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REVIEW
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Big Data in cardiac surgery: real world and perspectives

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Abstract

Big Data, and the derived analysis techniques, such as artificial intelligence and machine learning, have been considered a revolution in the modern practice of medicine. Big Data comes from multiple sources, encompassing electronic health records, clinical studies, imaging data, registries, administrative databases, patient-reported outcomes and OMICS profiles. The main objective of such analyses is to unveil hidden associations and patterns. In cardiac surgery, the main targets for the use of Big Data are the construction of predictive models to recognize patterns or associations better representing the individual risk or prognosis compared to classical surgical risk scores. The results of these studies contributed to kindle the interest for personalized medicine and contributed to recognize the limitations of randomized controlled trials in representing the real world. However, the main sources of evidence for guidelines and recommendations remain RCTs and meta-analysis. The extent of the revolution of Big Data and new analytical models in cardiac surgery is yet to be determined.

Keywords: Big Data, Cardiac surgery, Artificial intelligence, Machine learning, Coronary revascularization, Valvular heart diseases, Heart failure, Left ventricular assist devices

Introduction

The combination of data coming from multiple sources, and constituting databases, with significant possibility of integration and complex aggregation and discriminant analyses, defines the so-called Big Data, which intrinsically refers to extensive datasets, widely informative for a large number and variety of persons.

In fact, large and rapidly increasing amount of data (*Volume*), their multiple sources (i.e., clinical studies, registries, small database, administrative database, patient-reported outcomes, genomic profiles and environmental parameters) (*Variety*), the rapid data accumulation (*Velocity*) and their ability to truly represent a specific context (*Veracity*) characterize Big Data [1].

Analyses of these data may unveil patterns, trends and associations, and define reference models in aggregations of persons [2]. As data digitalization and information technology (IT) are spreading and improving performance [3–5], the use of Big Data is steeply increasing, becoming progressively a reference for many typical processes in medicine, such as the identification of the appropriate therapeutic choice by tailoring therapeutic options, the evaluation of short and mid-term, procedure-related or unrelated, risks of adverse events and the definition of the prognosis. To such an extent, Big Data may generate the basis for precision medicine, as factors impacting event occurrence is progressively available for the single subject and may improve effectiveness of cardiovascular therapies [6].

The place of Big Data is far from being well determined. Figure 1 offers a graphical synthesis of the present and future of Big Data.

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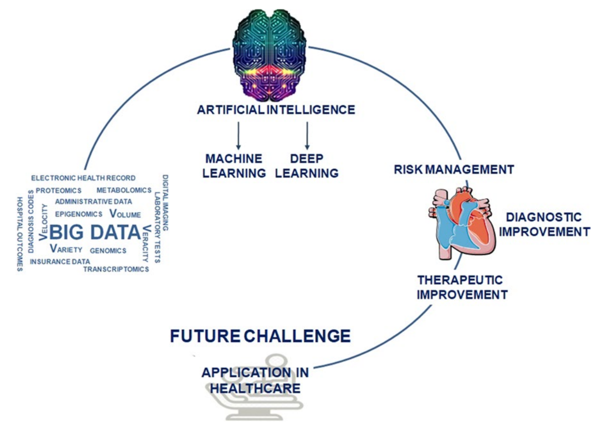

Fig. 1 Big Data elaboration allows an improvement of risk management, and diagnostic or therapeutic strategies in cardiac surgery. The future challenge will be the practical application in healthcare

Big Data: sources and analysis

The key points of the application of Big Data are the clinical usefulness and the balance between costs of sophisticated data analyses and the *expected* and *real* benefits (i) to patients, in terms of quality of care, outcomes and risk prediction; (ii) to operators, in terms of quality and security of processes, from the diagnosis to the choice of therapeutic options, in a perspective of resources saving.

Regarding the sources, Electronic Health Record (EHR) is the main source of Big Data. Administrative data, which are commonly employed for billing purposes in fee-for-service health systems, may turn helpful for a large spectrum of analytic goals, and may fuel risk modeling for clinical and economical purposes [7]. Several approaches are used to enable data aggregation from EHR and to facilitate their contribution to Big Data. The most relevant limitations of the use of these databases are the risk of misclassification and the impact of missing data [8].

Digital imaging significantly contributes to Big Data generation. Today, almost all medical images are stored in pixels or voxels [9], which can be processed by software aiming at improving data quality and diagnostic accuracy [10].

Finally, OMICS datasets, or genome, proteomic, transcriptomic, epigenomic, and metabolomic data, are readily available in digital and structured forms, allowing the recognition of patterns useful for grouping procedures; they are additional important sources for Big Data [11].

In cardiovascular medicine, the contribution of OMICS is enormous and hold a very high potential for Big Data generation and subsequent analysis. A valid example of the OMICS data analysis is that it is able to provide information on myocardial molecular profiles of cardiac surgical patients [12–14]. The variants identification by OMICS techniques allows performing association studies, which may turn useful to risk stratification and outcome prediction in the context of precision medicine [15–19], using appropriate systems for analyses [20–22].

When it comes to analyses of Big Data, classic statistics is limited. Independent storage systems, immediate access and relational databases procedures are crucial for Big Data analyses. Artificial intelligence (AI) is of a particular usefulness, conceived as computer and mathematical concept allowing "machines" to execute learning, problem-solving, patterns recognition, reasoning and planning, in a way that resembles "human thinking", therefore dealing with uncertainty, projection, and production that are well beyond extrapolating regression models validated in subsets of the general population, called validation samples, to approximate prediction in the general population.

The ability of such a technology to process decisions independently, recognize errors and readjust the decision or prediction models and processes, are the main characteristics of the AI, based on machine learning (ML) and deep learning (DL).

ML is the study of a mathematical algorithm model from sample data which in turn is used to generate predictions or decisions. ML algorithms can be supervised, unsupervised and reinforced [23]. DL is composed of artificial neural networks, with representation learning, to mimic human cognition. DL could be a module to automate predictive analysis, from which data is deduced in a non-linear way. The advantage of a non-linear interpretation is the better ability to identify and interpret more complex characteristics [24] and therefore is linked to a hierarchy of increasing complexity and abstraction [25]. DL is used for image evaluation, such as cardiac magnetic resonance scans; this requires adequate skills and systems [26, 27].

Logistic regression (LR) is a classic classification algorithm that makes a linear combination of input variables and uses the sigmoid function to output a probability.

Neurons in artificial neural networks (ANN) make a linear combination of the output value from the upper layers' neurons, pass it through sigmoid functions, and finally output a value to the next neurons [28].

The use of predictive models that evaluate the influence of covariates, in the prediction of the results, allows it to identify the patients for whom the intervention will be successful. However, in analyzing non-randomized diagnostic or therapeutic strategies, it is possible to compare non-similar groups, exposing patients to subsequent complications [2].

The present of Big Data in cardiac surgery and the road ahead

While procedures safety and outcomes in cardiac surgery have improved over the years in the majority of elective procedures, cardiac surgery is facing patients with increased complexity due to improved survival owing to refined cardiological, pneumological and oncological therapies. Changes in such a clinical context require rethinking clinical risk assessment and management as well as redefinition of optimal timing for surgical options.

So far, cardiac surgery has relied on logistic models to estimate the risk of events, including mortality associated with cardiac surgery, as essential components of routine clinical management of cardiac surgical patients. The EUROscore II and the Society of Thoracic Score (STS) scores are the logistic models for cardiac surgery-related risk stratification most commonly employed. Nevertheless, the prediction of those estimates is debated, especially in subsets of patients [29]. AI applied to Big Data has the potential to change the paradigm, from a theoretical and average risk prediction to simulations in single patients, weighting tailored therapeutic options and managing risks, and finally employing sustainable options to improve outcomes.

This is the most appealing application of the new concept of the meta-verse, an aggregate of Big Data, information technologies and AI converging to generate novel approaches to handle reality by navigating virtual near-future in clinical contexts, hopefully yielding time saving, less errors, more precision, variability due to operators, minimize costs and human effort while prolonging life with reasonable quality.

To such an extent, Big Data and AI have been applied in seminal studies in cardiac surgery in the field of myocardial revascularization, valvular heart diseases and end-stage heart failure (Table 1). Table 2 shows the ongoing trials focused on the application of Big Data-derived analysis in cardiac surgery.

Myocardial revascularization

In the field of surgical myocardial revascularization, structured data from EHR managed by the Society of Thoracic Surgeons, the American College of Cardiology (National Cardiovascular Data Registry), and the American Heart Association, represent a significant source for data analysis. Clinical records, and data from imaging, analyzed and interpreted using AI approaches, may integrate original approaches based on clinical registries and regression models (e.g.: neural networks) [9, 30].

One of the major challenging research tasks, to date, is to evaluate whether percutaneous coronary interventions (PCI) are superior over coronary artery bypass surgery (CABG) in specific clinical contexts. Randomized trials (RCTs) on myocardial revascularization have been used to answer this question, and to develop a tool for the identification of patients who may benefit from one therapeutic option over the other or a combination of both (hybrid revascularization), with minimized clinical risk and expenditure. Although RCTs are very effective to control treatment selection bias, they are low-performing in evaluating subgroups and they suffer from inappropriate statistical power in subset and possible *post-hoc* biases. Observational, nonrandomized data gathered from registries and large multi-sources databases, may be closer to real-world representing a very large majority of patients, and therefore may work better with single patients using AI based analytic modalities. In contrast, those sources of data may be affected by lower data control and potential biases in the outcome definition and assignment [31]. Weintraub and colleagues [32, 33] compared the effectiveness of different myocardial revascularization strategies by linking the American College of Cardiology Foundation (ACCF) National Cardiovascular Data Registry and the Society of Thoracic Surgery (STS) Adult Cardiac Surgery Databases, to data from claims from the Centers of Medicare and Medicaid. They demonstrated that the real-world mortality was not significantly different at 1-year from that anticipated by commonly used scores, while long term survival was higher in patients receiving CABG as compared with patients who underwent PCI. The method of analyses of these data required the use of probabilistic matching to identify patients throughout databases, adjusting for clinical covariates with the use of inverse probability weighting, and correction of residual confounding by means of a sensitivity analysis.

A valid example of cost-effective applicability of AI to Big Data in the field of myocardial revascularization is the ASCERT study (ACCF and STS Database Collaboration on the Comparative Effectiveness of Revascularization Strategies) [34], where two revascularization strategies (PCI versus CABG) were evaluated in patients suffering from stable ischemic heart disease. linking large converging databases, both clinical and administrative, to obtain data from 86,244 patients for CABG and 103,549 patients for PCI. Those figures are much larger than any proposed by RCTs. Interestingly, the authors found that patients undergoing CABG had better outcomes than those undergoing PCI, but at the expense of higher costs, allowing the calculation of the indicator of the incremental cost-effectiveness ratio expressed as cost per quality-adjusted life-year gained.

The role of some patients-related characteristics in determining outcomes in myocardial revascularization strategies are highlighted in the large study by Hlatkyet al. [35], where authors demonstrated lower long-term

Table 1 Artificial intelligence in cardiac surgery and cardiovascular diseases

Author	Title	Year	AI Model	Conclusions
Diller et al. [66]	Machine learning algorithms estimating prognosis and guiding therapy in adult congenital heart disease: Data from a single tertiary centre including 10 019 patients.	2019	Deep Learning	Prognostication and therapeutic guidance in patients with adult congenital heart disease (ACHD) or pulmonary hypertension
Diller et al. [67]	Utility of machine learning algorithms in assessing patients with a systemic right ventricle.	2018	Deep Learning. Convolutional neural networks	Recognizing transposition of the great arteries (TGA) after atrial switch procedure or congenitally corrected TGA (ccTGA) based on routine transthoracic echocardiograms. Delineation and segmentation of the systemic ventricle
Olive et al. [68]	Current monitoring and innovative predictive modeling to improve care in the pediatric cardiac intensive care unit.	2018	AI and machine learning	Predictive models created by AI and ML may lead to earlier detection of patients at risk for clinical decompensation, improving care for critically ill pediatric cardiac patients.
Ruiz-Fernández et al. [69]	Aid decision algorithms to estimate the risk in congenital heart surgery.	2017	Multilayer perceptron, self-organizing map, radial basis function networks and decision trees	Feasibility of development of CDSSs using AI algorithms. Such system would help to forecast the level of risk related to a congenital heart disease surgery.
Zhong et al. [70]	Machine learning prediction models for prognosis of critically ill patients after open-heart surgery	2021	Extreme gradient boosting, random forest, artificial neural network, and logistic regression	Model to predict 30-days mortality and complications (i.e.: septic shock, thrombocytopenia and liver disfunction) after open-heart surgery.
Meyer et al. [71]	Machine learning for real-time prediction of complications in critical care: A retrospective study	2018	deep learning methods (recurrent neural networks)	Predict severe complications (i.e.: mortality, renal failure with a need for renal replacement therapy, and postoperative bleeding leading to operative revision) during critical care in real time after cardiothoracic surgery.
Lei et al. [72]	Using Machine Learning to Predict Acute Kidney Injury After Aortic Arch Surgery	2020	Machine Learning: logistic regression model, support vector machine, random forest, and gradient boosting	Machine learning methods were found to predict AKI after aortic arch surgery significantly better than traditional logistic regression.
Tseng et al. [73]	Prediction of the development of acute kidney injury following cardiac surgery by machine learning	2020	Logistic regression, support vector machine (SVM), random forest (RF), extreme gradient boosting (XGboost), and ensemble (RF + XGboost)	AI methods predict cardiac surgery-associated acute kidney injury, which determines risks following cardiac surgery, enabling the optimization of postoperative treatment strategies.
Lee et al. [74]	Derivation and Validation of Machine Learning Approaches to Predict Acute Kidney Injury after Cardiac Surgery	2018	ML: decision tree, random forest, extreme gradient boosting, support vector machine, neural network classifier, and deep learning.	Using AI an Internet-based risk estimator was developed to estimate the risk of AKI at the end of surgery.
Kilic et al. [75]	Performance of a machine learning algorithm in predicting outcomes of aortic valve replacement.	2020	Extreme gradient boosting (XGBoost)	Predicting outcomes of surgical aortic valve replacement.
Wojnarski et al. [76]	Machine-learning phenotypic classification of bicuspid aortopathy	2018	Random forest analysis	Three distinct phenotypes of bicuspid valve-associated aortopathy were identified using machine-learning methodology.

Table 1 (continued)

Author	Title	Year	AI Model	Conclusions
Baskaran et al. [77]	Machine learning insight into the role of imaging and clinical variables for the prediction of obstructive coronary artery disease and revascularization: An exploratory analysis of the CONSERVE study	2020	ML: extreme gradient boosting (XGBoost)	For obstructive CAD, the ML model outperformed CAD consortium clinical score (CAD2). BMI is an important variable, although currently not included in most scores. In this ML model, imaging variables were most associated with revascularization
Cikes et al. [78]	Machine learning-based pheno-grouping in heart failure to identify responders to cardiac resynchronization therapy	2018	Unsupervised multiple kernel learning algorithm (MKL)	Integrating clinical parameters and full heart cycle imaging data, unsupervised ML can provide a clinically meaningful classification of a phenotypically heterogeneous HF cohort and might aid in optimizing specific therapies.
Ambale-Venkatesh et al. [79]	Cardiovascular Event Prediction by Machine Learning: The Multi-Ethnic Study of Atherosclerosis	2017	Random survival forest (RF) alone or in combination with other statistical approaches.	Machine learning in conjunction with deep phenotyping improves prediction accuracy in cardiovascular event prediction in an initially asymptomatic population.
Ayers et al. [80]	Using machine learning to improve survival prediction after heart transplantation	2021	Deep neural network, logistic regression, AdaBoost, and random forest	ML techniques can improve risk prediction in OHT compared to traditional approaches. This may have important implications in patient selection, programmatic evaluation, allocation policy, and patient counseling and prognostication.

Table 2 Ongoing trials on the application of big data and derived analysis techniques to cardiac surgery

Title	Location	Status	Description
Effects of AI Assisted Follow-up Strategy on Secondary Prevention in CABG Patients ClinicalTrials.gov Identifier: NCT04636996	Cardiovascular Institute and Fuwai Hospital, Beijing, Beijing, China	Not yet recruiting	Assess if AI assisted follow-up strategy will improve secondary prevention in CABG patients
Artificial Intelligence Guided Patient Selection for Atrial Fibrillation Catheter Ablation: Randomized Clinical Trial (AI-PAFA Trial) ClinicalTrials.gov Identifier: NCT04997824	Severance Hospital, Yonsei University Health System Seoul, Korea, Republic of	Not yet recruiting	Prediction of AF catheter ablation (AFCA) efficacy using artificial intelligence (AI)
Effect of Artificial Intelligence on Nutritional Status of Children Post Cardiac Surgery ClinicalTrials.gov Identifier: NCT04782635	Armed Forces Institute of Cardiology and National Institute of Heart Disease Rawalpindi, Punjab, Pakistan Maryam Zahid Rawalpindi, Punjab, Pakistan	Completed	Assess the effect of artificial intelligence on nutritional status of children post cardiac surgery in comparison to usual care group
Cloud-based ECG Monitoring and Healthcare Model Building on the Population With Coronary Artery Revascularization ClinicalTrials.gov Identifier: NCT04485143		Not yet recruiting	All subjects tracked the occurrence of adverse medical events within one year after discharge from the hospital. Based on the home-based remote personal care model for patients with CABG, a risk prediction model for heart failure and vascular restenosis was established to effectively reduce medical treatment, adverse events, and medical expenditure
Machine Learning Predict Acute Kidney Injury in Patients Following Cardiac Surgery ClinicalTrials.gov Identifier: NCT04966598	Chinese PLA General hospital Beijing, Beijing, China	Completed	Several prediction models based on machine learning technique are developed to allow early identification of patients who at the high risk of unfavorable kidney outcomes
Machine Learning-Based Prediction of Major Perioperative Allogeneic Blood Requirements in Cardiac Surgery (PREMATRICS) ClinicalTrials.gov Identifier: NCT04856618	Kepler University Hospital Linz, Upper Austria, Austria	Recruiting	If an accurate prediction model based on a few features could be created and those patients particularly at risk of massive transfusion of allogeneic blood could be identified, it would subsequently be possible to develop an adapted clinical pathway that would allow patient care to be improved and individualized interventions adapted to the situation to be implemented
Machine Learning-Based Risk Profile Classification of Patients Undergoing Elective Heart Valve Surgery ClinicalTrials.gov Identifier: NCT03724123		Completed	The investigators investigate the benefit of modern machine learning methods in personalized risk prediction in patients undergoing elective heart valve surgery
Remote Monitoring to Improve Physician Monitoring, Patient Satisfaction, and Predict Readmissions Following Surgery ClinicalTrials.gov Identifier: NCT03800329	Mayo Clinic in Rochester Rochester, Minnesota, United States	Completed	Measure data collected via machine learning algorithms to predict readmission following cardiac surgery

We interrogated ClinicalTrial.gov and EUDRACT databases with the following keywords: Coronary Heart Disease AND Artificial Intelligence, cardiac surgery AND Artificial Intelligence, cardiac surgery AND machine learning, cardiac surgery AND big data. A total of 811 studies were found on ClinicalTrial.gov and a total of 10 on EUDRACT; we selected the most appropriated for our purposes

CABG coronary artery bypass grafting, *AI* artificial intelligence, *AF* atrial fibrillation mortality with CABG rather than with PCI, in an unselected group of patients extracted by the general population of those undergoing those procedures, with outcomes substantially modified by factors such as diabetes, smoking habit, heart failure, and peripheral artery disease.

The fundamental study of Weintraub et al., by linking the STS database to that of the Centers for Medicare and Medicaid Services, showed that in stable patients, older than 65 years with multivessel coronary artery disease, CABG offers an advantage in terms of long-term survival.

While RCTs remain the only accepted evidence-based information gathered in medical guidelines, studies based on Big Data and AI added knowledge on the comparative effectiveness of the two therapeutic strategies. The place of Big Data analysis is therefore yet to be precisely determined.

Valvular heart diseases and cardiac imaging

The identification of significant valvular diseases has the potential to clarify the etiology, and/or reveal a consequence of ventricular failure, with or without dilatation, which may contribute to define the prognosis and to identify elements acting as triggers for worsening heart failure and hence prognosis. Echocardiography is used widely for assessment of cardiac structure and function, with diagnostic accuracy and reliability depending on the operators' skill, experience and expertise. In contexts such as high volume in busy environment, and emergency, machines enriched with a technology that analyses live imaging in real-time, continuously comparing it with a pool of reference images, may help optimizing the imaging protocol and identifying diseases or patterns of abnormalities, detecting trends over time and evaluating the stability of specific measurements. Those are intriguing perspectives that may be associated with the application of AI in the field of echocardiography. For instance, in mitral valvular regurgitation, recognition of increasing severity of the valvular insufficiency, ventricular dilatation and reduction in chamber shortening, atrial dilatation, as well as the worsening myocardial function assessed by means of semiautomated, relatively load-independent parameters, may parallelly run with the detection of clinical changes and even anticipate overt changes in symptoms and signs of heart failure (HF).

In echocardiography, automated views recognition and structures identification may be considered an initial step toward semi-assisted diagnostic studies. To such an extent, AI-based technology is a key element, as convolutional neural networks may be employed to identify key reference points on images, and then feature specific for diagnostic patterns. Identification of normal patterns, deviations from normal patterns or specific pathologies has been possible in experimental studies in more than 9 cases in 10 evaluated cases [36] in algorithm-based supervised machine learning [37]. A further step in AI-assisted echocardiography may be the identification of deviation from physiology or overt pathological conditions, such as left ventricular hypertrophy, hypertrophic cardiomyopathy [38, 39], ventricular dilatation and reduced chamber and myocardial function [40]. With 2-D speckle-tracking technology, an accurate semi-automated volume and systolic function quantification may be run bed-side and take a few minutes or seconds [41, 42]. In the context of valvular disease associated with ventricular dysfunction, an important role is played by quantification of contractility reserve, which impacts prognosis. Wall motion quantification is relevant to such an extent, with AI operated diagnostic modality pushing accuracy of wall motion quantification as high as 85% [43, 44], helping in the case of evaluation of ventricular contractility reserve and aiding in decision making on the best valvular disease management.

Assessment of mitral valve regurgitation severity may be aided by automated processes based on deep learning machines [45, 46]. With regard to aortic valve disease, identification of trends over time in ascending aorta and aortic root dimensions, ventricular dimensions and shortening, relies on reproducibility of imaging in specific views, and may provide important information impacting preclinical and, timely, clinical decision making. Moreover, aortic annulus sizing represents an important target of quantification, as to date transcatheter procedures for aortic valve replacement are increasing steeply [47].

Beyond echocardiography, the potential revolution of AI may be even more applicable and profound in more standardized diagnostic processes such those applicable to nuclear medicine, computed tomography and magnetic resonance imaging, which may suffer much less variability between-subjects due to body size [48, 49].

HF and mechanical circulatory support: selection of patients, prediction of adverse events and technology development

Heart transplantation (HTx) is the gold standard therapy in advanced HF, defined as persistence of symptoms and significant personal physical limitations despite optimized pharmacological and standard nonpharmacological therapy, associated with recurrent hospitalizations and need for escalation therapy including inotropes [50]. However, the number of organs available does not match the number of patients in need for organs as they slide toward a deterioration of the clinical conditions and require a timely intervention. Left Ventricular assist devices (LVAD) may help as bridge to HTx, or to candidacy or decision, or even as destination therapy in subjects with advanced or terminal heart failure [51, 52]. Those patients, suffering from end-stage HF, present with unique challenges: frailty [53], end-organ damage, risk for acute decompensations, and high mortality at short-term. Events as cardiogenic shock carries worsened prognosis. The therapeutic strategy shows multiple options, with multiple devices that can be employed in different phases of the clinical course [54].

Because of the high risk of surgery and the patients' characteristics, the prediction of peri-procedural adverse events and of the long-term complications are critical issues when planning LVAD implantation, impacting benefit and quality of life per costs [55], and healthcare sustainability. Data from registries and discriminant statistics are commonly used to identify potentially life-threatening conditions impacting prognosis and hospital stay duration after LVAD implantation [56].

However, the classic way for risk-prediction estimation is based on statistical methods that implies a proportional and statistically significant participation of several variables in a context where hazard is not proportional over time [57]. On a different approach, AI and Big Data may simulate the effects of decisions, and their interactions with an uncertain environment [58] and facilitate not only the prediction of specific pre-defined events.

Prediction of complications after LVAD implantation is relevant to sustainability of LVAD procedures. AI has been involved to recognize drive-line infections using photographic database as background source [59] and the identification of clusters of variables that predict right ventricular failure, bleeding, infection and pump failure due to pump thrombosis [60].

While statistically-based risk models have proven sub-optimal ability to predict mortality risk in LVAD, by use of Interagency Registry for Mechanically Assisted Circulatory Support (INTERMACS), data from 2006 to 2016, for a total of 16,120 patients included, and bootstrapping with 1000 replications in the testing set, improved 90-day discrimination from 0.707 [0.683–0.730] to 0.740 [0.717–0.762] and 1-year mortality from 0.691 [0.673–0.710] to 0.714 [0.695–0.734] (all $p < 0.001$). The net reclassification rate was up to 49% for 90-day mortality and 37% for 1-year mortality. The findings supported the concept that ML may increase the performance of a risk model for durable LVAD mortality compared to logistic regression-based algorithm [60]. Because continuous blood flow from LVAD is associated with increased risk of complications, as gastrointestinal bleeding, continuous pump speed generating flow is modulated to generate pulsatile flow. More importantly, pump speed of the LVAD may be controlled to assist left ventricles during a single beat to optimize systolic, versus diastolic assistance [61]. Diastolic versus systolic modulation of the pump speed may impact on flow pulsatility and diastolic assistance to reduce external myocardial work [62]. These mathematical models are limited in their applicability because the need for pressure feedback signals from the cardiovascular system require suitable integrated long-term pressure sensors. To date, novel AI based controllers, real-time deep convolutional neural network-based, are tested to estimate left ventricular preload using LVAD flow analyses and a sensorless adaptive control system, trained and evaluated through a number of cross validation settings and physiologic situations in different patient and different conditions, resulting in accurate pre-load evaluation (root mean squared error of 0.84 mmHg, reproducibility coefficient of 1.56 mmHg, coefficient of variation of 14.44%, and bias of 0.29 mmHg for the testing dataset) [63]. The system was able to use LVAD data to measure preload and prevent ventricular suction and pulmonary congestion [64].

Conclusions

After several years of intense research yielding a great number of scientific publications, a major gap exists between practical application of AI applied to Big Data and RCTs to guide practice in real work, in large part because AI and Big Data are yet to become controlled research tools on a large scale. Data quality control, missing data, privacy and potential conflicts of interests in a variety of stakeholders, costs of the technology required, and the need for high-performing information technology are still barriers for a routine and wide use of Big Data in the field of cardiac surgery research and clinical process.

Nevertheless, in the context of an enormous resource re-allocation due to the COVID-19 pandemic, that reduced significantly the research output in other fields of medicine, Big Data and AI may turn to be relevant tools.

The role of hypothesis generation in Big Data science is without doubt, but it should be considered as a complementary mean to obtain evidence [65].

However, the crucial match on usefulness of Big Data and AI in the near future is also played in the side of productivity, simulation, augmented reality aiding diagnostic and clinical decision making, communication with patients and generating precision medicine. These features have the potential to go well beyond the context of knowledge generated from RCTs to prove or unconfirm specific hypotheses, by using strict enrollment criteria to make homogenous the population. Hence, we all need to be familiar with those concepts and tool for the future, which is not that far away from now.

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References
1. Hilbert M. Big Data for development: a review of promises and challenges. Dev Policy Rev. 2016;34:135–74. https://doi.org/10.1111/dpr.1214.
2. Weintraub WS. Role of Big Data in cardiovascular research. J Am Heart Assoc. 2019;8(14):e012791. https://doi.org/10.1161/JAHA.119.012791.
3. De Mauro A, Greco M, Grimaldi M. A formal definition of Big Data based on its essential features. Libr Rev. 2016;65:122 – 35. https://doi.org/10.1108/LR-06-2015-0061.
4. Silverman EK, Schmidt HHHW, Anastasiadou E, Altucci L, Angelini M, Badimon L, Balligand JL, Benincasa G, Capasso G, Conte F, Di Costanzo A, Farina L, Fiscon G, Gatto L, Gentili M, Loscalzo J, Marchese C, Napoli C, Paci P, Petti M, Quackenbush J, Tieri P, Viggiano D, Vilahur G, Glass K, Baumbach J. Molecular networks in Network Medicine: Development and applications. Wiley Interdiscip Rev Syst Biol Med. 2020;12(6):e1489. https://doi.org/10.1002/wsbm.1489).
5. Xiong W, Yu Z, Bei Z, Zhao J, Zhang F, Zou Y, et al. A characterization of big data benchmarks. IEEE International Conference on Big Data. 2013; pp. 118–125. https://doi.org/10.1109/BigData.2013.6691707.
6. Weintraub WS, Fahed AC, Rumsfeld JS. Translational medicine in the era of big data and machine learning. Circ Res. 2018;123(11):1202–4. https://doi.org/10.1161/CIRCRESAHA.118.313944.
7. Frizzell JD, Liang L, Schulte PJ, Yancy CW, Heidenreich PA, Hernandez AF, Bhatt DL, Fonarow GC, Laskey WK. Prediction of 30-day all-cause readmissions in patients hospitalized for heart failure: comparison of machine learning and other statistical approaches. JAMA Cardiol. 2017;2(2):204–9. https://doi.org/10.1001/jamacardio.2016.3956.
8. Shahian DM, Silverstein T, Lovett AF, Wolf RE, Normand SL. Comparison of clinical and administrative data sources for hospital coronary artery bypass graft surgery report cards. Circulation. 2007;115(12):1518–27. https://doi.org/10.1161/CIRCULATIONAHA.106.633008.
9. Harvey H, Glocker B. A standardized approach for preparing imaging data for machine learning tasks in radiology. New York: Springer; 2019. p. 61–72. https://doi.org/10.1007/978-3-319-94878-2.
10. Telenti A, Lippert C, Chang PC, DePristo M. Deep learning of genomic variation and regulatory network data. Hum Mol Genet. 2018;27:R63–R71. https://doi.org/10.1093/hmg/ddy115.
11. Tcheng JE, Kelly J, Wosik J. Big Data: When and How Will it Impact Interventional Cardiology? ACC 2019; Expert Analysis.
12. Mansueto G, Benincasa G, Della Mura N, Nicoletti GF, Napoli C. Epigenetic-sensitive liquid biomarkers and personalised therapy in advanced heart failure: a focus on cell-free DNA and microRNAs. J Clin Pathol. 2020 Sep;73(9):535–43. https://doi.org/10.1136/jclinpath-2019-206404.
13. Vietri MT, D'Elia G, Benincasa G, Ferraro G, Caliendo G, Nicoletti GF, Napoli C. DNA methylation and breast cancer: a way forward (Review). Int J Oncol. 2021 Nov;59(5):98. https://doi.org/10.3892/ijo.2021.5278.
14. Martin J. Big data, big future. Biotechniques. 2020 Apr;68(4):166–8. https://doi.org/10.2144/btn-2020-0027.
15. Vietri MT, Molinari AM, Caliendo G, De Paola ML, Giovanna D, Gambardella AL, Petronella P, Cioffi M. Double heterozygosity in the BRCA1 and BRCA2 genes in Italian family. ClinChem Lab Med. 2013 Dec;51(12):2319–24. https://doi.org/10.1515/cclm-2013-0263.
16. Vietri MT, Caliendo G, Casamassimi A, Cioffi M, De Paola ML, Napoli N, Molinari AM. A novel PALB2 truncating mutation in an Italian family with male breast cancer. Oncol Rep. 2015;33(3):1243–7. https://doi.org/10.3892/or.2014.3685.
17. Sarno F, Benincasa G, List M, Barabasi AL, Baumbach J, Ciardiello F, Filetti S, Glass K, Loscalzo J, Marchese C, Maron BA, Paci P, Parini P, Petrillo E, SilvermanEK, Verrienti A, Altucci L, Napoli C. International Network Medicine Consortium. Clinical epigenetics settings for cancer and cardiovascular diseases: real-life applications of network medicine at the bedside. Clin Epigenetics. 2021;13(1):66. https://doi.org/10.1186/s13148-021-01047-z.).
18. Schiano C, Benincasa G, Franzese M, Della Mura N, Pane K, Salvatore M, Napoli C. Epigenetic-sensitive pathways in personalized therapy of major cardiovascular diseases. Pharmacol Ther. 2020;210:107514. https://doi.org/10.1016/j.pharmthera.2020.107514.
19. Khera AV, Chaffin M, Aragam KG, Haas ME, Roselli C, Choi SH, Natarajan P, Lander ES, Lubitz SA, Ellinor PT, Kathiresan S. Genomewide polygenic scores for common diseases identify individuals with risk equivalent to monogenic mutations. Nat Genet. 2018;50:1219–24. https://doi.org/10.1038/s41588-018-0183-z.
20. Weng LC, Preis SR, Hulme OL, Larson MG, Choi SH, Wang B, Trinquart L, McManus DD, Staerk L, Lin H, Lunetta KL, Ellinor PT, Benjamin EJ, Lubitz SA. Genetic predisposition, clinical risk factor burden, and lifetime risk of atrial fibrillation. Circulation. 2018;137:1027–38. https://doi.org/10.1161/CIRCULATIONAHA.117.031431.
21. Schiano C, Costa V, Aprile M, Grimaldi V, Maiello C, Esposito R, Soricelli A, Colantuoni V, Donatelli F, Ciccodicola A, Napoli C. Heartfailure: Pilot-transcriptomicanalysis of cardiactissue by RNA-sequencing. Cardiol J. 2017;24(5):539–53.
22. Schiano C, Franzese M, Geraci F, Zanfardino M, Maiello C, Palmieri V, Soricelli A, Grimaldi V, Coscioni E, Salvatore M, Napoli C. Machine Learning and Bioinformatics Framework Integration to Potential Familial DCM-Related Markers Discovery. Genes (Basel). 2021;12(12):1946.
23. Krittanawong C, Zhang H, Wang Z, Aydar M, Kitai T. Artificial intelligence in precision cardiovascular medicine. J Am Coll Cardiol. 2017;69(21):2657–64. https://doi.org/10.1016/j.jacc.2017.03.571.
24. Johnson KW, Torres Soto J, Glicksberg BS, Shameer K, Miotto R, Ali M, Ashley E, Dudley JT. Artificial intelligence in cardiology. J Am Coll Cardiol. 2018;71:2668–79. https://doi.org/10.1016/j.jacc.2018.03.521.
25. Khalsa RK, Khashkhusha A, Zaidi S, Harky A, Bashir M. Artificial intelligence and cardiac surgery during COVID-19 era. J Card Surg. 2021;36(5):1729–33. https://doi.org/10.1111/jocs.15417.
26. Kramer CM, Appelbaum E, Desai MY, Desvigne-Nickens P, DiMarco JP, Friedrich MG, Geller N, Heckler S, Ho CY, Jerosch-Herold M, Ivey EA, Keleti J, Kim DY, Kolm P, Kwong RY, Maron MS, Schulz-Menger J, Piechnik S, Watkins H, Weintraub WS, Wu P, Neubauer S. Hypertrophic Cardiomyopathy Registry: the rationale and design of an international, observational study of hypertrophic cardiomyopathy. Am Heart J. 2015;170:223–30. https://doi.org/10.1016/j.ahj.2015.05.013.
27. Infante T, Cavaliere C, Punzo B, Grimaldi V, Salvatore M, Napoli C. Radiogenomics and artificial intelligence approaches applied to cardiac

computed tomography angiography and cardiac magnetic resonance for precision medicine in coronary heart disease: a systematic review. Circ Cardiovasc Imaging. 2021 Dec;14(12):1133–46. https://doi.org/10.1161/CIRCIMAGING.121.013025.
28. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436–44. https://doi.org/10.1038/nature14539.
29. Goncharov M, Mejia OAV, Perez de Souza Arthur C, Orlandi BMM, Sousa A, Praça Oliveira MA, Atik FA, Segalote RC, Tiveron MG, de Barros E, Silva PGM, Nakazone MA, Lisboa LAF, Dallan LAO, Zheng Z, Hu S, Jatene FB. Correction: mortality risk prediction in high-risk patients undergoing coronary artery bypass grafting: are traditional risk scores accurate? PLoS ONE. 2021;16(10):e0258706. https://doi.org/10.1371/journal.pone.0258706.
30. Schlegl T, Waldstein SM, Vogl WD, Schmidt-Erfurth U, Langs G. Predicting semantic descriptions from medical images with convolutional neural networks. Inf Process Med Imaging. 2015;24:437–48. https://doi.org/10.1007/978-3-319-19992-4_34.
31. Jacobs JP, Shahian DM, Prager RL, Edwards FH, McDonald D, Han JM, D'Agostino RS, Jacobs ML, Kozower BD, Badhwar V, Thourani VH, Gaissert HA, Fernandez FG, Wright C, Fann JI, Paone G, Sanchez JA, Cleveland JC Jr, Brennan JM, Dokholyan RS, O'Brien SM, Peterson ED, Grover FL, Patterson GA. Introduction to the STS national database series: outcomes analysis, quality improvement, and patient safety. Ann Thorac Surg. 2015;100(6):1992–2000. https://doi.org/10.1016/j.athoracsur.2015.10.060.
32. Weintraub WS, Grau-Sepulveda MV, Weiss JM, O'Brien SM, Peterson ED, Kolm P, Zhang Z, Klein LW, Shaw RE, McKay C, Ritzenthaler LL, Popma JJ, Messenger JC, Shahian DM, Grover FL, Mayer JE, Shewan CM, Garratt KN, Moussa ID, Dangas GD, Edwards FH. Comparative effectiveness of revascularization strategies. N Engl J Med. 2012;366(16):1467–76. https://doi.org/10.1056/NEJMoa1110717.
33. Weintraub WS, Grau-Sepulveda MV, Weiss JM, Delong ER, Peterson ED, O'Brien SM, Kolm P, Klein LW, Shaw RE, McKay C, Ritzenthaler LL, Popma JJ, Messenger JC, Shahian DM, Grover FL, Mayer JE, Garratt KN, Moussa ID, Edwards FH, Dangas GD. Prediction of long-term mortality after percutaneous coronary intervention in older adults: results from the National Cardiovascular Data Registry. Circulation. 2012;125(12):1501–10. https://doi.org/10.1161/CIRCULATIONAHA.111.066969.
34. Zhang Z, Kolm P, Grau-Sepulveda MV, Ponirakis A, O'Brien SM, Klein LW, Shaw RE, McKay C, Shahian DM, Grover FL, Mayer JE, Garratt KN, Hlatky M, Edwards FH, Weintraub WS. Cost-effectiveness of revascularization strategies: the ASCERT study. J Am Coll Cardiol. 2015;65(1):1–11. https://doi.org/10.1016/j.jacc.2014.09.078.
35. Hlatky MA, Boothroyd DB, Baker L, Kazi DS, Solomon MD, Chang TI, Shilane D, Go AS. Comparative effectiveness of multivessel coronary bypass surgery and multivessel percutaneous coronary intervention: a cohort study. Ann Intern Med. 2013;158(10):727–34. https://doi.org/10.7326/0003-4819-158-10-201305210-00639.
36. Madani A, Arnaout R, Mofrad M, Arnaout R. Fast and accurate view classification of echocardiograms using deep learning. NPJ Digit Med. 2018;1:6. https://doi.org/10.1038/s41746-017-0013-1.
37. Khamis H, Zurakhov G, Azar V, Raz A, Friedman Z, Adam D. Automatic apical view classification of echocardiograms using a discriminative learning dictionary. Med Image Anal. 2017;36:15–21. https://doi.org/10.1016/j.media.2016.10.007.
38. Sengupta PP, Huang YM, Bansal M, Ashrafi A, Fisher M, Shameer K, Gall W, Dudley JT. Cognitive machine-learning algorithm for cardiac imaging: a pilot study for differentiating constrictive pericarditis from restrictive cardiomyopathy. Circulation: Cardiovasc Imaging. 2016;9(6):e004330. https://doi.org/10.1161/CIRCIMAGING.115.004330.
39. Mahmoud A, Bansal M, Sengupta PP. New cardiac imaging algorithms to diagnose constrictive pericarditis versus restrictive cardiomyopathy. Curr Cardiol Rep. 2017;19(5):43. https://doi.org/10.1007/s11886-017-0851-0.
40. Infante T, Francone M, De Rimini ML, Cavaliere C, Canonico R, Catalano C, Napoli C. Machine learning and network medicine: a novel approach for precision medicine and personalized therapy in cardiomyopathies. J Cardiovasc Med (Hagerstown). 2021;22(6):429–40.
41. Alsharqi M, Upton R, Mumith A, Leeson P. Artificial intelligence: a new clinical support tool for stress echocardiography. Expert Rev Med Dev. 2018;15(8):513–5. https://doi.org/10.1080/17434440.2018.1497482.
42. Knackstedt C, Bekkers SC, Schummers G, Schreckenberg M, Muraru D, Badano LP, Franke A, Bavishi C, Omar AM, Sengupta PP. Fully automated versus standard tracking of left ventricular ejection fraction and longitudinal strain: the FAST-EFs multicenter study. J Am Coll Cardiol. 2015;66(13):1456–66. https://doi.org/10.1016/j.jacc.2015.07.052.
43. Raghavendra U, Fujita H, Gudigar A, Shetty R, Nayak K, Pai U, Samanth J, Acharya UR. Automated technique for coronary artery disease characterization and classification using DD-DTDWT in ultrasound images. Biomed Signal Process Control. 2018;40:324–34.
44. Omar HA, Domingos JS, Patra A, Upton R, Leeson P, Noble JA. Quantification of cardiac bull's-eye map based on principal strain analysis for myocardial wall motion assessment in stress echocardiography. In: 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), 2018; pp. 1195–1198. https://doi.org/10.1109/ISBI.2018.8363785.
45. Cobey FC, Patel V, Gosling A, Ursprung E. The emperor has no clothes: recognizing the limits of current echocardiographic technology in perioperative quantification of mitral regurgitation. J Cardiothorac Vasc Anesth. 2017;31:1692–4. https://doi.org/10.1053/j.jvca.2017.03.012.
46. Cobey FC. Intelligent algorithms in perioperative echocardiography: a new era. J Am Soc Echocardiogr. 2017;30:A26–7. https://doi.org/10.1530/ERP-18-0056.
47. Queiros S, Morais P, Dubois C, Voigt JU, Fehske W, Kuhn A, Achenbach T, Fonseca JC, Vilaça JL, D'hooge J. Validation of a novel software tool for automatic aortic annular sizing in three-dimensional transesophageal echocardiographic images. J Am Soc Echocardiogr. 2018;31:515.e5-5252.e5. https://doi.org/10.1016/j.echo.2018.01.007.
48. Tsang W, Salgo IS, Medvedofsky D, Takeuchi M, Prater D, Weinert L, Yamat M, Mor-Avi V, Patel AR, Lang RM. Transthoracic 3D echocardiographic left heart chamber quantification using an automated adaptive analytics algorithm. JACC Cardiovasc Imaging. 2016;9:769–82. https://doi.org/10.1016/j.jcmg.2015.12.020.
49. Stebbing RV, Namburete AI, Upton R, Leeson P, Noble JA. Data-driven shape parameterization for segmentation of the right ventricle from 3D + t echocardiography. Med Image Anal. 2015;21:29–39. https://doi.org/10.1016/j.media.2014.12.002.
50. McDonagh TA, Metra M, Adamo M, Gardner RS, Baumbach A, Böhm M, Burri H, Butler J, Čelutkienė J, Chioncel O, Cleland JGF, Coats AJS, Crespo-Leiro MG, Farmakis D, Gilard M, Heymans S, Hoes AW, Jaarsma T, Jankowska EA, Lainscak M, Lam CSP, Lyon AR, McMurray JJV, Mebazaa A, Mindham R, Muneretto C, Francesco Piepoli M, Price S, Rosano GMC, Ruschitzka F, Kathrine Skibelund A. ESC Scientific Document Group. 2021 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure. Eur Heart J. 2021;42(36):3599–3726. https://doi.org/10.1093/eurheartj/ehab368. Erratum in: Eur Heart J. 2021 Oct 14.
51. Potapov EV, Antonides C, Crespo-Leiro MG, Combes A, Färber G, Hannan MM, Kukucka M, de Jonge N, Loforte A, Lund LH, Mohacsi P, Morshuis M, Netuka I, Özbaran M, Pappalardo F, Scandroglio AM, Schweiger M, Tsui S, Zimpfer D, Gustafsson F. 2019 EACTS Expert Consensus on long-term mechanical circulatory support. Eur J Cardiothorac Surg. 2019;56(2)(1):230–70. https://doi.org/10.1093/ejcts/ezz098.
52. Montisci A, Donatelli F, Cirri S, Coscioni E, Maiello C, Napoli C. Veno-arterial extracorporeal membrane oxygenation as bridge to heart transplantation: the way forward. Transplant Direct. 2021;7(8):e720. https://doi.org/10.1097/TXD.0000000000001172.
53. Flint KM, Matlock DD, Lindenfeld J, Allen LA. Frailty and the selection of patients for destination therapy left ventricular assist device. Circ Heart Fail. 2012;5(2):286–93. https://doi.org/10.1161/CIRCHEARTFAILURE.111.963215.
54. Pieri M, Contri R, Winterton D, Montorfano M, Colombo A, Zangrillo A, De Bonis M, Pappalardo F. The contemporary role of Impella in a comprehensive mechanical circulatory support program: a single institutional experience. BMC Cardiovasc Disord. 2015;15:126. https://doi.org/10.1186/s12872-015-0119-9.
55. Aissaoui N, Morshuis M, Maoulida H, Salem JE, Lebreton G, Brunn M, Chatellier G, Hagège A, Schoenbrodt M, Puymirat E, Latremouille C, Varnous S, Ouldamar S, Guillemain R, Diebold B, Guedeney P, Barreira M, Mutuon P, Guerot E, Paluszkiewicz L, Hakim-Meibodi K, Schulz U, Danchin N, Gummert J, Durand-Zaleski I, Leprince P, Fagon JY. Management of end-stage heart failure patients with or without ventricular assist device: an observational comparison of clinical and economic outcomes. Eur J Cardiothorac Surg. 2018;53(1):170–7. https://doi.org/10.1093/ejcts/ezx258.

56. Soliman OII, Akin S, Muslem R, Boersma E, Manintveld OC, Krabatsch T, Gummert JF, de By TMMH, Bogers AJJC, Zijlstra F, Mohacsi P, Caliskan K. EUROMACS Investigators. Derivation and validation of a novel right-sided heart failure model after implantation of continuous flow left ventricular assist devices: The EUROMACS (European Registry for Patients with Mechanical Circulatory Support) right-sided heart failure risk score. Circulation. 2018;137(9):891–906. https://doi.org/10.1161/CIRCULATIONAHA.117.030543.
57. Zhang Z, Reinikainen J, Adeleke KA, Pieterse ME, Groothuis-Oudshoorn CGM. Time-varying covariates and coefficients in Cox regression models. Ann Transl Med. 2018;6(7):121. https://doi.org/10.21037/atm.2018.02.12. P.
58. Karvounis EC, Tsipouras MG, Tzallas AT, Katertsidis NS, Stefanou K, Goletsis Y, Frigerio M, Verde A, Caruso R, Meyns B, Terrovitis J, Trivella MG, Fotiadis DI. A decision support system for the treatment of patients with ventricular assist device support. Methods Inf Med. 2014;53(2):121–36. https://doi.org/10.3414/ME13-01-0047.
59. Lüneburg N, Reiss N, Feldmann C, van der Meulen P, van de Steeg M, Schmidt T, Wendl R, Jansen S. Photographic LVAD Driveline Wound Infection Recognition Using Deep Learning. Stud Health Technol Inform. 2019;260:192–9.
60. Kilic A, Macickova J, Duan L, Movahedi F, Seese L, Zhang Y, Jacoski MV, Padman R. Machine learning approaches to analyzing adverse events following durable LVAD implantation. Ann Thorac Surg. 2021;112(3):770–7. https://doi.org/10.1016/j.athoracsur.2020.09.040.
61. Ogawa D, Kobayashi S, Yamazaki K, Motomura T, Nishimura T, Shimamura J, Tsukiya T, Mizuno T, Takewa Y, Tatsumi E. Mathematical evaluation of cardiac beat synchronization control used for a rotary blood pump. J Artif Organs. 2019;22(4):276–85. https://doi.org/10.1007/s10047-019-01117-3.
62. Ogawa D, Kobayashi S, Yamazaki K, Motomura T, Nishimura T, Shimamura J, Tsukiya T, Mizuno T, Takewa Y, Tatsumi E, Nishinaka T. Evaluation of cardiac beat synchronization control for a rotary blood pump on valvular regurgitation with a mathematical model. Artif Organs. 2021;45(2):124–34. https://doi.org/10.1111/aor.13795.
63. Fetanat M, Stevens M, Hayward C, Lovell NH. A Sensorless Control system for an implantable heart pump using a real-time deep convolutional neural network. IEEE Trans Biomed Eng. 2021;68(10):3029–38. https://doi.org/10.1109/TBME.2021.3061405.
64. Fetanat M, Stevens M, Jain P, Hayward C, Meijering E, Lovell NH. Fully Elman neural network: a novel deep recurrent neural network optimized by an improved Harris Hawks algorithm for classification of pulmonary arterial wedge pressure. IEEE Trans Biomed Eng. 2021. https://doi.org/10.1109/TBME.2021.3129459. PP.
65. Hulsen T, Jamuar SS, Moody AR, Karnes JH, Varga O, Hedensted S, Spreafico R, Hafler DA, McKinney EF. From Big Data to precision medicine. Front Med (Lausanne). 2019;6:34. https://doi.org/10.3389/fmed.2019.00034.
66. Diller GP, Kempny A, Babu-Narayan SV, Henrichs M, Brida M, Uebing A, Lammers AE, Baumgartner H, Li W, Wort SJ, Dimopoulos K, Gatzoulis MA. Machine learning algorithms estimating prognosis and guiding therapy in adult congenital heart disease: data from a single tertiary centre including 10 019 patients. Eur Heart J. 2019;40(13):1069–77. https://doi.org/10.1093/eurheartj/ehy915.
67. Diller GP, Babu-Narayan S, Li W, Radojevic J, Kempny A, Uebing A, Dimopoulos K, Baumgartner H, Gatzoulis MA, Orwat S. Utility of machine learning algorithms in assessing patients with a systemic right ventricle. Eur Heart J Cardiovasc Imaging. 2019;20(8):925–31. https://doi.org/10.1093/ehjci/jey211.
68. Olive MK, Owens GE. Current monitoring and innovative predictive modeling to improve care in the pediatric cardiac intensive care unit. TranslPediatr. 2018;7(2):120–8. https://doi.org/10.21037/tp.2018.04.03.
69. Ruiz-Fernández D, MonsalveTorra A, Soriano-Payá A, Marín-Alonso O, Triana Palencia E. Aid decision algorithms to estimate the risk in congenital heart surgery. Comput Methods Programs Biomed. 2016;126:118–27. https://doi.org/10.1016/j.cmpb.2015.12.021.
70. Zhong Z, Yuan X, Liu S, Yang Y, Liu F. Machine learning prediction models for prognosis of critically ill patients after open-heart surgery. Sci Rep. 2021;11(1):3384. https://doi.org/10.1038/s41598-021-83020-7.
71. Meyer A, Zverinski D, Pfahringer B, Kempfert J, Kuehne T, Sündermann SH, Stamm C, Hofmann T, Falk V, Eickhoff C. Machine learning for real-time prediction of complications in critical care: a retrospective study. Lancet Respir Med. 2018;6(12):905–14. https://doi.org/10.1016/S2213-2600(18)30300-X.
72. Lei G, Wang G, Zhang C, Chen Y, Yang X. Using machine learning to predict acute kidney injury after aortic arch surgery. J Cardiothorac Vasc Anesth. 2020;34(12):3321–8. https://doi.org/10.1053/j.jvca.2020.06.007.
73. Tseng PY, Chen YT, Wang CH, Chiu KM, Peng YS, Hsu SP, Chen KL, Yang CY, Lee OK. Prediction of the development of acute kidney injury following cardiac surgery by machine learning. Crit Care. 2020;24(1):478. https://doi.org/10.1186/s13054-020-03179-9.
74. Lee HC, Yoon HK, Nam K, Cho YJ, Kim TK, Kim WH, Bahk JH. Derivation and validation of machine learning approaches to predict acute kidney injury after cardiac surgery. J Clin Med. 2018;7(10):322. https://doi.org/10.3390/jcm7100322.
75. Kilic A, Goyal A, Miller JK, Gleason TG, Dubrawksi A. Performance of a machine learning algorithm in predicting outcomes of aortic valve replacement. Ann Thorac Surg. 2021;111(2):503–10. https://doi.org/10.1016/j.athoracsur.2020.05.107.
76. Wojnarski CM, Roselli EE, Idrees JJ, Zhu Y, Carnes TA, Lowry AM, Collier PH, Griffin B, Ehrlinger J, Blackstone EH, Svensson LG, Lytle BW. Machine-learning phenotypic classification of bicuspid aortopathy. J ThoracCardiovasc Surg. 2018;155(2):461–9.e4. https://doi.org/10.1016/j.jtcvs.2017.08.123.
77. Baskaran L, Ying X, Xu Z, Al'Aref SJ, Lee BC, Lee SE, Danad I, Park HB, Bathina R, Baggiano A, Beltrama V, Cerci R, Choi EY, Choi JH, Choi SY, Cole J, Doh JH, Ha SJ, Her AY, Kepka C, Kim JY, Kim JW, Kim SW, Kim W, Lu Y, Kumar A, Heo R, Lee JH, Sung JM, Valeti U, Andreini D, Pontone G, Han D, Villines TC, Lin F, Chang HJ, Min JK, Shaw LJ. Machine learning insight into the role of imaging and clinical variables for the prediction of obstructive coronary artery disease and revascularization: an exploratory analysis of the CONSERVE study. PLoS ONE. 2020;15(6):e0233791. https://doi.org/10.1371/journal.pone.0233791.
78. Cikes M, Sanchez-Martinez S, Claggett B, Duchateau N, Piella G, Butakoff C, Pouleur AC, Knappe D, Biering-Sørensen T, Kutyifa V, Moss A, Stein K, Solomon SD, Bijnens B. Machine learning-based phenogrouping in heart failure to identify responders to cardiac resynchronization therapy. Eur J Heart Fail. 2019;21(1):74–85. https://doi.org/10.1002/ejhf.1333.
79. Ambale-Venkatesh B, Yang X, Wu CO, Liu K, Hundley WG, McClelland R, Gomes AS, Folsom AR, Shea S, Guallar E, Bluemke DA, Lima JAC. Cardiovascular event prediction by machine learning: the multi-ethnic study of atherosclerosis. Circ Res. 2017;121(9):1092–101. https://doi.org/10.1161/CIRCRESAHA.117.311312.
80. Ayers B, Sandholm T, Gosev I, Prasad S, Kilic A. Using machine learning to improve survival prediction after heart transplantation. J Card Surg. 2021;36(11):4113–20. https://doi.org/10.1111/jocs.15917.

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