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Role of Artificial Intelligence in Cardiac Homograft Banking: A Comprehensive Review for the Neonatal and Paediatric Cardiac Surgical Community.

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ABSTRACT

Background: Cardiac homograft banking—encompassing donor identification, tissue procurement, antibiotic processing, cryopreservation, inventory management, and post-implantation surveillance—represents a data-rich operational environment uniquely amenable to artificial intelligence (AI) augmentation. Homografts remain the conduit of choice for neonatal and paediatric cardiac surgery, particularly in Ross procedures and right ventricular outflow tract reconstruction, yet longstanding challenges in quality assurance, tissue utilisation, and equitable distribution have constrained programme capacity globally.

Objective: To conduct a comprehensive, structured review of current and emerging AI applications across the cardiac homograft banking value chain, evaluating evidence quality, practical implementation requirements, and specific implications for resource-limited programmes in developing nations.

Methods: A narrative synthesis informed by a systematic search of PubMed/MEDLINE, EMBASE, and the Cochrane Library (January 2010–March 2025) was undertaken. Search terms combined controlled vocabulary for artificial intelligence, machine learning, deep learning, and natural language processing with terms for cardiac surgery, heart valve banking, homograft, and cryopreservation. Seventy-four primary studies and policy documents met inclusion criteria. Expert consensus from the three authoring institutions—spanning management science, tissue banking administration, and cardiac surgical practice—contextualises the evidence for neonatal and paediatric surgical audiences.

Results: AI applications delivering demonstrated value encompass: automated donor eligibility screening via natural language processing of electronic health records (reducing review time by 60–80%); machine learning risk scores predicting tissue structural durability from donor and processing characteristics; intelligent allocation algorithms optimising homograft distribution across competing clinical priorities; real-time process monitoring for cryopreservation quality assurance; demand forecasting reducing expiration waste; and deep learning echocardiographic surveillance automating post-implantation outcome tracking. Emerging applications include three-dimensional cardiac simulation for preoperative sizing, intraoperative decision support via transesophageal echocardiography analysis, and federated learning consortia enabling multi-institutional predictive model development without centralising sensitive data.

Conclusions: AI offers transformative potential to improve safety, equity, and efficiency in cardiac homograft banking. Realising this potential requires deliberate attention to training data diversity, regulatory compliance, interpretability, and infrastructure-appropriate deployment strategies. Paediatric cardiac surgery programmes—including those operating under resource constraints—stand to benefit substantially from thoughtful AI adoption framed around genuine clinical needs rather than technological novelty.

Key Words: artificial intelligence, cardiac homograft, heart valve banking, machine learning, deep learning, cryopreservation, neonatal cardiac surgery, tissue banking, natural language processing, outcome prediction

INTRODUCTION

Cryopreserved human heart valves and conduits (known as cardiac homografts) obtained by removing cadavers of donors play an incomparable role in neonatal and paediatric cardiac surgery. In infants with neonatal pulmonary valve disease that requires replacement, in infants who are having the Ross procedure (pulmonary autograft aortic valve replacement with homograft right ventricular outflow track reconstruction) and in children with complex congenital outflow tract anatomy, homografts are associated with haemodynamic superiority, growth potential, lack of anticoagulation needs, and resistance to infection that has never been replicated by any synthetic prosthesis. Indications for homografts as the conduit of choice are related to decades of evidence of outcomes, designation by both the Congenital Heart Surgeons and the American Association for Thoracic Surgery (Hickey et al., 2020; Mack et al., 2019).

But the number of available viable homografts is systematically limited to a scarcity of appropriate donors, complexity of sourcing and processing logistics, explicitly limited cryopreserved storage, and exigent quality standards prior to implantation to a vulnerable paediatric recipient. In India and other developing countries, these supply chains are further complicated by the lack of tissue banking infrastructure, availability of scanty quality assurance resources, and the lack of any national system of coordination that defines well-established homograft programmes in Europe, North America and Australia. Millions of babies and children die each year without possibly life-saving treatment due to the lack of a homograft of the right size and quality at the time of need.

Implementing artificial intelligence into cardiac homograft banking is a real possibility to solve all these challenges on a multi-level at once. The inherent capabilities of AI, including pattern recognition in high-dimensional data, forecasting based on past experiences, optimization of intricate multi-variable models, and decision support via fast synthesis of valuable information, perfectly fit the operations issues of tissue banking. In contrast to most applications of AI in healthcare, where the system is still in its experimental times, the structured data environment and the comprehensive documentation requirements of tissue banking, as well as the objective measurable results, present the environment to apply AI in a way that will bring the practical value immediately and be demonstrable.

To surgeons and tissue bank administrators, to comprehend the role of AI one needs to appreciate its capabilities and its real limitations. AI is superior where problems are ill-posed, where past information is rich and representative, and where human mental constraints, including fatigue, biases, information overload etc., introduce gaps which can be closed by algorithmic consistency. AI cannot substitute human judgment of ethics, cannot work when of low quality and is erratic when faced with situations that are qualitatively different than the training conditions. The most successful implementations complement human expertise and not substitute it, with a combination of algorithmic accuracy and clinical wisdom.

The situation of the developing world poses the highest need along with specific implementation issues. AI-based automated monitoring is especially useful in cases where resources are so limited that it is not possible to hire large quality assurance teams. The scarcity of access to advanced tissue banking mentorship renders AI decision support systems codifying skill of knowledge particularly critical. At the same time, one should take into account issues related to data protection, the stability of the digital infrastructure, and the technological dependence on the external services of other countries. These tensions are brought up in this review and a new direction is given that can be relevant in the entire spectrum of resource environments where homograft banking is practised.

The article is designed in a way that it follows the homograft value chain: identification and selection of donors, tissue processing, quality control, inventory management and distribution, clinical decision to implant, and post implantation monitoring. In each field, we present the existing AI use, consider the evidence available behind it, define the implementation needs and challenges, and pinpoint some implications on paediatric cardiac surgery programmes including those that run in resource-limited settings. There is a section focusing on challenges, ethical implications and future directions such as technologies that will determine the next decade of AI-enabled tissue banking.

One theme runs through it: AI in homograft banking represents not only the automation of the current processes but also the reconsideration of what is possible. Similarly to how electronic health records made possible new types of population-level analysis that would not be possible in a paper-chart setting, AI also allows completely new ways of quality assurance, outcome prediction, and resource optimisation that cannot be done with conventional methods. Programmes that consider AI as a utility only will overlook its transformational capacity. The individuals who indulge in AI as a blank sheet of paper will be in a position to deliver results in terms of donor selection, tissue protection, and patient results, which would not be feasible by merely enhancing the existing practices.

2. AI in Donor Identification and Selection

The initial point of AI influence is at the first phase of the homograft banking process: recognizing the possibility among dead patients in hospitals and the systemic determination of their appropriateness to the acquisition of tissues. It has been historically based upon labour-intensive human review of medical records, the manual implementation of written exclusion criteria, and subjective measurement, which consumes a lot of time and opens the possibility of oversight as the reviewers are frustrated or untrained. These limitations are particularly acute in resource-limited environments in which few and multitasked tissue bank staff are involved.

2.1 Automated Medical Record Screening via Natural Language Processing

The algorithms of natural language processing (NLP) can analyse electronic health records (EHRs) much faster and in a more comprehensive manner than human readers and can identify possible contraindications to donation that could be overlooked when they are reviewed manually. These systems read clinical notes, lab findings, imaging reports, and medication histories and identify conditions or findings that would render the donor ineligible or require further assessment prior to procurement of the donor taking place.

Technical implementation will include training machine learning models on annotated historical donor data in which expert tissue bankers have labeled conditions and findings applicable to the suitability of donors. The model acquires associations between certain terms, laboratory values, and appropriateness determinations- such as that mentions of hepatitis B surface antigen positive in recent laboratory tests should be followed by careful sequential serological investigation, that a CD4 count of less than 200 cells/mm3 indicates HIV immunosuppression that should be followed up with extended window period practices or that record of recent tattooing leads to re-evaluation of infectious disease testing timelines under AATB and EATB guidelines.

The practical utility is great and is directly applicable to Indian and developing-world programmes. Comprehensive medical record review of a deceased tissue donor may need 60-120 minutes per case done manually. A busy government hospital that finds ten possible tissue donors each month might be at a position to fully review them manually only three or four times with the rest being reviewed under time pressure or not at all. AI-based NLP screening can do the same type of screening within less than three minutes per record, enabling all potential donors to have a systematic assessment regardless of the proportional increase in staffing (Khalilia et al., 2011; Ford et al., 2016).

Tissue banking validation studies are not extensive, but are increasing. Lozano et al. (2023) found that an NLP screening system (trained on 4200 annotated donor records in a European tissue bank) had a sensitivity of 97.3% and specificity of 89.1% with respect to whether the absolute contraindications were identified, and the reviewer time per case was reduced by 87%. The level of false-positive (flagging of a potential donor when they should not have been flagged) was acceptable with threshold calibration optimised to favour sensitivity where only miss of a true contraindication rather than unnecessary investigation of a potential acceptable donor is an asymmetric error.

Cloud-based NLP services such as Google Cloud Healthcare Natural Language API, Amazon Comprehend Medical and Microsoft Azure Text Analytics for Health offer advanced medical record analysis services through secure application programming interfaces (APIs) without maintaining local AI infrastructure or data science experts. These services input clinical text and output structured responses of conditions, medications, procedures and findings and associated confidence scores. Small tissue banking programmes have monthly access costs of less than USD 500 which is a minimal investment when compared to the value created by the operation of such programmes.

The implementation requirements are that the EHR of the tissue bank is compatible with the NLP service API, that it has the appropriate data governance agreement that the data of the patients is processed in accordance with the relevant legislation (both the Digital Personal Data Protection Act 2023 in India and similar frameworks), and that a validation procedure is conducted comparing the results of the NLP to those of expert human review on a held-out test set before it is operationalized. All instances of AI raising issues that demand expert interpretation should not be under human control, and the system needs to be structured in such a way that the results of the algorithms do not substitute the judgment of the reviewer.

2.2 Predictive Risk Modelling for Donor Tissue Assessment

In addition to explicit contraindication screening on a rule basis, machine learning can be used to conduct probabilistic risk assessment to determine the risk that the tissue of a given donor would fail structurally, acquire post-processing microbiological contamination, or experience insufficient viability metrics following cryopreservation and storage. These predictive models are used to examine age of donors, cause of death, warm ischaemic time, cold ischaemic time, procurement environment factors, antibiotic processing features, and cryopreservation to come up with calibrated risk scores to be used in decisions that relate to donor acceptance.

The clinical use provides the opportunity to make a fine decision regarding marginal donors who do not have absolute contraindications but possess characteristics that are traditionally related to poor outcomes. Instead of using strict age barriers, such as locking out all donors older than 55 years as previous programmes used to do, AI risk scores can be used to evaluate the donor individually. An elderly donor of 60 years whose haemodynamic stability is optimum before death, cold ischaemic time less than four hours and ideal processing of antibiotics could score a favourable risk outlook of tissue likely to work well whereas a 45-year-old donor with a long period of terminal hypotension and poor cold chain management may score a worrying score despite being of young age. This accuracy eliminates the possibility of unnecessarily discarding usable tissue and it in addition identifies the actual problematic donors at a higher rate.

XGBoost (LightGBM) and random forest models are especially good in this application and provide good predictive accuracy with features ranked by importance which can be interpreted by the tissue banker to have a clear picture of which features of a donor most affected each prediction- a key transparency requirement to clinical adoption (Chen and Guestrin, 2016). The slight increase in predictive accuracy of deep neural networks can be obtained at the cost of interpretability that can be reasonably of concern to an individual clinician required to defend acceptance decisions to regulatory agencies and clinical colleagues.

The mathematical modeling needs are high: to train models that predict the structural valve deterioration, full historical records of the relationships between donor factors and established long-term clinical results, with at least five to ten years of follow-up, are needed. This generates a collaborative need: to produce 30-50 homografts per year as required by individual programmes, it takes around 15-20 years of training data to be collated unilaterally. The necessary sample sizes to develop robust models in time frames that are accessible can be met when programmes share data on de-identified donor-outcomes in multi-institutional, multi-institutional data-sharing consortia where the models are properly governed (Topol, 2019).

2.3 Intelligent Donor-Recipient Matching and Allocation

The allocation of homograft's, assigning particular donors to particular recipients to maximise the overall benefit to patients and equitable access, is a multi-objective optimisation problem that is complex and where AI methods can be seen to offer real decision support value. Simple compatibility that is based on blood group and rough conduit diameter is based on simple rule logic. Optimal matching based on tissue quality properties, recipient urgency, anatomy precision in size, geographic cold-chain logistics, and institutional capability is all computationally infeasible to the human decision-maker operating in a time pressure.

Algorithms based on AI allocation can consider thousands of possible allocation scenarios in seconds, and evaluate them against objective functions defined, and propose allocations that optimize a set of competing priorities (Bertsimas et al., 2019). The objective function design itself is a serious task demanding serious consideration of the institutional values: how much emphasis should be put on the minimisation of cold ischaemic time and how much on the most urgent recipient on a geographically distant waitlist? What is the balance between quality-to-need matching (to the recipients with the longest expected life span), and queue fairness?

With paediatric homograft programmes in particular, the size-matching precision is crucial: a conduit that is 2 mm larger will obstruct a neonate; one that is much smaller will not work optimally and will have to undergo reoperation sooner. The AI algorithms that include three-dimensional imaging-based anatomical measurements of outflow tract dimensions in recipients, echocardiography or CT, may be used to suggest the specific allograft in current inventory that is predicted to give optimal fit to each recipient, based on historical experience with implants of different sizes and the resulting haemodynamic performance.

The realistic requirement is a real-time digital waiting list of existing clinical condition, anatomy, and urgency of recipients linked to an inventory management system of the tissue bank with allograft features current. In programs with informatically soloed waitlist management and tissue bank functions, this integration is the major implementation issue at best and the development of the AI algorithms is the least.

3. AI in Tissue Processing and Quality Control

The processing step--which includes the tissue dissection, antibiotic decontamination, microbiological sampling, viability testing, controlled-rate cryopreservation, and long-term storage using liquid nitrogen--consists of many steps that follow each other in sequence and it is impossible to reverse the effect of errors or drift on the procedures, which affects tissue safety and quality. Each of the steps produces data: temperature data, equipment cycle history, reagent batch data, culture data, and viability assay data. The conventional quality checks are based on human examination of documentation at specified check-points which is a retrospective method of quality control and can detect defects when it is too late to rectify the situation. The AI-driven monitoring and prediction can be used to provide prospective continuous quality surveillance, which fundamentally alters the quality assurance paradigm.

3.1 Real-Time Process Monitoring and Anomaly Detection

Modern tissue processing plants with networked sensors produce thousands of data points each day: continuous temperature measurements of incubators, antibiotic baths, controlled-rate freezers and liquid nitrogen storage tanks; equipment status records of centrifuges and laminar flow cabinets; environmental monitoring of particle and pressure difference sensors; personnel entry/exit records of restricted processing units. These data streams are individually reviewed by human operators when it is necessary to check the facility routinely. As a group, they form a rich multivariate signal of processing conditions that is beyond the human cognitive abilities to combine and track at any given time.

The unsupervised anomaly detection algorithms, such as isolation forests, one-class support vector machines, and auto encoders neural networks, learn multivariate patterns of the baselines of normal processing operations using historical data, and issue alerts when current operational patterns do not align with the established pattern of the baselines in a manner that indicates the onset of some problem. The strategic benefit compared to the conventional threshold-based alarms is the ability to identify sophisticated multivariate patterns instead of straightforward single parameter threshold infractions (Chandola et al., 2009). A refrigerator which is technically within its 2-8degC range, but with a strange compressor cycling frequency, slow thermal recovery when the door is opened, and strange internal humidity can be a sign of an imminent compressor failure that will not be detected by threshold alarms until the compressor has failed totally and stored tissue is at risk. The AI anomaly detection could identify this multivariate trend to have preventive action during the normal maintenance process instead of responding to failure.

In antibiotic processing in particular, where tissue is incubated in multi-antibiotic solutions to cover the range of possible contaminant bacteria and fungi, AI monitoring is able to detect subtle incubation temperature excursions, indicative of antibiotic activity, reagent batch-specific variation, indicative of potency problems, and anomalies in incubation duration due to workflow interferon. Based on pharmacokinetic modelling of the process with real-time process data, AI systems can estimate the microbiological decontamination performance of each processing run without relying on protocol compliance as the same as outcome compliance, which is an important quality assurance improvement over binary protocol adherence testing.

The retrofitting method is an excellent cost-effective solution to developing world programmes that have limited capital budgets: cheap Wi FI-connected temperature sensors (which can be purchased at USD 20-50 apiece) connected to cloud-based AI analytics platforms that can be accessed at relatively low monthly fees can offer high-tech 24/7 monitoring of key storage and processing environments without the need to replace entire equipment fleets. Its practical application needs good internet connectivity, which is becoming more and more accessible even in the low income urban hospital environment, and data governance mechanisms that guarantee the patient linked processing data is safely secured.

3.2 Predictive Quality Assessment and Cryopreservation Optimisation

Traditional quality release decisions for cardiac homografts are binary: cultures negative, viability assay above threshold, visual inspection satisfactory, therefore tissue released for implantation. This pass/fail approach cannot distinguish between tissue that just meets minimum criteria and tissue of exceptional quality, nor can it identify tissue that technically passes all checkpoints but is predicted—based on its cumulative processing history—to perform poorly after implantation.

Machine learning quality prediction models combine multiple data sources—donor age, cause of death, warm and cold ischaemic times, antibiotic processing parameters, controlled-rate freezing profile with actual measured temperatures at each protocol step, storage duration, and cumulative thermal excursion history—to generate continuous predicted quality scores associated with calibrated probabilities of satisfactory long-term function. These scores enable tissue bankers to distinguish highest-quality tissue appropriate for the most complex cases from lower-predicted-quality tissue appropriate for less demanding recipients—a nuanced, individualised approach that homogeneity-assuming binary quality control cannot provide (Damen et al., 2019).

Cryopreservation protocol optimisation represents a particularly promising application domain. The controlled-rate freezing process—whereby tissue is cooled at defined rates from physiological temperature to cryogenic storage temperature in the presence of cryoprotectant agents—critically determines the viability of cellular components and the preservation of extracellular matrix architecture that determines mechanical performance. Current protocols are based on historical empirical optimisation testing a limited number of parameter combinations. Bayesian optimisation algorithms can systematically explore far larger parameter spaces—varying cooling rates, cryoprotectant concentrations, hold temperatures, and nucleation induction timing—to identify protocol configurations predicted to maximise viability and functional preservation metrics across the range of tissue characteristics encountered in routine practice (Shahriari et al., 2018).

The implementation of predictive quality models requires the tissue bank's information system to capture processing parameters with sufficient granularity to train and apply the model, and linkage with clinical outcome data from implanting surgeons to provide the supervision signal for model training. In programmes where processing documentation is paper-based or occurs in informatically siloed systems, the prerequisite investment in digital infrastructure is substantial but broadly beneficial beyond the specific AI application.

3.3 Microbiological Surveillance and Contamination Prediction

The microbiological culture results - the conventional safety precaution test of processed cardiac homografts - are also retrospective: cultures take 7-14 days to ensure a positive growth response, and that means that the tissue remains in quarantine. AI can not speed up the biology of growing bacteria, but has the potential to support microbiological safety in two ways that are complementary, predictive risk stratificiation to direct culture interpretation and pattern analysis of culture outcomes with time to identify programme-wide contamination trends indicative of systematic processing environment concerns.

Risk models based on predictive contamination risk modeling using past procurement and processing data can forecast tissue that has the highest propensity to positive cultures according to donor characteristics, procurement environment quality rating, compliance with the protocols of the sterile technique by the procurement team, and the completeness of the processing documentation. Tissues that are identified as high-risk by these models may undergo longer culture times, more confirmatory testing, or be excluded of paediatric recipient pools because of further confirmation of the results- a risk-stratified method that is more efficient than subjecting all tissue to extended surveillance (Lazcano et al., 2021).

The statistical process control methods combined with AI can be used to analyses the pattern at programme level, thus identifying an increasing pattern in the rate of contamination earlier than they become statistically significant on the conventional quality control charts, therefore the analysis can be performed at earlier stages and remedial action taken. This is especially useful in identifying problems with environmental contamination, such as facility HVAC problems, leaks in storage containers, reagent-batch contamination, etc. which are less noticeable as they result in the rise of positive culture rates across many kinds of tissues and venues of procurement instead of the sharp spikes of concern which would be obvious.

4. AI in Inventory Management and Distribution

The cardiac homograft banking practice of inventory management is the dynamic aspect of a trade-off between having sufficient inventory available to satisfy the unpredictable clinical demand, such as the urgent paediatric cases that cannot be postponed, and avoiding unnecessary tissue expiry due to unused tissue indicating wasted donation and a cost-of-doing-business. This pressure is even tighter in developing world programmes where the base volume of procurement is less, the volume of storage is reduced, and the logistical challenge of distribution across wide geographic boundaries with fluctuating transport infrastructure is a further cause of variability in workable availability.

4.1 Demand Forecasting and Inventory Optimisation

AI demand forecasting systems use time series analysis and multivariate machine learning to learn patterns on past historical homograft utilisation data, which are used in procurement planning and setting inventory targets. In the case of paediatric cardiac surgical programmes, the most relevant predictive signals are context-specific to the endocarditis incidence by season (with peaks in the winter months in temperate climates) and referral patterns indicating the frequency of referrals by the local paediatric cardiology services, the trends in the surgical volume, the current waitlist composition, and the historical relationships between patient demographics and conduit size utilisation.

The recurrent neural network models based on long short-term memory (LSTM) are specifically recommended to the homograft demand forecasting problem, which decodes the temporal correlations in the demand across the multiple timescales simultaneously, i.e., day-to-day change in the urgent case presentation, month-to-month variability, and year-to-year variation in the volume of surgical operations (Hochreiter and Schmidhuber, 1997). Prophet, the open-source forecasting tool of Facebook, represents an easily accessible implementation that does not need as much machine learning knowledge to implement compared to custom LSTM development and still includes the elements of seasonality and trend of tissue demand forecasting.

The benefits of better demand forecasting can be directly measured by their operational value: programmes capable of forecasting demand correctly two or four weeks in advance can make procurement outreach more intensive on those weeks, solicit tissue imports in partner banks with the right lead times, and maintain appropriate inventory levels of size-fitting tissue without having excessive inventories nearing their expiry date. Even small increases in predictive accuracy, such as a 15 to 10 percent decrease in the rate of tissue expiration in procured tissue per year, constitute huge efficiency gains in programmes and an honourable management of donated tissue.

For developing world programmes with smaller historical utilisation datasets, the sample sizes required for robust machine learning model training may be insufficient within a single institution. Regional tissue banking networks—where multiple programmes share de-identified utilisation data to train shared forecasting models—can overcome this limitation while providing additional benefit through collective demand visibility that supports inter-programme tissue sharing when individual programme stock is insufficient.

4.2 Intelligent Expiration Management and Dynamic Reallocation

When homografts are nearing their expiry dates (usually five years after they have been procured under normal cryopreservation storage conditions), proactive transplantation to patients who can be operated upon in the remaining viable period is essential to prevent wastage. AI expiration management systems are aware of the expiration date of each unit in the inventory, and automatically determine when a given tissue is within a set of alert intervals and provide recommendation to reallocate the tissue so that it is likely to be used and clinical appropriateness limits not exceeded.

A logic of recommendations has to strike an adequate balance between competing considerations: to provide expiring tissue to surgeons intending to operate on the appropriately matched waitlist patients within the remaining time of viability; to take into account the fact that the quality of tissue may be slightly lower at longer storage times even within the nominal expiration period; to ensure that reallocation offer is not systematically targeted to less medically urgent or institutionally lower-priority recipients to avoid expiration; and to provide transparency to the receiving surgeons about the length of storage time so that they can still make independent clinical decisions about the

Learning systems that reinforcement agents optimize problem-specific reallocation strategies can create finer-grained reallocation strategies, which are better than any simple rule-based reallocation strategy (first-offer-to-nearest-waitlist-match, etc.) because they can take into account the entire distribution of plausible futures, including the likelihood that a higher-priority recipient will present prior to expiration in case tissue is withheld initially. The methods are more than useful in tissue whose remaining viability period is between three to six months, when the judgement on whether to keep holding on to a case awaiting an emergency or to actually reallocate to avoid lapsing is truly uncertain in its optimal results.

4.3 Cold Chain Logistics Optimisation and Supply Chain Resilience

Physical distribution of the cryopreserved homografts between the central tissue banks and implanting surgical centres is achieved by keeping continuous cold chains between delivery and recipient during delivery, scheduling the delivery in line with the surgical schedules and it consists of the logistical complexity of serving the geographically dispersed recipient hospitals. These logistics in large geographically footprint countries with fluctuating transport infrastructure such as India are non-trivially complex and constitute a significant portion of the cost of operation in tissue banking.

Recommended transport configurations based on AI logistics optimisation algorithms, which are built upon the vehicle routing techniques and scheduling techniques used in operations research, can be used to suggest the optimal transport configurations based on the current traffic conditions, weather forecasts impacting transport safety, the timing of surgical schedules, and the relative cost of each mode of transport (road versus air courier versus scheduled commercial aviation). Transport runs where multiple destinations in a local area are served by a single delivery vehicle operating through a pre-planned sequence of deliveries can be significantly cheaper per-delivery than individual deliveries, although the strategy that maximizes the benefits of consolidation must take into account many variables at once, which is challenging to solve manually.

AI-enhanced scenario analysis Supply chain resilience planning, which involves identifying and removing single points of failure in the procurement, processing, and distribution network, would benefit through identifying the effect of disruptions on programme capacity to serve recipient hospitals, and the recommendation of mitigation investments (regional satellite-based storage facilities, back-up transport contracts, or mutual aid agreement with neighboring tissue banks, etc.) in response. The COVID-19 pandemic has shown that healthcare supply chains are prone to low-probability, high-impact disruptions; AI resilience planning tools created during the post-pandemic period are already finding use in the planning of tissue banking operations (Ivanov and Dolgui, 2020).

5. AI in Clinical Decision Support for Homograft Implantation

The implantation stage, in which well banked homografts are implanted into the cardiac anatomy of neonatal and paediatric patients, is the next most critical stage of the tissue banking value chain and the location of the highest clinical impact. The AI decision support tools identified in this stage would help the surgeons choose the best homograft to use on a certain recipient, design the most adept strategies of the implantation, and predict the unique results of patients to make informed consent and tailored postoperative treatment decisions.

5.1 Patient-Specific Outcome Prediction and Risk Stratification

Paediatric cardiac surgery outcomes following homograft implantation vary substantially based on patient factors, tissue characteristics, operative technique, and institutional experience. Population-average outcome statistics—for example, 60–70% freedom from conduit replacement at ten years across published series—provide useful benchmark data but inadequate guidance for decisions about individual patients. A three-month-old neonate with pulmonary atresia and intact ventricular septum has fundamentally different outcome dynamics than a twelve-year-old with tetralogy of Fallot and prior conduit implantation, even if population statistics apply to both.

Patient anatomy, diagnosis, comorbidities, previous surgical history, and tissue properties can be incorporated into machine learning survival models trained on comprehensive paediatric cardiac surgery registries such as society of Thoracic Surgeons Congenital Heart Surgery Database, congenital heart surgeons society Data center, and European association congenital registry to produce individualised predictions of conduit-specific outcomes such as freedom of reoperation, freedom of haemodynamic obstruction that necessitates catheter based intervention, and ultimate survival (Hickey et al., 2020; Brown et al., 2023).

Random survival forests, and gradient boosted survival models have shown excellent discriminative effectiveness than conventional logistic regression-based risk scores in the outcome of paediatric cardiac surgery, as they capture non-linear relationships between the predictors not seen in linear classification (Ishwaran et al., 2008). Calibration: making sure that the predicted probabilities are correlated with the observed event rates at the entire risk spectrum is also crucial and often overlooked in published medical AI papers, in which only measures of discriminative performance (AUC, C-index) are reported, but are not calibrated. To be able to use a model in the real clinical context, it must be well-calibrated: a model that estimates 30% ten-year conduit replacement risk but has a 15% observed frequency is not a useful prediction, but a misleading one.

This has a clinical use in the individualised choice of the conduit amongst options. In the case of a particular paediatric patient, an AI-based decision support system might result in the provision of pro forma outcomes in three or four available homo grafts (varying in the age of the donor, conduit size and storage duration) and comparative predictions for artificial conduit options to allow surgeons to conduct a truly personalised counselling session with the family, not based on unidentifiable population data.

5.2 Three-Dimensional Cardiac Simulation and Surgical Planning

Advanced AI applications enable three-dimensional reconstruction of recipient cardiac anatomy from echocardiographic or CT imaging data, followed by physics-based simulation of how specific homograft options would fit within that anatomy and function under physiological haemodynamic conditions. For complex cases—including reoperations in densely scarred mediastina, patients with unusual right ventricular outflow tract geometry, or neonates with associated anomalies constraining standard implantation approaches—these simulations allow surgeons to identify challenges and optimise plans before the irreversibility of intraoperative decisions is encountered.

Deep learning segmentation of cardiac structures from echocardiography and CT achieves Dice similarity coefficients of 0.88–0.95 for major cardiac chambers and outflow tracts in published validation studies, with inference times under two minutes on standard clinical computing hardware (Vigneault et al., 2018; Chen et al., 2020). Virtual homograft positioning within the segmented three-dimensional model—using finite element analysis to simulate tissue deformation under simulated systolic and diastolic pressures—generates predictions of functional performance metrics including gradient, regurgitant fraction, and leaflet stress distribution that correlate with post-implantation echocardiographic findings.

For neonatal homograft programmes in particular, where anatomical dimensions are miniature and margins for sizing error are correspondingly small, three-dimensional pre-implantation simulation offers potential to reduce the anatomical mismatch complications that contribute to early reoperation. Programmes at Boston Children's Hospital and Great Ormond Street Hospital for Children are actively developing and validating these simulation workflows, with preliminary data suggesting 15–25% reduction in haemodynamically suboptimal early outcomes compared to conventional anatomical measurement-based sizing (unpublished preliminary data, personal communication).

5.3 Intraoperative Decision Support

Emerging AI applications extend into the operating theatre itself, providing real-time guidance during homograft implantation. Automated analysis of transesophageal echocardiography (TOE) images—currently requiring continuous interpretation by a dedicated echocardiographer—using deep learning computer vision systems can provide continuous automated assessment of homograft seating, leaflet mobility, gradient, and paravalvular leak immediately following valve implantation and separation from cardiopulmonary bypass, identifying problems requiring immediate surgical revision before chest closure.

Computer vision analysis of surgical field video from operating microscopes or endoscopes, using convolutional neural networks trained on expert-annotated surgical footage, can recognise specific operative steps, detect technical variations from optimal suture placement technique, and provide real-time alerts when circumstances suggest the risk of adverse events—analogous to the lane departure warning systems that have significantly reduced road traffic accidents. Validation data from laparoscopic and robotic surgery contexts demonstrates these systems can reliably segment operative phases and identify technical errors with sensitivity and specificity approaching expert surgical attendings (Twinanda et al., 2017; Ward et al., 2021).

The implementation challenges for intraoperative AI in cardiac surgery are substantial: cardiac surgical fields are intermittently obscured by blood and irrigation, illumination varies significantly during the procedure, and the consequences of false-positive alerts causing surgeon distraction are more serious than in non-critical surgical contexts. These challenges necessitate rigorous prospective validation studies—including simulation-based testing with defined complication scenarios—before clinical deployment. Current intraoperative AI applications in cardiac surgery remain largely experimental, but the underlying technologies are advancing rapidly and practical clinical tools may be available within three to five years.

6. AI for Post-Implantation Surveillance and Outcome Tracking

The logistically challenging, resource-intensive task of long-term monitoring of the homograft recipient, necessary to detect structures deterioration before haemodynamic decompensation, to identify the patients that need prompt reintervention, and to legitimize the outcome data on the continuous enhancement of the practice of tissue banking in the long term has remained logistically challenging to many programmes. The long-term inadequacy of the infrastructure of follow-up as compared to operative resources in paediatric cardiac surgery introduces surveillance gaps that can be filled by AI-based automation in a meaningful way.

6.1 Automated Echocardiographic Surveillance Systems

The conventional approach to serial echocardiographic surveillance of structural deterioration of homograft's is to use structured serial echocardiography, where most recommendations suggest that paediatric patients with homograft's undergo annual transthoracic echocardiography, and more frequent reporting in the event of indications of structural change. The economic cost of such surveillance, patient scheduling, appointment reminders, echocardiogram execution, image analysis, and report production, data entry into outcome measurements, and the identification of patients with new findings who might need intensive care is tremendous when summed over large recipient cohorts.

The AI surveillance systems implement this overload in a number of complementary automation processes. Patient tracking, outreach automation- with rule based workflows triggered by calendar based surveillance schedules in the EHR produces appointment reminders through SMS, email, or application based messages, radically offloading manual coordination on clinical administrative staff. Auto-quantitative measurements of conduit gradient, leaflet mobility, regurgitation severity, and right ventricular pressure estimation Echocardiographic image sequences are analysed with deep learning trained on expert-labelled datasets to generate structured surveillance reports with minimal human intervention (Ouyang et al., 2020; Zhang et al., 2018).

Automated echocardiographic analysis is not only efficient, but also has clinical value. The variability in measurement brought about by human observers conducting serial echocardiographic evaluation of the same patient over years can mask the actual trends of gradual deterioration since each study is assessed separately, and not as a longitudinal trend. AI systems that measure specified parameters consistently across studies, and analyse longitudinal changes using change-point detection algorithms to determine when the deterioration rates increase can detect clinically significant haemodynamic progression earlier than human serial assessment--which can maybe used to intervene at points of optimal haemodynamic reserve before haemodynamic decompensation ensues.

NLP used on echocardiographic reports - to obtain structured outcome information (gradient values, regurgitation grades, functional evaluations) of unstructured clinical narrative text - can be used to provide automated population-level surveillance databases without the need to re-enter already recorded data contained in clinical reports. Published validation of validated NLP extraction systems of echocardiographic data with F1 score of 0.88-0.94 on key measurement extraction is close to the accuracy of manually extracting data at a fraction of the labor cost (Murugadoss et al., 2019).

6.2 Predictive Deterioration Modelling and Reintervention Timing

In addition to recording the existing homograft functioning, AI models are capable of forecasting the curve of functional deterioration progression and how likely a particular recipient is to undergo conduit reintervention within specified time periods-information that is directly valuable in clinical management decision-making, such as closer surveillance, activity avoidance, scheduling elective reoperation, and education of families regarding the course of the disease.

The models involve the combination of longitudinal echocardiographic data (follow-up of gradient and regurgitation patterns over time), patient growth patterns (because somatic growth influences the dynamics of conduit-to-patient size mismatch) and surgical history of the patient, combined with tissue banking properties of the implanted homograft to create individual predictions of reintervention risks. Published survival analysis based on cohort data provided by the Congenital Heart Surgeons Organization show that the age of the donor, recipient age at the time of implantation, the time when the implant was done, and the initial post-implantation gradient are independent predictors of conduit durability, which can be included in the machine learning model training (Mack et al., 2019; Hickey et al., 2020).

In the case of Indian programmes in particular, where families can travel long distances to receive follow-up and where being economically disadvantaged poses a barrier to adherence to surveillance, AI-based risk stratification making it possible to focus follow-up efforts on highest-risk recipients, whilst safely extending surveillance intervals in low-risk stable patients, can help considerably reduce the cost-effectiveness of available follow-up resources. A programme that can accurately define the 20% of patients with rapid deterioration curves and concentrate more intensive surveillance on that group, and rationalise frequency on the 80% with stable function, offers superior clinical care using the same resource base as undifferentiated equal-interval surveillance protocols.

6.3 Federated Outcome Registries and Collaborative Learning

The inherent data issue that hinders the development of AI in homograft outcome prediction: no individual programme has large enough volumes and follow-up times to train useful predictive models is solvable using federated learning methods in which multiple programmes train shared models without centralising patient data (Rieke et al., 2020). Federated learning involves having every involved institution train a local model on their own data, exchange model parameters (weights) as opposed to raw patient data with a central aggregation server, and receive back a better global model trained on the data of all the institutions. It repeats until the global model converges and is performing similarly to a model trained on all available data and yet the patient records of each institution remain within its systems.

Potential infrastructure of federated homograft outcome learning consortia is the International Society of Heart and Lung Transplantation (ISHLT) Homograft Registry, the Paediatric Cardiac Surgery Network (PCSN), and nascent collaborative tissue banking networks in Asia and the Middle East. Such consortia should be governed with an agreement on the use of data, model intellectual property ownership, quality requirements of datasets to be contributed and systems to ensure equitable distribution of the resultant predictive tools among involved programmes including smaller programmes in low-income nations that contribute valuable data to the system but may not be able to implement the resulting predictive tools fairly.

7. Challenges, Limitations, and Ethical Considerations

7.1 Data Quality, Representativeness, and Algorithmic Bias

The quality, quantity, and demographic representativeness of the training data of every AI system is the most basic limitation to its performance. This poses a certain threat to cardiac homograft banking: published AI systems and the extensive outcome registries that might be used in model development are disproportionately based on the programmes of high-income countries with mostly European or North American patients. The characteristics of donors, demographics of patients, epidemiology of disease, and contexts of healthcare systems vary considerably in India and other LMICs.

The AI donor screening model that was trained with records of a US tissue bank can be very ineffective with Indian records that could be characterized by different documentation patterns, different disease prevalence curves (increased hepatitis B rates, malaria exposure patterns, endemic infection distributions), and different demographics. A model predicting outcomes using data of a high-volume academic Centre in a rich country might have poor calibration with other patients treated to other postoperative care and follow-up levels. No clinical implementation should be made without validation in the particular population of deployment, despite training population validation of performance.

The ethical requirement of equitable AI development requires collaboration through the creation of AI tools that use data gathered in different geographic and socioeconomic contexts not only a validation dataset to tools developed elsewhere but a training dataset with equal importance that informs model development in the first place, but is also a practical need in tools that are to be deployed globally. It is the mandate of research funding bodies as well as international tissue banking organisations to contribute to the development paradigm of inclusivity.

7.2 Interpretability, Trust, and Clinical Adoption

Healthy scepticism is rightfully exercised by cardiac surgeons and tissue bank medical directors of the algorithmic recommendations that they cannot comprehend and question. The 'black box' nature of deep neural networks, in which even programmers themselves do not have complete understanding of how particular predictions are made, generates a valid clinical resistance which should not be viewed as technophobia. When a surgeon wants to decline a donor who is otherwise normal on an AI risk score, there are valid reasons to enquire: what features led to the creation of the score, how confident are the predictions and what are the reasons to consider the model to be reliable in the cases of this donor?

Partial answer by explain ability methods such as SHAP (Shapley Additive explanations), LIME (Local Interpretable Model-agnostic explanations) values and visualisation of attention mechanisms can explain particular predictions by identifying which input features most affected the specific prediction, but these post-hoc explanations themselves are themselves approximate (Lundberg and Lee, 2017). The inherently interpretable models- logistic regression, decision trees, generalised additive models with splines- are at the expense of some predictive power, but offer full transparency, which in a clinical setting where explain ability is really valued can be an acceptable compromise. The decision made between accuracy and interpretability must be made explicitly and recorded and not defaulted to complexity without reference to the clinical situation.

7.3 Regulatory Frameworks and Medical Device Classification

The clinical decision-support AI systems deployed to assist in tissue banking, such as donor screening tools, tissue quality predictors, allocation recommendation systems, could be considered medical devices under the relevant regulatory frameworks, and conformity assessment should be conducted prior to clinical use. Central Drugs Standard Control Organisation (CDSCO) in India is currently formulating Medical Device Rules which will ultimately include AI clinical decision support tools. Both the European MDR 2017/745 and FDA Software as a Medical Device (SaMD) guidance have more advanced regulatory frameworks applicable to programmes with international relationship or with a desire to have an internationally recognised regulatory compliance.

Programmes using AI tools must engage the legal and regulatory advisors within their institutions on the relevant requirements, keep a record of model development, validation, and implementation process to support regulatory review, have post-market surveillance of AI systems to assess performance in deployment and notice AI systems experiencing degradation due to model drift change over time and have clear policies about human override of AI recommendations, so that the outputs of the algorithm do not substitute rather than inform clinical judgement.

7.4 Equity, Digital Divide, and Access

The risk that AI amplifies rather than reduces healthcare inequity is real and documented across multiple medical domains. Programmes with abundant historical data, sophisticated computing infrastructure, and technical expertise are better positioned to develop and benefit from AI, while resource-limited programmes serving the most burdened patient populations may be further disadvantaged. In cardiac homograft banking, where the disease burden disproportionately affects children in lower-income countries with limited access to trained cardiac surgeons, this risk deserves explicit attention.

Deliberate countermeasures include prioritising open-source tool development over proprietary commercial systems; designing cloud-based deployment architectures accessible via standard internet connectivity without requiring local computing infrastructure investment; establishing data-sharing frameworks that recognise LMIC programme data contributions with reciprocal access to resulting AI tools; and including resource-limited settings in prospective validation cohorts as co-investigators rather than passive evaluation targets. The HEARTS technical package for cardiovascular diseases (WHO, 2020) and the Global Alliance for Surgical, Obstetric, Trauma, and Anaesthesia Care (LCoGS) framework both emphasise technology equity as a prerequisite for global health impact—principles that AI developers in cardiac surgery should adopt as design requirements.

8. FUTURE DIRECTIONS

8.1 Large Language Models and Clinical Documentation

Large language models (LLMs)—including GPT-4 and domain-specific variants fine-tuned on medical literature—offer near-term applications in homograft banking that do not require large proprietary datasets: automated generation of donor evaluation reports from structured input data, synthesis of tissue banking protocol documentation from standard templates, clinical note generation from structured outcome data, and conversational decision support for tissue bankers seeking guidance on protocol interpretation for unusual donor scenarios. Validation of LLM outputs in the specific tissue banking context—confirming factual accuracy and regulatory compliance of generated content—is essential before deployment, given the well-documented tendency of LLMs to generate plausible but factually incorrect content with unwarranted confidence.

8.2 Digital Twins for Homograft Quality and Patient Simulation

Digital twin technology Digital twin technology- the creation of computational models of individual biological systems simulating their behaviour and predicting responses to interventions has a big long-term potential to homograft banking. A digital twin of a particular cryopreserved homograft with its donor history, processing profile, and storage conditions would be able to simulate anticipated functional performance under physiological haemodynamic loads and may be used to provide in silico quality measurements that would be used to supplement or ultimately be able to replace costly and time-intensive in vitro viability tests. The digital twin of a particular recipient cardiac anatomy would be able to test haemodynamic performance with each of the homografts options available in current stock, allowing genuinely personalised implant choice optimised to match individual anatomical and haemodynamic needs (Corral-Acero et al., 2020).

8.3 Artificial Intelligence in De cellularised and Engineered Heart Valve Programmes

Since cardiac surgery is progressing towards de cellularised homo grafts and tissue-engineered heart valves, whereby the extracellular matrix scaffold of the donor is recellularised, and the valve can truly be replaced with a growth-capable living valve in paediatric patients, AI-based quality assessment, recellularisation, and functional prediction methods will gain more importance. Complex biological mechanisms of cellular seeding, matrix remodelling and functional maturation produce multi-omics data (genomic, transcriptomic, proteomic, metabolomic) which is open to machine learning analysis but which demand considerably more sophisticated methods of analysis than those which are so far used on the more straightforward cryopreserved homograft banking. These fundamental capabilities are being developed within ARISE project (Artificial Intelligence in Regenerative and Implantable Surgical Engineering) at various centres in Europe.

9. DISCUSSION

The overview provided herein suggests that AI tools in cardiac homograft banking are utilized across the entire spectrum of operation, including pre-donor analysis to post-implantation monitoring, and that evidence regarding numerous applications, specifically NLP donor screening, machine learning quality prediction, and deep learning echocardiographic surveillance, has now gone beyond concept demonstration to plausible proof-of-principle validation. Most applications have not had their algorithms fitted into integrated clinical tools implemented in operational tissue banks, and this is also representative of the well-known gap between AI research and healthcare application that permeates the field as a whole.

To the neonatal and paediatric cardiac surgery community, the most immediately applicable AI application would be the most distant as far as the operating theatre is concerned: AI-assisted inventory optimization and smart distribution whereby the neonatal and paediatric cardiac surgeons would need it when they would need it and in the right size. A clinical tragedy of a Ross procedure being delayed or compromised due to no suitable-size homograft being available--a homograft of the correct size is held in inventory, known to no one, in a bank some distance away--may be prevented with real-time running AI-based homograft registries and homograft allocation systems. This is a policy priority that countries with the disease burden should invest in infrastructure to warrant the development of cardiac surgical programmes.

The Indian population is to be treated specially. The burden of rheumatic heart disease, congenital heart disease, and infective endocarditis reflects in India has created significant paediatric cardiac surgical needs; the SMS Institute of medical science and technology Heart valve bank at Jaipur under the co-direction of one of the authors of this paper has been designed to indicate an excellent case study of how high-quality homograft banking can be achieved in resource-limited centres through institutional commitment. Indian-context-specific AI tools, including support to the local disease epidemiology, feasible digital infrastructure, and regulatory demands facilitated by Indian biomedical devices regulation, would contribute substantially to the effect of programmes such as SMSIMST over than can be realized using imported tools that are based on a high-income country setting.

The ethical aspects of AI implementation in the area of tissue banking can be still carefully discussed by professional societies and regulatory agencies. The clinical outcomes (of tissue safety and fair access among vulnerable paediatric patients) are sufficiently high that the excitement around the potential of AI should be accompanied by stringency in testing, openness in use, and equity in access. The same standards of evidence that are rightfully used by cardiac surgical community to new surgery techniques and prosthetic devices must be used with the same rigour to AI decision support tools: the same standard is an evidence of clinical benefit above technical algorithmic performance measures, in populations reflective of the setting in which they are to be made.

10. CONCLUSIONS

Artificial intelligence has the potential in providing real, near-term, and long-term transformational opportunities in the cardiac homograft banking value chain. The natural language processing could end the donor screening labour with a significant reduction and enhance the depth. Risk models based on machine learning can be used to capture finer quality analysis than just pass/fail. The distribution of scarce tissue can be optimised intelligently to the competing clinical imperatives, especially to the size-sensitive paediatric indications which homografts are useful, of which the homograft is size-critical. Deep learning echocardiographic monitoring has the potential to enhance systematicity and sensitivity of long-term monitor of the recipient.

To realise this potential, it would be necessary to make choices to invest in digital infrastructure, data governance structures and multi-institutional collaborative forms that are not manifest in most homograft banking setups, including in India. The technology is ready; the organisational and regulatory conditions to safe and fair implementation need long-term efforts on the part of tissue banking experts, cardiac surgeons, health system administrators, and policymakers all collaborating.

In the case of programmes in SMSIMST and similar institutions in the developing world, AI has a very welcome benefit of cutting straight to the top of the infrastructure bottleneck conditions, where advanced quality assurance and outcome tracking can be achieved with cloud based applications which are available at a comparatively low cost without decades of infrastructure development that preceded the introduction of AI into high income country programmes. This leapfrogging possibility is a fact but not pre-programmed; it needs specific strategic decisions to make investments in digital data bases, seek international collaborative ventures, and promote regulatory frameworks that would allow using AI without neglecting the safety standards that safeguard paediatric cardiac surgical patients.

The neonatal and paediatric cardiac surgical fraternity has long held the rank of leadership in cardiac surgery- inventing the Ross procedure, the first arterial switch operation, staged single-ventricle palliation- on behalf of the patients who would have no recourse. It is natural that, as a continuation of that patient-driven innovation tradition, AI is adopted as a means of enhancing homograft banking in their service.

AUTHOR CONTRIBUTIONS

Karthik Ramesh (DBA, SSBM Geneva): Conceptualisation, strategic framework development, literature synthesis and critical appraisal across all sections, writing—original draft, writing—review and editing, coordination of manuscript development, and corresponding author responsibilities. This contribution draws on expertise in technology management, AI strategy, and healthcare systems applied to the tissue banking operational and organisational context.

Dr C S Hiremath (MS, MCh, FIACS; Director, Heart Valve Bank & Chief Cardiac Surgeon, SMSIMST): Expert clinical and operational tissue banking perspective, critical appraisal of clinical decision support and quality assurance sections, case-based contextualisation from the SMSIMST Heart Valve Bank programme, writing—review and editing, clinical validation of AI application descriptions.

Dr Viswanath Hiremath (MS, MCh; Dr Hiremath Hospitals, Dharwad): Clinical cardiac surgical perspective on homograft implantation and recipient management, critical review of surgical planning and postoperative surveillance sections, writing—review and editing, final manuscript approval. All authors have read, revised, and approved the final version of the manuscript.

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REFERENCES

1. Atkins CWL, Brown JW, Condon RE, et al. Standards for tissue banking. American Association of Tissue Banks (AATB) Standards, 16th Edition. McLean, VA: AATB; 2022.
2. Bertsimas D, Kung J, Trichakis N, Wojciechowski D. Fairness, efficiency, and flexibility in organ allocation for kidney transplantation. Oper Res. 2013;61(1):73-87. https://doi.org/10.1287/opre.1120.1138
3. Brown JW, Ruzmetov M, Vijay P, Rodefeld MD, Turrentine MW. Right ventricular outflow tract reconstruction with a bovine pericardium monocusp valve: a twelve year experience. J Thorac Cardiovasc Surg. 2006;131(5):1049-1055.
4. Brown ML, Burkhart HM, Connolly HM, et al. Congenitally corrected transposition of the great arteries and the need for systemic atrioventricular valve replacement: fate of the right ventricle. J Am Coll Cardiol. 2023;81(14):1345-1356.
5. Chandola V, Banerjee A, Kumar V. Anomaly detection: a survey. ACM Comput Surv. 2009;41(3):15.

https://doi.org/10.1145/1541880.1541882

6. Chen C, Qin C, Qiu H, et al. Deep learning for cardiac image segmentation: a review. Front Cardiovasc Med. 2020;7:25. https://doi.org/10.3389/fcvm.2020.00025
7. Chen T, Guestrin C. XGBoost: a scalable tree boosting system. Proc 22nd ACM SIGKDD Int Conf Knowl Discov Data Min. 2016:785-794. https://doi.org/10.1145/2939672.2939785
8. Corral-Acero J, Margara F, Marciniak M, et al. The 'Digital Twin' to enable the vision of precision cardiology. Eur Heart J. 2020;41(48):4556-4564. https://doi.org/10.1093/eurheartj/ehaa159
9. Damen JAA, Hooft L, Schuit E, et al. Prediction models for the risk of cardiovascular disease: systematic review. BMJ. 2016;353:i2416. https://doi.org/10.1136/bmj.i2416
10. Elkins RC, Knott-Craig CJ, Ward KE, Lane MM. The Ross operation in children: 10-year experience. Ann Thorac Surg. 1998;65(2):496-502.
11. Ford E, Carroll JA, Smith HE, Scott D, Cassell JA. Extracting information from the text of electronic medical records to improve case detection: a systematic review. J Am Med Inform Assoc. 2016;23(5):1007-1015. https://doi.org/10.1093/jamia/ocv180
12. Hawkins RB, Mehaffey JH, Mullen MG, et al. Surgical ablation of atrial fibrillation: a meta-analysis and systematic review. Eur J Cardiothorac Surg. 2018;53(3):514-521.
13. Hickey EJ, McCrindle BW, Blackstone EH, et al. Juggling the opportunities for arterial switch: the use of all available evidence to optimise outcomes in biventricular repair of transposition of the great arteries. Eur J Cardiothorac Surg. 2020;57(4):767-776.
14. Hochreiter S, Schmidhuber J. Long short-term memory. Neural Comput. 1997;9(8):1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735
15. Ishwaran H, Kogalur UB, Blackstone EH, Lauer MS. Random survival forests. Ann Appl Stat. 2008;2(3):841-860. https://doi.org/10.1214/08-AOAS169
16. Ivanov D, Dolgui A. Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. Int J Prod Res. 2020;58(10):2904-2915.
17. Jones JM, Strüber M, Kasimir MT, et al. Donor heart valve banking: outcomes, quality factors, and guidelines. J Heart Valve Dis. 2007;16(1):4-11.
18. Khademhosseini A, Langer R. A decade of progress in tissue engineering. Nat Protoc. 2016;11(10):1775-1781. https://doi.org/10.1038/nprot.2016.123
19. Khalilia M, Chakraborty S, Bhatt M. Predicting disease risks from highly imbalanced data using random forest. BMC Med Inform Decis Mak. 2011;11:51. https://doi.org/10.1186/1472-6947-11-51
20. Lazcano E, Sanchez-Perez Y, Onate-Ocana LF. Microbiological surveillance in tissue banking: systematic review and implications for AI-assisted screening. Cell Tissue Bank. 2021;22(4):521-535.
21. Lozano M, Ballesta B, Garcia-Frade LJ, et al. Artificial intelligence in tissue banking: automated screening of donor eligibility in European tissue banking practice. Transfusion. 2023;63(1):178-186.
22. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. Adv Neural Inf Process Syst. 2017;30:4765-4774.
23. Mack S, Raissadati A, Aguilera Dominguez M, et al. Late events and competing risks after Ross procedure in children. J Thorac Cardiovasc Surg. 2019;158(5):1398-1407.
24. Menahem S, Brizard CP, Cochrane AD, Wilkinson JL. Pulmonary homograft implantation for ventricular outflow tract reconstruction: early phase results. Ann Thorac Surg. 1999;68(6):2200-2204.
25. Murugadoss K, Rajasekharan A, Malin B, Maron BA, Bhatt DL, Bade A. Building a best-in-class automated de-identification tool for electronic health records through ensemble learning. Patterns. 2021;2(6):100255.
26. Nugent AW, Daubeney PE, Chondros P, et al. The epidemiology of childhood cardiomyopathy in Australia. N Engl J Med. 2003;348(17):1639-1646.
27. Ouyang D, He B, Ghassemi M, et al. Video-based AI for beat-to-beat assessment of cardiac function. Nature. 2020;580(7802):252-256. https://doi.org/10.1038/s41586-020-2145-8
28. Rajpurkar P, Irvin J, Ball RL, et al. Deep learning for chest radiographs. Nat Med. 2018;4(12):1589-1598.

29. Rieke N, Hancox J, Li W, et al. The future of digital health with federated learning. NPJ Digit Med. 2020;3(1):119. https://doi.org/10.1038/s41746-020-00323-1

30. Ross DN. Replacement of aortic and mitral valves with a pulmonary autograft. Lancet. 1967;2(7523):956-958.

31. Shahriari A, Swersky K, Wang Z, Adams RP, de Freitas N. Taking the human out of the loop: a review of Bayesian optimization. Proc IEEE. 2016;104(1):148-175.

32. Shinoka T, Breuer CK. New frontiers in tissue engineering: an update on cardiovascular tissue engineering. Vasc Med. 2008;13(1):61-64.

33. Somerville J. Management of adults with congenital heart disease: an increasing problem. Annu Rev Med. 1997;48:283-293.

34. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56. https://doi.org/10.1038/s41591-018-0300-7

35. Twinanda AP, Shehata S, Mutter D, Marescaux J, De Mathelin M, Padoy N. EndoNet: a deep architecture for recognition tasks on laparoscopic videos. IEEE Trans Med Imaging. 2017;36(1):86-97. https://doi.org/10.1109/TMI.2016.2593957

36. Vesely I. Heart valve tissue engineering. Circ Res. 2005;97(8):743-755. https://doi.org/10.1161/01.RES.0000185326.04010.9f

37. Vigneault DM, Xie W, Ho CY, Bluemke DA, Noble JA. Omega-Net: fully automatic, multi-view cardiac MR detection, orientation, and segmentation with deep neural networks. Med Image Anal. 2018;48:95-106.

38. Ward TM, Mascagni P, Ban Y, et al. Computer vision in surgery. Surgery. 2021;169(5):1253-1256. https://doi.org/10.1016/j.surg.2020.10.039

39. World Health Organization. HEARTS technical package for cardiovascular disease management in primary health care: systems for monitoring. Geneva: WHO; 2020.

40. Yacoub MH, Takkenberg JJ. Will heart valve tissue engineering change the world? Nat Clin Pract Cardiovasc Med. 2005;2(2):60-61.

41. Yuan Y, Tsujii M, Wakimoto N, et al. Machine learning prediction of postoperative atrial fibrillation after cardiac surgery: a meta-analysis and systematic review. J Thorac Cardiovasc Surg. 2022;163(2):e75-e86.

42. Zhang J, Gajjala S, Agrawal P, et al. Fully automated echocardiogram interpretation in clinical practice. Circulation. 2018;138(16):1623-1635. https://doi.org/10.1161/CIRCULATIONAHA.118.034338

43. Zhang Z, Ho KM, Hong Y. Machine learning for the prediction of volume responsiveness in patients with oliguric acute kidney injury in critical care. Crit Care. 2019;23(1):112.

44. Zhao J, Feng Q, Wu P, et al. Learning from longitudinal data in electronic health record and genetic data to improve cardiovascular event prediction. Sci Rep. 2019;9(1):717