
by Michael R. Mathis, MD; Robert B. Schonberger, MD, MHCDS; Anthony L. Edelman, MD, MBA; Allison M. Janda, MD; Douglas A. Colquhoun, MB ChB, MSc, MPH; Michael L. Burns MD, PhD; and Nirav J. Shah, MD

In an era of near-complete adoption of electronic health records (EHRs) and coalescence of health data across departments and institutions, a growing recognition of practice variation has emerged. Perioperative care is no exception, with recent studies demonstrating wide institution-level variation in practices such as anesthetic techniques employed; medications administered; and operating room staffing models used. In some cases, practice variation is warranted—as explained by factors such as subspecialty training, local health resource constraints, and informed expectations of patients. Yet, in other cases variation is unexplained or unwarranted, and possibly attributable to a lack of practice benchmarking, suboptimal hospital resource allocation, or lack of precision care tailored to individual patient needs.

In some cases, such practice variation may be associated with worse outcomes, including anesthesia professional staffing ratio practice patterns, hospital level compliance with safety practices, and failure to rescue rates.

To address unexplained or unwarranted variation, modern quality improvement (QI) and research initiatives increasingly seek out multicenter learning-health systems approaches, integrating comparative effectiveness evidence drawn from practice variation across centers to develop performance benchmarks and quality measures. With strategic multicenter infrastructures in place, such benchmarks and quality measures can in turn be disseminated across participating institutions to rapidly iterate upon evolving best practices and enhance patient safety and health care value. One learning health system infrastructure relevant to perioperative care is the Multicenter Perioperative Outcomes Group (MPOG), which we cover in this article to illustrate (i) approaches necessary for integrating perioperative EHRs for research and quality improvement (QI); (ii) big data tools which can be used to effectively harness large volumes of perioperative health data amassed; and (iii) the value proposition of creating community sharing research and quality measure outputs to advance perioperative care and patient safety. Finally, with the rise of artificial intelligence and machine learning approaches offering new opportunities for enhancing health information gathering and clinical decision-making, we describe core challenges to successful, sustained implementation of artificial intelligence/machine learning methods and approaches to address such challenges.

**PRINCIPLES OF A LEARNING HEALTH SYSTEM GUIDED BY PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERIO PERI
From “Using Big Data Tools,” Preceding Page

MPOG has developed programs and tools to analyze big data

Table 1: Quality Improvement Programs within the Multicenter Perioperative Outcomes Group.

<table>
<thead>
<tr>
<th>PROGRAM</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>QI Measure Development</td>
<td>MPOG has developed over 60 process and outcome measures across several anesthetic, subspecialty, population, and public health domains. These measures are approved and reviewed at the Quality Committee, and the specifications made available publicly for all to review and use.</td>
</tr>
<tr>
<td>Practice level feedback</td>
<td>Our QI Reporting Tool enables practice leadership to visualize measure performance that is benchmarked locally and nationally, and understand variation in care by patient, case, and provider (Figure 2). Users can probe from health system-level performance to a single intraoperative anesthetic record or group of similar records to identify exemplars of practice or opportunities for improvement.</td>
</tr>
<tr>
<td>Individual provider feedback</td>
<td>MPOG sends monthly feedback via email to anesthesia professionals on QI measures selected by practice leaders for their institution. Performance on these measures is benchmarked locally, and can be linked to individual anesthetic records to enable the reflection that can more effectively lead to changes in practice.</td>
</tr>
<tr>
<td>QI Toolkits</td>
<td>To help remove barriers to education and implementation of QI initiatives, the MPOG Coordinating Center has developed toolkits that summarize the available evidence for our measures and provide implementation tips that can be applied locally. Toolkits exist for several domains of anesthesia care, including postoperative nausea and vomiting prevention, transfusion management, prevention of kidney injury, prevention of lung injury, and environmental sustainability.</td>
</tr>
<tr>
<td>Quality Collaborative Meetings</td>
<td>To reinforce and discuss the application of these quality measures, feedback platforms, and toolkits, MPOG organizes multiple collaborative meetings attended by anesthesiologist QI champions and surgeon collaborators.</td>
</tr>
</tbody>
</table>

EHR data are highly variable across institutions. As a result, a foundational component of MPOG is the methodology for translating EHR data across participating sites into pre-computed, validated phenotypes usable for research and QI.14 This rigorous process involves applying algorithms to integrate combinations of all the data types within MPOG to generate more reliable clinical inferences. These inferences serve as building blocks that enable both researchers to conduct analyses, and QI leaders and clinicians to understand variation in care patterns. Examples of phenotypes that are essential components of MPOG research and QI include anesthesia technique, American Society of Anesthesiologists physical status, and patients’ smoking status. In each of these cases, there are thousands of ways these data are documented across sites, and software algorithms developed by MPOG translate the data into interoperable phenotypes.

MPOG has developed programs and tools to analyze big data and enable inferences for nuanced and meaningful QI and research projects aimed at improving patient safety.

MPOG’s QI mission is governed by its Quality Committee, composed of anesthesia professional QI champions for each participating site. This committee approves and maintains quality measures reflecting the best available evidence with an established plan to revisit QI measures at regular intervals to accommodate the field’s expanding and evolving knowledge base. Ideas for new QI initiatives are generated from this committee as well as subspecialty subcommittees focused on pediatric, obstetric, geriatric, and cardiac anesthesia, each composed of quality champions and domain experts from participating institutions. These committees foster open discussions, collaboration, and the sharing of best practices and lessons learned.

Figure 2: Individual Provider Feedback on Perioperative Quality: Personalized Performance Emails.
EHR Data Are Highly Variable Across Institutions

From “Using Big Data Tools,” Preceding Page

In order for members to enact change at their institutions, MPOG has developed a series of programs built upon the computed phenotypes foundation. These programs include QI measure development, practice level feedback, individual provider feedback, QI toolkits, and quality collaborative meetings as described in Table 1. Further details describing all QI measures can be found at https://spec.mpog.org/ Measures/Public. Individual provider performance can be tracked and feedback can be provided to individuals (Figure 2).

To complement its QI mission, MPOG’s research mission is governed by its Research Committee, which coordinates clinical research efforts of MPOG by reviewing submitted proposals and tracking the progress of ongoing projects. This committee, composed of MPOG principal investigators from each participating site, evaluates all MPOG research proposals, provides crucial guidance on hypotheses and methodology, and ensures the scientific appropriateness of clinical research using MPOG data prior to a project’s approval. To enable meaningful research using MPOG data, the group has built several programs and tools to leverage the Registry. These programs include regular research committee meetings and an annual MPOG Retreat, as well as software tools (e.g., DataDirect®, Ann Arbor, Michigan) to develop research cohorts and streamline research queries.

PERFORMANCE IMPROVEMENT WITHIN THE STATE OF MICHIGAN

In the state of Michigan, MPOG is part of a Blue Cross Blue Shield of Michigan funded QI program, which functions as a learning health system. This program funds QI groups across a range of specialties and health conditions. Through the mechanisms described above, unblinded performance reviews, multispecialty collaborative meetings, and payor-driven financial incentives lead to substantial improvements. These are evidenced by improvements in important anesthetic care domains such as glycemic and temperature management, as well as achieving more cost-effective care for hospitals participating in this program (Table 2).

RESEARCH INITIATIVE: ASSESSMENTS OF MULTICENTER PRACTICE VARIATION AND PERIOPERATIVE CARE STRUCTURES

Given the breadth of perioperative practice variation across clinicians and sites, important research findings of MPOG have included studies which quantify the degree to which practice patterns are explained by the clinician or institution, rather than the patient or surgery. Such practice variation, potentially indicative of clinician training, personal practice preferences, or institution-level structures of clinical care and infrastructure, has been leveraged to study impact on patient outcomes. In some cases, practice variation—including anesthesia professional staffing ratios, hospital level compliance with safety practices, and failure to rescue rates—is associated with worse outcomes; whereas in other cases a lack of association exists with adverse outcomes, including overlapping surgeries by an attending surgeon or surgeries in which the surgeon operated overnight the day prior.

OPPORTUNITIES AND CHALLENGES INTRODUCED BY ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN PERIOPERATIVE CARE

Coinciding with the development of big data tools for processing electronic health record (EHR) data to perform multicenter research and QI, are opportunities to apply methods using artificial intelligence and machine learning to improve data quality, develop QI measures, and improve clinical care through predictive algorithm development. Given the complexities and granularity of perioperative EHR data, artificial intelligence/machine learning methods capable of handling large numbers of complex non-linear interactions across variables sometimes offer substantial advantages over classic statistical approaches. Yet, challenges exist to safe adoption of artificial intelligence/machine learning-based methods in perioperative learning health systems. These include (i) wide variations in the available clinician knowledge base regarding strengths and limitations; (ii) a need for clinical algorithm oversight and governance; (iii) the need to ensure fidelity of source data upon which artificial intelligence/machine learning algorithms are trained; and (iv) a systematic approach to recognizing and addressing biases potentially propagated in artificial intelligence/machine learning-based clinical decision support systems (Figure 3).

Related to clinician knowledge, artificial intelligence/machine learning education is being incorporated into medical curricula and continuing medical education opportunities in health care. Related to algorithm governance and oversight, QI and patient safety efforts propose frameworks for committees to monitor artificial intelligence/machine learning models deployed within a health system. With regard to data fidelity, approaches to diagnosing and remedying changes toEHR data quality ("dataset shift") are proposed, focusing on maintaining closed-loop communication between frontline clinicians and algorithm governance committees, which may enhance patient safety by promoting awareness of model under-performance and thereby educating clinicians as to clinical contexts for which the prediction model can be relied upon versus disregarded. Finally, as algorithmic bias concerns remain, opportunities to address differential model performance across varying clinical subgroups—particularly when racial, ethnic, and sex-based—include explicitly examining artificial intelligence/machine learning model performance in such subgroups.

CONCLUSION

Opportunities are ripe for coalescing perioperative EHR data across patients, clinicians, institutions, and regions to perform comparative effectiveness research and improve the quality and safety of anesthesia care. Perioperative learning health systems equipped with big data tools with appropriate leveraging of novel artificial intelligence/machine learning-based methods provide a platform for clinician communities to share data, exchange ideas, and disseminate

Table 2: Multicenter Perioperative Outcomes Group Examples of Quality Improvement Impact.

<table>
<thead>
<tr>
<th>QI INITIATIVE</th>
<th>PROGRAM AND RESULTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prevention of hypothermia</td>
<td>MPOG launched an initiative across the state of Michigan in 2018 to reduce intraoperative hypothermia. Process measures determining use of active warming and appropriate temperature monitoring and outcome measures determining rates of hypothermia were developed. MPOG sites in Michigan reduced hypothermia at the end of case from 10.8% to 5.6% from 2018 to 2023.</td>
</tr>
<tr>
<td>Treatment of hyperglycemia</td>
<td>MPOG launched an initiative in 2015 to improve management of hyperglycemia. Through measures determining appropriate checking and treatment of hyperglycemia, MPOG sites in Michigan participating in MPOG improved compliance for appropriate treatment of hyperglycemia with insulin from 59.7% in 2015 to 81% by 2023.</td>
</tr>
</tbody>
</table>

This is from data extracted from MPOG database 08/2023, and presented at the APSF conference, Las Vegas, 09/2023.
Challenges Exist to Safe Adoption of Artificial Intelligence

<table>
<thead>
<tr>
<th>Clinician Training</th>
<th>Governance / Oversight</th>
<th>Data Fidelity</th>
<th>Algorithmic Bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>Limited AI/ML knowledge</td>
<td>Models used for unintended purposes</td>
<td>Variation in EHR documentation</td>
<td>Differences in training versus testing datasets</td>
</tr>
<tr>
<td>Limited access to model performance</td>
<td>Inaccuracies leading to medical errors</td>
<td>Dataset shift</td>
<td>Differing performance across subgroups</td>
</tr>
</tbody>
</table>

Approaches to Enhance Safe Adoption

- Formal education on AI/ML
- Visibility into model performance & factors driving predictions
- Reporting guidelines for AI/ML-based clinical decision support tools
- Local AI/ML governance committees, federal oversight of algorithms
- Phenotypes as more reliable data labels
- Data Quality Dashboards
- Platforms to integrate diverse EHR data
- Analysis of algorithm performance across key subgroups
- Models predicting pathology rather than clinician actions

Figure 3: Considerations for Safe Adoption of Artificial Intelligence (AI) and Machine Learning (ML) into Perioperative Care.

From “Using Big Data Tools,” Preceding Page

Michael L. Burns, MD, is an assistant professor of anesthesiology at Michigan Medicine, University of Michigan, Ann Arbor, MI.

Nirav J. Shah is an associate professor of anesthesiology at Michigan Medicine, University of Michigan, Ann Arbor, MI.

Robert B. Schoenberger is an associate professor and vice chair for academic affairs in anesthesiology at the Yale School of Medicine, New Haven, CT.

Anthony L. Edelman is an assistant professor of anesthesiology and associate chair for adult anesthesiology at Michigan Medicine, University of Michigan, Ann Arbor, MI.

Allison M. Janda, MD, is an assistant professor of anesthesiology at Michigan Medicine, University of Michigan, Ann Arbor, MI.

Douglas A. Colquhoun, MB ChB, MSc, MPH, is an assistant professor of anesthesiology at Michigan Medicine, University of Michigan, Ann Arbor, MI.
Artificial Intelligence/Machine Learning Provide Platform for Clinicians to Share Data Regarding Best Practices

From “Using Big Data Tools,” Preceding Page

Blue Cross Blue Shield of Michigan/Blue Care Network and Multicenter Perioperative Outcomes Group work collaboratively, the opinions, beliefs, and viewpoints expressed by the authors do not necessarily reflect the opinions, beliefs, and viewpoints of Blue Cross Blue Shield of Michigan/Blue Care Network or any of its employees. Additionally, the opinions, beliefs, and viewpoints expressed by the authors do not necessarily reflect the opinions, beliefs, and viewpoints of the National Institutes of Health, or any of its employees. Industry contributors have had no role in the study.

REFERENCES
gery: a multicenter observational analysis. Anesthesiology. 2023;139:122–141. PMID: 3709403.
4. Burns ML, Saager L, Cassidy RB, et al. Association of anesthesiologist staffing ratio with surgical patient morbidity and
5. Sutherland K, Levesque JF. Unwarranted clinical variation in health care: definitions and proposal of an analytic frame-
6. Sessler DI. Implications of practice variability. Anesthesiol-
8. Portuondo JL, Farjah F, Massanweh NN. Association be-
tween hospital perioperative quality and long-term surv-
9. Casey JD, Courtright KR, Rice TW, Semler MW. What can a
learning healthcare system teach us about improving out-
10. Foley T, Vale L. A framework for understanding, designing, developing and evaluating learning health systems. Learn
Health Syst. 2023;7:e10315. PMID: 36654802.
11. Sheetz KH, Englesbe MJ. Expanding the quality collabora-
tive model as a blueprint for higher-value care. JAMA Health
12. Smith M, Saunders R, Stuckhardt L, McGinnis JM. Commit-
tee on the Learning Health Care System in America; Insti-
tute of Medicine. Best care at lower cost: the path to continuously learning health care in America. National Academies
Press (US); 2013 May 10. PMID: 24901184.
13. Olsen L, Asner D, McGinnis JM, eds. The Learning Health-
ations for integration of perioperative electronic health records across institutions for research and quality improve-
ment: the approach taken by the Multicenter Perioperative
org/Measures/Public. Accessed February 16, 2024.
toolkits/. Accessed February 16, 2024.
17. Howard R, Grant J, Leyden T, Englesbe M. Improving the
quality of health care through 25 years of statewide collabor-
oration in Michigan. NEJM Catalyst. 3:CATT.0153. doi:
10.1056/CATT.22.0153.
18. Collaborative quality initiatives—value partnerships.com —
blue cross blue shield of Michigan. https://valuepartners-
ships.com/programs/collaborative-quality-initiatives/.
Accessed February 16, 2024.
sia quality improvement participation lead to incremental
savings in a surgical quality collaborative population? A ret-
20. Sun E, Mello MM, Rishel CA, et al. Association of overlap-
21. Sun EC, Mello MM, Vaughn MT, et al. Assessment of periop-
erative outcomes among surgeons who operated the night
before. JAMA Intern Med. 2022;182:720–728. PMID:
35604661.
22. Howell MD, Corrado GS, DeSalvo KB. Three epochs of arti-
ficial intelligence in health care. JAMA. 2024;331:242–244.
PMID: 38227029.
model for the application of AI in health care. J Am Med
Inform Assoc. 2020;27:491–497. PMID: 36882262.
2021;385:283–286. PMID: 34260943.
ciples to address the impact of algorithms on racial and
ethnic disparities in health and health care. JAMA Netw
Open. 2023;6:e2345050. PMID: 3810001.

Workplace Violence Videos are Now Available Online

We know that workplace violence is toxic—impacting culture, teamwork, clinician wellbeing and patient safety. A 2021 Stoelting Conference Cross-sectional Survey showed 71.6% of perioperative respondents (anesthesiologists, certified anesthesia assistants, certified registered nurse anesthetists, OR nurses, recovery room nurses, surgeons) report experiencing nonphysical workplace violence.

APSF is pleased to release three trigger-video workshop modules on workplace violence focusing on: Discrimination, Physical Aggression and Incivility. These videos, along with their companion facilitation guides are freely available through the APSF website. Alex Hannen-berg, MD, Della Lin, MD, and Randy Steadman, MD, collaboratively produced these modules with filming logistics provided through UCLA’s Simulation Center.

Utilizing these workshop modules can open dialogue, jump start, and be integrated into existing workplace violence programs.

The videos and facilitation guides can be found at https://www.apsf.org/videos/workplace-violence/.