Institute for Healthcare Improvement

Innovation Project Final Report:
Data Analytics to Support Whole System Quality
Wave 65/October to December 2022

Project Type:

90-day Innovation Project: A full wave to scan, test, and document recommendations in a formal deliverable	*30-day Innovation Project:* A short project to scan, provide research assistance, or design an expert meeting

Executive Summary:
The ability to track, assemble, and use data is a critical element of effective quality management. Through this project, IHI's Innovation team identifies data analytic practices, standards, and platforms that can provide direct support for whole system quality (WSQ) throughout a healthcare organization. High-performing healthcare systems are actively harnessing data analytics to inform their quality management. Across systems, there is a high demand for data analytics for quality purposes which leads to tension between healthcare system's data analytic capabilities and capacity. There is further concern about the lack of identifiable quality control in practice, which is, in some cases, conflated with quality assurance. Yet, systems are taking strides to improve their data and data analytics processes and structures, develop system-wide enterprise data warehouses from sources such as the electronic health record, improve data visualization display and access in day-to-day practice, and establish data governance structures. Recommendations on how systems can use data analytics to support whole system quality include: 1) provide data support for an integrated vision of quality management at multiple levels, 2) recalibrate how data analytics are driven and distributed, and 3) optimize internal and external data analytic resources depending on context.

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Intent & Aim:
The threefold aim of this Innovation wave is to identify 1) health care systems' data needs, 2) best practices for data analytics and 3) the role of vendors to support whole system quality (WSQ) throughout a healthcare organization. Data analytics must be accessible and efficient to provide leaders, managers, and practitioners with meaningful and timely evidence to support quality control, quality planning, and quality improvement efforts in a multilevel healthcare operation. Accessible data is a crucial requirement for organizations that are seeking to advance their vision and mission with a wholistic approach to quality (e.g., the IHI Quintuple Aim).[1]

Background:
Reliable and accessible data and efficient data analytics is lacking in today's healthcare systems. Prior IHI work has both emphasized the need for an integrated, wholistic approach to improving healthcare system quality (e.g., Wave 54, Whole System Quality) and identified barriers to implementing new data-based technologies and tools (e.g., Wave 59, Tech Implementation and Quality Improvement, and Wave 64, Predictive Analytics to Improve Patient Safety). This project seeks to build upon these past waves with the intention of better understanding how data is used to support WSQ, the barriers to accessible data analytics for system improvement, and existing or emerging practices, standards, and tools that can enhance the use of data analytics for healthcare system quality management.

IHI's white paper on Whole System Quality (WSQ) details how leadership principles and practices that invest in a culture of learning can support more integrated and proactive quality management (quality planning, quality control, and quality improvement) in complex systems. In the WSQ model, data and data analytics are essential elements for systematically engaging leadership and staff in collective learning and dialogue.

Previous IHI health system diagnostic work informed our understanding of the data analytic needs of complex health systems. Across two, separate diagnostic projects commissioned by U.S.-based healthcare systems, IHI staff noted a marked tension between the need for data analytics and the ability of health systems to support those needs. As observed during a site visit, the hospital staff displayed a widespread desire for timely and easy access to data for planning, daily monitoring, and improvement. Yet, the hospital could not meet these requests. Barriers included the lack of infrastructure (e.g., prolonged process time of requests) and standardization (e.g. lack of interoperability with data and dashboards), misaligned focus (e.g., primary focus on the hospital operational needs—instead of the patient needs that requires more patient-centered data and data for improvement), workforce limitations (e.g., staff shortages), and competing siloed data aims and priorities such as administrative or payer data in contrast to clinical data. Furthermore, it was noted by hospital staff that data and data analytics were often used to validate previous decisions instead of informing planning for future clinical or management decision-making.

To further emphasize the complexity of these issues, the visual below reveals that within a complex system there are at least 3 dimensions to data and data analytics needs: the purpose and priorities of the system (using the elements of the IHI Quintuple Aim as an example), the types of data by quality activity (QP, QC, QI), and the types of data needed at different levels of the system (e.g., patient, provider, unit leads, system leads, and board members). Future work will describe how existing data systems provide visibility for the categories within these 3 dimensions.

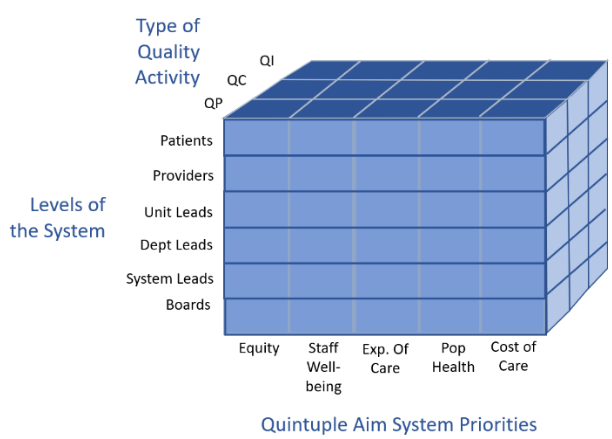

Figure 1. Matrixed Data Needs of a Complex System

Methods:
The 90-day wave included 2 phases. The first was a literature scan of healthcare and data analytics journals to identify the current state of data analytics to support healthcare system quality. The second was key informant interviews to gain further insight into the topic. See Table * for a list of organizations that took part in the interview phase.

Key informant interviews were oriented by three lines of inquiry:

1. **Data**: What data should be used to support strategic quality?
2. **Organizations**: What organizational structures for data analytics in support of strategic quality have been successful?
3. **Vendor Support**: How can vendors support organizations in their use of data analytics for strategic quality?

See Appendix B and C for a detailed interview guide.

Table 1. Key Informant Interviews: List of Organizations

Organizations
AdaptX
Hospital Israelita Albert Einstein
Bellin Health System
Cincinnati Children's Hospital Medical Center
East London NHS Trust Foundation
Health Catalyst
HealthPartners
Jefferson Health
Lahey Hospital & Medical Center
MemorialCare
Mass General Hospital
Penn Presbyterian Medical Center
Scotland NHS
St. Barts NHS Trust
Tufts Medicine
Virginia Mason Franciscan Health

Results:
In the following four sections, this project's findings will be discussed in detail. First, we provide a review of data analytic team structure and a basis for how data analytics teams are currently positioned within healthcare systems. Second, we lay out a set of principles on how data and data analytics can support WSQ. These principles are divided into data analytic principles and organizational principles. Third, we briefly reflect on the role and current execution of quality control. Finally, we consider the role of vendors to support data and data analytics to support WSQ.

A. <u>Data Analytic Team Structure</u>

In participating healthcare systems, the data analytic team is often centralized and, in some systems, was operationally separate from the IT (Information Technology) department. Some systems utilize decentralized or distributed data analytic groups or individuals, who work within multiple specific departments (e.g., cardiology) in contrast to (or in addition to) the centralized data team. The functions and sizes of data analytic teams varied. Data analytic departments supported some combination of 3 areas: business and finance, regulation, and clinical quality. Size varied based upon the department's functionality. For example, one system had approximately 30 full-time employees supporting business analytics and a smaller team of two to support clinical data analytics, while another system had approximately 4 full-time employees to support business analytics and another eight full-time employees with multi-functional roles supporting regulation, research, and data implementation and maintenance. Although dependent upon individual organizational structure, the data analytics team often reports to either the Chief Quality Officer or Chief Information Officer. In one system, a Chief Data Analytics Officer had recently been appointed, although the function and responsibilities of the role were not yet disclosed.

The use of data and data analytics to support strategic quality efforts within the clinical domain often aligned with wider organizational strategic aims, although clinical teams may focus on unrelated aims and metrics specific to the point of care. Some organizations discussed the importance of system-wide standard data and metrics. While standardization efforts can be time-consuming, these systems emphasized the need for data to be more cohesive system-wide with more clarity on operational definitions and metrics (e.g., numerator and denominator).

Data governance structures often assisted with the data and metrics standardization process. Additionally, data governance often assisted in prioritizing data and data analytic requests, particularly related to research or quality improvement projects. For some organizations, this process allowed them to reduce redundant requests and activities and ensure that focus was kept on strategic priorities

B. <u>Data Analytic and Organizational Principles to Support Whole System Quality</u>

Our findings have been organized into two sets of principles: data/data analytics and organizational structure/responsibility. Through these principles, the role and application data analytics to support whole system quality is detailed.

Table 2. Principles for Data Analytics to Support WSQ

Data Principles	Organizational Principles
Parsimony	Engagement
Standard Metrics and Prioritization	Self-Sufficient Workforce
Immediate Usefulness	Data Governance
Reliability and Credibility	

i. Data and Data Analytic Principles

Data principles refer to the role of data and data analytics in supporting Whole System Quality. This focuses on the design, implementation, and use of data broadly to support the maintenance and improvement of quality management system wide. The four data principles discussed are parsimony, standard metrics and data, immediate usefulness, and reliability and credibility. Like a puzzle, the principles detailed below work best when working together to create a clear picture of how data analytics can support WSQ across systems in alignment with strategic aims.

- *Parsimony*

The implementation and use of data analytics must be simple and balanced. As noted in the Whole System Measures 2.0, "To maintain a systems perspective, a small set of measures is required."[1] This sentiment was echoed by the systems interviewed as many emphasized the importance of focused strategic quality goals. This focus translates into a manageable set of goals, domains, and metrics tied directly to organizational strategy. Narrowing the scope, in this context, can create a cohesive system-wide aim, further promoting a culture of learning and improvement work. For example, an interviewed health system allowed clinicians to select up to three organization metrics to track through managing daily improvement (MDI) boards. As clinicians tracked performance tied to organizational metrics, they were encouraged to reassess and set targets accordingly, which could include switching the metrics tracked. A parsimonious approach to data analytics and WSQ both allows for a systems perspective to be maintained, while also creating ease and usefulness for staff to participate in aspects quality management during their daily practice.

Further consideration from the system perspective emphasizes the specificity of data-related needs to support quality demonstrating that the use of a small set of measures should account for the specific audience associated with different organizational or departmental levels, roles, and responsibilities.

- *Standard Data and Metrics*

For data to support WSQ, it is important that organizations have standard data, metrics, and prioritization processes. The main aim here is to emphasize the standardization of organizational data and its management. As Bai et al. (2018) notes, data criteria, definitions, and measuring techniques should meet the suggested data quality framework: accurate, complete, accessible, consistent, non-redundant, readable, useful, and trusted.[2] By streamlining and standardizing how data is identified, collected, managed, and stored within an organization, an integrated system-level framework can be established to sustain the use data analytics for WSQ, therefore, improving patient safety and quality, and minimizing the risk for data errors, delays, and misinterpretations. For example, if the pulmonology department collects and identifies data related to asthma with method-A and the emergency department collects and identifies data related to asthma with method-B, aggregating or comparing data will take much more effort than if they both use the same method. Standardizing definitions like the numerator and denominator can be challenging as consensus must be reached within an organization. But the effort is worthwhile as standardization of data and metrics can provide ease in system-wide quality management efforts. Standardization can also support the identification and tracking of organizational or departmental priorities which may impact what data is prioritized and how it is analyzed and disseminated.

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[1] Martin L, Nelson E, Rakover J, Chase A. Whole System Measures 2.0: A Compass for Health System Leaders. Cambridge, Massachusetts: Institute for Healthcare Improvement; 2016. (Available at ihi.org)

[2] Bai L, Meredith R, Burstein F. A data quality framework, method and tools for managing data quality in a health care setting: an action case study. Journal of Decision Systems. 2018;27(sup1):144-154. doi:10.1080/12460125.2018.1460161

As one interviewed organization noted, the process of standardizing data and metrics is ongoing and involves a significant amount of time and resources as gaining consensus on data and metrics can be an iterative process. This consensus, though, allows for the implementation of operational definitions (e.g., numerator/denominator agreement) which can ease data analytic processes and requests as the data can more easily be stratified. These benefits were echoed by another interviewed health care system who noted that their clear set of data and metrics allowed for data transparency, access to cascadable data, and created familiarity with data metrics for clinicians and staff interested in independently pulling and analyzing data. Because of this, changes to data metrics and measures were major events that only arose due to existing issues with the metric or lack of use (retiring a metric).

- *Immediate Usefulness*

Following IHI's Whole System Measures 2.0, data analytics to support WSQ must be useful to healthcare systems and staff with evidence to support the implementation of data-related processes or measures.[3] Here, immediate usefulness refers to both the processes associated with data analytics and the data itself. That is, in its ideal form, the implementation and ongoing use of data analytic platforms or processes should create ease in the workflow, not burden. Ease refers to user-friendly, accessible, clear applicability, and timely. Ultimately, the processes associated with data analytics should be accessible and timely so that the usefulness and impact of the data is immediate.

Therefore, the data provided must be standard, cascadable, and aligned with strategic quality aims. Organizations should standardize their data as discussed in the prior section. Data should be cascaded, which means the data can be analyzed at various levels of the organization and is appropriately accessible and appropriate for each aspect of quality management, organizational level, and strategic aim. For example, a healthcare system may identify reducing serious safety events as one of their strategic aims with the objective of reducing healthcare associated infections. Leaders at the department and unit level and associated clinicians and staff can then focus on specific issues and measures to support efforts related to the strategic aim, such as, central line-associated bloodstream infections (CLABSI). If a unit is focusing on reducing CLABSI cases, the associate outcome metric will be the data that is most immediately useful. But, if executive leadership would like to see the system's progression reducing overall healthcare associated infections, aggregated data may be more immediately useful to them such as the aggregated outcome measure data associated to CLABSI, catheter-associated urinary tract infections (CAUTI) and Surgical Site Infection (SSI) for abdominal hysterectomy and colon procedures.

Furthermore, considering ease and immediate usefulness of data and data analytics, it was noted by one interviewed organization that pushing out data and data analytics provided clinicians and staff with more immediately useful information in contrast to providing access to self-generated dashboards. While self-generated dashboards may still be useful for group specific or individual inquiries, this organization found that providing predetermined information on a visual dashboard accessible to all employees (e.g., statistical process control (SPC) charts on the duration between sepsis identification and medication administration) was more empowering and useful for clinicians and staff within their daily clinical practice.

Consequently, the immediate usefulness of the data will be context dependent. Organizations should aim to employ data and data analytics structures that can support standard and cascadable work in a timely and user-friendly manner that aligns with their strategic priorities, particularly those related to quality.

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[3] Martin L, Nelson E, Rakover J, Chase A. Whole System Measures 2.0: A Compass for Health System Leaders. Cambridge, Massachusetts: Institute for Healthcare Improvement; 2016. (Available at ihi.org)

➢ *Reliability and Credibility*

The data and data analytics provided must be reliable and credible in multiple manners. The data itself should be accurate, complete, non-redundant, readable, and useful.[4] The process of obtaining the data should be clear, accessible, and timely.[5] Having both reliable data and processes for obtaining data will increase staff and clinician trust in the organization's data analytics capacities and capabilities. High degrees of reliability and credibility may increase the productivity of quality work, including quality improvement efforts. Note that a high degree of reliability refers to data being reliable or representative, not absolute. This distinction acknowledges the process for extracting and analyzing data in a timely manner may warrant data of a lower degree than desired, although still with a high level of accuracy and reliability. Aspects discussed in "Organizational Principles" such as leadership engagement and data governance can further enhance the reliability of data and data analytic processes as well as the credibility of organizational data and data structures.

ii. Organizational Principles

Organizational principles refer to the role of the organization in supporting Whole System Quality. This includes the constituents of different levels of the organization such as leadership, clinicians, and staff and the structure and processes that organize and influence the workplace flow and culture.

➢ *Engagement*

To successfully implement data analytics, there must be institutional support and engagement. As noted in WSQ, this should be considered on multiple levels with emphasis on the role of leadership in supporting efforts to leverage data through sustainable processes. Success of the WSQ approach depends on leadership's prioritization of and investment in quality as a core organizational strategy and investment in data analytics to support strategic quality. All healthcare systems identify quality and safety as an important part of their strategic aims or long-term plans, but only a few recognize quality as *the* overarching organizational strategy. Instead, strategic differentiators such as size, growth, per unit costs, range of services, technology, and standings (e.g., Leapfrog Hospital Safety Grade and U.S. News rankings) can overshadow the impact that quality can have if positioned centrally within system's organizational aims and strategies. Healthcare systems that use quality as a strategic differentiator shift their strategic focus to quality and are proactive, intentional, and internally driven with their strategic priorities and long-term planning. With this approach, quality management aims can be identified and prioritized along organizational needs and interests preemptively allowing well-scoped and resourced quality management activities to be pursued and sustained.

To achieve a proactive approach towards quality management, leadership must also understand how data analytics can further bolster each aspect of quality management—quality planning, quality control, and quality improvement. Leaders must encourage and be involved in promoting a data-supported culture (e.g., developing or supporting data governance structure or using data to have line of sight to key quality priorities at the point of care) and be knowledgeable of data analytics to interpret and disseminate data-based outputs (e.g., able to read or explain run charts). Engagement and investment by leaders encourages, supports, and normalizes the learning practices across the organization as emphasized by

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[4] Bai L, Meredith R, Burstein F. A data quality framework, method and tools for managing data quality in a health care setting: an action case study. Journal of Decision Systems. 2018;27(sup1):144-154. doi:10.1080/12460125.2018.1460161

[5] Bradley E, Holmboe E, Mattera J, Roumanis S, Radford M, Krumholz H. Data feedback efforts in quality improvement: lessons learned from US hospitals. Qual Saf Health Care. 2004;13:26-31. doi:10.1136/qshc.2002.4408

WSQ.[6,7] By investing in a proactive approach to quality and engaging with data analytics, leaders set the tone of their organization.

In contrast to reactive approaches to quality management (e.g., reliance on quality assurance for informing system failures), leadership should integrate proactive quality management processes and structures into the operational structures (e.g., embedding an improvement mindset and utilizing Plan-Do-Study-Act cycles). For one system, their implementation of quality as a strategic differentiator began with integrating quality improvement into their operations and progressed to balance their quality improvement and quality assurance processes, and, finally to operationalize a comprehensive approach through a quality management system composed of quality planning, quality control, quality improvement, and quality assurance. The latter efforts began to integrate data analytics to support quality management processes and efforts. Like this organization, organizations successful in implementing WSQ have shifted the bulk of their quality management activities to support internally driven strategic quality aims and planning while fulfilling obligations of required external reporting (e.g., Joint Commissions and Centers for Medicare & Medicaid Services).

➢ *Self-Sufficient Workforce*

Self-sufficiency for the workforce is twofold as it refers to accessibility and capability. Accessibility refers to how accessible data or data analysis is. If the data warehouse enterprise is integrated with self-service analytic software that is user-friendly (e.g., plain language and standard definitions and metrics) and readily available, clinicians' and staffs' ability to independently complete data analysis queries may increase. The demand for data accessibility exists and has created tension between analytics team capability and capacity to meet data requests, as earlier discussed in the "Background." Self-service tools may help alleviate this tension by allowing those with data requests to complete their queries independently.

Capability, then, refers to clinicians' and staffs' familiarity with data analytic processes and platforms used by their healthcare system and their data literacy (e.g., their ability to interpret results). Like accessibility, clinicians and staff must be able to navigate data analytic platforms with ease. The platform should integrate into the workflow and be either intuitive to users or provide training. Even with user-friendliness or familiarity, clinicians and staff must also be able to interpret the output. Training and other educational support should be provided to improve clinicians' and staffs' data analytic literacy (e.g., reading a control chart, identifying variation).

Overall, self-service support was a mixed priority for healthcare systems IHI spoke with. While many had some form of self-service, most offerings were underdeveloped with varying levels of engagement with self-service tools and useability of tools. Systems with more developed tools aimed to allow staff and clinicians appropriate access to system data. For example, one healthcare system provided de-identified data on an employee platform that allowed for initial analysis opportunities. For further data requests that could not be met through the platform, clinicians and staff had to request data from the system's data governance structure, which prioritizes and redirects requests (should existing reports and related material

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[6] Sampath B, Rakover J, Baldoza K, Mate K, Lenoci-Edwards J, Barker P. Whole System Quality: A Unified Approach to Building Responsive, Resilient Health Care Systems. IHI White Paper. Boston: Institute for Healthcare Improvement; 2021. (Available at www.ihi.org)

[7] The Whole System Quality White Paper further elaborates on five leadership principles which further align with our recommendations for "Engagement": build a shared sense of purpose; practice systems thinking; engage in collective learning and dialogue; and practice personal inquiry and reflection.

meet request needs). Within this system, an emphasis was also placed upon aligning requests with organizational strategic priorities. Depending upon the technological platform and individuals' role and responsibility, data may or may not be identifiable. For example, hospital staff and clinicians using electronic health records tools like EPIC's Slicer-Dicer may have access to identifiable data, while those using hospital-related research databases have access to de-identified data.

Concerns surfaced on who controlled access to organizational data, how data needs were prioritized, and data literacy among staff and clinicians. The first two concerns raise the question, "How available should self-service tools be?" From a leadership perspective, it is productive to ensure that data use aligns with identified enterprise-wide aims and strategic plans, so oversight bodies such as a data analytics team or data governance body can reduce and prevent redundant or off-target data requests. From an operational perspective, providing self-service tools can alleviate request queues for clinical data analytics teams and allow those interested in learning from their work, or to conduct exploratory research, can do so independently prior to requesting permissions to formally design and implement a process or project. Solutions to concerns on end-user data literacy often encouraged educational opportunities and resource awareness. Implemented examples included training modules or webinars on data literacy, news reports or blurbs (e.g., push alerts on new products and email newsletters with updates and educational opportunities), weekly data office hours (e.g., 1:1 training and troubleshooting), data analytic rounds or listening sessions, and portal integrated education.

➢ *Data Governance*

For data analytics to be sustainable within a healthcare system, there must be a governance or oversight body. Structures like data governance can triage reporting requests, ensure the quality and accessibility of data and data analytics, and support the reception and implementation of feedback on existing structures and processes. It can also assist with master data management, data lifecycle management, and data security and privacy management.[8]

The implementation and use of a data governance structure varied among systems interviewed. The reasoning for this variation may be explained by Fleissner et al. (2014) who notes that there are four drivers that cause organizations to adapt a formal data governance structure:[9]

1. The organization gets so large that traditional management is not able to address data-related cross-functional activities
2. The organization's data systems get so complicated that traditional management is not able to address data-related cross-functional activities
3. The organization's Data Architects, service-oriented architecture teams, or other horizontally-focused groups need the support of a cross-functional program that takes an enterprise (rather than confined) view of data concerns and choices
4. Regulation, compliance, or contractual requirements call for formal data governance.

Data governance structures within interviewed healthcare organizations followed a council or committee structure enlisting support across the organization including clinicians from various departments, business

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[8] Wang Y, Kung L, Byrd TA. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. Technological Forecasting and Social Change. 2018;126:3-13. doi:10.1016/j.techfore.2015.12.019

[9] Fleissner B, Jasti K, Ales J, Thomas R. The Importance of Data Governance in Healthcare. Encore, A Quintiles Company; 2014.

and operational administrators and leaders, and data-related staff, such as data stewards, who are responsible for and manage data assets, data lineage, and data access defining standards and best practice for data analysis, modeling, and queries.[10] The data governance's aim and responsibilities varied but included a combination of cybersecurity, data management, data literacy, data stewardship, data requests and permissions, audits, and data and project prioritization. Committees and councils reported to various leadership positions including the Head of Analytics, Data Governance Director, Chief Operations Officer, and Information Systems Department. Data governance meetings also varied. For example, one system hosts a bi-weekly, one-hour data governance meeting, while another holds two data governance meetings—one monthly meeting for the system-wide council and a weekly meeting for data stewards. Organizational context creates this variability in structure and priorities, but the necessity of a data governance structure remains.

For systems beginning to design and implementation of a data governance body, though, Cooper (2020) identified six steps towards developing a successful data governance structure:[11]

1. Identify roles and responsibilities
2. Define data domains/elements
3. Establish data workflows
4. Establish data controls
    a. Define key controls, metrics, and data thresholds
    b. Develop report processes
    c. Establish a feedback mechanism
5. Identify authoritative data sources
6. Establish policies and standards

Systems should consider their specific context (e.g., resources, priorities, existing structures) when developing or assessing their individual data governance structure. For a more detailed example, please see the case study of University of Kansas Hospital and their efforts towards developing an effective healthcare data governance structure.

C. Quality Control

We draw attention to the balance that Juran proposed between the 3 quality management categories: Quality Planning, Quality Control and Quality Control (QC). Of the three, QC was the least well-understood in interviews and sometimes unrecognized by systems that were in fact deploying QC efforts. By contrast most organizations had unbalanced quality management systems, focusing primarily on QI. To be clear, QC differs from quality assurance. QC focuses on internal processes that ensure the stability

[10] Buttner P, Meyer M, Mikaelian R, Miller N, Ruhnau-Gee B. Healthcare Data Governance. American Health Information Management Association; 2022:1-15.

[11] Cooper C. What is data governance in healthcare? Collibra. Published December 16, 2020. https://www.collibra.com/us/en/blog/what-is-data-governance-in-healthcare

of daily operations while identifying and correcting abnormalities. In contrast, quality assurance (QA) is primarily an externally driven activity to inform stakeholders on whether systems are meeting quality goals. Since QA uses intermittent inspection, it involves notable lag time between delivery and reporting of services. For this project, we studied how data analytics could further bolster QC activities related to daily operations and care quality by providing real-time, near-time, or appropriate time information to support staff and clinicians' decision making close to the point-of-care.

In practice, various routes towards QC were undertaken. Recurring QC practices within various systems including those encouraged by WSQ: standard work (e.g., scorecards), huddles, data visualization (e.g., electronic whiteboards or MDI boards), and leadership presence at the point of care. Standard work supports QC by outlining the clinical and administrative processes, roles, and rationale. For example, some systems utilized scorecards with predefined performance indicators. Clinicians could adjust their scorecards to focus on a smaller set of indicators within the scope of their work. Huddles were common among the organizations interviewed. Huddles relied on near-time or daily data and clinician observations and took place at multiple levels such as at the unit, department, and leadership, although discussion and aims differed. This clinical information was shared and discussed during daily huddles as clinical teams determined care plans for patients within their unit. In addition to time-based huddles, others also utilized task-based huddles such as unit-based patient safety huddles. Data visualization varied. Whiteboards, both manual and electronic, were used across systems with data updating at different intervals. Daily intervals were most common, but shorter intervals were utilized as well. The metrics tracked through data visualization varied in their focus. Workflow metrics such as length of stay, patient transport, and discharge rates were utilized as well as clinical metrics such as early warning scores and other risk-based assessments. Some real-time data alerts are also accessible through the electronic health record where clinicians and staff can follow a patient's vitals or monitor for changes, which can also support 1:1 quality control efforts. Finally, leadership was often involved in QC activities at the point of care. In the systems we interviewed, members of the leadership team would join for clinician huddles or rounds.

Taking this a step further, one organization designed and implemented an Assistance Monitoring Center to support the detection of patients at risk of worsening conditions. Algorithms are programed to alert the Center of worsening patient condition, which is, then, relayed to the appropriate clinical teams, including rapid response teams. Run 24-hours a day, seven days a week, twelve monitoring employees are split into alternating shifts. During each shift, staff have access to up to sixteen screens with clinical displays tracking real- or near-time patient conditions and each has access to the electronic health record. Implementation and use of the monitoring system initially received pushback from frontline clinicians. However, strategies that educated staff on the Center's purpose and responsibilities (e.g., aim to increase the safety and quality of care, not to penalize clinicians or infringe upon clinical decision-making) and demonstrated effectiveness and value led to an increase in clinician buy-in. In addition to supporting efforts to identify clinical deterioration, the Center also helps to identify real-time serious events or clinical care risks in the operating room and birthing center.

Continuing to strengthen QC is vital to sustaining high-quality performance. Therefore, the data needed for QC must be actionable and impact the process of care. This data should be provided within the appropriate timeframe. While this project emphasizes immediate usefulness and real-time data, the concept of real-time data is context dependent. For example, while the Intensive Care Unit may need data minute by minute, a non-intensive care unit may need data hour by hour, and a primary care unit may need data week by week or month by month. It is important to identify a manageable timeframe within the daily workflow that is useful for practicing clinicians and staff. Furthermore, organizations need to be consistent in how they display data overtime with data visualization tools like run charts and statistical process control (SPC) charts. Consistency includes data definitions, data metrics, timeframe, type of visualization, and data display location.

In short, organizations should concentrate on clarifying the role of QC, differentiating from quality assurance, and developing standard work and practices, and demonstrating the reliability and usefulness of quality control practices.

D. On Vendors

This project's aims included identifying data platforms and vendors that may be capable of supporting data analytics for whole system quality. Notably, although many of the healthcare systems interviewed were vendor rich, most did not rely on vendors for consultation on clinical data analytic support related to quality management. Instead, most utilized internal resources, including processes and platforms, for data analytic processes, although we did identify specific instances in which external vendors supported health systems efforts as the following examples will highlight.

Focusing on internal development, one healthcare system internally developed and implemented a platform accessible through the institution's Intranet. This platform included access to the Quality and Safety Enterprise scorecard and associated metrics and data, radar dashboards for risk mitigation (including a daily huddle dashboard), and other improvement-related data (e.g., performance, metrics, and outcomes). By contrast, another organization interviewed is currently working with a vendor to develop a new, accessible front-end platform for data analytics as the platform capabilities they were interested in were not readily available on the market. In this model, all employees will have appropriate access to the data and analytics. Clinical, workforce, and financial data will be included. Self-service needs are also in development at this organization with current plans to build a standard data model with natural language queries using anonymous organizational data. A major limitation of data integration for this organization is that the multiple sites that form the system are not on a single proprietary database. For this organization, it was not feasible to build this platform alone. Vendor support was needed. Finally, on vendor support, one system was reliant on a vendor platform for self-service data analytic needs. To extract insights and identify root causes, this platform offers drill-down dashboards, decision support calculators, benchmark-driven analytics, and heat maps. The organization continued to invest in this vendor platform since physicians and staff have expressed a preference for the self-service tool which requires limited training and provides cascaded data insights. All data was blinded unless the user signed a disclosure.

Even with a varied use of vendors for consultation on data analytic support, interviewed healthcare systems did remain heavily reliant on vendors for health information technology platforms such as electronic health records (e.g., EPIC and Cerner), data aggregation, benchmarking data, and data visualization (e.g., Power BI and Tableau). In many aspects, these platforms provided support for quality management. For example, a handful of organizations interviewed utilized Tableau to produce monitoring and control dashboards, which were accessible to frontline clinicians. At one organization, this accessibility extended to allow clinicians and staff to utilize Tableau in self-service mode through EPIC to create specific dashboards such as by the hour reports on wait times, admissions, and discharge without treatment or medical advice. These uses of Tableau can support both quality control and quality improvement efforts. Additionally, a handful of interviewed systems discussed the use of EPIC's data exploration tool, SlicerDicer. For one organization, EPIC's SlicerDicer is their primary self-service tool. While there is no formal training or protected time for clinicians, residents are trained on SlicerDicer with protected time to completed required QI projects. Additional data analytics support is provided through a reporting workbench, which provides premade, reporting templates on acute and ambulatory care, although this platform is considered less user-friendly than SlicerDicer. Limitations were noted with the logic of SlicerDicer and user's data literacy (e.g., if not trained well, data can be skewed).

So, while vendor products were used mainly for supplemental data analytic support in a number of interviewed systems, vendors can play a significant role in supporting health care organizations' quality management practices and are well positioned to support systems in the nascent stages of data analytic design and implementation, less-resourced healthcare systems, or complex healthcare organization in need of additional infrastructure or workforce support for data-related cross-functional practices.

Table 3. Healthcare vendors discussed in interviews

Vendor	Services
Adpatx	Clinical management and analytic platform
Arcadia	Business intelligence platform
Cerner (Oracle)	• Electronic health record • Lights On Network (enterprise-level data analytics)
Clinovations (Optum)	Clinical management support across electronic health record lifecycle
Crimson (Optum)	Data aggregation platform across data systems including the electronic health record
EPIC	• Electronic health record • SlicerDicer (self-service reporting tool) • Data visualization
Health Catalyst	Data and data analytic technology and services
Mitus Health Analytics	Operational and clinical platform to manage risk, control cost, and provide data insights
Power BI (Microsoft)	Interactive data visualization software primarily for business intelligence
Qlik Sense (Microsoft)	Platform for visualizations, charts, interactive dashboards, and analytic apps
RLDatrix	Integrated governance, risk, and compliance (GRC) software solutions and services
SpotFire (TIBCO)	An artificial intelligence-based analytics platform
Tableau	Interactive data visualization software
Vizient	Health care performance improvement company

Please see Appendix C for notes on vendor interviews.

Conclusions and Recommendations:
The aim of this project is to provide insight into health care systems' data needs, data analytic best practices, and vendors' role in supporting WSQ throughout a healthcare organization. Data and data analytics are important aspects of quality management within healthcare systems. Even among high performing health systems there seems to be a great deal of variability and opportunity for improvement. As systems further invest in data practices, standards, and platforms, an opportunity exists to further develop the role of data and data analytics to support whole system quality.

Based on this extensive enquiry, we are making the following recommendations:

1. **Provide data support for an integrated vision of quality management at multiple levels:** In order to support Whole System Quality, health care systems should adopt a three-dimensional approach to data analytics. First, organizations should ensure that data analytics supports the key components of quality as defined by that organization. If quality is prioritized in the organization's vision, a corresponding level of data analytic resources (infrastructure and support) should be provided. Second, systems thinking should be employed with consideration given to multi-level needs and key quality management functions (QP, QI, QC, see Figure 1). Systems thinking emphasizes how interconnected elements of a system can work together in contrast to the pursuit of siloed practices and events.[12].

2. **Recalibrate how data analytics are driven and distributed**. For many organizations, their data analytic teams prioritized external interests and demands. While some of these interests and demands must be met for regulatory purposes, organizations are encouraged to further employ data analytics to support quality management. Emphasizing data analytics for quality management aims requires that organizations identify where data analytics can be most productive and efficient in their efforts to maintain and improve system-wide quality. One suggested opportunity for better data analytics support is quality control, – often a weak component of quality management. Quality control activities should be supported by nimble real-time data displays; improvements to data visualization could support efforts to engage with data analytics for WSQ.

3. **Optimize internal and external data analytic resources depending on context.** Executing the recommendations above will solicit the question: How do you do this? As illustrated through the report, there are various pathways to implementing data analytics to support WSQ and each pathway can be optimized for an individual system's unique needs and capabilities. Some organizations preferred to develop internal products and processes to support data analytics for quality purposes pivoting away from vendor support, specifically for data analytic needs. Others elected to engage with alternatives to internal development such as integrating self-service tools (e.g., EPIC's SlicerDicer) or to employ vendors for support with specific tasks (e.g., data aggregation, data visualization). Other systems benefitted from vendors' support in specific data-related areas as data demand grew and became more complex. Comprehensive vendor partnership is also an option for those without the organizational capabilities to internally develop and implement a data analytics team. It is recommended that organizations assess their data capabilities and capacities as well as their data needs to develop the best approach for their organization. An assessment for Data Analytics for Whole System Quality is available in Appendix D.

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[12] Sampath B, Rakover J, Baldoza K, Mate K, Lenoci-Edwards J, Barker P. Whole System Quality: A Unified Approach to Building Responsive, Resilient Health Care Systems. IHI White Paper. Boston: Institute for Healthcare Improvement; 2021. (Available at www.ihi.org)

Open Questions:

1. How can IHI provide actionable recommendations regarding data analytics for Health Systems who are interested in reorienting their strategy and data needs away from regulations and external recognition?
2. There is limited data support for quality control compared to healthcare system's focus on quality assurance, which is partly driven by regulation. How can IHI assist organizations in focusing more on real-time/near-time/appropriate-time quality control?
3. Is there an opportunity for IHI to help systems apply quality improvement to their data analytics team?
    a. Healthcare systems have two data challenges: (1) unnecessary data requests, and (2) the prioritization of data requests. These challenges both misuse analysts' time and lead to inefficient queues.
4. Does IHI need someone in house with a data skillset to support the needs of partner health organizations pursuing WSQ (e.g., as part of the IHI diagnostic and support team for WSQ work)?
5. Should IHI team with Data vendors (Health Catalyst, AdaptX, Jefferson Healthcare, Einstein) to support health systems who are re-designing their quality management systems in line with the principles of WSQ?
6.

Appendices:

a. Appendix A: Vendor Assessments

i. Assessment of Adaptx

"A nationally-acclaimed analytics team struggled with a daunting backlog. Clinical leaders posed endless questions, but costly Analytics resources were limited. Although the Analytics team had invested heavily in their health system's successful EMR rollout, they couldn't leverage that investment to provide timely, actionable analyses for hundreds of C-Suite leaders, service line chiefs, and frontline clinicians.

The Analytics team was swamped with resource intensive data mining projects and superuser-driven BI tools. As a result, they had to triage and limit clinicians' requests. Clinicians, in turn, were frustrated, as they had to rely on anecdotes and intuition to manage treatments and workflows across patients.

How could the Analytics team shift the paradigm to a scalable solution? How could Analytics leverage their EMR investments to drive quality, equity, and efficiency improvements across their health system?

The Analytics team deployed AdaptX's Mission Control Center as a self-service Adaptive Clinical Management™ solution. This freed Analytics from endless data mining projects by enabling clinical teams to directly access the real-world data collected by their EMR. Self-serve shifted query-writing and query-answering to clinicians, freeing Analysts to focus on highest-value opportunities. Instead of supporting only a limited number of data queries for leaders, Analysts now enable limitless clinical operations projects across entire departments.

Within hours of go-live of AdaptX, clinical leaders identified variations in care and opportunities for quality, equity, and efficiency improvements. Over the next year, clinicians freed up over 150,000 OR minutes, saved over 600 bed days, and reduced racial and language disparities across treatments and outcomes."

In the last 10 years, there has been a huge investment in electronic medical records leading to the creation of vast amounts of data. During this time, there have been steady rates of requests to access this data, but analytic resources cannot meet the need in practice. Therefore, organizations have developed methods to manage the queue including screening the data to determine relevance and need and developing prioritization mechanisms to determine the order for request of data. Both create roadblocks for data access.

Adaptx is a self-service tool that can help organizations utilize their data by decreasing the barriers to access and free analytic teams to work on strategic interests.

During our conversation with Dr. Dan Low from Adaptx, we discuss the following questions:

- Their approach to support quality management (quality planning, quality control and quality improvement) through data analytics
- What data sources they work with
- Their ability to cascade your data as illustrated in the data cube (Figure1)
- Data presentation particularly statistical process control charts (SPC)
- Ease of data access with their tool
- Training required.

We observed that the tool is simple and easy to use, requiring minimal training. The platform could present the data in an SPC format and was connected with an enterprise data warehouse (EDW). Dr. Low shared that two-thirds of all healthcare systems have an EDW. The data had the potential to be updated as frequently as every 10 minutes. In general, it is not used in a real time process but can access data in near time. This platform is best suited for quality improvement work and would be an excellent tool for quality planning. Limitations include the platform's ability to cascade data, lack of support for quality control, and lack of integration into real-time data displays

ii. Assessment of Health Catalyst

Health Catalyst is a data analytics company that provides a wide range of services: population health, patient engagement, clinical quality, patient safety, and revenue cycle management, among other services.

The company was founded in 2008 and was influenced by the work of Brent James at Intermountain and his work on quality healthcare and primarily works with the health care provider community, including a wide range of healthcare systems, although they do some work with insurance companies.

Health Catalyst can provide an analytic platform for data from various sources. Using this platform, users can analyze and develop new care models. It can complement its analytic work with quality improvement training to maximize the use of the analytics platform and tools. As an example, Health Catalyst can train analysts in quality improvement which helps them to understand better the request for quality improvement data. If an organization is inclined to, they could completely outsource their analytics team to Health Catalyst. Their product can replace an enterprise data warehouse.

When it comes to their work on the analytic platform a major value add is their ability to do data integration. A health system might have 50 to 60 disparate data systems and they have the experience and skill to bring them in to their analytic platform

From a quality control perspective, they have the ability to look at data in real time. For example, they can look for clinical triggers by constantly listening in real time. This is the same type of triggers that IHI has written about with our trigger tools.

Tom Burton discussed the five transformations you need to become a system of production.

1. Information distribution: get data out of silos into a centralized space to be integrated to generate insights. Analyst folks are occupied with reporting.
2. Governance transformation: This is the hardest part. You need to shift business strategy from growth as the answer to quality is the answer. You can never do data governance well unless it is in the overarching category of improvement governance.
3. Organized for improvement: most systems are not organized for improvement, but growth. They are also organized based upon regions and physical locations not frontline work processes.
4. Cost management transformation: this is done simultaneously with business model transformation. It includes a value-based care shift along with understand cost at a more granular level. There is a need to switch from cost-to-charge to activity-based system. Very few folks have made it to this part.
5. Business model transformation as described above.

Health Catalyst's approach has great synergy with what IHI does. They are a publicly traded company with about 1,300 employees and revenue of around $260 million dollars. They are continuing to grow even during the financial challenges that many health systems are facing.

b. Appendix B: Interview Guide for Health Systems

<u>Orienting Questions on Data Structures</u>

- What is the structure of your analytics team? How much time is spent on supporting regulation and how much supports clinical/strategic needs?
- Where does your business and/or clinical team live?
- Are there analysts dispersed in your organization, who do not work on the analytics team?
- Talk to us about your data analytic training for non-analytic staff (to do their own analysis).
- Discuss your prioritization of data analytic support. How do you decide how you spend your time? How do you decide the queue on requests for data?
- What quality improvement work have you done on your analytic support?

<u>Quality Planning</u>

- What is driving your quality strategy? And how is it tracked for planning, control, and improvement?
    - To what degree, are you doing this independently or with a third party?
    - Can you explain how data analytics informs the planning and design process that led to your current strategic goals and give us an example?
    - Do you have any guiding principles on the use of data analytics that inform your work?

Quality Control

- What type of quality control measures do you have in place to meet strategic quality goals and ensure reliable results?
    - How do data and data analytics inform this process?
    - What are the structures, processes, or resources in place to enhance quality performance to meet strategic aims?

Quality Improvement

- Can you tell us about the processes or structures that exist to support quality improvement initiatives?
    - What role does data and data analytics play?

Concluding Questions

- Do you work with any vendors on data analysis?
- What data visualization tools do you use? (Share and display data)

c. Appendix C: Interview Guide for Vendors

1. Discuss with us your approach to support quality management (quality planning, quality control and quality improvement) through data analytics.
2. What data sources do/can you work with?
3. Can you cascade your data as illustrated in the data cube (figure1)? If so, how many levels?
4. How do you present your data? Can you present it in statistical process control charts when that makes sense?
5. Who can access the data? And where can they access the data? How do you make sure the data is accessible in the user's workflow? How much training does someone need to use this data? How flexible are your tools?
6. How would you work or partner with IHI on this?
7. How much support can you provide an organization with internal analytic processes?

d. Appendix D: Data Analytics for Whole System Quality Assessment

IHI Data Analytics to Support Whole System Quality (WSQ) Self-Assessment Questions
Data Analytic Structure (DAS)
How does the analytics team support Whole Systems Quality? *Who is on the team? Where are they located within the organization? Is the team centralized or decentralized?*
How are the organization's strategic aims and priorities and their corresponding metrics clearly identified and communicated throughout the system?
How are standard data domains, terms, and definitions identified and implemented across the organization?
What is the prioritization process for data requests from the field?
What types of data visualization does your organization use to show data? If run charts are employed, describe what type and how these are used.
Data Elements for Quality Control (DEQC)
How does the organization manage the data to ensure that clinical processes and expected outcomes stay in control?
Is there data analytic support for real-time/near-time/appropriate-time quality control? If so, describe the organizational data supporting quality control and how it is displayed.
How is data for quality control communicated? What type of visual displays are used?
Does your organization have huddles? If so, who is included, what is the frequency, and what data is provided?
Data Analytic Tools and Support (DATS)
What self-service tools for data analytics are available to staff and clinicians?
What educational or professional development opportunities or trainings are available for data literacy and use of data for understanding variation, planning and improvement?
Data Governance (DG)
Describe the structure and function of data governance entities in your organization.
Who are the key stakeholders involved in data governance, and what are their roles and responsibilities? (e.g., data stewards, data analyst/scientists, data owners)
Describe how data requests from users, managers and leaders are prioritized. To what extent does the data request prioritization track the key goals of the organization's mission and vision?
What are the key challenges and successes associated with data governance in the organization, and how are they being addressed?
Additional Markers for Consideration (Drivers from WSQ)

- Engagement in Quality Activities
    - What data support is provided to teams undertaking QI work
- Culture
    - What metrics of staff well-being are used, and how often are they measured?"