BRITISH JOURNAL OF HOSPITAL MEDICINE

EDITORIAL

Data Infrastructure for Improvement in Perioperative Medicine: Experience at a London Tertiary Hospital

Daniel Bendel[1,*], Teresa Wong[2], James Bedford[1], Peter M Odor[1]

[1]Department of Anaesthesia and Perioperative Medicine, University College London Hospitals NHS Trust, London, UK
[2]Department of Anaesthesia, Woodlands Health, Singapore, Singapore
*Correspondence: daniel.bendel@nhs.net (Daniel Bendel)

Abstract

Adoption of electronic health record systems offers an opportunity to collate massive volumes of complex information about patient care. Healthcare data can inform performance management, enable predictive analytics and enhance strategic decision making. A data-driven approach to improving patient care is vital to address the growing burden of morbidity and mortality associated with major surgery. We describe our methodology for transforming and utilising process of care data in an electronic health record system to develop a registry for quality improvement purposes in patients undergoing major surgery at a single UK hospital. We highlight development of our data-driven vision, technical aspects of processing raw data into metrics relevant to clinical decision making, alongside challenges encountered. Finally, we outline how our data infrastructure supports clinical governance, quality improvement and research. In sharing our experiences, we hope to enable others to embed and access the transformative clinical insights that healthcare data can yield.

Key words: perioperative medicine; big data; quality improvement; dataset

Submitted: 27 March 2024 Revised: 1 July 2024 Accepted: 8 July 2024

Introduction

Over the past decade, healthcare has undergone digitalisation, altering how patients access care, providers deliver services, and organisations manage data. The most fundamental has been adoption of electronic healthcare records (EHRs), allowing healthcare providers to store and access patient information digitally.

Over 90% of all National Health Service (NHS) Trusts have now switched to EHRs (Department of Health and Social Care, 2022; NHS Digital, 2023), offering unique opportunities based on scale. Digital transformation in elective surgical services is not only a healthcare imperative but also a strategic priority for an NHS seeking to improve hospital service quality, optimise resource utilisation and reduce patient waiting times. However, the adoption of EHRs represents a fundamental change to the conduct of medical record keeping. End-users are committed to new workflows, often necessitating leaps in digital literacy. The associated learning curve, in addition to variations in usability and intuitiveness of EHR design may add further frustration. In addition, modifications are often required in order to secure the capture of data relevant to local clinical and organisational priorities. In

How to cite this article:
Bendel D, Wong T, Bedford J, Odor PM. Data Infrastructure for Improvement in Perioperative Medicine: Experience at a London Tertiary Hospital. Br J Hosp Med. 2024. https://doi.org/10.12968/hmed.2024.0128

order to ensure the provision of usable data, new processes regarding training and digital infrastructure have therefore become necessary.

EHRs capture large volumes of high-density, time-indexed data throughout routine processes of care for elective surgical healthcare encounters, especially during critical periods such as the provision of anaesthesia or in post-operative critical care. However, such data is only useful if the contents are accurate, relevant, and reliable. Accuracy and consistency in data input are vital foundations in the analytics chain, often hampered by variability in healthcare provider interactions with EHRs or lack of opportunity to input structured, objective data. Even with accurate input, too much data can overwhelm, making it difficult to extract meaningful insights and make informed decisions. Likewise, most EHRs are not interoperable, with raw data exports from one Trust not easily aligning with others. Healthcare professionals need tools and technologies to effectively manage and analyse large volumes of data to derive actionable insights.

Data registries offer a solution to translate large quantities of raw EHR data into usable formats compatible between different NHS hospitals. Registries are databases specifically designed to collect standardised data on patients. By specifying which data is included and how, often with a layer of data normalisation and error filtering, a concise dataset is curated from a larger source of raw data. By providing a structured collection of standardised data, registries produce high-quality analytics.

Most national perioperative data registries require manual data extraction from a sample of healthcare records and input into a discrete database. This methodology limits completeness and efficiency and may introduce selection bias – all of which further limit interpretation. Examples of manually collected registries include The Royal College of Anaesthetists' National Audit Projects (NAPs), which typically study rare clinical events such as anaphylaxis or perioperative cardiac arrest (Kane et al, 2022; Kemp et al, 2018); the Perioperative Quality Improvement Programme (PQIP); the National Emergency Laparotomy Audit (NELA); and the US-based National Surgical Quality Improvement Programme (NSQIP) (Eugene et al, 2018; Ko et al, 2015; Moonesinghe et al, 2022).

Most EHRs allow a purely digital, and automated methodology for generating data registries, which feature every patient meeting the relevant inclusion criteria. Whilst examples of automated inter-hospital perioperative data registries already exist, such as the US-based Multicentre Perioperative Outcomes Group (MPOG) (Kheterpal, 2011), the UK still lacks a common, national perioperative data set specification.

Our goal was to adapt existing perioperative datasets into a format that could be described using automated, data-engineered methodology within an EHR, thus generating a comprehensive perioperative registry of all patients undergoing major surgery for local clinical performance monitoring, quality improvement and research. We chose to describe these metrics in an interoperable manner, allowing for their application across other EHRs across the NHS. In November 2020 a new 10 bed, dedicated surgical critical care unit was opened at University College London Hospitals (UCLH) NHS Foundation Trust; we planned to use this oppor-

tunity to establish a data-led culture for managing our operational performance of care for patients undergoing major elective surgery and, ultimately, improve patient outcomes.

Developing Data Infrastructure for Perioperative Care in a Tertiary NHS Trust

UCLH adopted Epic in April 2019 (https://www.epic.com/software/). Since then, all written communication, physiological observations, blood tests and radiological investigations have been consolidated into the single EHR platform, alongside app-based tools for patients. The Epic platform includes enterprise data warehouses, consisting of relational databases accessible via Structured Query Language (SQL). Epic offers frontline clinicians built in tools for data visualisation and analytics, but—based upon the principles discussed above—we were keen to invest in a methodology that provided greater control and precision over which data sources were used.

Dataset Development

Our first task was to define the metrics serving as our key performance indicators; key markers of perioperative quality recorded during routine care for major or high-risk surgery. We identified examples of existing perioperative data registries and their data definitions. Examples included the American Society of Enhanced Recovery Perioperative Quality Initiative (POQI), as well as PQIP (Moonesinghe et al, 2019; Moonesinghe et al, 2022). In order to achieve a standardised and therefore interoperable basis for the data registry, we reviewed recommendations regarding core outcome measures in perioperative care, including the standardised end-points in perioperative medicine (StEP), COMPAC and COMET initiatives (Abbott et al, 2018; Bampoe et al, 2018; Barnes et al, 2019; Beattie et al, 2021; Boney et al, 2022; Buggy et al, 2018; Haller et al, 2019; Moonesinghe et al, 2019; Myles et al, 2018; Prinsen et al, 2014; Williamson et al, 2017).

A local group of experts was convened, with representatives covering anaesthesia, surgery, critical care and data architecture within Epic. We compared the existing datasets and outcome measures against data already captured during routine care. For each proposed metric, the group considered a triad of prioritisation; the importance of the metric to clinical decision making, the completeness or reliability of existing data, and the expected technical investment required to generate the necessary data extraction. Quality measures were considered across Donabedian's Quality of Care Framework, including structure, process, and outcome measures (Donabedian, 2005).

It was important that the core dataset predominantly consisted of data collected during routine perioperative care to minimise the administrative burden on clinical staff. An evidence base was required to justify each metric, as well as a plan for utilisation (e.g., for outcome measurement or risk modelling).

The final dataset was developed by consensus amongst panel members. Due to relevance, overlap and the expected use profile, we included the entire PQIP

dataset alongside additional outcomes based on standardised definitions. Our plan was to develop a dataset that anticipated most needs by clinicians for quality improvement and research purposes, hence adoption of an existing UK-based registry with proven value in these areas. By acting as a modular library of data exports, clinicians can access our default metrics with any specialist items being developed ad hoc, integrating into the library over time. Crucially, our methodology also meant the capture of items not easily recorded by manual record review, such as haemodynamic measurements or details of intraoperative lung ventilation.

Working with Informatics Engineering Teams: An Integrated Approach

Two relational databases capture Epic data: "Caboodle" and "Clarity". Caboodle represents a subset of the larger Clarity database. It includes multiple data sources (including non-Epic data), and a simpler data model optimised for retrieval. We therefore curated a library of SQL scripts aimed at extracting data from the Caboodle database.

An agile development framework was adopted for this task (Beck et al, 2001). Small sections of the dataset were approached at a time, with iterative improvements and re-testing yielding progressive refinements to the SQL scripts. We prioritised accurate output from small sections over a wider, but less accurate, basic registry function. Comprehensive testing and interface improvements were adopted in stages, improving the efficiency of implementation. Structured weekly meetings ensured a dialogue between clinicians and data technicians, thus aligning the development of SQL code with ongoing clinical direction. Each aspect of the dataset was scrutinised in an iterative manner, against known results on a cohort of test patients. In outlining "hits" and "misses", we ascertained which items of the dataset were being reported correctly, and which data items warranted closer inspection to minimise errors. Consequently, we were able to work with data engineering teams to rapidly amend code, accounting for the specifics of each data item. Irregularities were flagged up and remedied in a contemporaneous manner, enabling us to troubleshoot analytics as the project progressed. A library of accurate SQL queries subsequently emerged.

The Data Pipeline: Making the Data Trustworthy

Raw healthcare data is prone to inaccuracy, as problems, pitfalls and errors in data entry are inherent throughout data generation and storage. Examples include incorrect, incomplete and inconsistent data entry and technical faults within networked data input devices, such as monitoring equipment. Most NHS hospitals lack data quality monitoring teams similar to those in the USA, where data completeness is a more important driver of billing. We therefore needed to address the variation in data quality, and chose to standardise data definitions across all aspects of care. This included incorporating filters to remove erroneous data whilst triangulating data from multiple hierarchical sources.

We based our parameters on existing work by the MPOG group, which convenes data in a standardised manner across multiple US hospitals, all using different EHRs (Kheterpal, 2011). Within the MPOG schematic, each aspect of care is defined by its "data phenotype", which specifies variables that characterise a clinical metric, either from raw data or by inference.

For each metric we explored multiple potential data provenances to identify the best "source of truth". For a minority of data items, finding this source of truth was straightforward. For example, a pre-operative haemoglobin test result was defined simply by the required laboratory test result, units of measurement and timeframe relative to the day of surgery (namely, up to 6 months prior).

However, more complex, inferred phenotypes were also required. For example, the type of anaesthesia provided during surgery (i.e., general, sedation, regional or local anaesthesia), was not reliably recorded within Epic. Instead, anaesthetists reliably input drug administrations and procedure notes. Early attempts to describe general anaesthesia with volatile anaesthetic drugs defined these episodes in binary terms, using either the presence of a procedure for airway device insertion and the presence or absence of volatile anaesthetic drugs recorded within the breathing circuit by gas analysers. However, clinically insignificant, but detectable, concentrations of volatile anaesthetic drugs present in breathing circuits during episodes of non-volatile anaesthesia triggered incorrect outputs. We filtered out these erroneous results by defining the minimum threshold concentrations and time limits of volatile anaesthesia required to fulfil our volatile general anaesthetic data phenotype. Similarly, a gaseous induction of general anaesthesia was differentiated from maintenance phase anaesthesia by reference to the timing of airway device insertion. Scripting the necessary SQL code relied on numerous clinical limits that were apparent in iterative testing, further highlighting the need for close collaboration between clinicians and data engineering.

Our data phenotypes eventually allowed for inferences across many facets of perioperative care. Whilst the data extraction scripts are specific to data structures within our local EHRs, the phenotypes have been developed using common principles, reference points and logic rules. They are sufficiently standardised to allow for the development of data extraction and future collaboration with other EHRs, thus conferring interoperability.

However, a minority of data items were not routinely or reliably recorded in the standard process of care documentation, requiring a different approach. We therefore tackled this at source: data entry.

Improving Data Capture: Making Clinical Documentation "Smart"

Free text documentation in EHRs is often the default mode of documentation. This is challenging to analyse, particularly for automated reporting. This is also true for clinical data such as ECGs, which are stored within Epic as graphic images (rather than objective data for interpretative diagnoses). To address this challenge,

we implemented a new documentation strategy in our surgical critical care unit by utilising bespoke documentation templates, using Smart Data Elements (SDEs).

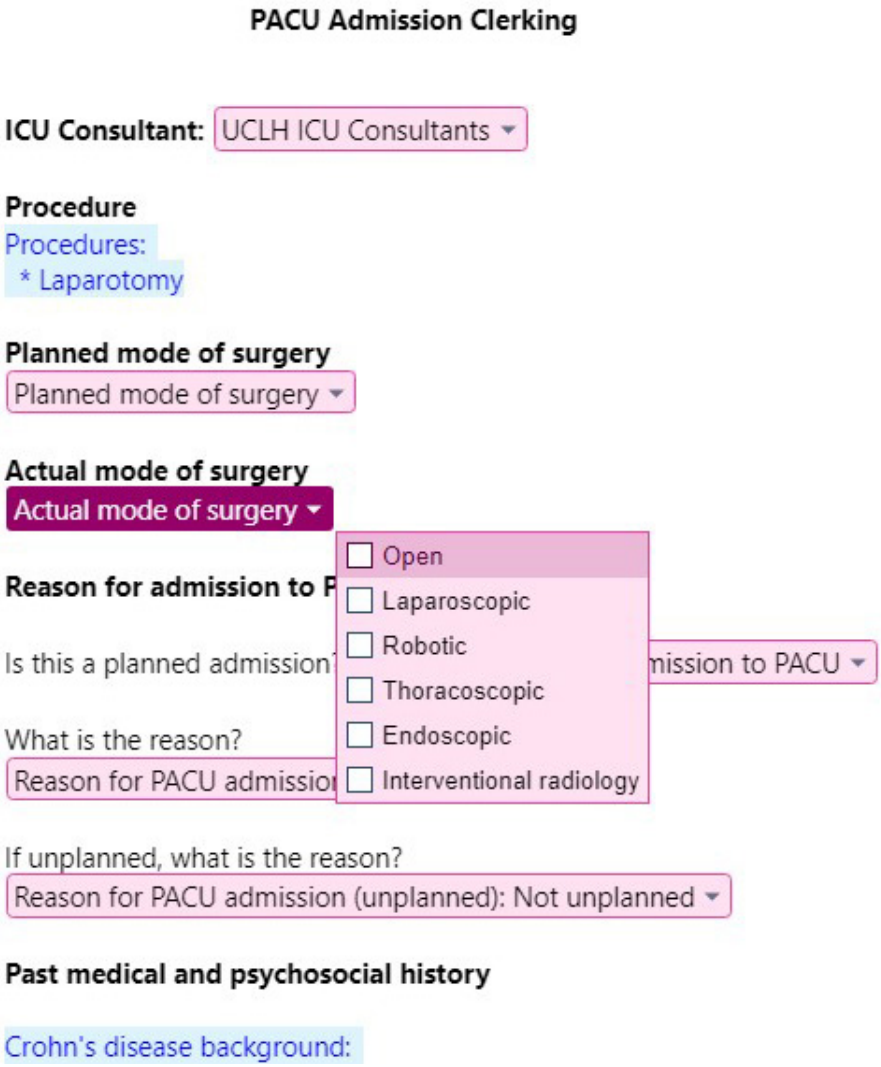

Fig. 1. Detail of the admission clerking.

SDEs are a feature within Epic that enables structured and retrievable data entry. At the user end, SDEs can take various forms, including drop-down menus (SmartLists), or entry to database fields (FlowSheets). Our goal was to streamline the documentation process by creating bespoke templates for our clinical review notes, incorporating SDEs that captured metrics previously recorded as unstructured free text. Our goals were twofold: to improve data capture and to streamline clinical data entry workflow.

We utilised SmartLists to allow clinicians to input structured data during the documentation of routine clinical care. This included the admission note templates, daily consultant reviews, overnight medical documentation and discharge summaries (Fig. 1). By streamlining the documentation burden and re-structuring the user interface we directed clinicians to input additional data entry via bespoke Flowsheets and Smart Data Elements (e.g., the daily postoperative morbidity survey—Fig. 2),

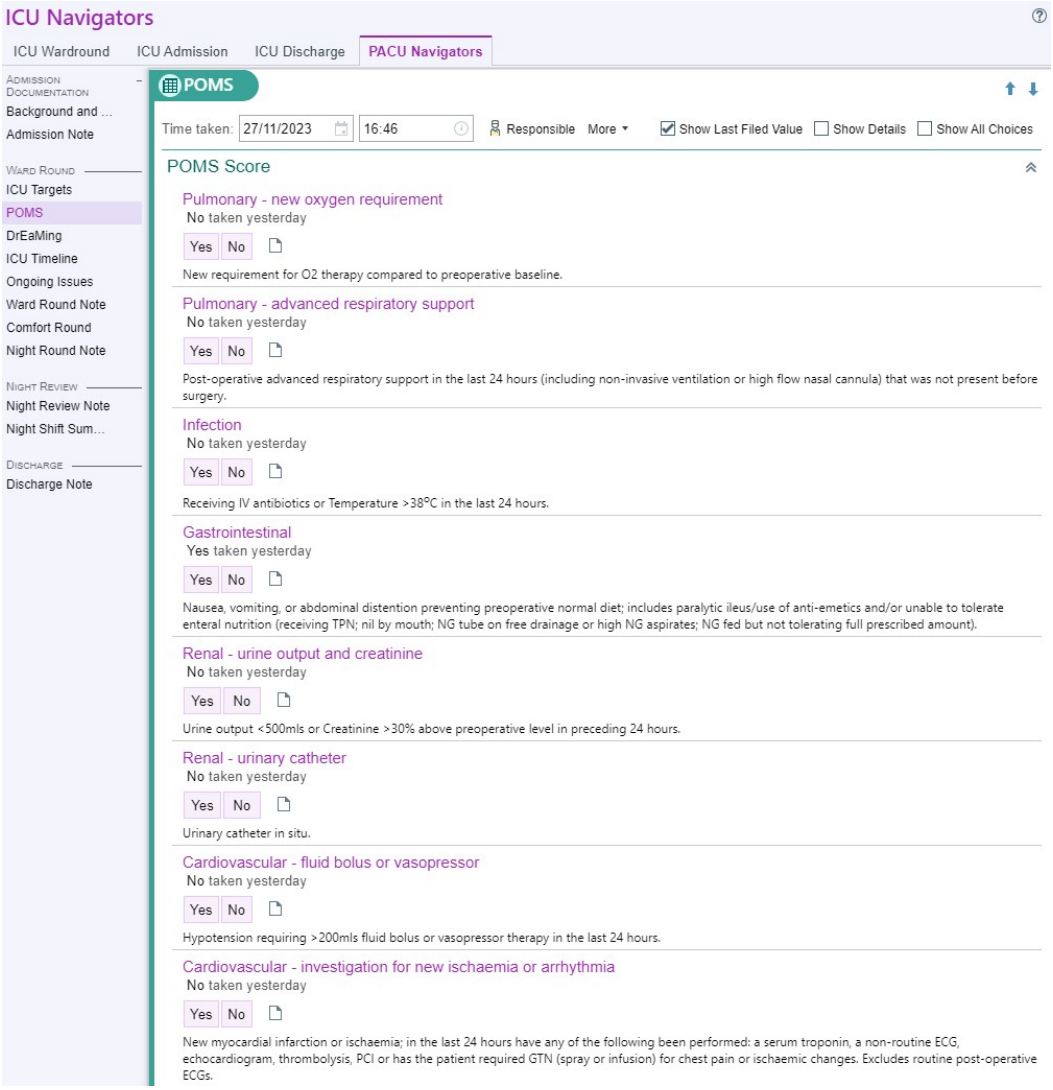

Fig. 2. An example of the use of SmartForms.

minimising unstructured free text entry for examination findings and subjective impressions. This approach addressed the shortfall in our required perioperative data capture without increasing the time required for clinical documentation.

To assess the impact on our end-users (junior doctors and nursing staff), we performed observational exercises, feedback collations and user surveys one month after the changes were implemented to assess their acceptability. Feedback was considered and the process was repeated at regular intervals. The survey results demonstrated that the new documentation templates were viewed as an improvement, significantly streamlining both the ease and speed of clinical documentation within Epic.

In this way, we ensured consistency in the type and quality of data captured. Secondly, we improved the capture of clinically relevant data not previously recorded. Thirdly, we demonstrably reduced the administrative load, allowing doctors and nursing staff to focus on clinical care.

Reporting

Progress towards reporting comprised several key stages: exporting, cleaning, analysing, and presenting the data. Initially, data were extracted from Epic and exported in the versatile .csv file format, universally recognised for simplicity and compatibility across various software platforms.

The data were loaded into the RStudio environment, a powerful and widely used tool in data science (Allaire, 2023). RStudio offers a robust platform for data manipulation, providing a suite of functions and capabilities essential for handling complex datasets. Within this environment, the data were cleaned, an essential step to ensure accuracy and reliability. This involved identifying and rectifying inconsistencies, missing values, and potential outliers.

For the analysis, the Tidyverse suite of packages in R was employed (Wickham, 2023). With user-friendly syntax and powerful data manipulation capabilities, Tidyverse provided a comprehensive toolkit for exploring and modelling the data. This suite enabled the transformation of raw, complex healthcare data into a structured and interpretable format, facilitating in-depth analysis.

Finally, the cleaned and analysed data were presented in an intuitive and interactive dashboard format using the Flexdashboard package. Flexdashboard is a tool within R that allows for the creation of dynamic and visually appealing dashboards. These dashboards provided a user-friendly interface for healthcare professionals to interact with the data.

To improve the quality and efficiency of patient care, we incorporated continuous displays such as run charts and Statistical Process Control (SPC) charts. These tools now support us in monitoring variations in care processes and outcomes over time, enabling the identification of trends and potential areas for improvement (Figs. 3,4, synthetic data).

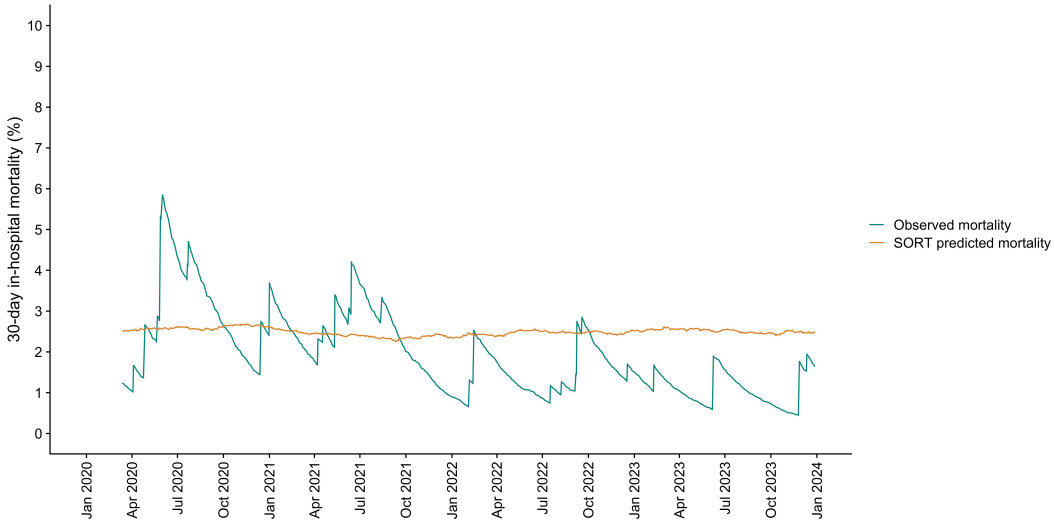

Fig. 3. Mortality figures.

The data displays focused on two main priorities: firstly, an operational priority aimed at obtaining a high-level overview of the surgical critical care service. This

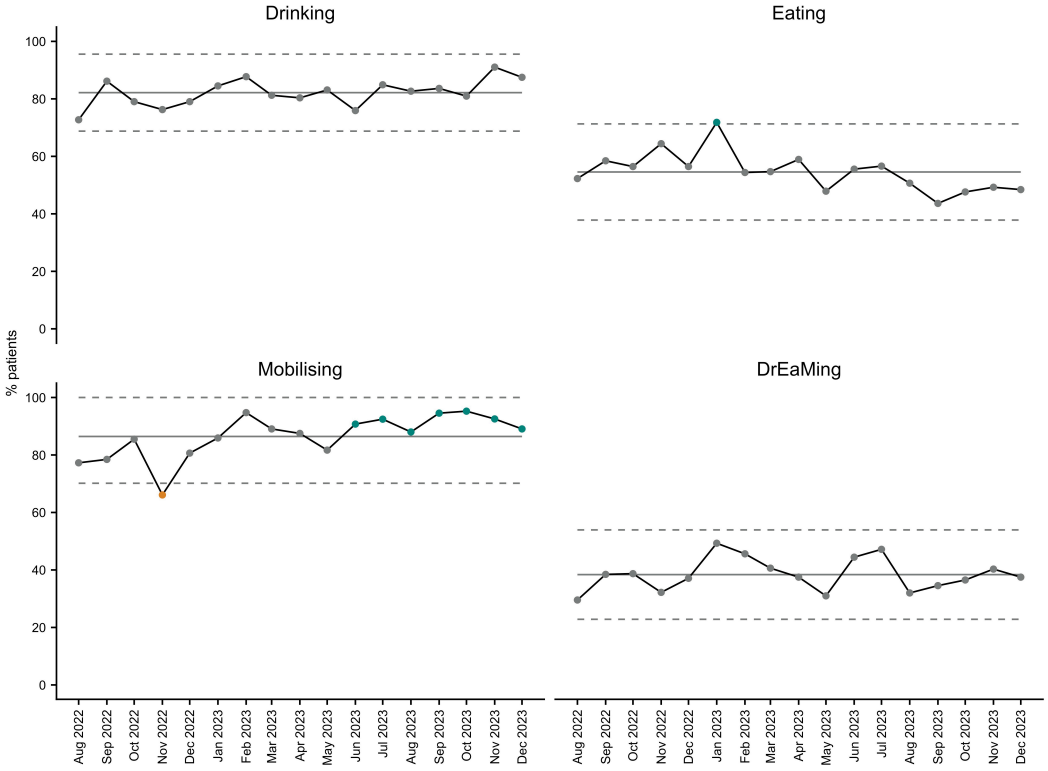

Fig. 4. A run chart demonstrating the reporting of Drinking, Eating and Mobilising ("DrEaMing") rates for governance purposes.

aspect involved analysing and visualising data to assess the efficiency and effectiveness of the unit's operations, and identifying areas where improvements could be made to enhance patient flow, resource utilisation, and overall service delivery.

Secondly, the focus was on patient-level care processes and outcomes, crucial for undertaking targeted quality improvement. By analysing individual patient data, the project could identify patterns and trends in patient outcomes, assess the effectiveness of various care processes, and pinpoint areas where changes could lead to improved patient care and outcomes.

Incorporating these continuous displays and focusing on these two priorities allowed the project to maintain a balanced approach to quality improvement, addressing both the operational efficiency of healthcare services and the individualised care processes that directly impact patient outcomes.

Conclusion

Our approach to developing a data-driven culture for perioperative healthcare necessitated several phases and required continual close collaboration between clinical and technical staff. We began by identifying and targeting the data of interest, creating new ways of capturing structured data where necessary. A data management layer then filters out irrelevant information, engineers inferences from primary data where appropriate, and allows for the presentation of clinical metrics relevant to clinical and organisational decision making, quality improvement and research. We recommend that these data-driven analytics for perioperative care be considered

as part of new EHRs launches, ideally using common data phenotypes that allow for interoperability and national collaboration. Embedding data-driven processes at EHR implementation offers the best opportunity for a data-driven culture to thrive at the point of inception. Now that EHRs are widespread within the NHS, a digitally-derived dataset that can be agreed upon and shared amongst national anaesthetic, surgical and critical care teams should likewise be a national priority and already has considerable clinical and political support (Goldacre, 2022). Whilst these technical and technological underpinnings are important, so too is a top-level approach to data utilisation: giving individuals the mandate, support and opportunity to use local data for healthcare improvement initiatives.

Whilst we have demonstrated the successful implementation of a perioperative data platform, work remains regarding layers of further analytics. Likewise, the progression towards a fully realised data-driven culture requires embedding the data platform within local governance and research activities, which necessitates engaging with the relevant key stakeholders responsible for audit, governance and research. However, in outlining the development of our perioperative care data platform, we demonstrate the rationale, feasibility, process, utility and potential that such data platforms can offer.

Key Points

- Define the key metrics, referring to the literature where appropriate.
- Embed these metrics into daily documentation, preserving ease of use for the end-user.
- Work with data technicians to ensure the validity of extracted data.
- Embrace an agile framework and take an iterative approach during development.
- The resulting data platform displays metrics of interest in several meaningful ways. Use run charts and data dashboards to describe organisational performance and fuel governance and research.

Availability of Data and Materials

All data included in this study are available upon request by contact with the corresponding author.

Author Contributions

DB, TW, JB and PMO conceived and collaborated on the project. All authors contributed to editing the manuscript and suggesting key revisions to the body of the text. All authors contributed to important editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

Acknowledgement

Not applicable.

Funding

This research received no external funding.

Conflict of Interest

Teresa Wong is an employee of Woodlands Health, where she is deputy Chief Medical Information Officer and a certified process analyst for Optime and Anaesthesia. Other authors declare no conflict of interest.

References

Abbott TEF, Fowler AJ, Pelosi P, Gama de Abreu M, Møller AM, Canet J, et al. A systematic review and consensus definitions for standardised end-points in perioperative medicine: pulmonary complications. British Journal of Anaesthesia. 2018; 120: 1066–1079. https://doi.org/10.1016/j.bja.2018.02.007

Allaire J. RStudio. Posit, PBC. 2023. Available at: https://posit.co/download/rstudio-desktop/ (Accessed: 14 December 2023).

Bampoe S, Cook T, Fleisher L, Grocott MPW, Neuman M, Story D, et al. Clinical indicators for reporting the effectiveness of patient quality and safety-related interventions: a protocol of a systematic review and Delphi consensus process as part of the international Standardised Endpoints for Perioperative Medicine initiative (StEP). BMJ Open. 2018; 8: e023427. https://doi.org/10.1136/bmjopen-2018-023427

Barnes J, Hunter J, Harris S, Shankar-Hari M, Diouf E, Jammer I, et al. Systematic review and consensus definitions for the Standardised Endpoints in Perioperative Medicine (StEP) initiative: infection and sepsis. British Journal of Anaesthesia. 2019; 122: 500–508. https://doi.org/10.1016/j.bja.2019.01.009

Beattie WS, Lalu M, Bocock M, Feng S, Wijeysundera DN, Nagele P, et al. Systematic review and consensus definitions for the Standardized Endpoints in Perioperative Medicine (StEP) initiative: cardiovascular outcomes. British Journal of Anaesthesia. 2021; 126: 56–66. https://doi.org/10.1016/j.bja.2020.09.023

Beck K, Beedle M, van Bennekum A, Cockburn A, Cunningham W, Fowler M, et al. The Agile Manifesto. 2001. Available at: https://agilemanifesto.org/ (Accessed: 21 December 2023).

Boney O, Moonesinghe SR, Myles PS, Grocott MPW, StEP-COMPAC group. Core Outcome Measures for Perioperative and Anaesthetic Care (COMPAC): a modified Delphi process to develop a core outcome set for trials in perioperative care and anaesthesia. British Journal of Anaesthesia. 2022; 128: 174–185. https://doi.org/10.1016/j.bja.2021.09.027

Buggy DJ, Freeman J, Johnson MZ, Leslie K, Riedel B, Sessler DI, et al. Systematic review and consensus definitions for standardised endpoints in perioperative medicine: postoperative cancer outcomes. British Journal of Anaesthesia. 2018; 121: 38–44. https://doi.org/10.1016/j.bja.2018.03.020

Department of Health and Social Care. A plan for digital health and social care. 2022. Available at: https://www.gov.uk/government/publications/a-plan-for-digital-health-and-social-care (Accessed: 29 June 2022).

Donabedian A. Evaluating the quality of medical care. 1966. The Milbank Quarterly. 2005; 83: 691–729. https://doi.org/10.1111/j.1468-0009.2005.00397.x

Eugene N, Oliver CM, Bassett MG, Poulton TE, Kuryba A, Johnston C, et al. Development and internal validation of a novel risk adjustment model for adult patients undergoing emergency laparotomy surgery:

the National Emergency Laparotomy Audit risk model. British Journal of Anaesthesia. 2018; 121: 739–748. https://doi.org/10.1016/j.bja.2018.06.026

Elliott A. Better, broader, safer: using health data for research and analysis (the Goldacre review). Journal of Radiological Protection: Official Journal of the Society for Radiological Protection. 2022; 42: 10.1088/1361–6498/ac89f8. https://doi.org/10.1088/1361-6498/ac89f8

Goldacre B. Data saves lives: reshaping health and social care with data. 2022. Available at: https://www.gov.uk/government/publications/data-saves-lives-reshaping-health-and-social-care-with-data/data-saves-lives-reshaping-health-and-social-care-with-data (Accessed: 15 June 2022).

Haller G, Bampoe S, Cook T, Fleisher LA, Grocott MPW, Neuman M, et al. Systematic review and consensus definitions for the Standardised Endpoints in Perioperative Medicine initiative: clinical indicators. British Journal of Anaesthesia. 2019; 123: 228–237. https://doi.org/10.1016/j.bja.2019.04.041

Kane AD, Armstrong RA, Kursumovic E, Cook TM, Oglesby FC, Cortes L, et al. Methods of the 7^{th} National Audit Project (NAP7) of the Royal College of Anaesthetists: peri-operative cardiac arrest. Anaesthesia. 2022; 77: 1376–1385. https://doi.org/10.1111/anae.15856

Kemp H, Marinho S, Cook TM, Farmer L, Bellamy M, Egner W, et al. An observational national study of anaesthetic workload and seniority across the working week and weekend in the UK in 2016: the 6th National Audit Project (NAP6) Activity Survey. British Journal of Anaesthesia. 2018; 121: 134–145. https://doi.org/10.1016/j.bja.2018.04.010

Kheterpal S. Clinical research using an information system: the multicenter perioperative outcomes group. Anesthesiology Clinics. 2011; 29: 377–388. https://doi.org/10.1016/j.anclin.2011.06.002

Ko CY, Hall BL, Hart AJ, Cohen ME, Hoyt DB. The American College of Surgeons National Surgical Quality Improvement Program: achieving better and safer surgery. Joint Commission Journal on Quality and Patient Safety. 2015; 41: 199–204. https://doi.org/10.1016/s1553-7250(15)41026-8

Moonesinghe SR, Jackson AIR, Boney O, Stevenson N, Chan MTV, Cook TM, et al. Systematic review and consensus definitions for the Standardised Endpoints in Perioperative Medicine initiative: patient-centred outcomes. British Journal of Anaesthesia. 2019; 123: 664–670. https://doi.org/10.1016/j.bja.2019.07.020

Moonesinghe SR, McGuckin D, Martin P, Bedford J, Wagstaff D, Gilhooly D, et al. The Perioperative Quality Improvement Programme (PQIP patient study): protocol for a UK multicentre, prospective cohort study to measure quality of care and outcomes after major surgery. Perioperative Medicine (London, England). 2022; 11: 37. https://doi.org/10.1186/s13741-022-00262-3

Myles PS, Boney O, Botti M, Cyna AM, Gan TJ, Jensen MP, et al. Systematic review and consensus definitions for the Standardised Endpoints in Perioperative Medicine (StEP) initiative: patient comfort. British Journal of Anaesthesia. 2018; 120: 705–711. https://doi.org/10.1016/j.bja.2017.12.037

NHS Digital. 90% of NHS trusts now have electronic patient records. 2023. Available at: https://digital.nhs.uk/news/2023/90-of-nhs-trusts-now-have-electronic-patient-records (Accessed: 20 November 2023).

Prinsen CAC, Vohra S, Rose MR, King-Jones S, Ishaque S, Bhaloo Z, et al. Core Outcome Measures in Effectiveness Trials (COMET) initiative: protocol for an international Delphi study to achieve consensus on how to select outcome measurement instruments for outcomes included in a 'core outcome set'. Trials. 2014; 15: 247. https://doi.org/10.1186/1745-6215-15-247

Wickham H. Tidyverse. 2023. Available at: https://www.tidyverse.org/ (Accessed: 13 December 2023).

Williamson PR, Altman DG, Bagley H, Barnes KL, Blazeby JM, Brookes ST, et al. The COMET Handbook: version 1.0. Trials. 2017; 18: 280. https://doi.org/10.1186/s13063-017-1978-4