From Acquisition to Analysis: How AI is Revolutionizing Cardiac MRI

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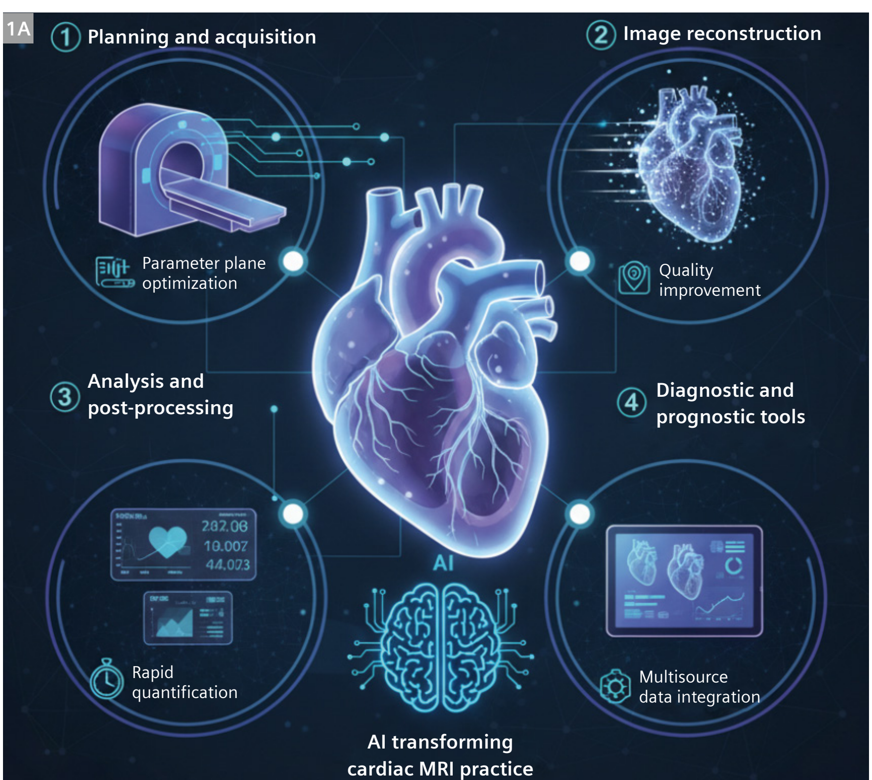
Introduction

Artificial intelligence (AI) is emerging as a powerful ally in cardiac MRI, addressing many of the challenges that previously limited its efficiency and accessibility. By automating and optimizing steps from protocol planning and image acquisition to reconstruction, analysis, and integration with clinical data, AI can make cardiac MRI faster, more consistent, and more widely available. Far from replacing clinicians, AI supports them by reducing repetitive tasks, improving reproducibility, and enabling the extraction of advanced diagnostic and prognostic information.

An important aspect of this evolution is the integration of cardiac MRI into a multimodality framework where it is combined with other imaging techniques such as echocardiography or CT, and with clinical, biological, and electrophysiological data. This approach paves the way for advanced concepts like the digital twin – a virtual model of the patient's heart that can guide diagnosis and therapy planning, further enhancing precision and personalization in cardiovascular care.

In this article, we will explore how AI is transforming our cardiac MRI practice in four main domains (Fig. 1):

1. **Planning and acquisition:** including automated plane prescription and parameter optimization
2. **Image reconstruction:** accelerating acquisitions and improving image quality
3. **Image analysis and post-processing:** enabling rapid and consistent quantification
4. **Development of diagnostic and prognostic tools:** integrating imaging with multisource and multimodal patient data



1 **(1A)** Artificial intelligence is transforming cardiac MRI by enhancing image acquisition, reconstruction, post-processing, and diagnosis.

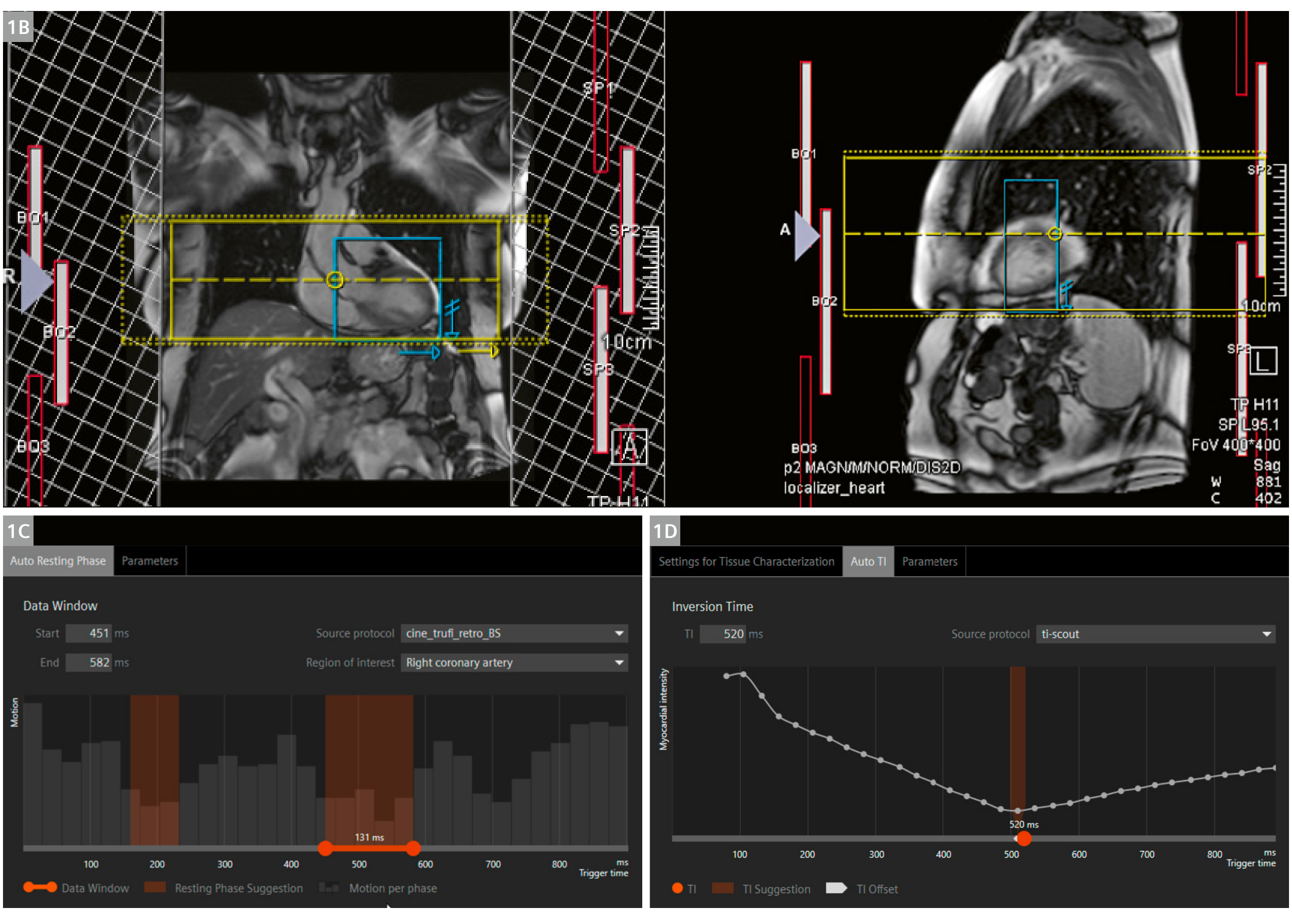
Through these advances, AI is enhancing both the efficiency and the diagnostic power of cardiac MRI, ultimately contributing to better patient outcomes.

AI-assisted planning and acquisition

One of the most visible improvements is AI-assisted slice positioning for cardiac MRI exams. Traditionally, slice positioning relied heavily on operator expertise, with variability due to operator experience and patient anatomy. Now, AI automatically detects cardiac landmarks from the localizer images and proposes standard short- and long-axis views with high precision, allowing quick confirmation or adjustment. This ensures more consistent orientation between patients and in follow-up scans of the same patient. Such reproducibility is essential for both quality patient care and data consistency in longitudinal studies.

AI algorithms also assist in adapting imaging parameters to the patient's individual anatomy and clinical indication. A notable example is automatic inversion time (TI) estimation for late gadolinium enhancement. Unlike manual interpretation of the TI scout, which sometimes requires repeated acquisitions, AI calculates the optimal value directly from the scout images. The technologist still retains the ability to review and adjust the suggested TI value if needed, which ensures flexibility and clinical oversight. This reduces scan time, minimizes breath-hold repetitions for the patient, and improves image consistency across patients.

These AI tools are particularly valuable in our environment at Lariboisière Hospital. We are a tertiary referral center with strong expertise in cardiac imaging, and as a university hospital we routinely manage patients with complex and severe pathologies. Our technologists work across all imaging modalities and organ systems. Our scanners are shared between multiple specialties, which means that dedicated cardiac MRI technologists are not always available. AI solutions that simplify acquisition and standardize quality therefore benefit everyone by ensuring consistently high-quality images regardless of the operator's primary area of expertise. They also shorten examination times, reduce repeated sequences, and bring greater standard-



1 **(1B)** AutoPositioning automatically places the heart in the isocenter and plans slices, volumes, navigators, and saturation bands. **(1C)** AutoRestingPhase detects the optimal data acquisition window during the cardiac resting phase. **(1D)** AutoTI proposes the optimal inversion time for delayed enhancement measurement.

ization, which is especially valuable in research involving large patient cohorts and multiple operators. These capabilities allow our technologists to spend less time on manual adjustments and more on patient comfort, while clinicians gain more reliable datasets for reconstruction, analysis, and integration with other modalities.

Looking ahead, smart prescan guidance systems could take this further by analyzing patient-specific data such as heart rate, ventricular morphology, or implanted devices even before the patient enters the scanner room. This would allow AI to propose optimized protocols, minimize unnecessary sequences, and ensure all essential information is acquired, improving efficiency and reproducibility in both high-volume clinical practice and multicenter research.

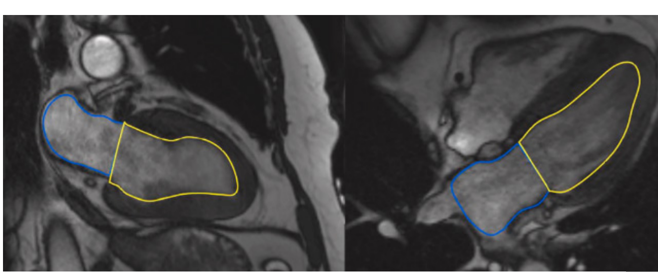
AI-powered reconstruction for consistent, high-quality cardiac MRI

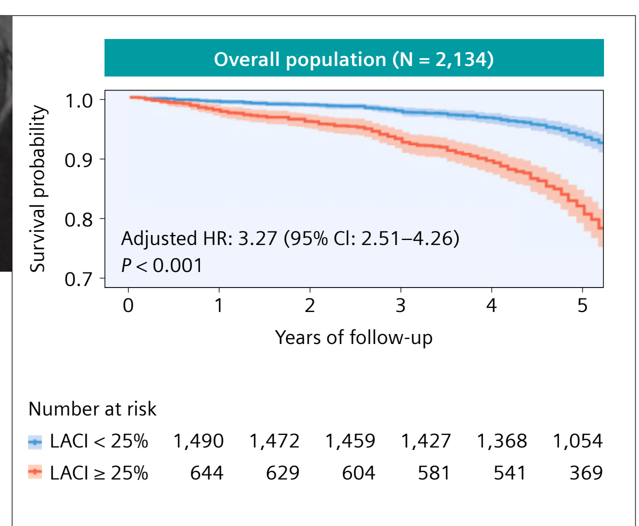
AI-based image reconstruction has become one of the most impactful applications of artificial intelligence in medical imaging. By learning from large datasets of high-quality images, deep learning algorithms can remove noise, reduce artifacts, and even predict missing data, allowing significant acceleration of acquisition without compromising diagnostic quality. These methods are now integrated into clinical scanners, such as the 1.5T MAGNETOM Sola, to improve workflow efficiency, enable shorter breath-holds, and enhance image sharpness. Beyond saving time, AI reconstruction also ensures more consistent image quality between patients and operators, which is critical for longitudinal follow-up and multicenter research studies. Importantly, these algorithms are always validated against raw *k*-space data to guarantee authenticity and preserve diagnostic reliability.

One pertinent example in the cardiovascular MRI offering from Siemens Healthineers is an AI-based reconstruction tool for T2 STIR sequences, which are essential for detecting myocardial edema. In clinical practice, and especially in the assessment of acute myocarditis, T2 STIR is interpreted together with T2 mapping to confirm and quantify edema. In our tertiary referral setting at Lariboisière Hospital, patients often present with severe or complex cardiovascular conditions, including myocarditis with arrhythmia or limited breath-holding capacity. These factors can compromise conventional T2 STIR image quality. The AI-enhanced reconstruction denoises the images, improves the myocardium–blood contrast, and reduces motion artifacts, resulting in clearer visualization of areas of edema. This translates into greater diagnostic confidence for clinicians, more reliable detection of subtle lesions, and improved consistency across patient populations and imaging operators.

From acquisition to insights: AI in post-processing for cardiac MRI

Artificial intelligence now plays a central role in post-processing for cardiac MRI, transforming tasks that were once manual and time-consuming into fast, reproducible, and operator-independent steps. Automated segmentation of the ventricles, atria, and myocardium allows direct quantification of volumes, function, mass, and tissue characteristics within seconds. This reduces variability between operators and ensures consistent measurements, even in complex cases with significant anatomical or pathological changes. Inline processing at the MRI console is also an important evolution that enables several analyses to be performed automatically before the patient even leaves the scanner room. These analyses include auto-





2 Example of a fully automated AI analysis to calculate the left atrioventricular coupling index (LACI). The AI algorithm automatically delineates the left atrial (yellow contour) and left ventricular (blue contour) volumes at end-diastole and computes their ratio. In more than 2,000 patients undergoing stress cardiac MRI, an elevated LACI (≥ 25%) identified by AI was strongly associated with a higher risk of hospitalization for heart failure or cardiovascular death during follow-up (Kaplan-Meier survival curves, adjusted HR 3.27, 95% CI 2.51–4.26, $p < 0.001$).

mated calculation of ventricular function from cine sequences, inline T1 and T2 mapping quantification, and strain analysis from feature tracking.

One of the current challenges lies in the automatic segmentation of late gadolinium enhancement (LGE). The wide variety of enhancement patterns across different pathologies, and variations between imaging sequences, make it difficult for algorithms to deliver consistently accurate results in every case. Even when advanced image analysis can identify highly relevant diagnostic and prognostic markers – such the left atrial coupling index (LACI) [1] – their use in clinical routine is often limited by the time required for manual measurements. This highlights the strong potential of fully automated algorithms that can perform these complex segmentations and calculations under the supervision of physicians, ensuring both speed and reliability while preserving clinical oversight (Fig. 2).

The impact on efficiency is considerable: Physicians spend less time on repetitive and manual processing steps and can focus more on interpretation and clinical decision-making while benefiting from standardized, high-quality outputs that facilitate reporting. In addition, the availability of structured and machine-readable quantitative data supports downstream applications such as multimodality integration, phenomapping, and prognostic modeling. AI in image analysis is therefore not only a time-saver but also a cornerstone for building robust diagnostic and prognostic tools for patient care.

AI-driven diagnostic and prognostic tools in multimodality cardiac imaging

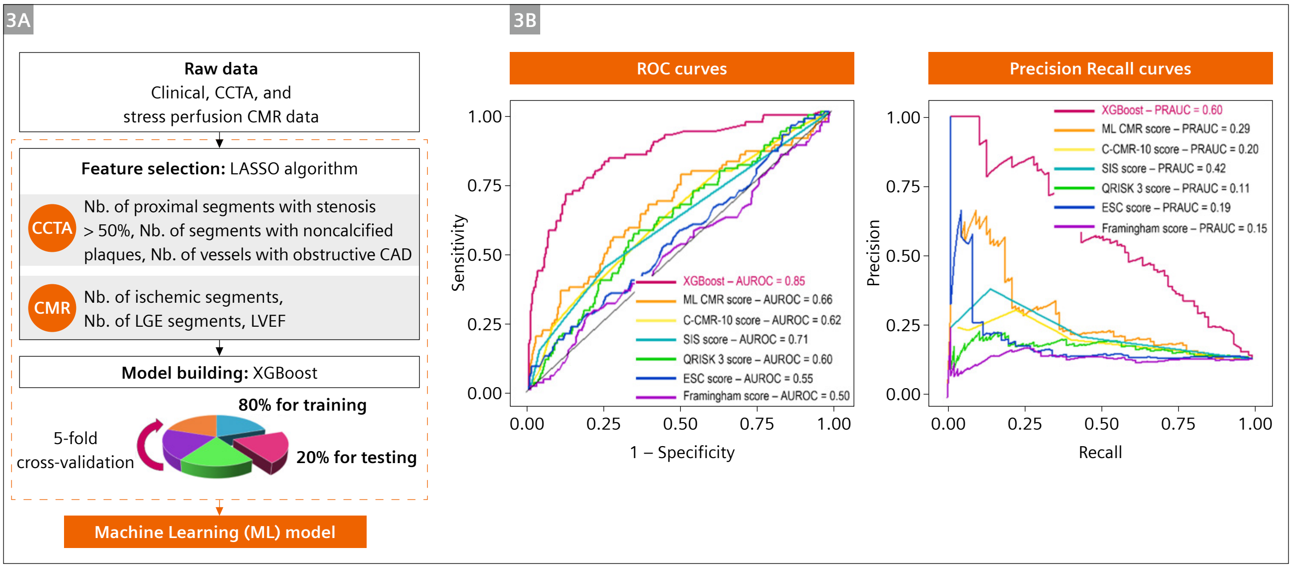
Artificial intelligence has opened up new possibilities for creating powerful diagnostic and prognostic tools in cardiac MRI, enabling a shift from purely descriptive imaging towards predictive and decision-support systems. The first step in this process is the identification of relevant variables – a task at which AI algorithms such as the random forest excel. By processing hundreds of clinical, biological, and imaging parameters, these algorithms can rank features according to their importance for predicting patient outcomes, while avoiding redundancy from highly correlated variables. Once the most informative parameters are selected, a second step involves building a prognostic model. Advanced machine learning methods, such as multiple fractional polynomial modelling, combine and transform these variables into a predictive score that can outperform traditional risk models like the Framingham or ESC scores.

Beyond single-event prediction, AI can be applied to phenomapping, a form of unsupervised learning that groups patients into homogeneous clusters based on multimodal data. In cardiac MRI, this approach has proven valuable in heterogeneous conditions such as heart failure with preserved ejection fraction, pulmonary hypertension, and dilated cardiomyopathy. By revealing subgroups with distinct prognoses, phenomapping can guide both follow-up strategies and therapeutic decisions. Moreover, integrating cardiac MRI data with other modalities – such as echocardiography, CT, biomarkers, and even genetic information – moves us closer to the concept of the digital twin, a virtual replica of the patient's heart used to simulate disease evolution and test interventions before they are applied in real life.

A recent example from our team illustrates the potential of this approach [2]. In a large multicenter study of over 2,000 patients with newly diagnosed coronary artery disease, we developed a machine learning model that combined stress cardiac MRI and coronary CT angiography parameters, alongside clinical and electrocardiographic variables, to predict major adverse cardiovascular events. Using automated feature selection (least absolute shrinkage and selection operator) and an XGBoost algorithm, the model significantly outperformed existing prognostic scores and single-modality approaches, both in internal validation and in two independent external datasets (Fig. 3). This work demonstrates how AI can integrate complementary information from different imaging modalities to deliver more accurate and personalized risk stratification.

Random forest is a machine-learning method designed to classify or predict binary events (such as the presence or absence of disease). It builds a large number of decision trees, each trained on a random subset of the data and variables. The final prediction is obtained by majority vote across all trees, which reduces overfitting and improves accuracy compared to a single tree. Random forest can also rank variables according to their contribution to the prediction, helping to identify the most important risk factors.

A **digital twin for cardiac MRI** is a virtual model of the patient's heart. It combines imaging data with computational simulations to replicate actual cardiac structure and function. The digital twin can be used to produce patient-specific analyses and predictions, and test different treatment options before involving the patient.



3 Machine-learning model using coronary CT angiography (CCTA) and stress CMRI to predict major adverse cardiovascular events.
(3A) The machine-learning-model method involved automated feature selection by least absolute shrinkage and selection operator (LASSO; three CCTA variables in the blue box and three CMRI variables in the green box), model building with an XGBoost algorithm, and five repetitions of 10-fold stratified cross-validation for the entire process.
(3B) Area under the receiver-operating characteristic curve (AUROC) and the precision recall curve (PRAUC) for the prediction of major adverse cardiovascular events (MACEs). The ML model had significantly higher AUROC and PRAUC for MACE prediction than all other risk scores ($p < 0.001$).

The ultimate goal of these AI-powered diagnostic and prognostic tools is to provide clinicians with accurate, reproducible, and actionable insights, enabling earlier interventions, more personalized treatment strategies, and improved outcomes for patients with cardiovascular disease.

Conclusion

Artificial intelligence is now a key driver in the evolution of cardiac MRI, with tangible benefits across all stages of the workflow from acquisition planning to reconstruction, image analysis, and advanced prognostic modeling. Current tools already reduce operator dependency, shorten examination times and improve reproducibility while paving the way for the extraction of new diagnostic and prognostic biomarkers.

The next step will be the seamless integration of multimodal data combining cardiac MRI with other imaging modalities and clinical and biological information to build comprehensive digital twins and decision-support systems. These advances will not replace clinicians; they will empower them, allowing more time for critical thinking and patient-centered decision making.

As we stand at the frontier of this transformation, our role as physicians is to ensure that these technologies are developed, validated, and implemented with the highest standards of scientific rigor, clinical relevance, and patient safety. In doing so, we can fully harness the potential of AI to deliver earlier, more precise, and more personalized care to our patients.

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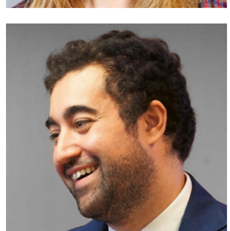

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