Multinational AI Research: How to Engage Globally

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Declaration of Interest





We have no conflicts to declare

Challenges that need global engagement





- Data availability and data sharing
- Generalizability
- Mitigation of unintended bias
- Data protection and privacy preserving
- Validation of performance for regulatory approval
- Clinical education for global adoption of AI-enabled solutions
- Democratization: opportunities for low- and middle-income countries



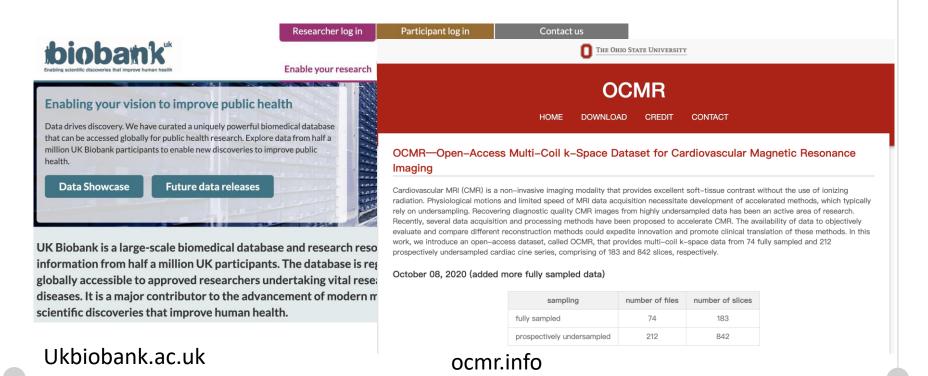


- Biobanks and Registries
- Benchmark challenges
- Global effort for annotations/labels





Biobanks







SCMR Registry

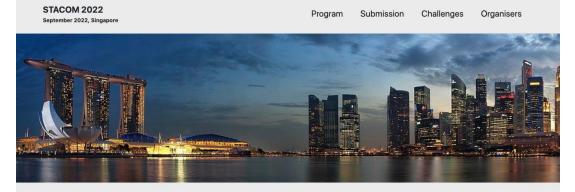


Challenges





MICCAI



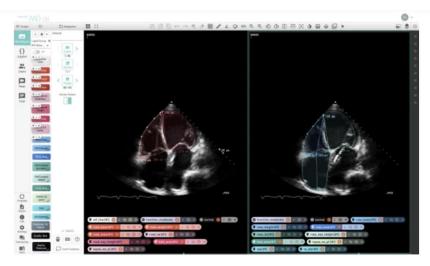
The Statistical Atlases and Computational Modeling of the Heart (STACOM) workshop has been running annually at MICCAI since 2010. The 13th edition of STACOM workshop is going to be held in conjunction with the MICCAI 2022 in Singapore. The STACOM workshop is aiming to create a collaborative forum for young/senior researchers (engineers, biophysicists, mathematicians) and clinicians, working on: statistical analysis of cardiac morphology and dynamics, computational modelling of the heart and fluid dynamics, data/models sharing, personalisation of cardiac electro-mechanical models, quantitative image analysis and translational methods into clinical practice.

https://stacom.github.io/stacom2022/

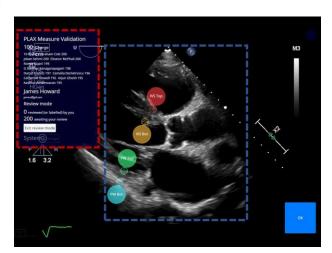




Efforts for annotations/labels



Cloud-based tools such as MD.ai can be used to generate expert-annotated datasets and evaluate them against clinical experts via a secure connection. An implementation of MD.ai in which clinical experts make a variety of 2D measurements to quantify cardiac function is shown. Credit: MD.ai Inc, NY.



The unity interface (www.unityimaging.net)

Nature Machine Intelligence 3:929–935 (2021)

Circ Cardiovasc Imaging. 2021;14:e011951.

Generalizability

SCMR Society for Cardiovascular Magnetic Resonance

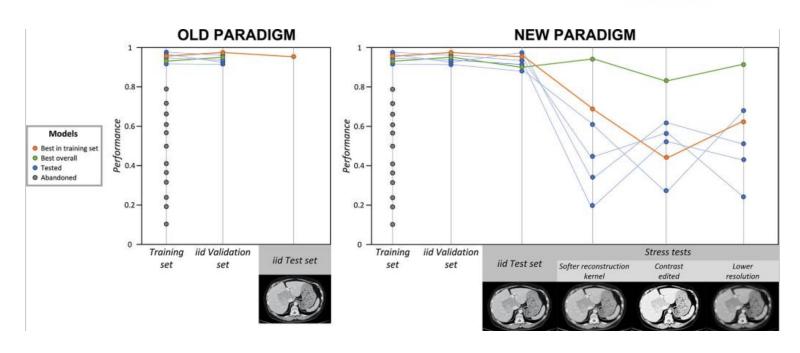


- Across sites and vendors
- Across imaging sequences and applications
- Across patient cohorts
- Across race and gender

Generalizability







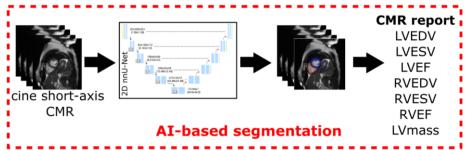
Radiol Artif Intell. 2021 Nov; 3(6): e210097.

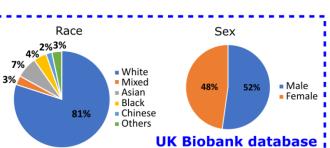
Generalizability





Across race and gender





N = 1,250	Dice	Absolute difference			
	similarity	LVEDV	LVESV	LVmass	RVEDV
Total	93.0 (3.8)	4.6 (3.0)	3.7 (3.1)	7.4 (5.6)	6.2 (4.7)
Male	93.0 (3.6)	4.7 (3.0)	3.7 (2.9)	7.9 (6.2)*	6.1 (4.6)
Female	93.1 (4.0)	4.6 (3.0)	3.6 (3.2)	6.8 (5.0)*	6.3 (4.7)
White	93.9 (3.1)	4.2 (2.7)*	3.3 (2.8)*	7.1 (5.9)*	5.9 (4.7)*
Mixed	86.7 (2.1)	7.1 (3.5)*	6.2 (2.9)*	7.7 (4.3)	8.5 (3.1)*
Asian	89.8 (4.4)	6.1 (3.5)*	4.9 (4.1)*	8.7 (4.3)*	8.2 (4.3)*
Black	89.9 (2.6)	6.2 (3.3)*	4.3 (3.8)	7.3 (3.7)	7.9 (2.7)*
Chinese	86.3 (5.5)	8.0 (3.9)*	6.4 (4.1)*	10.6 (4.8)*	8.2 (4.0)
Others	88.8 (2.8)	6.3 (3.2)*	5.7 (4.0)	7.6 (3.6)	7.3 (5.7)

Frontiers Cardiovasc. Med., 07 April 2022 | https://doi.org/10.3389/fcvm.2022.859310

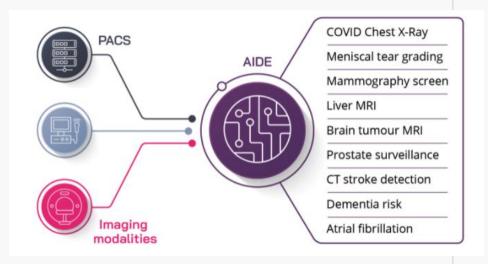
AI4VBH





Data Pathway:

- Retrospective cases identified by GSTT team
- Images (MRI exams, over time) obtained from PACS
- Associated clinical information (height, weight, diagnosis, type of interventions) obtained from reports
- Data is anonymised (identifying information removed, including exact dates)
- Ported to database at KCL
- Processing by approved personnel
- Relationships, markers, predictions identified, published
- Tools tested prospectively at GSTT and elsewhere

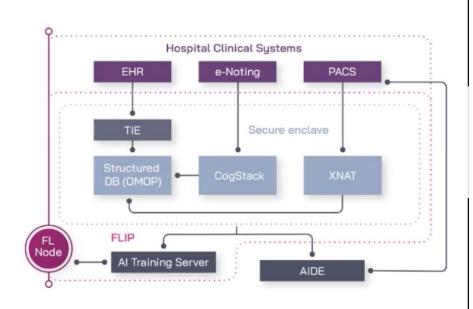


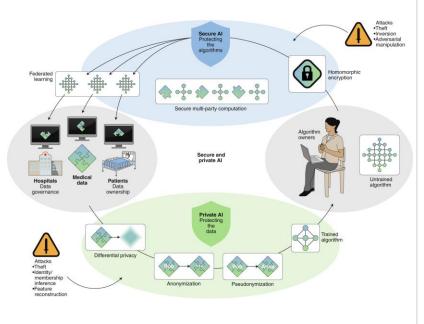
Data protection and Privacy preserving





Federated learning





npj Digital Medicine (2020) 3:119; Nature Machine Intelligence 2: 305-311 (2020)

Validation for regulatory approval





- Multicenter studies and evaluation
- Multicenter Clinical trials



https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1270.pdf https://www.nhsx.nhs.uk/ai-lab/ai-lab-programmes/the-national-strategy-for-ai-in-health-and-social-care/

Clinical education for global adoption of Al-enabled solutions





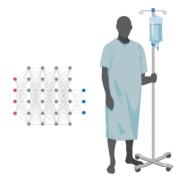
Al training domains

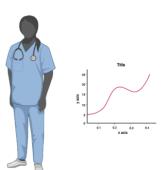
Data entry and curation
ML theory and statistics
Algorithm interpretation

Explainable AI communication

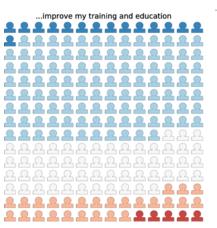
AI ethics

Information overload resilience

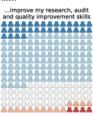




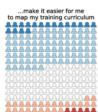
Al systems being used in healthcare will...

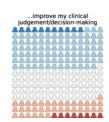










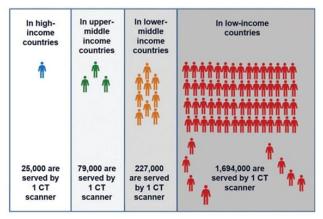


Democratization: opportunities for low and middle-income countries





Artificial Intelligence in Low- and Middle-Income Countries: Innovating Global Health Radiology



Comparison of CT accessibility in low-, middle-, and high-income countries.

- Artificial intelligence (AI) introduction in low- and middle-income countries (LMICs) should proceed differently than in high-income countries.
- Large differences in personnel, clinical experience, disease patterns, demographics, digital infrastructure, and radiology equipment dictate the need for a global health radiology AI strategy.
- A comprehensive model for AI adoption in LMICs integrates clinical education, infrastructure deployment, and phased AI introduction.

Mollura DJ et al. Published Online:: October 6, 2020 https://doi.org/10.1148/radiol.2020201434



Summary





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