EJAIC

Eur J Anaesthesiol Intensive Care Med 2023; **2**:5(e0032)

OPEN

REVIEW ARTICLE

Big data in anaesthesia: a narrative, nonsystematic review

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Data generation is growing with the use of 'anaesthesia information management systems' (AIMS), but the appropriate use of data for scientific purposes is often wasted by a lack of integration. This narrative review aims to describe the use of routinely collected data and its potential usefulness to improve the quality of care, first by defining the six levels of integration of electronic health records as proposed by the National Health Service (NHS) illustrated by examples in anaesthesia practice. Secondly, by explaining what measures can be taken to profit from those data on the micro-system level (for the patient), the meso-system (for the department and the hospital institution) and the macro-system (for healthcare and public health). We will next describe a homemade AIMS solution and the opportunities which result from his integration on the different levels and the research prospects implied. Opportunities outside of high-income countries will also be presented. All lead to the conclusion that a core dataset for peri-operative global research may facilitate a framework for the integration of large volumes of data from electronic health records. It will allow a constant re-evaluation of our practice as anaesthesiologists to offer the best care for patients. In this regard, the training of some anaesthesiologists in data science and artificial intelligence is of paramount importance. We must also take into account the ecological footprint of data centres as these are energy-consuming. It is essential to prepare for these changes and turn the speciality of anaesthesia, collaborating with data scientists, into a more prominent role of peri-operative medicine.

Published online 4 August 2023

KEY POINTS

- Electronic data generation increases with the use of 'Anaesthesia Information Management Systems' (AIMS).
- This narrative review describes why and how to extract routinely collected data from electronic health records and how to integrate these data.
- Collaboration with data specialists has proven to be able to play a role in the interpretation of routinely collected data.

Introduction

The number of surgical procedures is growing across the world, from approximately 220 million major surgical cases to 310 million in less than one decade.[1]

Anaesthetists are seen as technology and innovation adopters.[2] Electronic data generation is growing with the use of 'anaesthesia information management systems' (AIMS), but the appropriate utilisation of data for scientific purposes is not always realised, and the data are underutilised for outcomes research.[3] A full integration of data, from AIMS into the hospital's electronic health records (EHR), allows for an individualised patient information profile and provides healthcare intervention details.[4,5] Clinical interpretation of electronically collected information creates an opportunity to improve the quality of care and research capacity. The amount of data generated by current anaesthesia practices tends to make traditional data processing challenging, requiring specialised tools for processing large 'big data' sets.[6]

Moreover, data analytics applied to big data (deep learning methodology) have the potential to support the development of outcomes research[6] and translational peri-operative

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DOI:10.1097/EA9.0000000000000032

research.[7] Data warehouses in anaesthesia are no longer used solely for reading the quality of care, but are increasingly the source of clinical research.[8] The scientific reading of data collected in anaesthesia and the use of machine learning are revolutionising research in this field.[9]

Mortality as an endpoint or outcome remains an unambiguous indicator of healthcare quality, but the definition of postoperative mortality as an outcome variable varies in clinical studies.[10]

This study aims to describe practical applications of routinely collected peri-operative data and its potential to improve the quality of anaesthesia care. Firstly, we present a framework for structuring the levels of integration of electronic health records, with concrete examples of applications for each level. Then, we discuss our experience with a data bank in one of our institutions.

Methodology

This work aims to connect evidence and concrete examples linked to the description of structural aspects in care settings, illustrated by the authors' own experiences. Hence, we designed it as a narrative, nonsystematic review of the literature in parallel with unpublished data. We obtained ethical approval from the university hospital CHU Charleroi (Belgium) to use these anonymised data for research purposes (P17/02_18/01 CCB 325201730849). All the analyses were conducted in Belgium, and in accordance with the Belgian and European legislation.

Level of integration of electronic health records

A classification of the electronic health records (EHR) has been proposed by the National Health Service (NHS).[11] This applies to the EHR but is transferable for the advanced level of computerisation in anaesthesia and its integration capacity (Fig. 1). Those levels are convenient

Fig. 1 Integration scale from the National Health Service system for electronic health records. Adapted with permission from[11].

Data for the levels 2 to 6 include the data from the previous level plus the new data for that level - as listed in column 2.

in that in order to reach the next level the previous one must be settled, so the complexity of the system ramps up in parallel to the sophistication of the possible applications. The structure of the system allows the creation of a roadmap of integration and an audit of an existing system. The hierarchy of the NHS levels as a roadmap will help hospital institutions and state entities launch data-based projects in healthcare on sound foundations by limiting the risk of overambitious projects. This approach will enable the efficient use of precious financial and human resources, especially in times of economic scarcity. For example, it would be futile to launch a project for the implementation of decision support tools (level 4) in an institution wherein the files are not yet digitised (level 1).

Level 1 to 3

Level 1, essentially administrative, is essential. This integration in the hospital file should be perfect. Examples have been published in anaesthesia and have demonstrated their utility. Spring *et al.*[12] for example, developed a process called ABAS 'Anaesthesia billing alert system', which identifies the absence of billing for certain anaesthesia procedures. Nair *et al.*[13] have improved this system by using billing for certain anaesthesia procedures, with paybacks of up to $400 000 through the introduction of an on-screen billing reminder system (Pop-up Alert).

Level 2 integrates care processes and allows the transmission of information between different systems. For example, for patients identified during pre-operative consultation as being at risk of postoperative nausea and vomiting a good example of such development is described in the study by Kooij *et al.*,[14] which demonstrates that information transmission in the operating room allows a better identification of the latter and improves adherence to the guidelines for the prophylaxis of postoperative nausea and vomiting from 38 to 73%.

Level 3 allows the transmission of information between different providers or care services. This is illustrated by Nair *et al.*[15] who evaluate the accuracy of an important drug prescription in the peri-operative period. This system resulted in an improvement from the baseline of 65.8 to 94.6% after its introduction. Similarly, Terrel *et al.*[16] show that appropriate information decreases drug prescribing that is detrimental to kidney function from 74 to 43%. Nair's team was also able to show a better compliance with antibiotic prophylaxis protocols by using such developments.[17]

These first three levels should be a part of the basic computerised medical record. Structured information such as laboratory results or drugs should also be available. Currently, almost all medical devices have integrated or in-scope computers, which facilitates the development of these first 3 levels.

Level 4 to 6

Once these first three levels have been acquired, the higher levels (4 to 6) can be achieved and incorporate more elaborate processes. The fourth level provides decision support algorithms. For example, Kooij *et al.*[18] have shown a more judicious administration of drugs to prevent postoperative nausea and vomiting was possible through such systems. Nair *et al.*,[19] by introducing into a specific module of 'AIMS', information to improve antibiotic administration could show an improvement in the timing of antibiotic administration from 62.5 to 83.9%. Monitoring of blood pressure in the operating room[20] was improved by the Smart Anesthesia Messenger ('SAM' warning system), which warned doctors and nurses of a lack of measurement after 6 min. They have also been able to demonstrate in another study,[20] a decrease from 15.8 to 6.1/1000 in the proportion of blood pressure measurements greater than 15 min apart. The mean unmeasured time beyond 15 min was 22.9 min ($n = 188$) before the SAM introduction.

In a multicentre study in the same field but with a different methodology (pre and post intervention and 212 706 anaesthetic charts),[21] the authors achieved a decrease from 1.48 to 0.79% in the incidence of intervals without a blood pressure for 10 min.

The fifth level corresponds to a computer tool that provides speciality support. This may include, for example, prescription and pharmacy products and would be able to automatically process this information to manage anaesthesia drug delivery. This type of innovation has been described in the literature,[22–25] and a recent review summarises the different methods and their performance in terms of reducing episodes of underdosage or drug overdoses.[26]

The sixth level is the transmission of this advanced information. To date, there are no such developments in the field of anaesthesia, but in the context of ongoing developments, they can certainly be achieved in the long term. We can think of an international (or European-level) structured bank of peri-operative data, which would help develop new prediction tools or validate existing solutions in different populations.

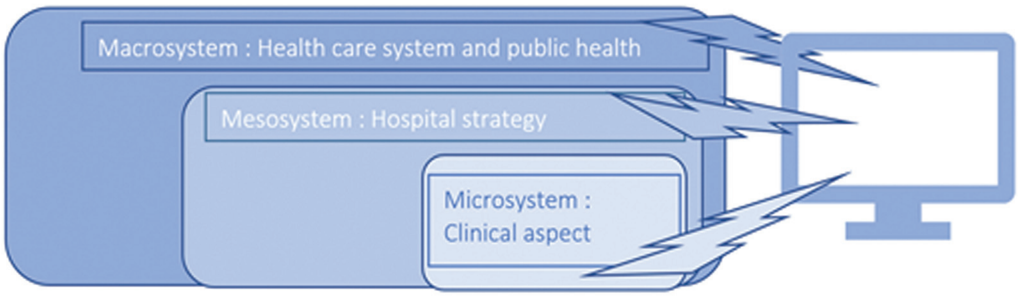
These levels of integration, when implemented, have benefits on three different tiers: the micro-system tier when it benefits directly the patient, the meso-system tier when it benefits the institution and finally the macro-system tier when it benefits the healthcare system.

The interaction of these three tiers has an impact on policy-making and public health, see Fig. 2.

Micro-system tier, for the patient

Avoiding hypocapnia may decrease postoperative death.[27] Computerisation makes it possible to develop electronic intervention warnings, fed by a data collecting system, designed to feedback to the anaesthesiologist. This global vision suggests that the majority of patients could be more appropriately ventilated. This choice of parameter is important because it not only significantly modifies the patient outcome, but also because

Fig. 2 Structure and interaction of healthcare levels. Personal figure based on reading of[38,39].



anaesthetists are able to adjust their practice using the information made available to them.

Another example of benefit to the patient is the presence of an anaesthesia nurse to specifically assist the anaesthetist physician during the entire procedure. The presence of a nurse anaesthetist assisting the anaesthesiologist has been found to be associated with lower postoperative mortality. In this article,[28] it is the cross-referencing of the administrative data of the members of the anaesthesia team and the patient outcomes that allowed the observation of an association of the additional presence of anaesthesia nurses with lower mortality. Assistance by a qualified nurse in anaesthesia is not recognised at a national level in Belgium, although it does occur in some centres and it exists in other neighbouring countries. Many aspects need to be considered to inform whether changes need to be put in place and the professional policies adapted. This integrates training issues and financial burden responsibilities that go beyond the initial objective of this approach. Nevertheless, despite the potential limitations discussed, we note that mortality is significantly lower when a nurse anaesthetist is present with a doctor.

These examples were chosen not only for the impact on the patient outcome, but also because we as clinicians have a real ability to influence the choices that have been evaluated.

Mesosystem tier, department and hospital institution

Data integration at the institution level can have various beneficial effects, such as improving the use of the operating theatre and the availability of infrastructure and increasing efficiency. For example, in our institution, extracting data from the anaesthesia chart for management purposes (such as duration of surgical procedures) has increased the room occupancy rate from 75% to more than 95%, while also improving the perception of availability of operating rooms for the surgical team. The clinical lead team presents a quarterly dashboard containing important information for the management of the operating room. This work improves trust and collaboration for the same purpose, and optimal efficiency of the institution. Themes such as the distribution of operating activities, the occupancy rate of the rooms and various statistics such as rotas or theatre sessions can be integrated in a decision-making tool. More specific aspects related to the financing of the operating room, such as the standard operating duration, can be challenged with real data.[29] The linking of certain information, such as the computerised anaesthesia record and operating room information management systems (ORIMS), will make it possible to update the changes of rooms in the operating theatre and to maintain the quality of the actual operating room occupancy data, despite the numerous scheduling changes.[30]

Another benefit for the service and the hospital is to provide useful information to support research and teaching activities. A consistent data structure enables high-performance and cost-effective multicentre searches.[31] This reduces the cost of the research protocols and the time required to obtain usable results. Positioning oneself by supporting teaching and research opens new avenues, especially when IT technologies are a part of an innovation framework.

Macro-system tier, for healthcare and public health

The potential of the methodology put in place should go beyond the scope of a patient, an institution or service and incorporate the framework of public health issues. Like the patient benefits and those of the clinical department, one example has been selected for demonstration: peri-operative mortality. This is often (for pragmatic reasons of access to information) evaluated by counting intra-hospital deaths.[10] The originality of the work conducted in Belgium by one of the authors[32] was the linkage of the data with those of the the national database used by social security institutions (Crossroads Bank for Social Security, CBSS) from the outset. The enumeration of deaths, therefore, considers extra-hospital deaths as well. At a time when the trend is to shorten the average length of stay of patients, monitoring the outcome after discharge is important. Postoperative home care has important issues that cannot be fully understood without a comprehensive measure of patient mortality. In the context of this thesis, we have shown that if we did not consider these external events, one-fifth of deaths would not be counted.[32] Thirty-day mortality provides a difficult but unambiguous indicator. However, a significant number of actions must be taken to discover indicators related to a possible death. In a speciality that has safety as a priority prerogative, intra-operative deaths are relatively rare, although they are more common when patients have significant comorbidities. This is why it has been recommended to include the recordings over a long period of time, to integrate at least 50 000 anaesthetics,[33] and to register both in-hospital and out-of-hospital death.[32]

A successfully implemented system at the macro level is the voluntary Swedish Perioperative Register (SPOR),[34] which was launched in 2013 to collect data on waiting times for surgery and has 159 variables in version 4.0. As of early 2023, more than 4.8 million procedures had been uploaded to the registry. An example of the system's application is the evaluation of the impact of the COVID-19 pandemic on surgery volume in Sweden.[35]

Other possible uses of integrated data systems have been proposed. These include the organisation of the operating theatres, including billing, timing and strategic analysis of the clinical activity.[29] For example, a periodic comparison between the existence of a computerised protocol for anaesthesia and the central billing can help the financial service to automatically request and allow recovery of collection of fees.

Regarding the timing, objective measures of operating room occupancy can help to better schedule clinical activity. This may help the operating room managers and, more globally, the clinical/strategic leaders suggesting choices to management based on objective data.

All those elements demonstrate that significant savings in medications and anaesthesia-related costs can be achieved and largely compensate for the investment, at all micro, meso and macro-system levels.[36]

Although there are still many areas left to explore, we primarily focused on themes that allowed for continuous evaluation and potential corrections, and where it was feasible to compare results with artificial intelligence analysis techniques.[37]

A practical example of electronic data use in our institution

To illustrate the use of AIMS, we will describe our real-life experience of a system having reached level 4 with micro, meso and potentially macro applications.[38] We will also delineate the dilemma between innovation and the ability to understand and communicate models in innovative AI techniques ('explainability'). This is followed by a discussion of the cost-effectiveness of research and development of home-made solutions.

A home-made AIMS solution integrated into the EHR with a link to the CBSS was developed in 2010, in Belgium. This allows for the assessment of postoperative, intra-operative and extra-hospital, mortality. This development has helped benchmark the surgical postoperative mortality rate. Some indicators have been examined with a classic study and a set of procedures related to analysing and discovering useful, actionable knowledge through a datamining process.[39] The AIMS comprises a locally coded electronic anaesthesia management chart that is connected to the anaesthesia machine, enabling the collection of real-time data such as haemodynamic parameters and machine settings. Following the procedure, the data are validated by the anaesthesiologist and exported to a locally coded SQL data warehouse. In addition to the anaesthesia data, administrative information from other hospital departments and data from the CBSS are also included, providing a total of 203 variables that can be exported to a CSV table for analysis.

The technical developments realised within the framework of this project were the creation of a computer tool that allowed capture and recording of multiple signals coming from different sources with a view to their subsequent exploitation. This network was developed on the principles of the AIMS project.[40–42]

A number of improvements were made between 2010 and 2011.[5] The tool now not only integrates both a computerised record of the anaesthetic parameters to the patient, but also hospital data such as length of stay, care units of passage, hospital mortality, and extra-hospital mortality thanks to a link with the CBSS. These observations were then transformed into information, through the preparation and processing of the various databases formed to obtain a 'data warehouse'. This allows for potential research projects. Processes similar to ours have been described in the literature.[43,44] The integration within the same 'data warehouse' of multiple provenance data (hospital administrative and clinical) allows the use of these data at a wider level, beyond the hospital institution, and thereby provides useful public health information.

Innovative applications of integrated data

In parallel, the integrated data was used for hypothesis generating research projects. The primary objective was to determine anaesthesia variables associated with survival and death at 30 days. As records are added, the information changes and computer-based machine learning processes can enrich scientific knowledge.[45] This preliminary step is essential before progressing to more advanced projects of artificial intelligence.

The necessary steps included the choice of a knowledge discovery process (KDP), data analysis, data preprocessing (preparation and reduction) and as a machine learning technique, supervised learning. For the latter, several methods exist: the Bayesian approach, regression models, neural networks or decision trees.

As part of this study, supervised learning with decision trees were used. This choice makes it possible to obtain a compromise between the computer innovation and the understanding of the results and thus preserve an 'explainability' of the models. Indeed, the clinician must be able to understand the computer proposals and be able to explain possible choices that would result from this automatic information.

The precision of the result of the algorithms is inversely proportional to the level of understanding.[46] Simple algorithms, while being less precise, will provide knowledge support for a decision to be made and they will, by their simplicity, provide a better understanding of suggestions, see Fig. 3. Conversely, the more advanced and precise the algorithms, the more they will look like a black box decision, becoming incomprehensible to the practitioner. This means that the responsibilities should be carefully reassessed in the context of 'closed loops'.

Cost-effectiveness for tools development

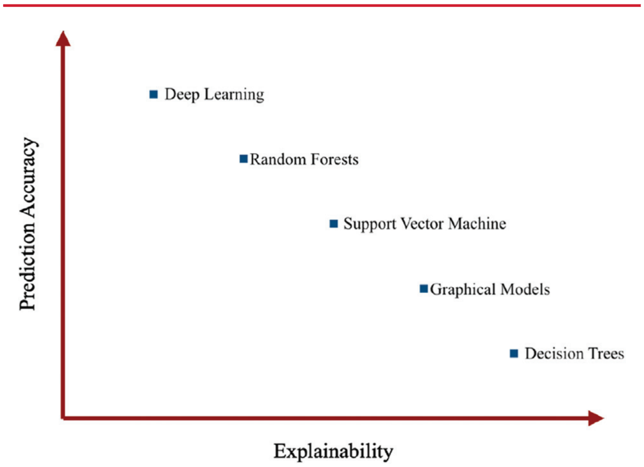
These technical solutions can be developed in-house as was the case in our project. This was possible through collaboration between business experience, enlightened practitioners (comfortable with the limitations and opportunities of big data) and IT development capability via commercial solutions. The internal approach offers the advantage of lower development and production costs than existing commercial solutions. It has been shown, in this specific context and in this work,[39] that from 10 previous external installation attempts in the institution, the internal solution was more advantageous.[39]

In anaesthesia, the current solutions are most often commercial. However, it is important to realise that these solutions must be user friendly, and integrated with interfaces and other communication systems within a hospital to avoid redundancies, and technical incompatibilities, and respect the NHS scale of integration (Fig. 1).

Another issue is the lack of validation of the majority of tools; when a product is developed, trained and validated, it is on a specific population. There is a significant risk of error when the product is then applied to a population on which it has not been validated.[47] Furthermore, many e-health products lack clinical validation.[48] An in-house product has the advantage of being perfectly calibrated for the local population of the institution.

This is the price to be paid for complete integration of computerised systems and the creation of advanced decision support systems as described by the model proposed by the NHS[11] in its scale of development.

Fig. 3 Illustration of the complex relationship between accuracy and 'explainability' of different analytic methods (figure produced by the authors based on information from Dam *et al.*[46]).



Classical statistical approach and comparison with deep learning with the decision trees in our institution

By 2022, more than 150 000 anaesthetics had been recorded in a structured way for research in our data warehouse. These anaesthetic procedures were analysed using classical statistical analysis and innovative approaches in the university hospital in Belgium.

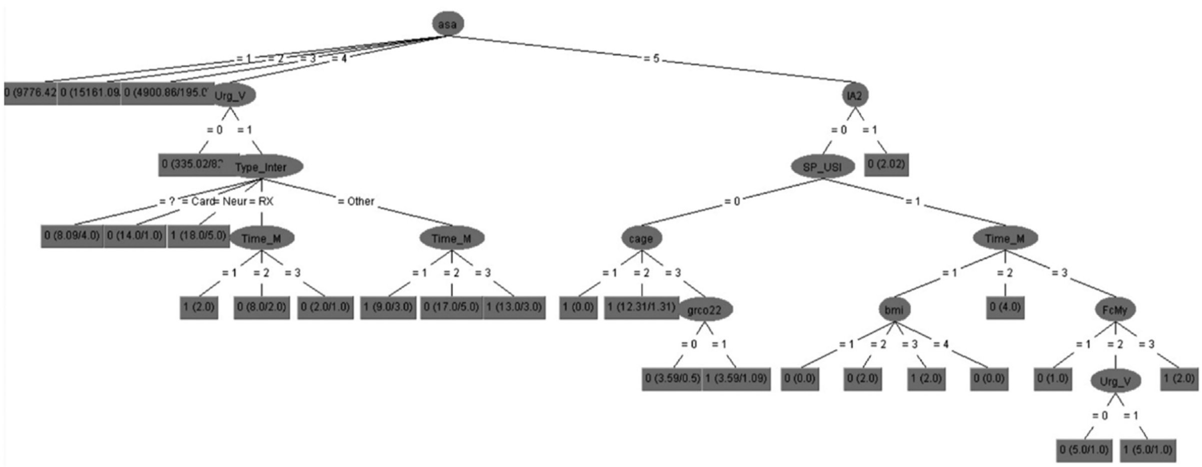
The classical approach focused on three variables and permitted comparison of the pertinence between classical methods and deep learning. Classical statistical analysis typically includes the use of Chi-square or Fisher's exact tests for categorical variables, Student's *t*-tests for quantitative variables and the Wilcoxon rank sum test for skewed data.

The three variables chosen in this work were hypocapnia, the benefit of having an anaesthesia nurse and the evaluation of extra-hospital mortality. These variables have been clearly described as independent risk factors for postoperative mortality, rendering possible the comparison of these results with those obtained by a decision tree analysis. Other variables such as emergency, ASA score and age were also included as co-factors, as we have previously described their association with postoperative outcomes.[32,39]

Without going into the details that are beyond the scope of this review, our results confirmed the importance of these risk factors but also helped to better interpret the place of the newer ones. For ASA 1 to 3, the most relevant variable is the ASA Score. For ASA 4 patients, it is the ASA score and the emergency variable that predict mortality the best. For ASA 5 patients, the presence of the anaesthesia nurse, the cardiac or neurosurgical interventions, the duration of the intervention, the BMI, the type of intervention and the hypocapnia are the variables retained by the classifier. In summary, the prediction of survival is excellent, but the prediction of death is not efficient (98.9 and 60%, respectively). The trees are size 40 and have 27 leaves (Fig. 4).[39,49]

In the literature, the variables retained were obvious and demonstrated,[50–55] but what our analysis adds is some

Fig. 4 Decision trees for 30 days mortality.[49]



The nodes in the tree represent criteria selected by the model. At the final division, the model assigns patients to either a 0 group (low risk of mortality) or a 1 group (high risk of mortality). asa, ASA score; Urg_V, emergency; type_inter, type of intervention; Time_M, duration of the procedure; IA2, presence of an anaesthesia nurse; SP_USI, patient came from the Intensive Care Unit; cage, age of the patient; BMI, body mass index; grco22, intra-operative capnometry; FcMy, intra-operative cardiac frequency.

information to better interpret the effect of the newly integrated variables (i.e. the anaesthesia care team and the influence of hypocapnia). Further research is required to assess if the implementation of those prediction tools in clinical practice will have a significant impact.

Limitations

The main limitation of our work is that the number of cases evaluated remains fairly small compared to the national surgical volume. For example, 150 000 anaesthetics out of 2 million per year in Belgium represents only 7.5% of the anaesthesia cases. The single centre approach is the reason for this small percentage and could be improved by national, or international collaborations.

The second limitation is the choice of mortality as an ‘endpoint’: despite its indisputable importance, it imperfectly reflects the quality and efficiency of the care given. It is an indicator that reflects biases related to the patient’s most significant underlying health problems rather than the practice of anaesthesia and the surgical techniques.[32]

The third limitation is the validity of certain data collected, such as the severity classification of the hospital stay and the different coding, manually entered by people who depend in different departments and whose purpose is to calculate the financial impact of the stay rather than clinical outcomes.

The fourth limitation is the unfinished nature of this work, lying between computer science, medicine and public health. Collaborations and exchanges between faculties have not been fully exploited; even though the work has opened many avenues for future research, there is still much to develop.[39]

In this regard, the training of medically qualified practitioners in data science and artificial intelligence is of paramount importance, not necessarily to develop the product themselves but to guide or adjust the work of the industry or the local information technology (IT) team so as to be consistent with the demands of the healthcare providers. The same can be said about the developers of those solutions. To create efficient products, they must have a good understanding of the ‘ground reality’ in a hospital. In Belgium, an initiative has been launched to create a certificate in artificial intelligence (AI) in healthcare, open to doctors, engineers and informaticians. This course has the goal of introducing doctors of all ages to AI techniques and at the same time to introduce engineers and informaticians to the requirements of AI in healthcare.[56] A similar course has existed in Italy since 2019.[57] Within the Northwestern University Feinberg School of Medicine, Chicago, a centre has been created that includes data science in the medical studies course,[58] with the aim of making the medical students real assets for the industry or their institutions.

Despite these limitations, the developing exploration system has been able to answer many questions and solve a multitude of problems.[39]

Computer development and exploitation of acquired data are not yet included in the daily practice of physicians. This leads to some isolation in research concepts on medical data and ‘datamining’. However, mutual support in promising environments is essential in a field wherein the quality of communication is crucial. This is also important for convincing health care professionals and decision-makers of the added value of these kinds of developments.

The ecological impact of computerisation and data centres are not to be forgotten. The number of data centres is rapidly increasing, and the required energy to cool the systems represented 1% of the global power consumption in 2018.[59] However, with new technologies come new energy-saving potential in the form of more efficient cooling or storage methods.[59,60]

Thus, computerisation contributes to the quality of care, and opens opportunities and reflections on the place to be given to computer science and its large volumes of data, in the clinical domains, in management of care and in public health.

Only for high-income countries?

Context

The biggest challenge we face as clinicians is not generating data on peri-operative care but using these data as evidence to drive change. Moonesinghe and Peden[61] refer to the 'Improvement Science' framework of the outcome being dependent on context and mechanisms. The context is assessed at three tiers: macro (national or international), meso (institutional) and micro (team) tiers. The reliability of an intervention for improvement will depend on the context in which it is implemented.[61] Variation in the availability of physical resources, human resources, overall systems support and communication, may pose a significant limitations on the use of data for improving quality of care in the African context.[62]

Requirements

The fragmentation of health data systems at all tiers (micro, meso and macro) further threaten the application of principles of appropriate data stewardship, such as the FAIR (Findable, Accessible, Interoperable and Reusable) data guidance principles.[38,63] Adherence to these principles allows for optimal use of 'big data', for example the application of data science and machine learning. To be reusable, health data must be of good quality. In health, incentives should exist to enhance existing data repositories, and the privacy of patients must be protected.[64] Interoperable data and metadata allow machines to find and use data points that form part of large sets of data.[48] Scalable systems are more likely to be sustainable.[65]

Opportunity

Research projects such as the African Surgical Outcomes Study, a multicentre observational study in which 25 countries participated, created the opportunity to establish a network of researchers across the continent.[66] These colleagues can be seen as the user community for data repositories established during data capturing in global research, which would incentivise them to enrich these repositories further.[67] However, to enable access to data, trustworthy data management and governance processes must be established. Such processes must provide equitable access but can be threatened by diverse agendas for health data use on the continent.

Conceptually, a core dataset for peri-operative global research may facilitate a framework for the integration of large volumes of data from electronic health records on a local or higher level. The core dataset should be simple, and easy for clinicians to manually capture at the bedside, the advantages include monitoring the quality of care provided on a local level, the level of workflow and centralised data for potential research.[68]

Conclusion

The anaesthesia speciality requires important re-evaluation to stay up to date with relevant technological advances and to provide adequate care. According to recent advances in artificial intelligence,[45] these processes, initially descriptive, could, in the future, turn into a message of prevention (predictive analysis). The dynamic use of particular algorithms could lead to practice changes by providing advice before the occurrence of adverse events. This level of sophistication requires deep learning and appropriate feedback loops. Both of these concepts have been missing previously and are probably the cause of previous failures. However, these advances in machine learning will not only lead to innovation but they will also create challenges for anaesthesiologists. One of the biggest challenges clinicians will face will be validating the safety and efficacy of these systems.[69] Close collaboration between research in anaesthesia and computer science is essential. Computerisation of data and analysis of patient outcomes is a perspective that needs to be followed and clinicians must be active in this process.[70]

It is essential to prepare for these changes and turn the speciality of anaesthesia into a more inclusive role of peri-operative medicine in order to reinforce the relevance and robustness of our analysis aiming to improve the quality of care.[71,72]

Acknowledgements relating to this article

Assistance with the article: the authors would like to thank Hyla Kluyts, M.D. (Sefako Makgatho Health Sciences University, Pretoria, South Africa) for her constructive review and scientific input.

Financial support and sponsorship: no external funding.

Conflicts of interest: PD is the owner and the CEO of Soft4doc, a company developing online management solutions for healthcare professionals. The other authors have no conflict of interest to declare.

Authors' contributions:

Philippe Dony: wrote the first draft of the manuscript, contributed to the writing of the manuscript, approved the final version of this

article and has read, and confirmed meeting the ICMJE criteria for authorship.

Rémi Florquin: contributed to the design, revised and updated the manuscript and confirmed meeting the ICMJE criteria for authorship.

Patrice Forget: contributed to the design, writing of the manuscript, critically reviewed it, approved the final version of this article and has read, and confirmed meeting the ICMJE criteria for authorship.

This manuscript was handled by Ayten Saracoglu.

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