





15:45 - 17:25

Session 4: Specific post-market considerations for AI MDs



15:45 - 16:00

Monitoring of endpoints (surrogate and non-surrogate)



Leo Hovestadt

Chair, Global Diagnostic Imaging, Healthcare IT & Radiation Therapy Trade Association (DITTA) & Medical Device Coordination Group Working Groups (CIE WG)





Overview – Al endpoint categories

Agenda:

Al endpoints categories

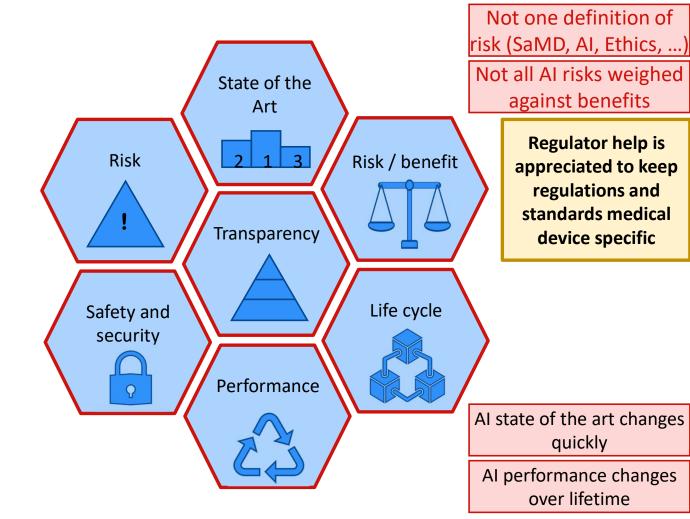
Transparency matrix and endpoints



Insider transparency: PMCF endpoints

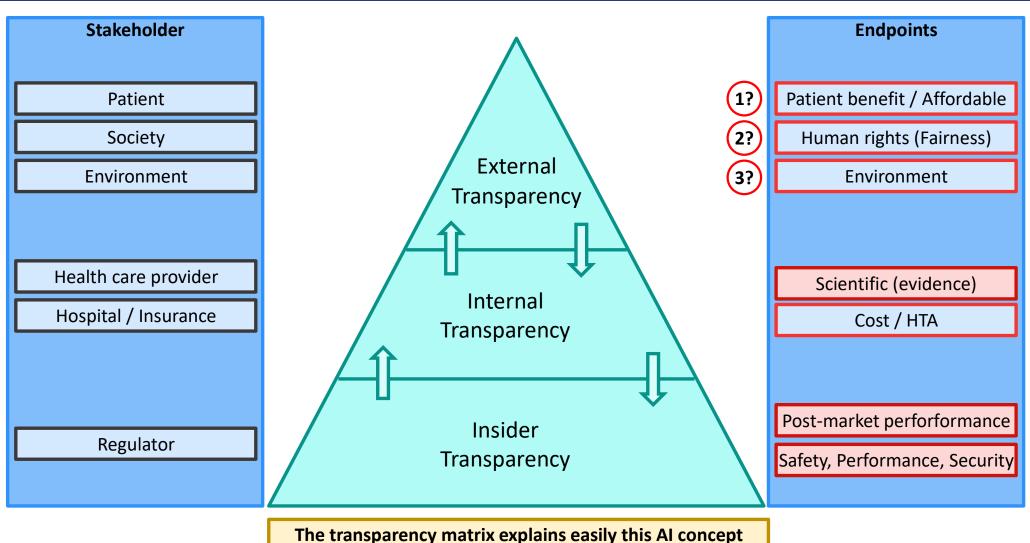


Internal transparency: IDEAL endpoints

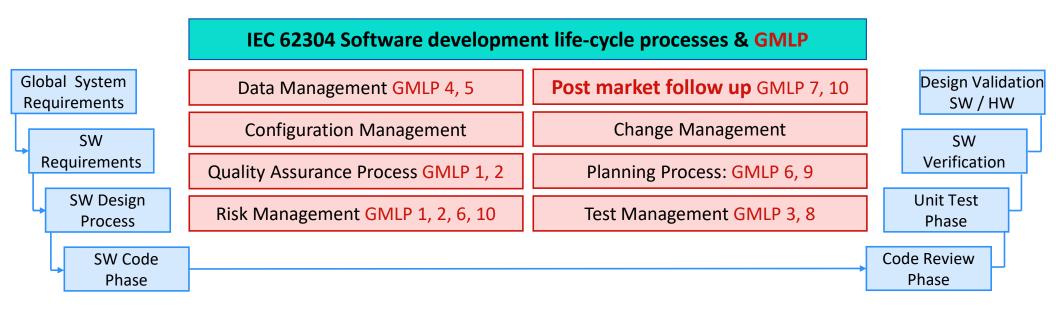


Transparency matrix and AI endpoint stakeholders





Insider transparency: AI PMCF endpoints and SamD life cycle and GMLP



GMLP PMCF endpoint examples

GMLP 6, 10 Commissioning: Endpoint for overfitting of deployed model

GMLP 6 Life cycle: Endpoint for performance degradation

GMLP 7 Life cycle: Endpoint for growing usability issues

PMCF example related issues

GMLP 10 Life cycle: Plan algorithm retraining and change

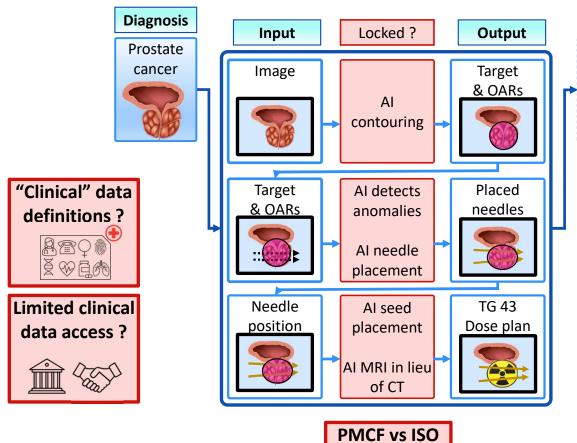
management

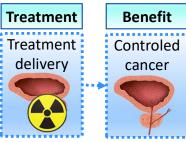
GMLP 10 Life cycle: Plan usage of sandboxes

GMLP 10 End of life: Manage disposal of the training data

GMLP integrates well in IEC 62304

Insider transparency AI PMCF endpoint reflections





Complexities?

- Al treats, diagnosis, drives, informs, ...
- Prognosis, patient management...
- Machine / deep learning, unsupervised, ...

Relation to premarket endpoints?

- Valid clinical association
- Analytical verification / validation
- Clinical validation

14155 ?

GMLP integrates well in IEC 62304

Internal transparency: R-IDEAL endpoints for radiotherapy: reflections

Milestones	Purpose	Endpoints (Outcomes)	Study design
Stage 0 Predicate studies	 How to use the innovation (software, coils needed)? Why and in whom to use the innovation? 	 MR sequences, dedicated coils, etc. Inter-rater reproducibility Treatment strategies, patient selection 	Phantom studies, delineation studies, planning studies, model-based studies
Stage 1 Idea	First time use of the innovation for treatment delivery in men	Proof of concept	Structured case report
Stage 2a Development	Technical optimization of the innovation for treatment delivery	Technical improvements, feasibility, and safety	Prospective small uninterrupted case series
Stage 2b Exploration	Provide proof of early clinical effectiveness and safety of the innovation	 Early effectiveness: toxicity tumor response local recurrence (with spacious information) 	Prospective study with preferably randomized component: RCT; cmRCT; random allocation of limited available treatment slots to eligible patients; Comparison with matched (historical) controls
	Formal comparison of innovation against standard treatment Development of clinical guidelines?	 Effectiveness compared to standard treatment: (disease-free) survival /recurrence / toxicity PROMs, CTC-PRO, Cost effectiveness 	RCT, cmRCT, registry-based trial Scientific (evidence)? Safety, Performance
Stage 4 Long-term evaluation	Long-term outcomes of the innovation, post-marketing, and surveillance Clinical guidelines by clinicians or manufacturers?	Long-term toxicity, long-term (disease-free) survival, rare side effects, Patient-Reported Outcomes	Prospective registries, including all patients treated with the innovation Post-market monitoring



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Back-up slide - Good Machine Learning Practices (GMLP)

- 1. Multi-Disciplinary Expertise Is Leveraged Throughout the Total Product Life Cycle: In-depth understanding of a model's intended integration into clinical workflow, and the desired benefits and associated patient risks, can help ensure that ML-enabled medical devices are safe and effective and address clinically meaningful needs over the lifecycle of the device.
- 2. Good Software Engineering and Security Practices Are Implemented: Model design is implemented with attention to the "fundamentals": good software engineering practices, data quality assurance, data management, and robust cybersecurity practices. These practices include methodical risk management and design process that can appropriately capture and communicate design, implementation, and risk management decisions and rationale, as well as ensure data authenticity and integrity.
- 3. Clinical Study Participants and Data Sets Are Representative of the Intended Patient Population: Data collection protocols should ensure that the relevant characteristics of the intended patient population (for example, in terms of age, gender, sex, race, and ethnicity), use, and measurement inputs are sufficiently represented in a sample of adequate size in the clinical study and training and test datasets, so that results can be reasonably generalized to the population of interest. This is important to manage any bias, promote appropriate and generalizable performance across the intended patient population, assess usability, and identify circumstances where the model may underperform.
- **4. Training Data Sets Are Independent of Test Sets**: Training and test datasets are selected and maintained to be appropriately independent of one another. All potential sources of dependence, including patient, data acquisition, and site factors, are considered and addressed to assure independence.
- **5. Selected Reference Datasets Are Based Upon Best Available Methods**: Accepted, best available methods for developing a reference dataset (that is, a reference standard) ensure that clinically relevant and well characterized data are collected and the limitations of the reference are understood. If available, accepted reference datasets in model development and testing that promote and demonstrate model robustness and generalizability across the intended patient population are used.
- 6. Model Design Is Tailored to the Available Data and Reflects the Intended Use of the Device: Model design is suited to the available data and supports the active mitigation of known risks, like overfitting, performance degradation, and security risks. The clinical benefits and risks related to the product are well understood, used to derive clinically meaningful performance goals for testing, and support that the product can safely and effectively achieve its intended use. Considerations include the impact of both global and local performance and uncertainty/variability in the device inputs, outputs, intended patient populations, and clinical use conditions.
- **7. Focus Is Placed on the Performance of the Human-Al Team**: Where the model has a "human in the loop," human factors considerations and the human interpretability of the model outputs are addressed with emphasis on the performance of the Human-Al team, rather than just the performance of the model in isolation.
- 8. Testing Demonstrates Device Performance during Clinically Relevant Conditions: Statistically sound test plans are developed and executed to generate clinically relevant device performance information independently of the training data set. Considerations include the intended patient population, important subgroups, clinical environment and use by the Human-AI team, measurement inputs, and potential confounding factors.
- 9. Users Are Provided Clear, Essential Information: Users are provided ready access to clear, contextually relevant information that is appropriate for the intended audience (such as health care providers or patients) including: the product's intended use and indications for use, performance of the model for appropriate subgroups, characteristics of the data used to train and test the model, acceptable inputs, known limitations, user interface interpretation, and clinical workflow integration of the model. Users are also made aware of device modifications and updates from real-world performance monitoring, the basis for decision-making when available, and a means to communicate product concerns to the developer.
- 10. Deployed Models Are Monitored for Performance and Re-training Risks are Managed: Deployed models have the capability to be monitored in "real world" use with a focus on maintained or improved safety and performance. Additionally, when models are periodically or continually trained after deployment, there are appropriate controls in place to manage risks of overfitting, unintended bias, or degradation of the model (for example, dataset drift) that may impact the safety and performance of the model as it is used by the Human-Al team.



16:00 - 16:20

Bias in the post-market phase



Anindita Saha

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Bias in the Post-Market Phase

Pat Baird, Philips

March 27, 2023





What do we mean by "Bias"?

"Bias" is defined in IMDRF's Machine Learning-enabled Medical Devices: Key Terms and Definitions:

Systematic difference in treatment of certain objects, people, or groups in comparison to others.

Note 1 to entry: Treatment is any kind of action, including perception, observation, representation, prediction or decision. (ISO/IEC TR 24027:2021)

Note: The term 'Bias' is used **in different ways in different fields.** For example, in data science, bias is often defined with a statistical/mathematical meaning while in law, bias is often used to **mean unfair or unfairly prejudiced/partial**.

ISO/IEC TR 24027 refers to systems having both "wanted" and "unwanted" bias depending on the intended purpose of an AI(-based) system.

Sources of bias include:

- human cognitive biases (including automation bias, societal bias, and confirmation bias),
- data biases (including statistical bias, data processing bias, and data aggregation bias), and
- bias introduced by engineering decisions (e.g., during feature engineering, via algorithm selection, and model bias)

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BIBO!

We are familiar with the concept of "Garbage In, Garbage Out (GIGO)" – there is a similar term "Bias In, Bias Out (BIBO)"

Bias is like a magnifying mirror – it reflects (and possibly enhances) bias that already exists in healthcare.





A system trained to detect breast cancer did not perform as well on African-American women; they weren't fully represented in the training set as the developers did not realize that tissue density varies by race.

A system intended to detect early onset of a disease used healthcare costs as a proxy measure for how sick a patient is. Unfortunately, some patients are poor and could not afford proper treatment of their disease. The software concluded that people that live in poor neighborhoods were at low-risk because they didn't seek medical care..

Positive Bias: A hospital once approached me and started asking questions about the patient demographics used to train one of our products. They did not want a product that was trained with a large, diverse dataset (e.g. representing patients across the country); they wanted something that was specifically trained for **their** patients (e.g. patients living in a retirement community on the beach..)



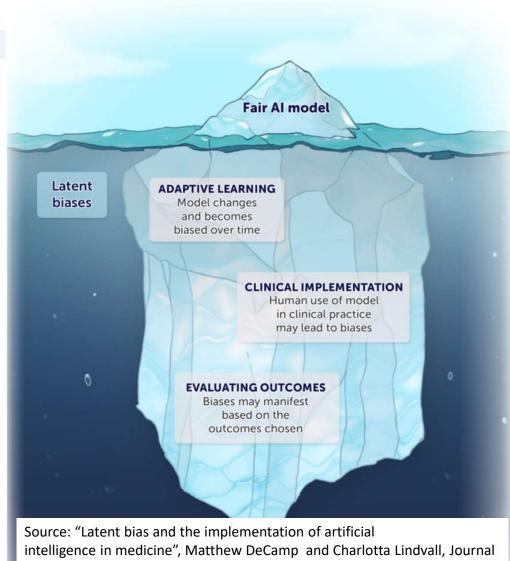
Bias in the Post-Market Phase

A seemingly fair AI model could involve latent biases after clinical implementation.

"Increasing recognition of biases in artificial intelligence (AI) algorithms has motivated the guest to build fair models, free of biases. However, building fair models may be only half the challenge. A seemingly fair model could involve, directly or indirectly, what we call "latent biases." Just as latent errors are generally described as errors "waiting to happen" in complex systems, latent biases are biases waiting to happen."

One of the goals of post-market activities will be to monitor for bias...





of the American Medical Informatics Association, 00(0), 2020, 1-4

Similarities & Differences

There are similar problems in post-market as there are in pre-market. For example, one of the challenges is getting data from small, rural hospitals with limited resources – this is true in the post-market phase as well. The patient demographics for those hospitals is likely different than patients in large city hospitals.

Post-market data isn't always of the same quality as pre-market data, but for the system to effectively learn, we need high quality data & need to be aware of potential bias in that data.



Additional considerations

One of my committees recently released a paper about bias management, and it included a discussion of post-market activities. The recommended data collection process was similar to our current processes; the differences were in the review of the data:

- Identify necessary changes to existing residual impact assessments of bias source/ type/sequence combinations (i.e., impact level, likelihood of occurrence, likelihood of impact).
- Identify new bias source/type/sequence combinations.
- Identify new uses or foreseeable misuses of the system that may drive new or changed bias source/type/sequence combinations.
- Identify changes to the stated benefits of the system.
- Identify changes in what may be considered positive, negative, or neutral bias.
- Identify changes in the criteria for determining the acceptability of bias at both a bias source/type/sequence combination level and a system level.
- Identify new bias mitigations for existing bias source/type/sequence combinations.





Additional considerations

That committee is currently working on a paper about ML post-market considerations, and when I mentioned this presentation to them, they wanted to add:

- 1. Post-market might detect types of bias that were not identified during development.
- 2. Target demographic can change over time the patient population may change (drift.)
- 3. The deployment model for the product and the listening model for post-market information might have bias (e.g. small hospital example)
- Because we are not collecting ALL data, we might not know about ALL potential biases.

Because of these factors, for learning systems, consideration should be given for what is needed in a rollback plan.





Resources

Bias has gotten a lot of attention and many papers, guidance, and standards have already been created – the IMDRF can leverage the existing work. Example resources include:

- NMPA AI Framework
- ISO/IEC TR 24027:2021 Information technology Artificial intelligence (AI) Bias in AI systems and AI aided decision making
- IEEE P7003 Algorithmic Bias Considerations
- Bias in Artificial Intelligence in Healthcare Deliverables, AFDO/RAPS Healthcare Products AI Global Initiative
- CTA 2116 (draft) The Use of Artificial Intelligence in Health Care: Best Practices and Recommendations for Bias Management





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16:20 - 16:40

Change management



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Director, Medical Devices, Medical Devices Cluster, Health Products Regulation Group, Health Sciences Authority



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SVP – Chief Regulatory Officer, SOPHiA Genetics











Specific Post-market Considerations for AI MDs

Dr Rama Sethuraman

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27 March 2023





Regulatory Approach for Change Management in Al Medical Devices

Singapore Perspective



Health Sciences Authority





HSA's Role in Health Products Regulation

Our Role

- Ensure that pharmaceuticals, biologics, <u>medical devices</u> and health-related products in Singapore are wisely regulated to meet appropriate standards of safety, quality and efficacy throughout the product life cycle
- Ensure timely access to good quality & safe health products
- Support the health and biomedical sciences industry and facilitating its development

Our Regulatory Philosophy

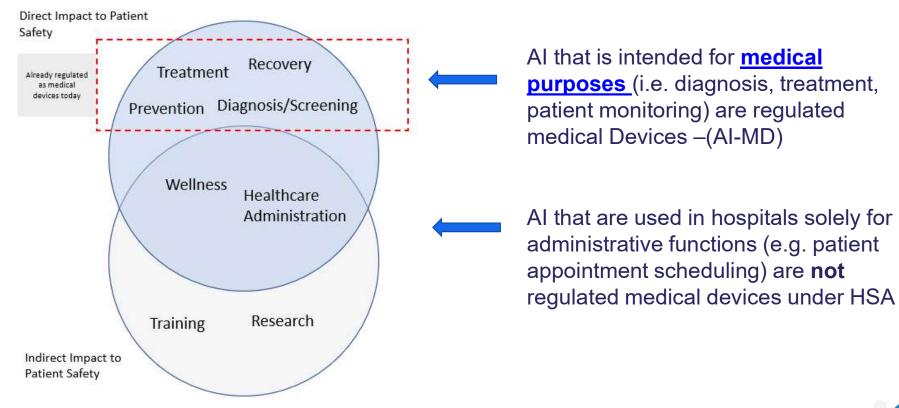
- Benefits outweigh foreseeable risks
- 2 Risk-based approach

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- 3 Confidence-based approach
- Adoption and judicious adaption of international standards & best practices
- 5 Forging strategic partnership both regionally in ASEAN and internationally

Artificial Intelligence based Medical Devices (AI-MD)

Use-cases of AI in Healthcare





Legislative definition of "Medical Device" can be found in the First Schedule of the Health Products Act 2007: http://statutes.agc.gov.sg/

Regulating Al-MDs: Need for a Tailored Approach

- Unique manufacturing processes (model selection, training, validating, re-training, bug fixing, programming) and facilities
- Short development time and short lifecycle
- Constant change and updates (intended changes and unintended or consequential changes)
 - o Learning from real world use data and improving performance
- Connectivity and Data related risks
 - Cybersecurity, Data integrity, Data security
- Continuous learning and deployment of upgrades or newer versions
 - Version controls; Traceability
 - o Ability to track and revert to older versions; Recall actions



Risk Classification of Al-MDs

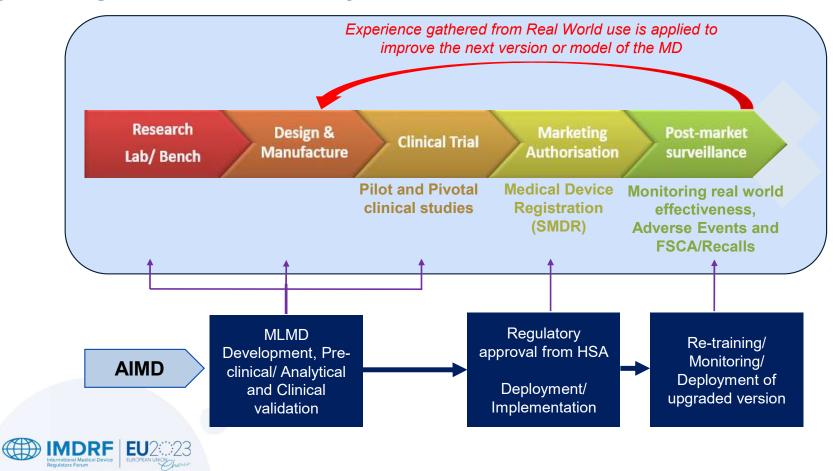
- Risk Classification approach for Al-MDs is similar to the approach for SaMDs
 - HSA Guidelines on Risk Classification of SaMD* and Qualification of CDSS# published in April 2022;
 Accessible online at: https://www.hsa.gov.sg/medical-devices/guidance-documents
 - Aligned to the IMDRF's guidelines on risk categorisation for SaMD
 - o In assigning risk class, manufacturer's intent based on design and claims for their AI-MD is considered
 - Functionalities and Features (e.g. analyse, monitor, adjust or control therapy)
 - Output from the AI-MD (e.g. triage, recommend, diagnose, therapy recommendations)





*SaMD – Software as Medical Device (aka Standalone Medical Mobile applications in Regulations in Singapore)
#CDSS – Clinical Decision Support Software

Regulating Al-MD – A Lifecycle Approach



Change Management for Medical Devices

- A risk calibrated approach to regulating post-approval changes for medical devices
- Significance of the change based on the intended and any consequential impact on the registered medical device, arising from the change such as
 - Impact on the device safety/quality/efficacy
 - o Impact on the approved performance specifications
 - o Impact on the clinical use cases (e.g. disease condition, patient types)
 - o Impact on the device functionalities
- Level of HSA's regulatory oversight titrated based on the significance of the change to the medical device;
 Includes
 - Evaluation and approval process
 - Notification
 - No submission required

NOTE: Changes that result in a new intended use for the medical device will require new pre-market application



Change Management for Al-MDs

- During pre-market evaluation, manufacturers are required to provide the following information for their AI-MDs
 - Specifications of their AI-MD including the input data types and parameters, clinical association with the output parameters, nature of output and indications for use that has been validated for the AI-MD
 - o Procedures implemented to monitor and manage the current performance and also future retraining and implementation of changes to their Al-MDs which could include managing the training and validation datasets, re-training of algorithm, performance evaluation and upgrades
- In particular, for continuous learning algorithm based Al-MDs, the learning process including process controls, verification, ongoing model monitoring measures and the allowable range of performance specifications should be clearly defined
- All post-approval changes to the Al-MD must be managed within the processes established by the manufacturer and under their QMS
 - Any changes to the pre specified procedures and specifications would typically affect the AI-MD performance and deemed significant. Such changes would likely require evaluation and approval by HSA



Change Management for AI-MDs

Technical/Review Changes Subject to Evaluation & Approval	 Significant changes that impact the safety/quality/efficacy of registered Al-MD or the approved performance specifications Addition of new functionalities or new indications for use New versions of Al-MD with enhanced performance Change to the degree of automation of the Al-MD For continuous learning algorithms: Changes to inclusion/exclusion criteria for real world input data and allowable boundaries for change to performance specifications pre-defined 	
Administrative Changes Subject to Approval	 Changes to the administrative information submitted during registration of the AI-MD including changes that would require updates to the information listed on the Singapore Medical Device Register 	
Notification Changes	 Changes with typically low impact on the registered AI-MD May be implemented immediately upon receipt of the acknowledgement email from HSA upon notification via online system 	
Changes that require no action	Changes with no known or foreseeable impact on the registered Al-MD To be managed by the manufacturer under their QMS	

Regulatory Oversight Stratified based on the significance of the change



Change Management for Al-MDs - Examples



For locked and continuous learning algorithm based AI-MDs

Examples of significant changes to Al-MDs subject to evaluation and approval by HSA (Technical Changes)

- Changes to the input data to generate the same clinical output from the AI-MD potential impact on clinical association with output
- Change to the output results presented which are based on the approved input parameters

Example – Approved wound scanner intended to report the length and width of the wound.

New output parameter will include the depth of wound. There is no change to the indication for use.





For locked and continuous learning algorithm based AI-MDs

Examples of significant changes to Al-MDs subject to evaluation and approval by HSA (Technical Changes)

- Change to the output results presented by the AI-MD, which are based on the approved input parameters/ image modality and involves expansion of the approved indications for use of AI-MD Example –The approved software can identify certain types of intra-cranial tumours from MRI images (e.g. Meningioma and Chordoma). The change involves inclusion of an additional intra-cranial tumour (e.g. Craniopharyngioma) in the AI-MD's output
- Change to the approved workflow such that the patient result/therapy will no longer be required to be reviewed/supervised by the health care provider/trained professional/user (i.e. no human intervention is required) – Full-automation of AI-MD
 - Example Removal of the review of the AI-MD's output results by a nurse and specialist from the workflow for deployment and use of the AI-MD.

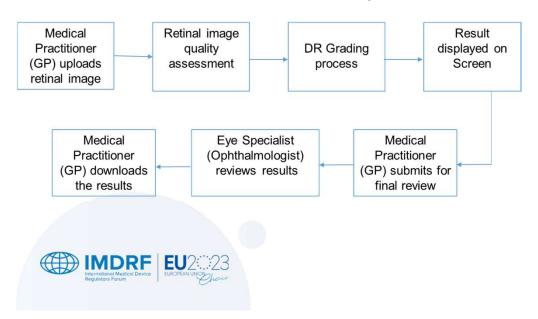


Change in the Workflow for deployment of AI-MD

Al-MD's Original intended use during pre-market evaluation:

To screen and grade Diabetic Retinopathy (DR) in patients/general population through colour fundus retinal images. The results are intended to be subsequently verified and certified by an eye specialist before forwarding to the Primary Health Care Professional as a report.

- All outputs to be reviewed by specialists





Disease Severity Level*

- 1. Unable to grade
- 2. Normal

Non disease -

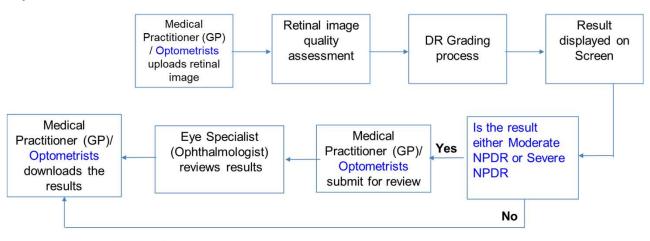
- Mild NPDR
- 4. Moderate NPDR
- Severe NPDF

*American Academy of Ophthalmology

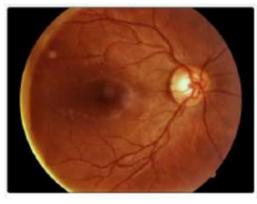
Change in the Workflow for deployment of AI-MD

Change in Workflow post-approval

Only moderate NPDR or severe NPDR outputs will be referred to specialist







Regulatory Considerations:

- Increased reliance on AI-MD output for Normal and Mild NDPR cases
- Need for more robust validation studies especially with mild NPDR cases
- Clear instructions to be provided for situations where the Al-MD would potentially generate incorrect outputs (i.e. moderate NPDR reported as mild NPDR)

Regulatory Guidelines for Software Medical Devices – A Life Cycle

Approach

This document provides clarity on the regulatory requirements for software medical devices throughout its entire life cycle and covers:

- Quality Management System (QMS) for software medical devices
- Dealer's licensing requirements
- Pre-market product registration requirements
- Change notification
- Post-market management of software medical devices
- Cybersecurity
- Artificial Intelligence Medical Device

Reference: "Regulatory Guidelines for Software Medical Devices - A Life Cycle Approach" available at HSA | Guidance documents for medical devices







April 2022

Regulatory Guidelines for Software Medical Devices -A Life Cycle Approach

Revision 2 0



Guidelines for Implementation of AI-MDs in Healthcare

The Ministry of Health, Singapore in collaboration with the Health Sciences Authority (HSA) and Integrated Health Information Systems (IHiS), has published a guideline on good practices for AI developers and implementers (e.g. healthcare institutions - hospitals, clinicals, laboratories, etc.)

Some of the key recommendations include:

- Exercise clinical governance and oversight over the adoption and implementation
- Contingency plans to remove the AIMD from the operational workflow

Reference: https://www.moh.gov.sg/licensing-andregulation/artificial-intelligence-in-healthcare





ARTIFICIAL INTELLIGENCE IN HEALTHCARE GUIDELINES (AIHGle)

Developed by:







Endorsed by:









Published Oct 2021





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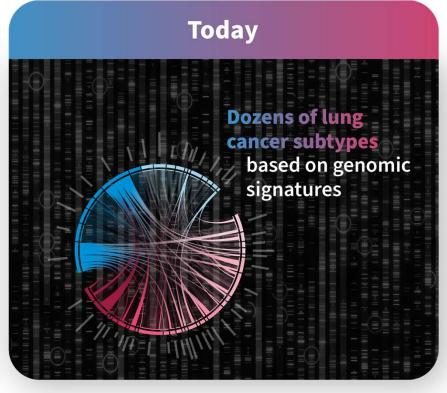
Specific post-market considerations for AI MDs: Change Management

Melissa Finocchio, Chief Regulatory Officer SOPHiA GENETICS

27 March 2023

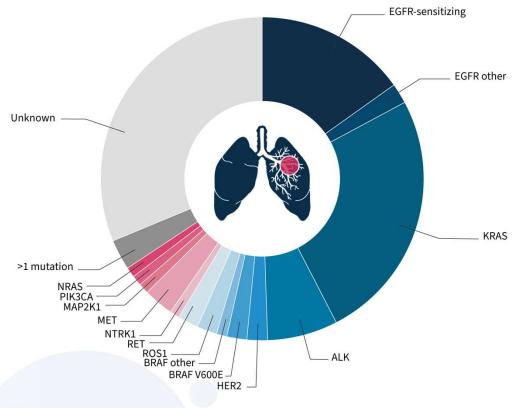
What is change?







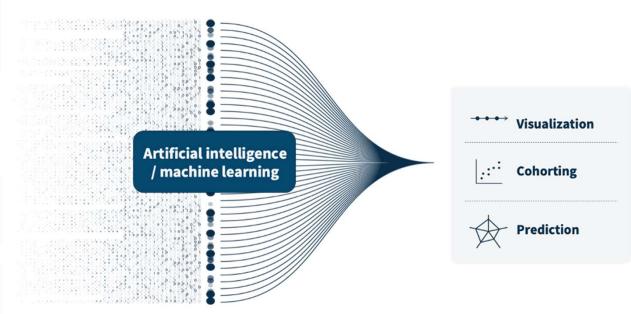
Lung Cancer is increasingly a collection of rare diseases



- Specific variants (e.g., KRAS G12C)
- Co-mutations
- Tumor mutational fingerprint evolving over time



Multimodality is further increasing the complexity





data



...and the rate of change

Globally Connected Devices



Adaptive devices need adaptive change management

- Focus on training & processes
- Continuous growth vs Discrete changes
- Careful monitoring & feedback







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16:40 - 10:10

PMS for AI software



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Haeung Lee

Director, Corelinesoft







Post-Market Surveillance – considerations for artificial intelligence software

Lesley-Anne Farmer

Medical Devices and Product Quality Division

Therapeutic Goods Administration







Scope - 2 considerations

Consideration 1 - Monitoring devices with Al

Criteria, methods, and strategies to monitor safety and performance: specific considerations for AI (ML)

Consideration 2 – Using AI data

Challenges and opportunities when collecting or generating data for digital medical devices







Consideration 1: Monitoring devices with Al

Regulatory requirements and what is acceptable are important and critical considerations to how and what is monitored

For AI software, some of the main areas under consideration for postmarket surveillance include:

- Transparency
- Labelling
- How general software trends are applicable to Al
- Which medical specialisations are adopting AI most quickly
- How health professionals use AI products
- Signal evolution and design
- Governance of Al and data for adaptive systems
- Adverse event surveillance and what 'manufacturer' activities are undertaken



Some challenges

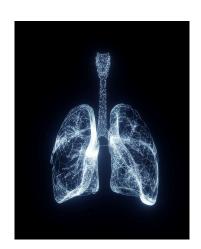
- New players do not have well-developed processes to support ongoing post market obligations
- Increasing sophistication/version updates not always factored into post market changes (especially if the changes do not require regulatory re-approval)
- Human factors how people use software vs its design (intended purpose) and reporting of adverse events – do users KNOW it is an adverse event?
- Traceability of errors and their role in adverse events
- Some differences in classification of devices globally and post market obligations
- Using Al which may have bias and/or not be applicable to certain population cohorts – does this skew adverse event data?



Transparency and surveillance

Looking inside the product and using this information for surveillance

- Data AND model
- Al often sits inside a software "shell"
- What data is needed by regulator for post market issues that is specific to AI? e.g. logging and beyond



Using the product and what channels

- Human factors consumers, patients, health professionals
- Understanding the purpose
- Scale of deployment

Signal evolution and design for AI products

- Clear leading medical specialisations target surveillance design to these
- Digitalisation of pathology significant changes in workflow and processes
- Keeping up with changes to theory/literature
- Target efforts
- For consumer products speed of adoption
- Consider whole life cycle from design
- Still need to consider other software signals not just Al



Ongoing responsibilities post-approval

Building in good practices through the lifecycle

Governance, monitoring and surveillance systems are critical to:

- periodically verify that the product continue to work as intended
- detect if it develops any unintended bias or further performance drift

Al and software generally

- Focus on getting to market means Al/software living environment may not be adequately addressed
- Ecosystem compatibility maintenance
- Consumer facing devices, or self-management of a serious condition face further requirements to mitigate patient risks through its service life
- Updates or patches as 'recall' actions or notifications based on regulatory requirements



Adverse event surveillance

Planning for the unthinkable



- Ongoing surveillance and monitoring of complaints and adverse events regarding harm to a user or patient
- Software design should have data capture/ logs
- Manufacturer adequately resourcing the quality and post-market team
- Planning for timeframes and resourcing needed to investigate, respond, notify regulatory authorities and minimise risks from adverse events or issues
- Manufacturer needs channels to contact local agents or distributors for complaints and regulatory action, that are across different geographic regions
- Communication channels for updates, patches, recall actions to end users, or patients, or health providers

Consideration 2: Using Al data Collecting or generating data

Regulatory requirements and what is acceptable for post market surveillance are important and critical considerations for manufacturers

- Clinical evidence guidance
- Real world evidence and real world data guidance
- Clear feedback to manufacturers by the regulator on what is expected

Real world evidence and real world data

Key points in relation to post-market surveillance:

- Real-world data collected from AI software in a proper study design can contribute to post-market clinical follow up
- Create real-world evidence for any applicable extension of intended purpose.
- Sources can include device output, sensors, patient entered data, EMRs, among others



Challenges

Post market challenges for use of data generated by Al

- Experience with other software shows that data may be difficult to get and timeliness becomes significant Monitoring for performance including development of bias and data drift – as for other Al
- Analysis of population segments and other sub-groups to check performance across spectrum of intended use including target population, equipment, user
- Monitoring for repeatability and reproducibility
- Variability of device output across use on same or similar patients/conditions, by same or different operators
- Opaque or black box models may introduce further risk and thus warrant higher stringency of monitoring
- Clinical reference standard may not be available for novel Al models



Opportunities

Post-market monitoring of data generated by AI can:

- Give further external validation of devices to support generalisability of model performance, i.e. ability to perform in a new use environment or new sample of patients.
- Track further clinical endpoints beyond model accuracy, for example mortality, rate of ICU admission, or other patient outcomes.
- Under a proper study design create real-world evidence for subsequent pre-market decision making on indication expansion.
- Confidence in accuracy of generated data is paramount





Department of Health and Aged Care

Therapeutic Goods Administration









Hae Ung Lee, Ph.D. Coreline Soft Co., Ltd.

OVERVIEW

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Company Introduction

> Leading large scale AI deployment











> Product Overview - Clinical Products











Clinical products I

aview:LCS



Key Features

- 1. Nodule CAD Sensitivity: 0.97, Specificity: 0.7644
- 2. F/up Mode(Automatic Nodule Matching)
- 3. Lung RADS(1.0/1.1)
- 4. Volumetric measurement & Volume Doubling Time(VDT)
- 5. Brock Score calculation
- 6. EUPS compliance





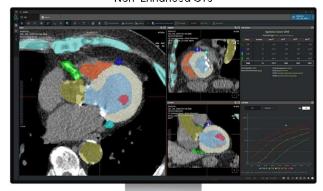
Key Features

- 1. Fully automated processing
- 2. Phenotyping
 - Emphysema
- Airway
- Fissure Integrity Vessel



Clinical products II





Key Features

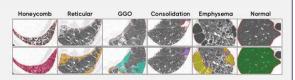
- 1. Fully Automated and Fast
- 2. Scores on each Vessel
- 3. Agatston, Volume and Mass Score

aview:Lung Texture



Key Features

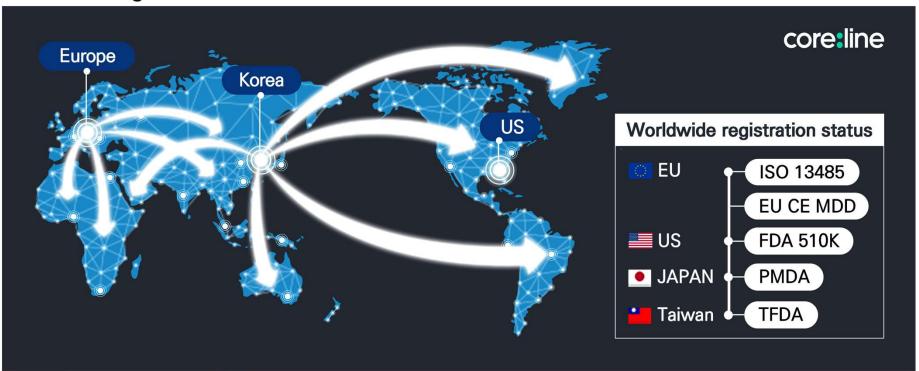
- 1. Fully Automated using AI
- 2. Lung/Lobe segmentation based on AI
- 3. 6 Patterns Classification





Company Introduction

> Worldwide registration status





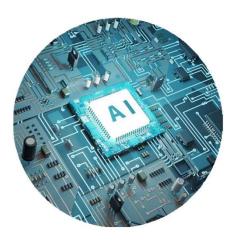
- > Key actions for PMS
 - Vigilance Analysis
 - Real world Data analysis
 - Comply with regulatory requirements
 - Safety and effectiveness
 - Literature search
 - Cybersecurity information sharing networks searching



> How to conduct



O1Develop PMS plan



02 Implement the plan



O3
Generate PMS
report based on the findings



- > PMS Plan
 - Collecting and analyzing data
 - Following up on collected complaint
 - Communicating information to regulators and users
 - Taking corrective actions on devices
 - Producing a PMCF (Post-Market Clinical Following-up) plan or a rationale for why PMCF is not required





> Reporting

Region	Report Type	Details
US	Periodic Adverse Drug Experience Report (PADER/PAER)	Required by FDA
	Post-Market Surveillance Report (PMSR)	Required for low-risk Class I devices
EU	Periodic Safety Update Report (PSUR)	Required for Class IIa, Class Iib, and Class III devices
Korea	Report on production and export performance of medical devices	Reported annually
	Report on supply history of medical devices	Reported annually



> Continuous Learning Capabilities



Pre-market assessment is no longer sufficient



Control the learning process and respective changes



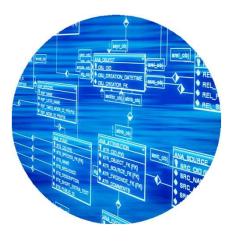
Change Notification



Addition or reduction of input data type to generate the same output



Output results based on the approved input parameters (including changes for interpretation)



Approved workflow



> Change Notification related to a continuous learning algorithm



Exclusion/inclusion criteria for input data



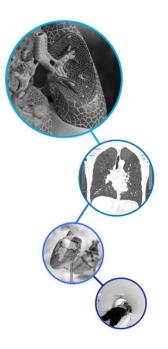
Defined boundaries



Baseline performance specifications



- > Performance in Real World Setting
 - High quality machine learning from private datasets
 - But, limited learning data



NELSON	Lung Cancer Screeining CT dataset
Dutch-Belgian Lung Cancer Screening Trial	- CT dataset
UKLS	Lung Cancer Screening
UK Lung Screening Trial	- CT dataset 3,000 cases
Russian LS	Lung Cancer Screening
Moscow Lung Screen Trial	- CT dataset 2,000 cases
SNUH	· 홍복부 전이암
서울대학교병원,Collecting	CT dataset 12,200 cases
Russian LS	· 17개병원
(Korean Obstructive Lung Disease Cohort)	・音学CT dataset 477 cases
A ILD Project	· 8개 병원
10개 병원, Collecting)	ILD CT dataset 762 cases
ROBINSCA (Risk Or Benefit IN Screening for Cardiovascular Diseases)	Coronary Artery Calcification CT dataset (2,000 cases)
(man or occurrent in occording to constitution occurrent)	
A Dr. Answer	Coronary Artery Calcification CT dataset (8,000 cases)
(서울아산병원, 분당서울대병원, 신존세브란스병원)	· C1 dataset (8,000 cases)
	I BUILDE STEEL STE
RT-ACS Project (신춘세브란스병원, 서울아산병원, Collecting)	 방사선종양치료계획 Multi-Contouring CT dataset 800 cases (목표)



- > Performance in Real World Setting
 - Different setting from pre-market assessment
 - Different Data set
 - Uncontrolled clinical environment





Performance Evaluation for Real World Setting





THANK YOU / QUESTIONS

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Disclaime

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17:00 - 17:25

Panel discussion

Similarities and differences in considerations for software and AI in the post-market phase



Matthias Neumann

Deputy Head Medical Devices Safety Unit, German Federal Ministry of Health (Moderator)



Jesús Rueda Rodríguez

Director General Strategies, Special Projects and International Affairs, MedTech Europe (Moderator)



