cell transfusions with no hemoglobin measurement within 48 hours prior to the transfusion are excluded from the numerator and denominator. These scenarios are rare, typically occurring in approximately 2% of blood transfusions based on analyses of GEMINI data
Denominator	Total number of red blood cell transfusions in hospitalizations discharged during the reporting period
Numerator	The total number of appropriate[a] red blood cell transfusions in hospitalizations discharged during the reporting period
Data Source	Data extracted from hospital electronic patient records and standardized by subject matter experts
Risk Adjustment	None
Desired Value	A higher rate of appropriate red blood cell transfusion is desirable.
Comments	None

[a]Appropriate blood transfusions are defined by the most recent pre-transfusion hemoglobin value less than 80 g/L within 48 hours prior to transfusion. We use the date/time of when the red blood cell product was issued from the blood bank instead of the date/time when the transfusion was administered because the latter value is not widely available in electronic health record data. We make the assumption that blood products will be transfused shortly after leaving the blood bank.

Risk Adjustment

Risk-Adjusted Quality Indicators

It is difficult to assess hospital performance in a fair manner. Certain hospitals may treat sicker patients and thus may appear to perform worse despite delivering high quality care. Risk adjustment aims to address these differences by holding constant the case mix and patient severity so that fair hospital comparisons can be made.

Risk adjustment compares what we observed during the reporting period to what we should expect based on a hospital's case mix and patient severity. Our expectation is based on regression models trained on historical data at all hospitals during the four years immediately prior to the reporting period. These regression models are developed using methodology from the Canadian Institute for Health Information and Kaiser Permanente, and consider a patient's age, sex, diagnosis group, Charlson comorbidity index score[11] at admission-, a modified laboratory-based acute physiology score (mLAPS) based on 12 biochemical parameters at admission,[12-14] and whether the admission was elective or urgent. Separate regression models are fit for each diagnosis group, allowing each diagnosis group to have their own associations between risk-adjustment variables and quality indicators.

Variables Used in Risk-Adjustment Models

Table 10 provides a summary of the variables used in risk-adjustment models for each indicator. Regression models are fit with these variables for each diagnosis group.

Table 10: Summary of Variables in Risk-Adjustment Models

	In-Hospital Mortality	7-Day Readmissions	30-Day Readmissions	Total LOS	Acute LOS	Routine Bloodwork	Advanced Imaging
Age	X	X	X	X	X	X	X
Sex	X	X	X	X	X	X	X
Charlson comorbidity index score	X	X	X	X	X	X	X
Elective admission	X	X	X	X	X	X	X
mLAPS	X	X	X	X	X	X	X
Number of acute care hospitalizations in the past 6 months		X	X	X	X	X	X
Total length of stay	X						
Transfer in from acute care	X						
COVID-19 as a risk factor	X						

Abbreviations: LOS, length of stay; mLAPS, modified laboratory-based acute physiology score.

AGE

Age is defined as the number of years between date of birth and hospital admission. It is coded as an integer value and is modeled as a restricted cubic spline. Age is included in risk-adjustment models for all indicators.

SEX

Sex is captured by two categories: female and non-female. Data for males and other sexes are combined into "non-female" as the data on other sexes are too limited to model as separate categories. Sex is included in risk-adjustment models for all indicators.

CHARLSON COMORBIDITY INDEX SCORE

Charlson comorbidity index score is based on ICD-10-CA diagnosis codes that were present at admission and does not consider diagnoses made during hospitalization. The score includes all emergency department diagnoses and inpatient diagnoses classified as pre-admit comorbidities or transfer diagnoses (diagnosis type 1, W, X, Y). Specific circumstances where secondary diagnoses (diagnosis type 3) and most responsible diagnoses (diagnosis type M) are included are outlined in the CIHI Hospital Standardized Mortality Ratio (HSMR), pages 18–22.[15] Encounters with no emergency department diagnosis codes and no eligible inpatient diagnosis codes are assigned a value of zero. The Charlson comorbidity index score is modeled as a linear term and is included in risk-adjustment models for all indicators.

ELECTIVE ADMISSION

Elective admission is defined by two categories: elective or not-elective admission determined based on DAD admit category L. It is included in risk adjustment models for all indicators.

MODIFIED LABORATORY-BASED ACUTE PHYSIOLOGY SCORE

The laboratory-based acute physiology score (LAPS) is a measure of illness severity based on 13 laboratory parameters that is validated as a predictor of in-hospital mortality when combined with patient characteristics listed above.[12,13] The LAPS score is not disease specific and has been validated in hospitalized patients irrespective of their disease condition, including in Ontario hospitals.[13] The LAPS score considers serum albumin, anion gap, arterial pH, arterial $PaCO_2$, arterial PaO_2, total serum bilirubin, blood urea nitrogen, serum creatinine, serum glucose, serum sodium, serum troponin, hematocrit, and total white blood cell count. We apply a modified LAPS score (mLAPS) that excludes troponin because there is no way to reconcile high-sensitivity troponin tests when calculating the score. GEMINI has validated the mLAPS score in 28 Ontario hospitals.[14] We consider only laboratory tests performed before admission to ensure that post-treatment values are not considered. We assume that laboratory tests that were not performed would be normal. The mLAPS score is a modeled as a linear term and is included in risk-adjustment models for all indicators.

NUMBER OF ACUTE CARE HOSPITALIZATIONS IN THE PAST 6 MONTHS

The number of acute care hospitalizations in the past 6 months is defined by three categories: 0, 1, and 2+, representing the number of times a person has been discharged from acute care during the 6 months prior to the admission date. The number of acute care hospitalizations in the past 6 months is included in all risk-adjustment models except mortality (mortality is excluded based on CIHI's HSMR).[15]

TOTAL LENGTH OF STAY

Total length of stay is defined as the number of days between admission and discharge. This variable is modeled as a linear term and is included only in risk-adjustment models for mortality (length of stay is included as a variable in mortality models based on CIHI's HSMR).[15] Note that HSMR models total length of stay as six categories while we model it as a linear term. This is due to singular model fits when applying the categorical approach.

TRANSFER IN FROM ACUTE CARE

Transfer in from an acute care institution is defined by two categories: transferred in or not transferred in from an acute care institution. This value is determined based on the DAD field, "Institution From" and is augmented using the Ontario Ministry of Health's Master Numbering System.[16] We include transfer in from an acute care institution as a variable in mortality models based on CIHI's HSMR.[15]

COVID-19 AS A RISK FACTOR

Hospitalizations where COVID-19 is the most responsible discharge diagnosis are treated as a separate diagnosis group for risk adjustment of all indicators. Where it is not the most responsible discharge diagnosis, COVID-19 has been added as a risk factor to mortality indicator models for all diagnosis groups. "COVID-19 as a risk factor" is defined by two categories: COVID-19 present and COVID-19 not present. As a risk factor, it is determined by inpatient diagnosis code U07.1, or U07.2 as a pre-admit diagnosis, post-admit comorbidity, or service transfer diagnosis (diagnosis type 1, 2, W, X, Y). We include COVID-19 as a risk factor in mortality models for all diagnosis groups based on CIHI's HSMR.[15]

Interaction Terms

All risk-adjustment models include two-way interaction terms between Charlson comorbidity index score, mLAPS, and age.

Diagnosis Group

Risk-adjustment models are fit separately within each diagnosis group to allow for diagnosis-specific intercepts and associations between risk-adjustment variables and quality indicators. Diagnoses are grouped using the Clinical Classifications Software Refined (see Patient Diagnoses, above, for details).[6] Diagnosis groups with fewer than 200 hospitalizations (150 events for binary indicators) in the training data are grouped into an “Other” catch-all diagnosis group. The “Other” group is then broken down into three subgroups based on observed values of the quality indicator in the training data. These subgroups are based on event rates for binary indicators and geometric mean for numeric indicators.

Consistent with CIHI’s HSMR,[15] risk adjustment for mortality is limited to diagnosis groups accounting for 80% of in-hospital deaths in GeMQIN-participating hospitals (based on training data—the 4 years of data immediately prior to the reporting period). Risk-adjusted values for all other indicators consider all diagnosis groups. The default setting for the in-hospital mortality indicator page excludes hospitalizations with palliative care as the most responsible discharge diagnosis when determining these diagnosis groups. Hospitalizations with palliative care as the most responsible discharge diagnosis are included when the “Exclude” filter on the top left of the indicator page is set to “Nothing.”

Missing Data

Patients with no Ontario Health Insurance Plan (OHIP) card number cannot be tracked between admissions, resulting in missing values for the number of acute care hospitalizations in the past 6 months. For our modelling, these missing values are assumed to be 0. Patients without an OHIP card number represent approximately 2% of all hospitalizations at each hospital.

Risk-Adjustment Models for Binary Quality Indicators

We used logistic regression models to risk-adjust binary quality indicators (7-day readmission, 30-day readmission, and in-hospital mortality). All analyses were performed in R version 4.1.0,[17] and models were fit using the lrm function from the rms package.[18]

We evaluated models using Harrell's bias correction and 1,000 bootstrap iterations.[19-22] Evaluation metrics include the brier (skill) score, c-statistic, Nagelkerke's R^2, calibration slope, calibration intercept, integrated calibration index, 50th/90th/99th percentile absolute difference between smoothed calibration curves and the diagonal line of best fit, and visual inspection of bootstrapped calibration curves. All variables were retained in the models regardless of statistical significance, and models were not altered based on results of model evaluation. We assumed that observations from the same patient are conditionally independent in all risk-adjustment models.

All risk-adjustment variables for 7-day and 30-day readmissions were taken from the last encounter of the index episode of care from which the patient was discharged.

Risk-Adjustment Models for Numeric Quality Indicators

We used semiparametric ordinal regression models to risk-adjust numeric quality indicators (total length of stay, acute length of stay, number of routine bloodwork tests, and number of advanced imaging tests). Semiparametric ordinal models were chosen for several reasons: they do not require a distributional assumption for the outcome given covariates, the coefficient estimates are completely robust to extreme outcome values, they require no assumption of equal variance, and they have the ability to handle arbitrary clumping at zero (particularly relevant for advanced imaging). All analyses were performed in R version 4.1.0[17] and models were fit using the orm function from the rms package.[18]

We evaluated models using Harrell's bias correction and 1,000 bootstrap iterations.[19-22] Evaluation metrics include spearman's Rho, Nagelkerke's R^2, calibration slope, visual inspection of agreement between observed and estimated mean values, and visual inspection for parallelism of the link function transformed inverse cumulative probability function of one minus the empirical distribution function stratified by fitted values from ordinary least squares regression.[23] All variables were retained in the models regardless of statistical significance and models were not altered based on results of model evaluation. We assumed observations from the same patient are conditionally independent in all risk-adjustment models.

We compared model fit for each numeric indicator using logit, probit, and loglog link functions in three of the five largest diagnosis groups, chosen at random. Parallelism was inspected for each link function and the transformed outcome was regressed on fitted values from ordinary least squares regression to assess consistency of slopes across arbitrary cutpoints. All models use a logit link.

Total and acute length of stay values were rounded to one decimal point when fitting risk-adjustment models.

Institutional Assessment for Binary Quality Indicators

Hospital assessments for binary quality indicators (i.e., in-hospital mortality, 7-day readmission, 30-day readmission) use an observed-to-expected ratio framework consistent with CIHI's HSMR. The observed number of events during the reporting period is compared to the expected number of events. The expected number of events is the sum of predicted probabilities (from risk-adjustment models) for all encounters at that hospital during the reporting period. A ratio above 1 means that observed values were higher than expected; a value below 1 means that observed values were lower than expected. A 95% confidence interval is calculated around the ratio using Byar's approximation (below). The ratio is multiplied by the combined event rate at all hospitals during the reporting period so that results can be interpreted as rates on a more meaningful scale. For example, if a hospital had 1.2 times more deaths than expected and the combined network-wide in-hospital mortality rate was 6%, the risk adjusted mortality rate at that hospital would be 1.2 × 6% = 7.2%. We apply no corrections for multiple testing.

Byar's Approximation:
95% CIL = O / E * (1 - 1 / (9 * O) - Z / (3 * sqrt(O)))^3
95% CIU = (O + 1) / E * (1 - (1 / (9 * (O + 1))) + Z / (3 * sqrt(O + 1)))^3

Where CI is confidence interval, E is expected, O is observed, L is lower, U is upper, and Z is 1.96.

Institutional Assessment for Numeric Quality Indicators

Hospital assessments for numeric quality indicators (i.e., total and acute length of stay, routine bloodwork, advanced imaging) use a random intercept regression framework.[24-26] A negative binomial regression is fit with expected values as a fixed effect and with hospitals as random intercepts. Expected values are centered encounter-level estimated means (from risk-adjustment models) for all encounters at all hospitals during the reporting period. The hospital-level random intercepts represent hospital-specific deviations from the average intercept, holding expected values constant.

An empirical Bayes estimate of each hospital's random intercept is calculated along with its standard error. Standard 95% CIs are constructed around these estimates. The overall model intercept is added so all estimates and confidence intervals are in units of log(estimated mean) and the antilog is taken so that results can be interpreted as estimated means. Hospital effects are assumed to be normally distributed. Models were tested for zero-inflation using scaled residuals from simulating the fitted model, and no zero-inflation was present. All analyses were performed in R version 4.1.0.[17] Models were fit using the glmmTMB function from the glmmTMB package,[26] and zero-inflation was tested using the DHARMa package.[27]

How to Interpret Risk-Adjusted Institutional Assessments

Risk-adjusted values should be interpreted in the context of their 95% CIs. These intervals reflect uncertainty in the hospital's risk-adjusted values. A hospital whose entire interval is below the expected value will be classified as "below average" and colored blue. A hospital whose entire interval is above the expected value will be classified as "above average" and colored magenta. A hospital whose interval contains the expected value will be classified as "average" and colored gray. Note that "above average" and "below average" describe the direction of the effect and should not be interpreted as "good" or "bad" (e.g., a risk-adjusted mortality rate below average is desirable).

Each hospital's risk-adjusted value should be interpreted based on its position relative to the expected value (solid vertical black line). Risk-adjusted values are not designed for direct comparison between individual hospitals, and risk-adjusted values are not designed to rank hospitals relative to one another.

Why Are My Unadjusted Numbers Different From My Risk-Adjusted Numbers?

Unadjusted numbers are raw data. They are summary statistics describing what was observed during the reporting period. Unadjusted numbers do not take into account differences in case mix or patient severity. Risk-adjusted numbers compare what was observed during the reporting period against what would be expected based on the case mix and patient severity at a given hospital.

Unadjusted values will be notably different than risk adjusted values for total length of stay, acute length of stay, and in-hospital mortality due to calculation methods. Length of stay values differ because unadjusted values are medians, while risk-adjusted values are estimated means. Mortality values differ because risk-adjustment only considers diagnosis groups accounting for 80% of mortality, consistent with CIHI's HSMR[15] (i.e., risk-adjusted mortality estimates are based on a subgroup of patients from high-mortality diagnosis groups).

Considerations Regarding COVID-19

The COVID-19 pandemic has evolved substantially over time. Ontario's population has become increasingly vaccinated, the demographics of people infected with COVID-19 have shifted, new treatments have become available for both mild and severe COVID-19, and the virulence of dominant COVID-19 variants has shifted. The time-varying nature of the COVID-19 pandemic makes it difficult to estimate baseline risk of patients hospitalized with COVID-19 using historical data, leading to an overestimation of baseline risk during the reporting period. As such, observed in-hospital mortality is lower than expected mortality based on risk-adjustment models at most hospitals. Because of this, we do not present any diagnosis-specific risk-adjusted estimates for COVID-19.

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