



Data surveillance on the clinical data used for health system funding in Ontario Lori Kirby, Maureen Kelly Data Quality Department **Canadian Institute for Health Information**



Canadian Institute for Health Information

d'information sur la santé

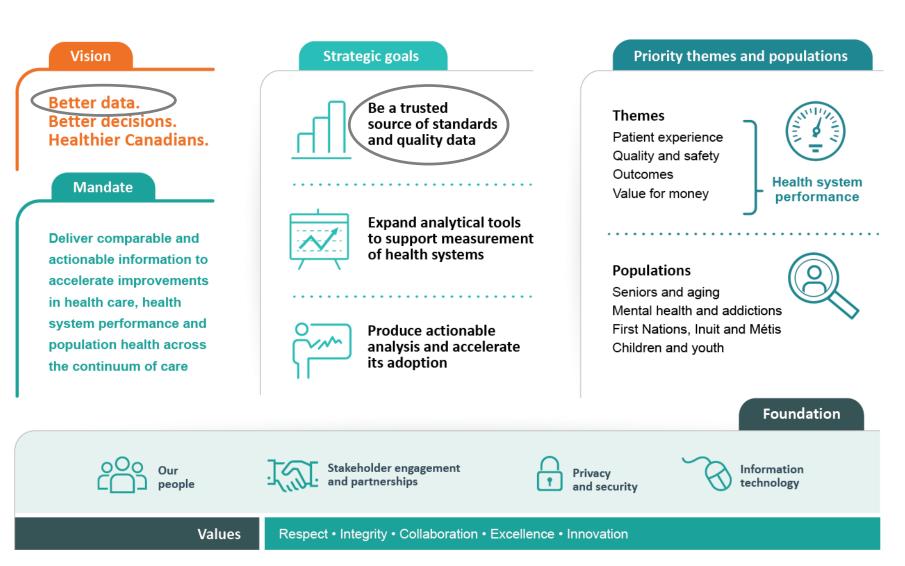
Outline



- About Data Quality at CIHI
- What is data surveillance?
- CIHI's data surveillance pilot
- Big Data insights



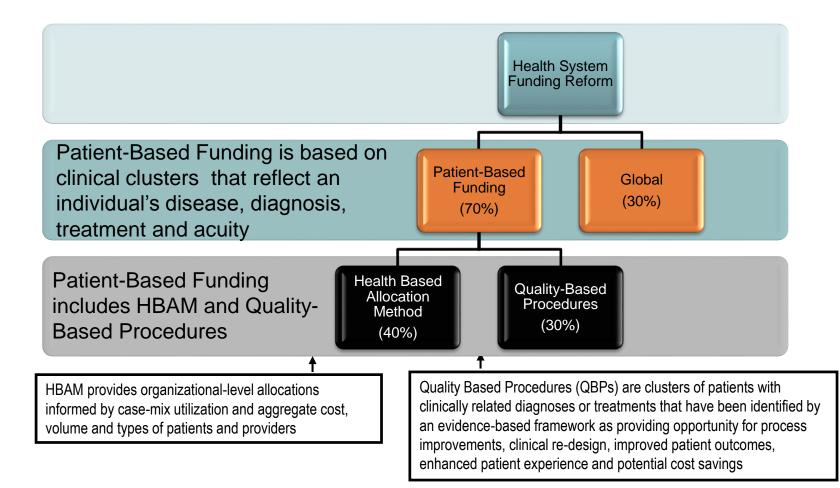
Data Quality Is Fundamental to CIHI



Health System Funding Reform in Ontario



- Calls for increased focus on data quality
- Clinical administrative data being used to determine funding allocations to regions and hospitals



Increased focus on data quality



- Impacts on data quality can be both **positive** and **negative**:
 - Positive: People pay more attention to the data and its quality; more complete and timely submissions



- Negative: Manipulation of data/coding/clinical practice to maximize funding (i.e. gaming)
- To prevent and minimize the impact on data quality, CIHI is exploring options for developing systems and processes Data Surveillance specifically targeted toward these issues

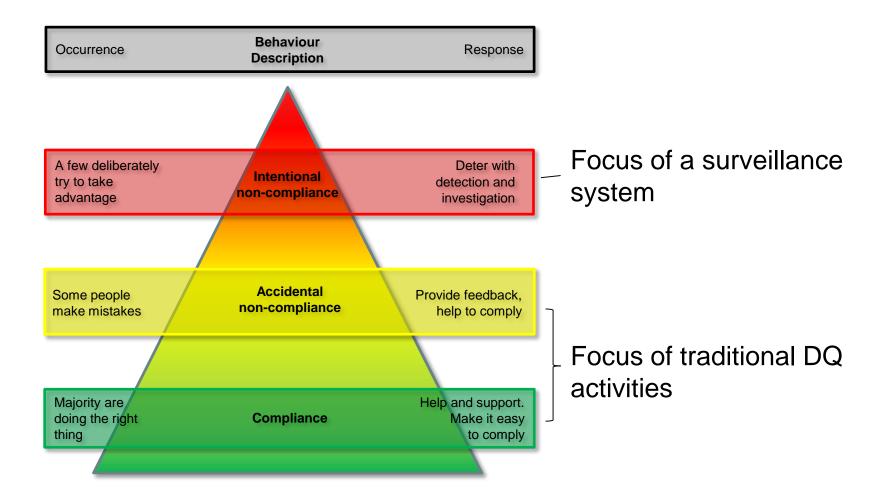


What do we mean by "data surveillance"?



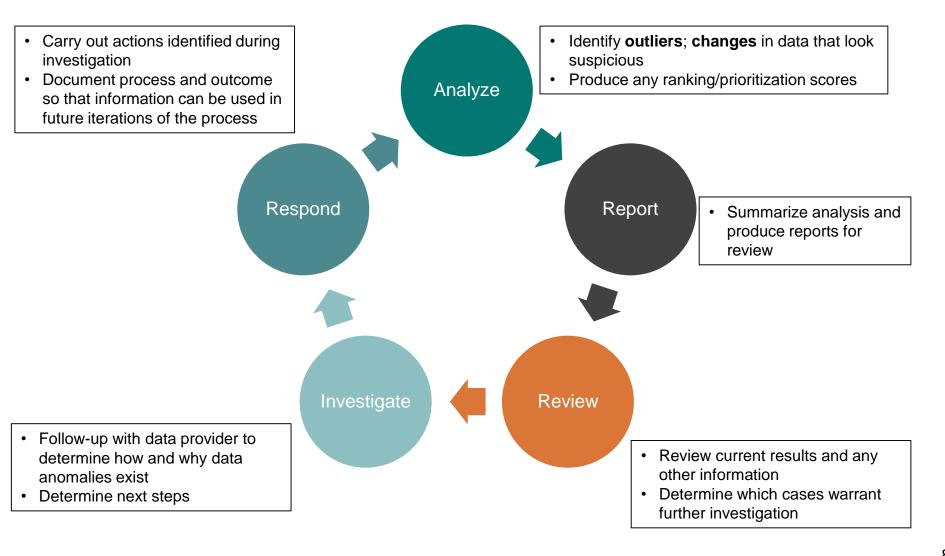
Surveillance is targeted to those trying to taking advantage of the system





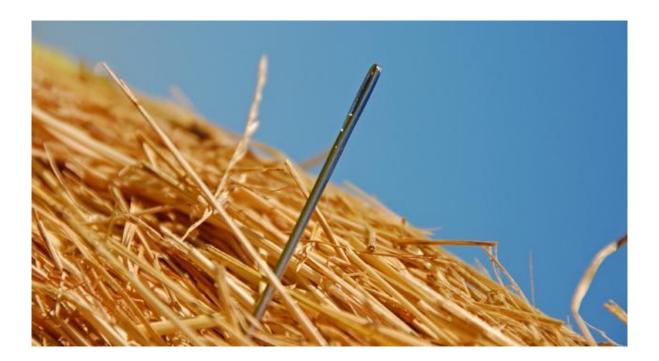
The Surveillance Process: Data into Action







CIHI's Data Surveillance Pilot



Pilot Overview



- Objective: Identify outliers in Ontario acute care data from CIHI's
 Discharge Abstract Database
- **Outcome:** Produce an **overall data quality score** to prioritize which facilities may warrant further analysis and investigation
- **Focus:** Multiple elements that impact Ontario's funding formula:
 - Special Care Units (SCU)
 - Discharge to Home Care
 - Quality Based Procedures (QBP's)
 - Comorbidities

• Methods:

 Applied 3 different analytical techniques using SAS Enterprise Miner to identify outliers



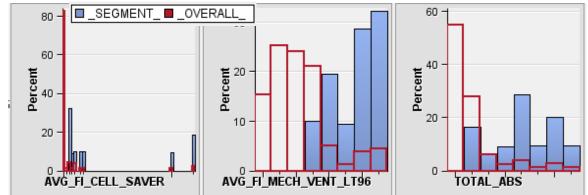
Methodology 1 – Segmentation Model using Cluster Analysis

 Identify "segments" – facilities – with similar patterns of SCU data
 Facilities are grouped based on distribution of all variables
 Identified outlier group – segment 5 -1000 –

-3000

-2000





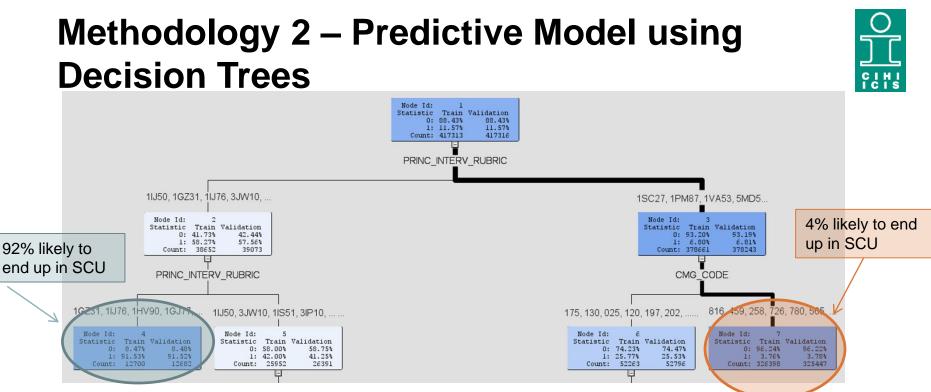


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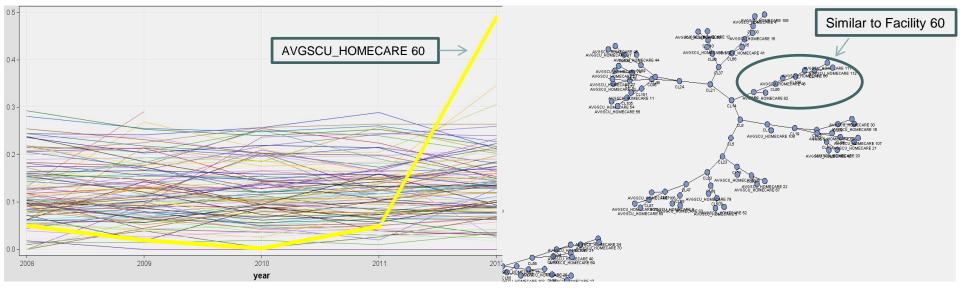
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- Tree built to predict the likelihood of being in an SCU
- Model based on 2009-2010 data and then applied to 2013-2014 data
- Most Important Variables:
 - Principle Intervention Code (ruberik level)
 - Case Mix Group Code
 - Number of Intervention Episodes before SCU
- Calculate ratio of how many SCU occurred (observed) vs how many predicted by the model (expected)

Methodology 3 – Time Series Model

- Using Time Series to compare facility-level volumes for discharge to home care
- Identify the facility with the most significant change over time, set it as a target
- · Identify the facilities that are most similar to the target facility
- Process will be repeated for other variables:
 - Volumes of Quality Based Procedures
 - Number of comorbidities coded











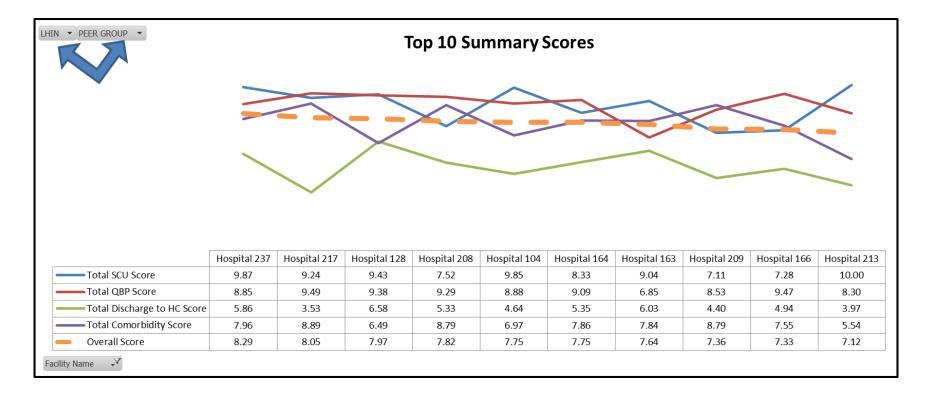
Overall Score Card

Facility Name	LHIN	PEER GROUP	Total Score	SCU Score	QBP Score	Discharge to HC Score	Comorbidity Score
Hosptial 237	LHIN H	Teaching	8.29	9.87	8.85	5.86	7.96
Hosptial 217	LHIN M	Teaching	8.05	9.24	9.49	3.53	8.89
Hosptial 128	LHIN M	Teaching	7.97	9.43	9.38	6.58	6.49
Hosptial 208	LHIN L	Teaching	7.82	7.52	9.29	5.33	8.79
Hosptial 104	LHIN K	Teaching	7.75	9.85	8.88	4.64	6.97
Hosptial 164	LHIN F	Teaching	7.75	8.33	9.09	5.35	7.86
Hosptial 163	LHIN F	Teaching	7.64	9 .0 4	6.85	6.03	7.84
Hosptial 209	LHIN J	Teaching	7.36	7.11	8.53	4.40	8.79
Hosptial 166	LHIN F	Teaching	7.33	7.28	9.47	4.94	7.55
Hosptial 213	LHIN M	Teaching	7.12	10.00	8.30	3.97	5.54
Hosptial 126	LHIN M	Teaching	7.05	6.60	8.57	2.62	9.43
Hosptial 205	LHIN K	Large Community	7.02	8.51	6.70	6.59	6.03
Hosptial 236	LHIN D	Teaching	6.96	6.06	9.08	4.70	7.94
Hosptial 119	LHIN K	Large Community	6.93	9.44	7.77	7.61	3.42
Hosptial 240	LHIN D	Teaching	6.57	9.15	2.89	4.57	7.78
Hosptial 138	LHIN L	Small	6.31	6.74	4.16	6.78	7.00
Hosptial 150	LHIN D	Small	6.29	6.70	3.32	7.38	7.13
Hosptial 159	LHIN N	Large Community	6.25	7.36	8.04	6.84	3.55
Hosptial 258	LHIN C	Large Community	6.25	5.46	9.46	6.18	4.93
Hosptial 101	LHIN L	Large Community	6.20	7.64	7.72	7.81	2.69

Score:	close to zero
	range of caution
	top outliers

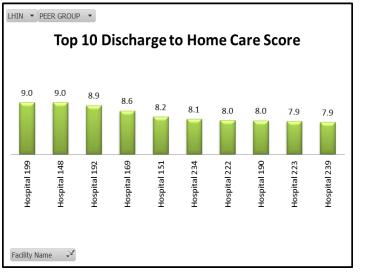
Dashboard Summary

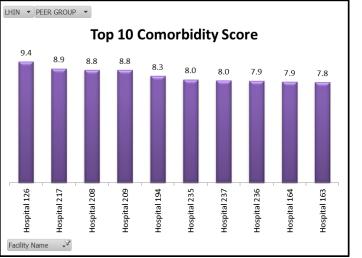


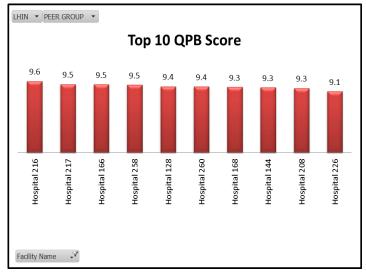


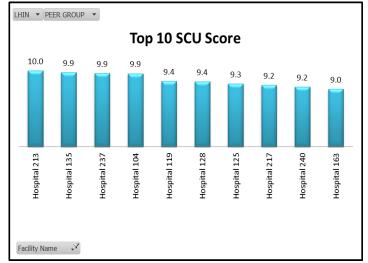


Dashboard Summary









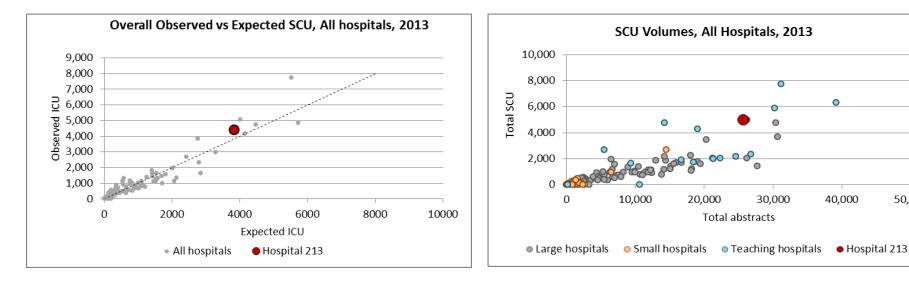
Facility Level Drilldown

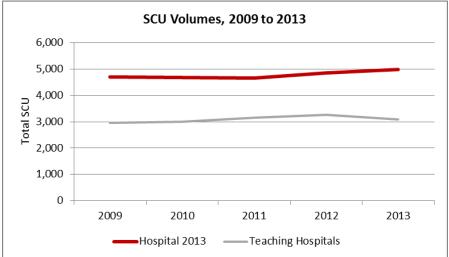


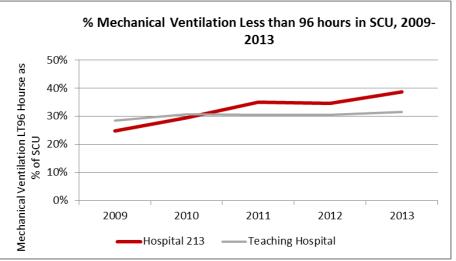
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Where do we go from here?



Next Steps



- Found anomalies in the data; we need to understand why they exist
- Continue to work collaboratively with Ontario Ministry of Health and Long-Term Care to ensure that this work adds value and can be used to improve the quality of the data used in the funding formula
- Apply knowledge and tools to other jurisdictions and areas in CIHI (health system performance indicators)

Big Data Insights



- Techniques are useful if used correctly
 - Techniques can identify lots of anomalies; needs to be targeted and have insight into which issues are important
 - Conclusions can only be as good as the models they are based on: need to assess model efficacy and robustness
- Data mining software (SAS Enterprise Miner)
 - Significantly increased staff productivity in developing and refining models
 - Easy to use interface, but need to know what you are doing
- Don't forget about the power of simple statistics
- Need to be able to describe methods in plain language



Questions?









Thank you!

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