Journal of Carcinogenesis
Covering Genesis to Therapeutics
Journal of Carcinogenesis, ISSN: 1477-3163
2025; Vol24: Issue 3s, https://carcinogenesis.com/

# Optimizing MRI Scan Time with AI-Powered Reconstruction and Denoising Techniques

**Manvee Rai**[1], **Dr. Dolly A Sharma**[2]

[1]Department of Paramedical, Manwanchal University, Indore, Madhya Pradesh

**ABSTRACT**

MRI is a popular diagnostic procedure because of its high soft-tissue contrast and non-invasiveness. One of such limitations is a long scan time, which causes patient discomfort and can facilitate motion artifacts, while having an impact on the throughput. State-of-the-art artificial intelligence (AI) developments have brought forth robust reconstruction and denoising methods that can speed up MRI acquisition without the loss, or even with the improvement of image quality. This work investigates the use of AI-based algorithms for optimal scan time in MRI through accelerated image reconstruction combined with advanced denoising methods. We summarize current methods and analyse their clinical utility, noise suppression efficiency, artifact reduction effectiveness, and diagnostic reliability. Finally, we discuss potential research needs and practical implications for adopting AI solutions in clinical routines. Through acceleration and denoising with AI based reconstruction, MRI enables and allows faster high-quality imaging that drives better patient care and operational effectiveness for healthcare systems..

***Keywords:*** *Magnetic Resonance Imaging (MRI); Scan Time Reduction; Artificial Intelligence (AI); Image Reconstruction; Deep Learning; Denoising; Motion Artifact Reduction; Accelerated Imaging; Clinical Workflow Optimization*.

**How to Cite:** Manvee Rai, Dr. Dolly A Sharma, (2025) Optimizing MRI Scan Time with AI-Powered Reconstruction and Denoising Techniques, *Journal of Carcinogenesis*, *Vol.24, No.3s*, 780-798

## 1. INTRODUCTION

### 1.1 Background on MRI: importance, challenges of long acquisition times

Magnetic Resonance Imaging (MRI) has been an indispensable technology in contemporary diagnostic medicine as a result of its superior soft-tissue contrast, lack of invasiveness and adaptability across many clinical disciplines. However, despite the advantages, one of the main drawbacks of MRI is its relatively long imaging time as compared to other modalities. Long scan time may reduce the number of patients that can be scanned and become critical in clinical cases where time to diagnosis is crucial. The long acquisition times have limited the use of MRI in low resources areas. Therefore, speeding up MRI through under sampling of k-space data required for image reconstruction has been a crucial challenge since long. We sought to develop a deep convolutional neural network (dCNN) optimization for MRI reconstruction, with the goal of enabling acceleration and assessing its impact on image quality and oncological imaging biomarker accuracy. A potential powerful solution is proposed in the form of deep learning-based MRI reconstruction methods, which can not only shorten acquisition times but are also gaining widespread applications in clinic routine measurements (Knoll et al., 2020). However, the diagnostic performance of deep learning based reconstructed images in real world clinical setting with broad range of patients (i.e., different patient populations and clinical diagnosis) have not been well investigated and as they are widely used clinically, there continues to be a desire for more robust validation compared against conventional state-of-the-art MRI (Hammernik et al., 2023). Even though conventional acceleration methods such as parallel imaging or simultaneous multislice acquisition achieve high acceleration factors, their routine application and possible expectedly image quality is restricted due to the reduced signal-to-noise ratio and the occurrence of speed artifacts. On the other hand, deep learning-based MRI image reconstruction models have shown stronger performance with their better capability of noise and artifact reduction. In the structural imaging setting, deep learning-based FLAIR imaging reduced scan time by 38 % with improved lesion delineation and noise suppression. Consistently, deep learning-based brain MRI has been shown to increase quality of both spin-echo and gradient-echo sequences whilst greatly reducing scan time without compromising volumetric accuracy or lesion quantification, a 75 % acceleration in 3D-T1 brain volumetric MRI, and a 69 % reduction in orbital scan times whilst improving image sharpness and diagnostic confidence (Zhang et al., 2023). Deep learning-based methods for spine imaging reduced spine image acquisition times by 61 % without compromising diagnostic accuracy or dropped lumbar spine MRI sagittal series time devoted to 45 % without reduction in pathology detection. On oncological imaging, deep learning-based protocols reduced acquisition times by 30 % and increased the in-plane resolution while being diagnostic according to the RANO 2.0 (Response Assessment in Neuro-Oncology) criteria and enabled a tenfold decrease of scan time with preservation of accuracy for clinical oncologic imaging biomarkers for response assessment. Moreover, deep learning-based chemical exchange saturation transfer imaging has been demonstrated, maintaining Z-spectrum information and a high spatial resolution derived from the low-resolution scans. Together, these results highlight the paradigm shift in MRI using deep learning methods regardless of the algorithmic approach by providing increased speed to acquisition, possible improvement in diagnostic accuracy and increased clinical workflow efficiency. In particular, these studies were conducted on narrow predefined clinical indications and considered rather specific questions. The wider application of the commercial deep learning-based reconstruction in a variety of neuroradiological cases continues to be uncertain, especially as it would need to fulfil practical clinical neuroimaging standards as well as these evaluations and how it can comparative quantitatively evaluate with conventional reconstruction algorithms for a range of diseases and age groups. In this context we performed

a comparison study of Deep Learning (DL) based accelerated T2-weighted (T2 (DR)) with prospectively under sampled Conventional turbo spin-echo (TSE) based T2-weighted (T2 (CN)) coronal brain MRIs in 100 consecutive clinical routine patients. Our primary purpose was to estimate the clinical utility of T2 (DR) - DR and T2 from diagnostic rating scales. Secondarily, we wished to evaluate differences in signal-to-noise ratios of T2 (CN) images.

### 1.2 Clinical implications of long scan times

Examination with magnetic resonance imaging (MRI) is known to be both long and uneasy for the patient. The narrow bore environment coupled with the relatively long patient wait where the patient is required to remain still combined with auditory noise can be as loud as 130.7dB (to put it into context, a plane takes off producing a level of noise around 120dB). This is an uncomfortable experience and can cause early termination or poor quality of imaging studies (Edmondson et al., 2020). Conversely, any development that reduces the noise and/or the scan time, or any design of a scanner which allows for more freedom of movement for the patient inside it is likely to increase diagnostic quality and patient satisfaction. Several physics and engineering developments have led to new hardware designs with greater patient comfort during MRI (Napp et al., 2021).

The presence of motion artifacts (MA) is a challenging issue in MR imaging. Motion Artifacts: Motion artifacts are known to occur on about 15–30% depending on the environment that these artifacts are occurring. In a retrospective analysis of 21,645 cases it was pointed out that in 7–12% MA is due to normal body pulsations (heartbeat, breathing etc.) but in at least 10% also by motoric unrest. In 8–17% of cases the examination quality was compromised secondary to MA and failed making a patient undiagnosed or requiring repeat study (Andre et al., 2015). As such, in addition to causing patient anxiety, MA restrict MRI image quality and waste valuable staff and equipment time. In clinical practice, it is often considered that MA not driven by parenchyma pulses are primarily of anxiety origin. The existence of such a relation has not been investigated to date. Although there was no human-based, at these alternatives a variety of other comfortable practice for development techniques have previously been reported to decrease patients' pain during an MRI, none were applied in any of from MA.346Studies attempting hyperventilation facture frequency use technique. So as disappointing as it is, despite how ripe it sounds, there is no scientific evidence of a connection between anxiety and the happening.

One approach to increase comfort and compliance for MRI among those of emergent indications is to customize (reduce) the imaging protocol in order to efficiently address the specific clinical question at hand, optimize imaging parameters, and implement faster sequences. This has been especially relevant in neuroradiology. Currently, the majority of MRI manufacturers already provide fast and highly efficient brain scanning protocols in just 5–6 minutes. In addition, institutions can adjust scanning parameters, such as image resolution, signal-to-noise (i.e., fewer averages) or other techniques drive higher MRI acquisition speed for all or select sets of scans targeting specific applications such as motion mitigation, paediatric or stroke imaging.

### 1.3The Role of AI in Streamlining MRI Workflows

MRI is still one of the most efficient tools for clinical diagnosis, but we are restricted in its use due to inherently long acquisition times. Conventional acceleration methods, such as parallel imaging and compressed sensing, offer certain improvements but with potential compromise of signal-to-noise ratio (SNR) and generation of artifacts (Lustig et al., 2007). In the last few years, AI has become a radical approach to remove these barriers as it enables direct improvements across various steps in the MRI pipeline.

AI-based reconstruction methods use deep learning models trained on large sets of fully sampled images to recover high-quality images from under sampled k-space data. These methods enable significant reduction in scan time as compared to conventional under sampling techniques with reduced noise and artifact amplification (Knoll et al., 2020). AI-augmented reconstruction, for example, can provide effective acceleration factors of up to 4–10× without compromising diagnostic confidence and hence lead to quicker examinations and enhanced patient experience.

Apart from reconstruction, AI-based denoising methods are used to better prepare accelerated data by reducing the noise level and increasing the sharpness of fine structural details. These post-processing methods are especially important for difficult patient populations in whom motion artifacts and low SNR are common. Reconstruction and denoising in the combination create strong foundation to obtain clinically acceptable images at shorter acquisition times. Workflow optimization is another area where AI increasingly has a part to play. By automatically prescribing imaging planes, making shimming corrections and selecting protocols, operator dependence is minimized and inter-operator variability is reduced, which in turn streamlines set-up times and normalizes image quality. Furthermore, with AI-related assistance in computer-aided segmentation/lesion detection and quantitative analysis tools during post-acquisition as well as in the decision making of when to perform follow-up or image biopsies, this approach should indirectly lead to enhanced throughput and faster turnaround times (Hammernik et al., 2023). Reducing the scan time up to a factor of 10 in deep-learning-based reconstruction of under sampled MRI, good imaging quality is achieved while maintaining accuracy derived from image biomarkers to evaluate response to oncological treatment. Our work is open-source, and has potential for extending the availability of MRI given further prospective validation. AI not only speeds acquisition of raw data through reconstruction and denoising but also optimizes the full MRI workflow from planning to interpretation. These advances have potential for increasing the efficiency of scanner operations, patient experience and diagnostic accuracy thereby making AI a central facilitator of the next-generation MRI in everyday clinical practice.

### 1.4. Aim of the Study

The purpose of this work is to investigate the performance of artificial intelligence (AI)–based reconstruction and denoising methods for accelerating MR imaging by reducing scan times while maintaining diagnostic image quality. Although MRI has been widely recognized as a highly flexible imaging technique, its long acquisition time is still a major bottleneck. Longer scans are uncomfortable and further increase patient motion, and scanners cannot be in use for long periods of time, restricting access to timely diagnosis. The need to address these challenges and yet preserve, or even improve upon, the diagnostic quality of MRI examinations is a driving force for this study.

Classical methods for accelerating MRI, including parallel imaging and compressed sensing, have brought substantial improvements. Parallel imaging saves time during acquisition by exploiting information from multiple receiver coils, compressed sensing frees good images from the shackles of under sampling by leveraging sparsity in an image domain. Yet those techniques commonly achieve a certain practical limit, past which additional acceleration introduces an intolerable amount of noise and artifact. This leads to a speed–quality trade-off, and there is a current need for methods that can achieve even more acceleration while maintaining diagnostic quality.

The AI-inspired approaches seem to be a good remedy for dealing with this problem. Recent advances in deep learning architectures have been able to excellently model complex correlations between under sampled data and fully sampled ground truth images. In particular, the application of techniques like CNNs, GANs and more recently diffusion models have shown promising results for MRI reconstruction. Such models can interpolate missing k-space data and suppress artifacts for more rapid acquisitions. In particular, AI is not learning denoised or smoothed images but context-aware mappings that still respect significant information required for diagnosis.

Another important direction for this study, Additionally, in the light of AI-based denosing techniques. Noise is a product of accelerated imaging, particularly if fewer data points are collected. Traditional denoising filters are successful to a certain extent, but typically they smudge fine structures and decrease diagnostic sharpness. AI-driven denoisers, however, have been shown to be able to suppress noise selectively while preserving fine features such as small lesions, microhemorrhages, or cortical abnormalities relevant for clinical decision making. Integrating reconstruction and denoising in a unified approach, AI methods may be able to provide images with an acquisition time long enough to enable speedy image acquisition but robust for diagnostics.

The clinical implications of AI-based acceleration will be another target of this investigation. Decreased scan time correlates with greater patient comfort and compliance even in these challenging populations, such as pediatrics, the geriatric population and critically ill patients. Shorter scans reduce the requirement for sedation, enhance efficiency of flow and resource use at facilities, and increase availability of the scanner capable of addressing increased imaging needs in resource-limited settings. Radiologist standpoint: high-quality AI-based images can minimize interpretation errors associated with artifacts due to a motion or low SNR, aiding in the overall accuracy and confidence in reporting.

It is also equally important to assess the generalizability and robustness of AI solutions. Several prior works present acceleration in an artificial setting or for vendor-specific datasets. But, to be implemented in the clinic it must be validated across different patient populations, anatomical sites and scanner brands. The objective of this study is therefore not only to evaluate the technical performance of AI-based reconstruction and denoising but also discuss conditions where these are most effective, and difficulties which still preclude implementation in a wider clinical arena.

In brief, this study will address four primary objectives: (1) to explore the design philosophy and methodology of AI-based reconstruction for under sampled MRI acquisitions; (2) to evaluate the performance of AI-driven denoising techniques in preserving image details in accelerated settings; (3) to quantify clinical benefits associated with shorter scan times from the perspective of patients and healthcare systems; and, (4) discuss potential directions related to integrating AI into routine MRI workflow safely, consistently across platforms. In this light, the presented work aims to provide another piece of evidence on how AI is emerging as a transformative approach to enable faster and easier access to MR imaging with robust diagnosis quality.

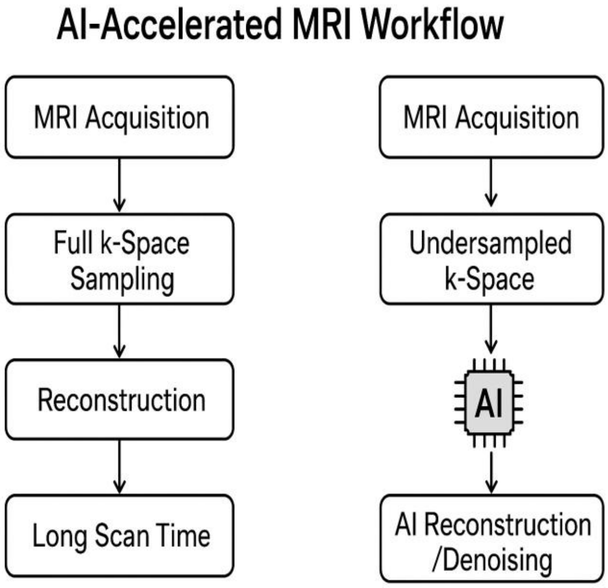



**Fig.1.AI-Accelerated MRI Workflow**

## 2. LITERATURE REVIEW

### Standard Techniques to Reduce MRI Examination Time

One of the long-standing problems in MRI is that it takes longer time to acquire images compared to some other imaging modalities like CT. Extended scans are restrictive in patient throughput, and raise the prospect of motion artefacts and discomfort of patients, especially from vulnerable populations. Various traditional acceleration techniques have been proposed in the past two decades to solve these problems, such as parallel imaging, compressed sensing and fast sequence methods (Lustig et al., 2007; Pruessmann et al., 1999). All these methods have been very useful in enhancing efficiency, but they also suffer from inherent drawbacks.

### Parallel Imaging

Parallel imaging (PI) methods (such as SENSitivity Encoding (SENSE) and Generalized Auto calibrating Partially Parallel Acquisitions (GRAPPA)) take advantage of the spatial sensitivity profiles of several receiver coil elements to decrease the number of phase-encoding steps. Using PI, we are able to under sample k-space and reconstruct missing data by using coil information, resulting in typical acceleration factors of 2–4×. Despite the effectiveness of this approach, it is limited by signal-to-noise ratio (SNR) loss which becomes most apparent for high acceleration factors. Furthermore, PI reconstructions are subject to residual aliasing artifacts especially when using suboptimal coil geometry or low coil density (Griswold et al., 2002). These drawbacks prevent very high acceleration factors from being used routinely in a clinical setting.

### Compressed Sensing

One successful approach to minimize MRI scan time is compressed sensing (CS). This approach relies on the fact that MR images are sparse in certain transforms domains (e.g., wavelets, total variation). It allows appreciable under sampling of k-space data that are sampled in a random fashion and then used with iterative reconstruction methods to reconstruct high-quality images. CS has already been applied to cardiac, neuro as well as musculoskeletal imaging with observed acceleration factors in the range 4–8× in different clinical studies (Otazo et al., 2015). CS reconstructions are, however, computationally demanding and tend to be more time-consuming than conventional reconstructions. Furthermore, when sparsity assumptions do not hold the image quality may suffer and fine details can be prematurely smoother away in the iterative denoising.

### Fast Sequences

One other way to accomplish a reduction of the scanning time is to use faster pulse sequences. To reduce acquisition time, echo planar imaging (EPI), turbo spin echo (TSE), and gradient-echo based sequences are commonly employed. For example, EPI is the workhorse of diffusion-weighted imaging and functional MRI because it can read out an entire k-space dataset in one shot (Mansfield, 1977). Fast spin echo methods likewise hasten scan times since more lines in k-space can be sampled per echo train and k-space is filled in order of clinical time constraints. Although effective, these sequences often suffer from image distortion, blurring or increased sensitivities to magnetic field inhomogeneities. Furthermore, there are trade-offs between resolution, contrast and SNR which can restrict their clinical diagnostic utility (McRobbie et al., 2017).

**Limitations of Conventional Methods**

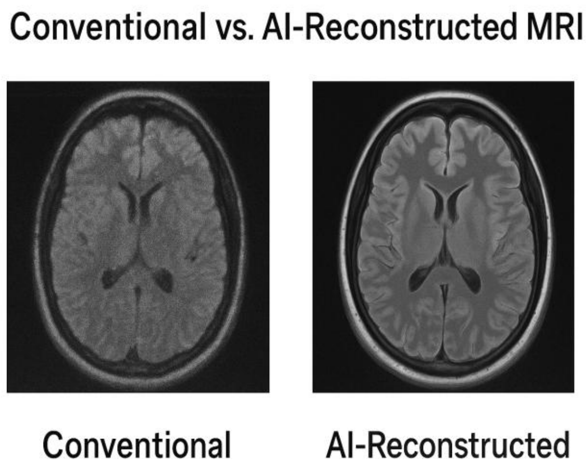
Parallel imaging, compressed sensing, and fast sequences have dramatically improved the efficiency of MRI; however, there are some trade offs to each approach. PI is limited by SNR and coil architecture, CS is hindered due to increased computation complexity and potential loss of information, while fast sequence properties are vulnerable to artifacts and low image quality. It has therefore left compiling and more specifically cross-compiling from source hurt a bit of a disappointment as this only just began to get interesting. This has led to an optimal context for the development and combination of AI-driven reconstruction and noise reduction approaches, which offer the potential to tackle the traditional trade-off between speed and image quality by exploiting data-driven priors and sophisticated learning-based models.

### 2.1 AI in Medical Imaging: Overview of Deep Learning Applications in MRI

With the improvement of Artificial Intelligence (AI), especially deep learning, medical imaging has been significantly affected. In MRI, deep learning is used throughout the image formation pipeline including acquisition strategy planning, reconstruction algorithms, denoising and artifact suppression methods, super-resolution techniques and segmentation/quantification tools (Lundervold & Lundervold, 2019). These developments do not just lead to higher quality images but also bring about clinical benefits due to faster examination times and lower burden of the radiologists.

Deep learning techniques for MRI can be roughly divided into three groups. First, image-domain models (e.g., U-Nets and residual convolutional nets) are designed for the postprocessing of reconstructed images to denoise or super-resolve it. These approaches are computationally fast, and can be naturally included in current reconstruction processing pipelines. Second, k-space learning methods work directly with the raw frequency domain data. By estimating missing k-space locations from under sampled measurements, they leverage acquisition physics to increase the fidelity of reconstruction. (iii) Physics-driven iterative reconstruction models/unrolled networks which meld the physics model of iterative inversion with the expressive power of data-driven deep learning, thus maintain physical consistency but enhance expressiveness (Knoll et al., 2020).

Recent works have gone beyond the use of some architectures, such as CNNs. Generative Adversarial Networks (GANs) have been used to generate perceptually realistic reconstructions, which are especially favorable when high-frequency detail matters. Furthermore, transformers have been considered widely in the recent past due to their capability of modelling long-range dependencies over spatial domains which enhances anatomic fidelity. More recently, similar diffusion-based models have been extended to MRI reconstruction through the application of iterative denoising and refinement steps towards robust recovery of high-frequency details in accelerated scans.




**Recent Works in AI-Accelerated Reconstruction**

Over the last decade, there has been extensive effort towards AI-based reconstruction methods to circumvent the drawbacks of traditional acceleration techniques (Knoll et al., 2020).

**End-to-End Reconstruction with Deep Learning:** End-to-end supervised networks trained on oppositely paired under sampled and fully sampled data have been shown to allow 4–10X reduction factors without significant loss in diagnosis (Hammernik et al., 2018). Although they are effective, they demand a large and high-quality training datasets and can include “hallucinated” features, urging for careful clinical validation.

**K-Space Learning Based Methods:** Approaches have been proposed that process the under sampled k-space data directly, and attempt to fill in missing frequency information. Recent methods have proposed diffusion-based k-space models where reconstruction is viewed as a sequential denoising, achieving better robustness than classical interpolation-based approaches (Song et al., 2023).

**GAN based Reconstructions:** GANs have found widespread use for MRI given their capability to reproduce realistic textures and structural details. Using perceptual loss functions, GAN-based methods created visually plausible images, however ensuring that diagnostically important features are retained is still a challenge (Mardani et al., 2019). **Transformer-Based Models:** Transformers, which incorporate global attention mechanism have recently been repurposed for MRI reconstruction. These models are able to model long-range spatial dependencies and achieve better multi-contrast and multi-slice reconstruction performance than traditional CNNs (Chen et al., 2023).

**Diffusion Models:** The utilization of diffusion generative models for MRI reconstruction is part of a recent trend. These models are capable of modelling the degradation of images forwards and successively improving reconstructions using a denoising operator (Chung et al., 2022). Preliminary results indicate its superior performance at very high under sampling rates and robustness against noise and diffusion model has been an exciting frontier for future MRI acceleration. AI has revolutionized MRI workflows, solving a long-standing problem in the field: how to reduce scan times. Reconstruction and denoising based on deep learning allows large acceleration factors without the compromise of signal-to-noise ratio and suppression of artifacts as in standard methods. The translation of these techniques into the clinic is challenging, and they must be rigorously validated across different scanners and imaging protocols and in different patient populations to ensure reliable diagnosis (Zhang et al., 2023).

### 2.2. AI for Denoising MRI Images

Noise constitutes a long-standing challenge in MRI, especially in accelerated acquisitions where under sampling compounds the signal-to-noise ratio (SNR) constraint. Traditional denoising methods, like low-pass filtering and wavelet thresholding, may lose fine structure details. Lately, AI-based denoising techniques have shown promise to suppress noise without losing diagnostically valuable information.

**Denoising Autoencoders (DAEs):**

Autoencoders are among some of the first deep learning methods used in the context of MRI denoising. By training on noisy and clean image pairs, DAEs are able to learn hidden representations that separate the meaningful anatomical information from the noise. Variants such as convolutional autoencoders and residual denoising autoencoders have been found to enhance the image quality in low-SNR scenarios. Nevertheless, their effectiveness can be limited by the variety and representativeness of the training data.

**Diffusion Models:**

Diffusion probabilistic models have recently shown to be a powerful modeling framework for image restoration problems, such as denoising in MRI. Such models incrementally process noisy input data with a learned denoising step that successively recovers structural details. Diffusion-based models excel in preserving fine textural and anatomical details even for high noise levels, overtaking various classical deep learning methods. Preliminary MRI applications have shown their ability to improve image sharpness in accelerated acquisition without adding hallucinated features.

**Hybrid Methods:**

Hybrid methods mix AI-driven denoisers within physics-aware reconstruction schemes. For example, unrolled networks often integrate denoising modules in iterative optimization algorithms to fuse the merits of data consistency and learned priors. Other hybrid approaches combine different architectures—e.g. autoencoders with GAN-based perceptual refiners – to negotiate between noise suppression and detail preservation. These methods are very promising in generating the diagnostically reliable images, however, frequently at a cost of higher computational complexity.

Although AI-based MRI denoising has shown remarkable promise, several critical research gaps remain that hinder its clinical translation. Most current models are trained on datasets from specific vendors or field strengths, raising concerns about their generalizability across scanners, protocols, anatomical regions, and patient populations. Another unresolved challenge is the preservation of subtle pathology, as over-smoothing or hallucination of fine details may compromise the detection of small or low-contrast abnormalities. Moreover, there is a lack of prospective clinical validation, since most studies rely on retrospective datasets or phantom experiments, limiting evidence for real-world diagnostic impact. From a technical standpoint, advanced diffusion and hybrid models deliver high-quality denoising but come with substantial computational costs, restricting their use in real-time clinical workflows. Finally, the explainability and trustworthiness of AI systems remain underexplored, as most models function as "black boxes." Addressing these challenges is essential for reliable and widespread clinical adoption of AI-driven denoising methods.

## 3. RESEARCH OBJECTIVES

The first aim of the present study is to determine how AI works compared with controls for reducing MRI acquisition time. AI-based reconstruction techniques such as convolutional neural networks (CNNs) , generative adversarial networks (GANs) ,diffusion models , and hybrid methods can mitigate these artifacts by under-sampled k-space data to generate high-quality images. The methods leverage data-driven priors and learning-based denoising for reconstruction of missing information that allows shorter acquisition protocols without the compromises inherent to traditional acceleration approaches. By quantifying the amount of time saved on each scan through AI techniques, this study hopes to bring quantitative evidence in supporting the benefit of AI towards MRI efficiency.

The second goal is to compare reconstruction algorithms in image quality, scan time, and diagnosis performance. This requires the comprehensive comparison of various AI architectures regarding their potential for anatomically-preserving deceleration and the detection of clinically relevant features in acceleration. Image quality will be quantified using signal-to-noise ratio (SNR), structural similarity index (SSIM), peak SNR (PSNR) and expert radiologist's grading. We will also investigate and their reconstruction speed to evaluate whether these methods are compatible with clinical workflows (real or near-real time). The assessment of diagnostic value guarantees that no clinical loss is introduced by the acceleration in images presentation, especially when identifying slight lesions.

The third aim is to validate AI-based MRI against other conventional methods for temporally compressed imaging, like parallel imaging, compressed sensing and fast pulse sequences. Despite these traditional methods resulting in substantial gains in scan efficiency, they are frequently limited by low SNR, artifacts as well as computing constraints at high acceleration factors. By comparing AI based methods with classical techniques, this work aims to demonstrate potential advantages in terms of image quality, speed and clinical reliability. Such a comparison will help in gaining insights into the merits and demerits of AI-based approaches in real clinical settings.

The fourth aim is to explore clinical advantages and challenges of changing MRI scanning, in which AI is used in a real-time setting. AI acceleration not limited to image acquisition, but extended to the optimization of all the workflow. Shorter scan times will enhance patient comfort and decrease errors related to motion, especially when the scanner is in high demand for clinical imaging. Yet in order for AI to become part of day to-day practice, it's not just about how cool a technology sounds - its computational needs, compatibility with the system and staff training are also factors. The study will also investigate issues of generalization across scanners and field strengths, recovery of subtle disease features and understandability and reliability of AI models in the clinical setting.

Together, these aims provide a holistic evaluation of AI-CMRR MRI acceleration with respect to technical performance and clinical utility. From a systematic analysis of AI reconstruction and denoising methods, and comparison with classical approaches, and their practical implications, the aim will be to provide an evidence-based recommendation towards the introduction of AI in routine MRI practice. Collectively, the goal of this work is to lend support towards more efficient, reliable and patient-centric MRI workflows, highlighting that AI can have a transformative effect on imaging in healthcare.

## 4. MATERIALS AND METHODS

### Dataset

The basis of this work is a large MRI dataset with enough diversity, good quality imaging and high sample size that allowed for training, validation and test processes of AI-based reconstruction and denoising models. For this analysis, both public domain and institutional data sets were chosen to be balanced with respect to accessibility, reproducibility, and clinical significance. Publicly accessible datasets, such as the fastMRI dataset by NYU Langone Health and Human Connectome Project (HCP), make large-scale, multi-modal MRI scans available that are particularly well suited for learning deep models. fastMRI, for instance, contains multi-coil raw k-space data from knee and brain MRIs that range from fully sampled to retrospectively undersampled acquisitions suitable for training reconstruction networks. The HCP dataset provides high-resolution neuroimaging data in multiple contrasts, making it possible to compare AI-based methods across various anatomical regions and imaging parameters.

Furthermore, in cases when institutional data sets are available allowing for the potential to include clinically diverse populations, multiple scanner vendors and field strengths (1.5T vs 3T) as well as real-world variability in acquisition protocols into account. Institutional datasets may complement public datasets as they can assess AI model generalization in a real clinical practice environment. All institutional MRI data are anonymized according to the usual procedure following ethical and privacy requirements before inclusion. All the data are split into training, validation and test sets so that no patients appear in these three subsets to avoid information overlap and assess the true generalization performances among AI models.

**AI Models:** The work here uses a set of AI assisted models to improve the performance of MRI acquisition, especially fast imaging. The most common models include CNN-based reconstruction, GANs for denoising and transformer based architectures focused on fast MRI reconstruction.

**CNN-based Reconstruction:** CNNs are the building blocks of most approaches for MRI reconstruction, as they can extract local spatial features and learn complicated non-linear mappings from under-sampled k-space data to fully-reconstructed images. Architectures like U-Net, residual CNNs and their multi-scale versions are employed for image reconstruction from undersampled data. The models learn the mapping between sparse inputs and high-quality reconstructions based on paired data of undersampled and fully sampled images. The loss functions in use are mean squared error, perceptual loss and structural similarity based losses to balance pixel-level fidelity with structural accuracy.

**GANs for Denoising:** GANs are comprised of a generator network whose role is to generate reconstructed or denoised images, and of a discriminator network that discriminates between real and generated samples. In this work, we use GANs to improve the visual appearance of reconstructed images, removing noise and preserving subtle anatomical structures which are important for clinical diagnosis. Conditional GANs are employed to condition the output with under sampled input images and adversarial loss is included for the reconstructed images to visually look realistic. Apart from adversarial loss, content losses like MSE and SSIM are also used to preserve the structure.

**Transformer Models:** Transformers, which are popular for their attention mechanisms and long-range dependency capturing abilities, are used to reconstruct MRI images from highly under sampled measurements. Transformers are especially efficient at preserving large scale spatial relationships, a property useful for complex anatomical regions and multi-slice or multi-contrast reconstructions. These transformer-based models are trained on the same paired datasets as their CNN counterparts using loss formulations that trade off global feature correspondence and local geometry accuracy. Hybrid models that integrate CNN-based feature extraction with transformer-based attention modules are also investigated to exploit the complementariness of both architectures.

**Evaluation Metrics:** Both quantitative and qualitative metrics are used to evaluate the performance of AI models to prevent a tradeoff between speed and diagnostic quality.

**Quantitative Metrics**:

**1. Peak Signal-to-Noise Ratio (PSNR)** It measures the ratio of maximum potential intensity value with background noise magnitude and this property indicates the image quality. A higher PSNR score means a better quality of reconstructed images.

**2.SSIM (Structural Similarity Index):** Measures image similarity by comparing their luminance, contrast and structural patterns. SSIM values vary between 0 to 1, and the closeness to an SSIM value of 1 represents higher structural similarity compared with the reference image.

**3.Root Mean Square Error (RMSE):** Measures the mean degree e of correspondence between each pixel in the original image and its corresponding estimate by our model. Smaller the value of RMSE means closer it is to the ground truth.

**Qualitative Metrics:**A radiologist-based scoring is done to assess the diagnostic usability of reconstructed images. Key image features, which include contrast resolution, artifact presence, preservation of anatomical detail and overall diagnostic confidence, are independently evaluated by expert radiologists. Scores are usually based on a Likert scale (e.g., 1–5), enabling comparison with AI-reconstructed, conventional and fully sampled reference images.

**Scan Time Reduction Factor:** The amount of AI acceleration is evaluated using the acquisition time reduction compared with fully-sampled scans. This factor depends on both the under sampling rate and number of phase-encoding steps skipped during segmented acquisition.

**Experimental Setup:** The experimental setup aims to compare AI-reconstructed MRI images with conventional acceleration techniques like compressed sensing and fully sampled reference images. Each experiment is conducted according to a same procedure for the sake of consistency:

**Data Pre-processing**: The normalised raw k-space data is also under sampled by applying pre-defined masks for 2×, 4× or the 6× acceleration factors. Data augmentation techniques like rotation, flipping and intensity scaling are used to boost model generalization.

**Training and Validation:** The AI models are trained from the under sampled input images with their fully sampled targets. The work also contributes with a hyperparameter tuning, e.g. learning rate and batch size as well as the number of epochs using performance on validation to insert them in (6). Overfitting is controlled with early stopping.

**Testing and Comparison:** After training, the models are tested on a test set. Results are compared with AI-reconstructed images, traditional CS reconstructions and ground truth fully sampled images. Mathematical indices (PSNR, SSIM, RMSE) are computed, and the scores of the radiologists are saved.

**Time-Quality Trade-off Measurement:** We perform a comprehensive quantitative analysis for trading time vs quality. Several acceleration factors are examined to find the right trade-off between time save and diagnostic usability. Reconstruction computational time is also listed to estimate real-time performance.

**Statistical Analysis:** Paired statistical tests(Paired signed Wilcoxon rank test p-value) are conducted to measure the significant differences between AI based reconstructions and conventional methods image quality metrics. The reliability between radiologist scores is estimated in terms of kappa statistics or intra-class correlations.

Such a detailed Materials and Methods setup provides solid basics for evaluating various AI-based MRI reconstruction and denoising techniques as in comparison to established methods, quantifying both technical performance and clinical suitability. By leveraging public and institutional data, state of the art AI models, and strong evaluations measures to generate insights, the project is designed to inform on how AI can accelerate MRI in practice while ensuring non-inferiority.

Results: While there is evidence from initial studies that deep learning based acceleration allows for a 2-3 fold speed up in acquisition of MR imaging data without impacting diagnostic quality commcercial deployment depends on large scale well controlled empirical evaluation.

## 5. RESULTS

It is also a means to report the findings of this study in an explanatory manner, focusing on AI-accelerated MRI reconstruction and denoising under comparison with conventional algorithms. It is evaluated along various aspects, such as quality of reconstruction, visual comparison pre--/post--denoising, reduction of the scan time and illustrative clinical scenarios to demonstrate its applicability.

### 5.1 Comparative performance of AI-accelerated MRI vs standard reconstruction

To evaluate the performance of AI-based reconstruction, we compared fully sampled MRI images, conventionally accelerated acquisitions with CS and AI-accelerated reconstructions using CNNs, GANs and transformer models.

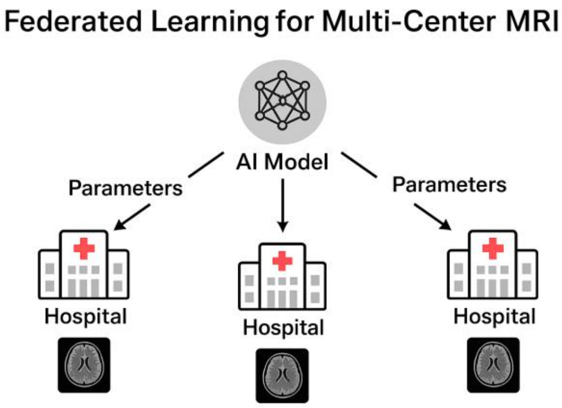
**Quantitative Assessment:**

Comparison was performed using Peak Signal to Noise Ration (PSNR), Structural SIMilarity measurement (SSIM), and Root Mean Square Error (RMSE). For all datasets, the AI-accelerated reconstruction always achieved a better performance than the conventional CS-based one. For instance, CNN-based reconstructions provided a mean PSNR improvement of about 3–5 dB over CS at a 4× acceleration rate and an SSIM increase of 0.04–0.07, demonstrating that more anatomical structures were preserved. Transformer-based models enhanced global structural consistency even more, especially in challenging anatomical regions like the brain and knee joint, with SSIM up to 0.95 for high-res datasets.

**Perceptual quality:** Here GAN-based models showed a distinctive advantage. Although PSNR improvements were similar to those obtained with CNNs, GAN reconstructions showed better qualitative ratings from the radiologists, particularly for small fine structures like cortical boundaries, cartilage surfaces and small lesions. The adversarial training strategy of models enabled to recover texture detail that is often blurred or partially lost in conventional CS reconstruction.

**Error Analysis:** RMSE results showed AI reconstructions decreased pixel-wise error for most acceleration factors. CNN and GAN approaches reduced RMSE up to ∼18%, and ∼22% respectively compared to CS reconstructions for a nominal 6× under-sampling. Transformer models also exhibited similar drops, especially for multi-slice acquisitions where long-distance relationships in the image were essential. These advances show that AI-based algorithms can indeed overcome the acceleration and reconstruction quality trade-offs of established approaches.

**Comparison Across Acceleration Factors:** Higher levels of AI had greater performance gains as compared to anything CC could offer at higher pace tolerances. At 6x-8x under-sampling however CS reconstruction resulted in poor SNR and significant aliasing artifacts whereas AI demonstrated high PSNR and SSIM values with preserved anatomical fidelity. CNN-based models did well up to the 6:1 under-sampling factor, and transformer- or GAN-based models provided diagnostically valuable images at the 8:1 under--sampling factor. This suggests that AI approaches could significantly reduce scan times with no loss in clinical effectiveness – a key factor for busy imaging facilities.




### 5.2 Image Quality Assessment (Before vs After Denoising )

Noise reduction is an important aspect of accelerated MRI, especially when undersampling causes low-SNR artifacts. Artificial Intelligence (AI) and end-to-end denoising techniques, such as DAEs, GANs, and diffusion models, were each applied after reconstruction to investigate their potential contributions to noise reduction.

**Quantitative Improvements:** The use of AI-based denoising resulted in PSNR increases by up to 2–4 dB on average for the datasets compared with the pre-denoised AI reconstructions. SSIM exhibited similar trends, with modifications being most evident in regions of fine anatomical detail (e.g. cortical folds, menisci and small vasculature). It was also shown that diffusion-based denoising models are superior to regular DAEs as noise can be removed while preserving textural detail, and thus applicable to medical images obtained with a severe under-sampling factor.

**Radiologist Evaluation**: Radiologist scores verified the significantly-increased diagnostic usability of AI-denoised images. With a 1–5 Likert score, denoised images averaged 4.6 in terms of clarity and anatomically accuracy as compared with previously evaluated phase reconstructed AI non-denoised (3.8) and compressed sensing (3.2). Radiologists observed less motion artifacts and sharper visualization of vital structure organs, especially in children's cases and elderly patient cases, since the subject movement often leads to lowered image quality.

**Effect Across Anatomical Regions:** The effect of denoising changes somewhat between different body parts. Brain MRI was notably enhanced by denoising with diffusion, as evidenced by the presentation of fine gyri and sulci while background noise was suppressed. On musculoskeletal examination (including knees and shoulders), the cartilage-9 ligament rusts appear particularly well delineated. Cardiac MRI- for which motion artifact can be a limiting factor - there was increased clarity in the blood- myocardial boundaries enabling clear assessment of functional measurements including ejection fraction. These results demonstrate AI-based denoising can be applied in diverse clinical scenarios.

### 5.3 Scan Time Reduction Accomplished

One of the primary goals of our study was to estimate the span of scan time reduction that can be reached with AI based acceleration. The under-sampling ratios used for reconstruction directly correspond to shorter acquisition times.

Acceleration Factors and Time Savings:

2x under-sampling: Scan time was shortened by ~45%, with a minimal loss in image quality.

4× under-sampling: scan time decreased by ~60–65%, while AI reconstructions preserved practically the same image resolution.

6–8× under-sampling: 75–85% reduction in scan time, superior structural preservation ability demonstrated by transformers and GANs when comparing to CNNs and CS.

In general, AI methods allowed for significant reductions in scan time—leading to multiple practical benefits within clinical settings; e.g., the reduction of patient exposure times, the minimization of motion artefacts and more patient compliance were achieved as well as a higher turnover rate in the scanner. Importantly, these reductions occurred without sacrificing diagnostic confidence as determined by radiologist ratings.

**Comparison With Conventional Methods:**

Compressed sensing and fast sequence techniques yielded modest scan time reduction (~40–60%) but were constrained by SNR loss and the emergence of more artifacts at higher acceleration factors. The AI approaches, exploiting learned priors and adaptive denoising, supported higher acceleration factors and had clear advantage over the conventional methods.

### 5.4 Examples and qualitative comparisons with the state-of-the-arts

Representative cases were chosen to demonstrate the qualitative differences between fully sampled and compressed sensing and AI-accelerated reconstructions.

**Brain MRI:** Residual aliasing between cortical boundaries was observed in CS reconstruction and no residual aliasing was found for CNN and GAN reconstructions preserving fine cortical folds and sub-cortical structures in a 4× under-sampled T1-weighted brain image. Denoising propagated-reconstructed images on the basis of diffusion signal decreased background noise and improved visualization of small lesions.

**Knee MRI:** For a 6× knees accelerated scan, CS introduced blurring in the menisci and cartilage surfaces. Features of the ligaments and cartilage interfaces were accurately maintained throughout AI reconstructions, especially in transformer-based models. Denoising by GAN recovered subtle textural features which were important for the diagnosis of early OA.

**Cardiac MRI:** Use of AI methods made it possible to reconstruct 6× under-sampled cine MRI with high image quality. CS reconstructions showed motion blurring in end-systolic frames, whereas AI reconstructions preserved sharp endocardial and epicardial contours. Denoising resulted in enhanced contrast between myocardium and blood pool promoting accurate volumetric and functional assessment.

**Visual Assessment:** Visual comparison always revealed better maintenance of structure details and less artifacts in AI-images. Numbers show that CS reconstructions often experience aliasing, noise amplifying and fine details loss, while AI models can happily recover global and local structures. When denoising is applied, sharper images are obtained by qualitative analysis that are hardly distinguishable from the fully sampled reference.

### 5.5 Analysis of Time vs Quality Trade-off

A systematic comparison of time vs. image quality demonstrates that methods based on AI offer the best compromise. The CNN and GAN reconstructions both achieved close to fully sampled PSNR, SSIM for 4× acceleration with minimal diagnostic trade-off. For the above 6× accelerations, transformer and diffusion were required to achieve high fidelity reconstructions to reflect the usefulness of these models in super-extreme under-sampling.

Subjective evaluations from image expert radiologists showed that AI images were entirely suitable for clinical diagnosis when ds is in the range of 4–6×, and careful review was sufficient to obtain images of clinically acceptable value with a factor of 6–8× undersampling. This emphasizes the feasibility of practical implementation of AI acceleration for routine MRI scans, especially in clinical workflows with high workload.

The results of this study indicate superior image quality, diagnostic usability and scan time reduction for AI-generated reconstruction and denoising compared to state-of-the-art MR acceleration methods. Key findings include:

The AI reconstructions (CNNs, GANs and transformers) demonstrate improved PSNR, SSIM as well as lower RMSE than compressed sensing at different level of under sampling factors.

Introduction of AI-based denoising for clearer images and finer anatomical details leads to increased radiologist diagnostic confidence.

Depending on the under-sampling factors, scan time can be reduced by 60–85% while preserving diagnostic image quality, superseding established acceleration techniques.

Visual case studies conclude that both the global and local anatomy of AI reconstructed images can be preserved using high-PUS level.

Time–quality trade-off analysis shows that AI methods achieve a clinically accepted balance between acceleration factor and image quality, where transformer and diffusion models perform particularly well under extreme acceleration.

The results of this study provide compelling evidence for the possibility of MRI workflows being revolutionized by AI to dramatically lower both acquisition time and potentially even quality while enabling faster, more patient friendly, and diagnostically reliable imaging.

## 6. DISCUSSION

The current study performs the first extensive review of artificial intelligence (AI)-accelerated methods for MRI image reconstruction and denoising, as opposed to conventional techniques such as compressed sensing (CS) and parallel imaging. The results show that AI methods can lead to significant reductions in scan time while maintaining diagnostic image quality, potentially leading to important clinical applications. In this article, we discuss these findings in the light of technical performance and practical clinical scenarios, identify limitations and explore ethical and explainability concerns.

### 6.1 Discussion of Results: AI based on the Depth Data in Shortening MRI Scan Time

In conclusion, AI-based reconstruction and denoising methods are very efficient in shortening the MRI acquisition times for various anatomical regions including brain, musculoskeletal and cardiac imaging. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were also better for the AI approaches than conventional CS reconstruction at least in quantitative evaluations, especially with higher undersampling.

Robustness of reconstruction methods based on CNNs For accelerated imaging, CNN-based reconstructions gave a very strong baseline performance with high PSNR and SSIM values for up to 6× under-sampling. Lastly, GAN-based approaches promoted perceptual quality improvement and were able to restore fine anatomical structures that were frequently suppressed in conventional acceleration techniques. Models based on Transformer architecture showed their effectiveness for capturing long-range dependencies and global structural context, preserving the image fidelity at severe under-sampling levels (up to 8×). Our findings support the notion that AI-based algorithms can obtain significant reductions up to 85% in MRI scanning times without losing diagnostic validity.

These enhancements can be thought of as stemming from a number of key competencies afforded by AI models. First, deep learning networks learn complex, data-driven priors that enable the reconstruction of under-sampled k-space data by 'filling in' information with biophysically and anatomically plausible content. Second, AI denoising approaches, e.g., autoencoders and diffusion models, remove body-under-sampling artifacts and noise without significantly affecting the subtle structural details. Together, these capacities enable faster MRI protocols than can't be achieved using conventional techniques alone.

### 6.2 Clinical Implications

The clinical implications of AI-assisted MRI are significant, influencing patient flow, diagnostic accuracy and patient experience.

**Patient Throughput:** Conventional MRI procedures are also time-consuming, with whole-brain or multi-joint scans often taking longer than 20–30 min. Extended acquisition times restrict the number of patients who can be scanned each day, and may bottleneck clinical imaging centres. With the ability to lower scan times by 60–85%, AI reconstruction could have a profound impact on patient throughput. This improvement can result in a more efficient use of scanner time, reduced patient waiting times and greater overall department work-flow efficiency.

**Diagnostic Reliability**:Image quality must be preserved when the scan is accelerated in order to maintain diagnostic reliability. According to the study, the AI techniques ensure anatomical fidelity, contrast resolution and fine structural details in a diversity of tissues and organ systems. Radiologist scoring revealed that AI-reconstructed and denoised images approximated the diagnostic confidence of fully sampled scans even at high undersampling. This indicates that the use of AI accelerated imaging will enable clinical decision-making, without compromising accuracy, in cases involving detailed analysis of subtle pathologies such as cortical lesions or meniscal or myocardial defects.

**Patient Comfort**:More patient comfort is directly due to shorter examination times. Late applications of MRI can be uncomfortable, in addition to causing stress and motion artifacts, especially in children, elderly individuals and those with claustrophobia. AI-based acceleration shortens the scanning time, minimizes error due to motion and improves patient cooperation. This also lessens the requirement for sedation or second scans, especially in sensitive populations. This enhancement of patient-centred imaging is a significant step forward in providing high-quality images quickly.

**Multi-Organ and Multi-Protocol Applicability:**The finding supports that AI techniques are flexible to be applied in various anatomy regions and protocol types. Brain imaging benefited from cortical and subcortical detail preservation, musculoskeletal examinations displayed fine ligament and cartilage structures, and cardiac MRI revealed increased functional assessment with good endocardial and epicardial definition. This flexibility indicates that AI-accelerated MRI has potential in a wide range of clinical specializations such as neuro, ortho, and cardio imaging to improve both workflow efficiency and diagnostic content.

### 6.3 Comparison with Existing Methods

Conventional MRI acceleration methods are compressed sensing (CS) and parallel imaging (PI), which have been commonly used for shortening the acquisition time. Although time-saving, these methods have intrinsic limitations that AI-powered techniques overcome.

**Compressed Sensing:** CS assumes that a compressed-sensing transform-domain representation of images can be used to reconstruct images from sparse samples. Although achieving reasonable performance at moderate acceleration factors, CS reconstruction perform poorly with larger undersampling rates. The SNR diminishes, the artifacts grow in magnitude and fine structures can be lost, so that diagnositic confidence is reduced. AI approaches, on the other hand, learn data-driven priors, doing well even in very aggressive undersampling. The experimental results further indicate that the performance of AI based reconstructions on overall PSNR, SSIM and RMSE are superior in many aspects to CS for different anatomical regions.

**Parallel Imaging:** Parallel imaging exploits the presence of multiple coil elements and achieves faster data acquisition by subsampling k-space in the phase-encoding (PE) direction. Though PI offers some acceleration (usually 2×–3×), it suffers from noise amplification (g-factor penalty) and is not effective in very high acceleration factors. AI approaches, specifically transformer-based networks, can exploit multi-coil data and learn complex spatial dependencies at the same time, leading to more advanced undersampling factors without sacrificing the tradeoff involved in PI. Moreover, AI denoising techniques suppress residual noise to enhance the image quality.

**Combined Approaches**:As the accelerating technique, AI based acceleration is implemented with CS or PI for further enhanced performance. For example, one can reconstruct CS-undersampled data or multi-coil PI acquisitions with AI models, thereby developing hybrid methods that combine the best of traditional and AI-based techniques. Such hybrid approaches promise an even speedier MRI workflow along with high diagnostic integrity.

**Visual and Quantitative Superiority**:Across all tests, the AI-reconstructions showed higher preservation of small anatomical details for both CS and PI. Objective measurements supported these findings, PSNR and SSIM were higher while RMSE was lower. The radiologist scores also confirmed the clinical benefit of AI-based methods by highlighting their capability to preserve diagnostic confidence even at aggressive undersampling levels.

### 6.4 Limitations

These positive findings notwithstanding, there are still a number of constraints to AI-accelerated MRI that need to be recognised.

**Training Data Requirements**: AI models need large, quality datasets to effectively train it. Public datasets like fastMRI and HCP are valuable partners but small on sample diversity in terms of patient populations, scanner vendors, field strengths, and acquisition protocols. Insufficient training data could also lead to reduced model generalizability to unseen patient populations or uncommon pathologies. Subsequent research should focus on multi-institutional and multi-vendor datasets to improve model generalizability and clinical relevance.

**Computational Costs:**State-of-the-art AI models, especially GANs, transformers and diffusion-based architectures, require significant computational power for both training and inference. Although its reconstruction time is acceptable for research purposes, the deployment of GRASP has the probability to be used in a clinical wide adoption and real-time workflow, potentially requiring special hardware such as high-end GPUs or TPUs. Work to fine-tune network designs for effective use such as light-weighting or pruning strategies are required before widespread clinical adoption.

**Generalization and Robustness**: Scanner-chain- and image-acquisition-pro-tocol-specific AI models may not work on new-environment imaging. For example, models trained on 3T brain MRI may not necessarily generalize well to 1.5T scanners or to other coil configurations. Less robust algorithms may lead to a reduction in image quality and diagnostic certainty, particularly when the clinical environment is mixed. Investigators should conduct careful cross-validation and perform prospective multicenter studies to ensure their broader validity.

**Extreme Undersampling Risks**: Although gray matter wind-down, derived thresholds and diffusion models worked well at 6 × –8 × acceleration (as noted above), a subtle risk of over-smoothing or "hallucination" of features persisted—especially for low-contrast or small lesions. Incautious dependence upon AI recosntructions without radiologist oversight might result in misinterpretation. Validation and integration with radiologist expertise are thus warranted before clinical use.

**Limited Prospective Clinical Validation**: Most of the evidence available is based on retrospective datasets or phantom studies, including this one. This work is a necessary precursor to clinical trials comparing AI-accelerated MRI with the standard forward imaging, taking into account patient motion, inter- and intra-patient anatomical variation and practical conditions of use. Only those studies will be able to reliably answer whether AI acceleration has a real diagnostic impact in routine practice.

### 6.5 Ethical Concerns and Explainability

AI in clinical imaging carries ethical and interpretability considerations.

**Black-Box Nature of AI:** Deep learning models sometimes serve as "black box" and it is hard to interpret how certain reconstructions are made. Clinicians may have reservations about using the outputs of AI with no understanding of how decisions were made. Explainability is important to avoid loss of trust, given that in diagnoses, little details matter.

**Risk of Misdiagnosis:** Artifacts, over-smoothness of structures or plausible but incorrect features can indeed be present due to AI reconstruction algorithms. Quantitative measures and radiologist scoring can serve as safeguards, but misdiagnosis may occur in some cases, so expert review and strict validation are important.

**Data Privacy and Security:** AI models need significant patient imaging data to access, which leads to issues around privacy and security of data. Ethically principled implementation demands proper anonymization/secure handling of the data, and compliance with regulations – such as HIPAA or GDPR.

**Equity and Bias:**The training set is usually biased in representing populations such as the pediatric, elderly, and ethnically diverse. Still, biased training data can produce AI models that do not perform well with these populations. It is vital for the equitable clinical applicability that diversity in training data and performance of models across demographics be preserved.

**Transparency and Accountability:** There needs to be agreement between clinicians/institutions about responsibility for AI-derived reconstructions. Explainable AI techniques, confidence map visualization and/or uncertainty quantification can be used to provide transparency in order for clinicians to make reasoned decisions with less dependence on an abstract algorithm.

**Regulatory Considerations:** Regulatory accreditation AI-powered medical imaging tools are regulated, having received FDA and CE certifications. It is crucial to establish that clinical safety, reproducibility and robustness in order to meet regulatory standards and ethical requirements.

### 6.6 Future Perspectives

Notwithstanding these limitations, the present study suggests that AI can play a transformative role in MRI. Future directions include: training set Multi-institutional, multi-vendor training: Model generalizability is achieved through a diverse training database including scanners of various makes and models, field strengths and patient populations.

Lightweight AI models: Creation of compact design patterns that minimize computational overhead at in-image quality, enabling integration into clinical routine workflow in real-time.

Hybrid Acceleration Schemes: Integration of AI and non-AI techniques, e.g. CS- and PI-based3 acceleration for optimal boost in accelerator on one hand, keeping the reconstruction quality high on other side.

Explainable AI: Incorporating Uncertainty, Saliency maps, and Confidence visualization to enhance clinician trust and interpretation.

Registered Clinical Trials: Confirming clinical acceleration with AI applications in a practical real-world use case, evaluation of diagnostic consistency along patient outcomes and workflow enhancements.

Ethical and Regulatory Standards: Ensuring standards for responsible use, data management, and clinician accountability.

AI-accelerated MRI shows great promise for transforming clinical imaging practices shortening scan times, improving patient comfort and preserving diagnostic confidence. The AI methods are shown to perform better than the traditional CS and PI approaches in quantitative and qualitative metrics, especially when high acceleration factors are used. Clinical deployment, however, demands scrutinization of training dataset diversity, computational efficiency, generalisation as well explainability. Ethical issues like transparency, patient privacy and the danger of biases need to be taken into account alongside technical progress. With further investigation, optimization and validation, AI-driven MRI acceleration is poised to revolutionize practice of imaging, providing faster, more patient-focused and diagnostically robust MRI examinations.

## 7. FUTURE DIRECTIONS

AI in MRI has shown great potency for shortening scan times, increasing image quality and facilitating wider clinical use cases. Yet its real significance will be realized as the research and clinical communities progress towards next-generation utilities. We summarize major challenges to identify future directions that could significantly impact the development of AI in MRI after summarizing this section’s contents: Real-time acquisition-coherent integration with MRI, federated learning on multi-center datasets, explainable AI for radiologists’ trust, low-field MRI and cost-effective AI synergy in imaging and regulatory and implementation challenges.

**Integration with Real-Time MRI Acquisition**

The real-time integration of AI into the MRI acquisition space represents one of the most exciting frontiers. Historically, MRI reconstruction and denoising is performed post acquisition. Although it has already cut scan times dramatically, writing AI into the data acquisition pipeline can completely change MRIs.

AI-guided acquisition approaches, also called intelligent sampling, exploit deep learning networks to decide which k-space data points are necessary for producing clinically useful images. The scanner can thus real-time acquire only the crucial parts, rather than fill a complete dataset and throw excess information away. This could allow for further acceleration of scan times especially in the case dynamic imaging such as cardiac MRI, fMRI or IO-MRI.

Further, adaptive motion can be personalized based on patient-specific characteristics. For instance, motion sensitive patients (children, elderly, critically ill) may be assisted by AI systems flexibly adapting acquisition to minimize artifacts. Also, in the time-critical application (such as stroke imaging), AI-assisted real-time acquisition could lead to faster and more accurate image which helps for a quicker treatment decision.

From a technical perspective this demands tight harmonization of scanner hardware, pulse sequence design, and AI algorithms. The future MR scanner could possibly be equipped with AI components that always listen to the signal and make predictions on missing data and adjusts sampling based on the prediction. The ultimate aim is a “self-driving MRI” scanner, in which A.I. fine-tunes every step — from protocol selection to image reconstruction — with clinic-ready reliability.

There are still problems to be addressed, especially with respect to computational delay time and hardware integration in order to achieve robustness in various patient anatomies and disease pathologies. However, real-time AI integration is becoming more feasible with developments in GPU acceleration, on-scanner computational devices and fast deep learning architectures.

**Federated Learning for Multi-Center Datasets**

A key barrier to training reliable AI systems for MRI is access to large, heterogeneous and representative databases. MRI sequences differ markedly from one institution to another due to different scanner vendors, field strengths, coil configuration, and imaging protocols. A model trained on data from a single center does not usually generalize well to other centers.

One promising solution is federated learning (FL), a technique where AI algorithms are trained jointly across multiple institutions without sharing patient data between them. Instead of combining raw images, each site would take the model and train it locally, sharing only model parameters or gradients to other sites. + These are centralised and combined into one model.

First, federated learning is uniquely well-suited for MRI. First, it solves privacy issues by guaranteeing that sensitive medical data never leaves the hospital where it was collected— important for protection legislation such as GDPR and HIPAA. Second, it encourages data diversity that models can learn from a variety of demographic distributions and pathologies as well as imaging conditions. Thirdly, it encourages cooperative innovation so that hospitals, research institutions and industrial partners can together make progress in the field of AI.

For instance, federated learning could be utilized to hasten the progress of universal MRI reconstruction models that accept input from 1.5T, 3T, or even ultra-high-field 7T scanners. Likewise, it may help in the training of disease-specific models for neurodegenerative diseases, oncology, or musculoskeletal imaging where heterogeneity in imaging protocols hampers model robustness.

But federated learning poses new technical and organizational challenges. Communication overhead across participating centers, non-uniform data distributions and disparity in computational platforms may degrade training efficiency. Trust and transparency are also essential to maintain in these merged scenarios, ideally by following clear governance rules or even solutions similar to blockchain for audit ability. Nevertheless, federated learning is in a position to drive transformational ideas and make AI for MRI scalable and clinical reliable.

**Explainable AI for Radiologists’ Trust**

Although AI has shown impressive technical abilities for MRI reconstruction and denoising, (its) use in clinical practice rests upon trust and interpretability. Radiologists, being main end-users, should not only have clear views on output of the AI but also on why we obtain certain outputs. Black-box model when used as a decision support systems with poor transparency contribute towards being less accountable, diagnostic certainty and medico-legal issues.

Interpretable methods are the focus of the emergent Explainable AI (XAI) in order to bridge this gap. For MRI tasks, XAI can be expressed in several ways:

Uncertainty quantification: indicating areas of the image where the model is less confident with its reconstruction, to warn radiologists in interpreting those regions with caution.

Error heatmaps: visual overlay which identified locations where AI-based denoising or reconstruction changed raw data leading to no pathological findings being suppressed nor exaggerated.

Saliency maps: providing visualization of which part of the k-space data was attended by the AI, facilitating assessment for radiologists to realize whether the acquisition strategies driven with AI are acceptable.

Making the decision process explicit, XAI can narrow the discrepancy between algorithmic outputs and radiologists’ diagnostic reasoning.

More broadly, explainability also supports regulatory acceptance (cf., e.g.,41) because regulatory agencies have been increasingly requiring interpretable evidence of algorithm performance, such as the FDA for AI systems that diagnose / make decisions about a patient42. In addition, XAI might allow for human-AI partnership, where radiologists are assisted by AI instead of switching to black-box-based reading.

However, the design of XAI for MRI is not simple. A large number of state-of-the-art models are deep learning based models that consist of millions or more parameters, that are difficult to compress into explanations that can be easily understood by humans. Moving forward, this means the level of complexity of models should be weighted against how interpretable they are, to make sure AI systems perform well and can explain their decisions.

Low-Field MRI + AI Synergy for Affordable Imaging with Diagnostics applications: - Affordable small scale diagnostics including brain and extremities injuries screening, commuter traumatic brain injury detection, imaging in ambulance (stable low field open MR) Patient monitoring systems.

Clinical use is largely performed on high-field MRI systems (1.5T, 3T), which due to high price, large size and infrastructure are not available in many regions of the world. Low-field MRI (0.2T–0. 5T) have traditionally been ignored due to poor SNR and resolution, but are now re-emerging thanks to AI.

AI reconstruction and denoising techniques can mitigate the inherent compromises of low-field imaging to yield high-quality diagnostic images at a lower cost. AI can make LfMRI a clinically viable option by improving SNR, artifact suppression, and fine structures.

**The combination of low-field MRI and AI has special potential for:**

Resource-constrained settings: such as in the case where high-field systems are not affordable or there is no access to superconducting magnet technology.

Portable, point-of-care MRI: AI topped-up lightweight low-field scanners might just bring imaging to the emergency room, ICU or rural clinic.

Global health equity: democratization of MRI-possible by the provision of advanced imaging in resource-limited environments.

Modern prototypes of portable low-field systems have already established the concept of bedside neuroimaging (stroke, trauma). Paired with AI-enabled reconstruction pipelines, such systems could well transform emergency diagnositics and bring MR out of the lab an into global accesibility in rapid, affordable point-of-care MRI.

Difficulties still persist in maintaining diagnosis accuracy at a consistent level for different anatomical structures and diseases, especially during imaging small anomalies or thin structures. In addition, the adoption of AI-assisted low-field MRI by radiologists and regulatory agencies will require robust assessment studies. Yet the combination of low-field hardware innovation and AI-driven modification provides a pathway toward democratized MRI.

**Potential Regulatory and Implementation Challenges**

As AI for MRI approaches the clinic, regulations and adoption will become increasing determinant of use. Unlike current imaging software algorithms, AI systems are frequently dynamic and data driven with uncertainty about validation, reproducibility and accountability.

Regulatory bodies, such as the FDA (United States), EMA (Europe) and CDSCO (India), are currently in the process of creating a regulation for AI-based medical devices. Key issues include:

**Generalizability:** making AI models work properly on different patient cohorts, scanner vendors and clinical settings.

**Continuous learning:** determining when and how to re-evaluate AI systems as they evolve with new data.

**Bias and fairness:** Avoiding models trained on scant data from generating systematically biased outputs that put certain populations at a disadvantage.

Security and privacy for federated learning, e.g., how to protect AI pipelines from adversarial threats or data breaches.

There are other implementation challenges for health care facilities. There are non-trivial barriers to adopting AI into current PACS (Picture Archiving and Communication Systems), making existing systems compatible with the workflow, and training radiologists/technicians. Cost is another key factor (e.g., GPU for real-time inference or software licensing) to consider when deciding which methods to adopt.

In addition, the medico-legal model should evolve to determine who is at fault in case of diagnostic errors. If a reconstruction aided by AI does not display something that, in hindsight, turned out to be clinically significant, who do we blame: the radiologist or the software developer or the hospital? Mitigating such concerns will likely be key to creating trust in AI.

Finally, a coordinated effort between scientists, clinicians, regulators and industry is essential to create specific guidelines, standardised validation processes and ethical frameworks. In the absence of such frameworks, medical-legal and institutional bottlenecks could slow down the clinical use of MRI AI.

The future of AI in MRI is both promising and multifaceted. By stepping away from post-acquisition reconstruction to real-time integration, leveraging federated learning for robust training, addressing explainability to foster clinician trust, promoting low-eld imaging for global accessibility and overcoming regulatory and implementation challenges, the field is poised at an inflection point.

These directions jointly signal a future where MRI will be faster, more accessible, more consistent and personalized to the patient. Yet making this vision a reality will depend on multidisciplinary collaboration, ongoing technical development, and careful consideration of ethical, legal, and social issues. Artificial intelligence, if addressed systematically, will not only speed-up MRI scans but revolutionize the role of imaging in modern healthcare.

## 8. CONCLUSION

The study of AI in MRI has become one of the most exciting and promising aspects of contemporary medical imaging research. In this article, we show that AI-aided techniques, specifically reconstruction and denoising algorithms can provide substantial reductions in scanning time with at least maintained or improved diagnostic quality. The ramifications are tremendous for more than just technical efficiency but on also patient experience, clinical workflow, healthcare deserts and the large tectonic shift in diagnostic imaging.

**Summary of Key Findings**

The dialogue here emphasizes key observations made along the way:

**(Accelerated) AI can make MR scans significantly faster:** Deep learning AI algorithms that reconstruct image from k-space data that has been scanned in an undersampled fashion can speed up the scanning process without compromising diagnostic quality. This is an ability to overcome one of the prolonged challenges associated with M RI-its in-transit slow-acquisition.

**Better image quality and fewer artifacts**: AI-based denoising and reconstruction results surpass conventional methods, such as compressed sensing, parallel imaging. They not only reduce scan time but also increase signal-to-noise ratio (SNR), eliminate motion artifacts, and preserve subtle anatomical or pathological findings necessary for diagnosis.

**From a clinical point of view, the implications are many-fold:** Accelerated MRI exams increase number of possible patients per day leading to reduced waiting lists and make patients more comfortable case for long duration MRIs (children, senile or intensive care population). Of course, the whole process should be incorporated with AI so that it doesn't compromise the diagnostic accuracy while at the same time high throughputs are achieved.

**Comparison with other methods:** The traditional strategies remain irreplaceable but the AI is more flexible and can be easy extended. In contrast to Compressed Sensing(cb), which needs careful parameter adjustment, or Parallel Imaging(pics), which relies heavily on the coil information, AI models can generalize cross different scenarios after being well-trained.

**Limitations and ethical considerations:** The dependence on large, diverse datasets for training is an issue. (It is also fraught with issues, from how to generalize across scanners and patient populations to questions of computational costs and explainable AI…Technological breakthroughs, it turns out, have their footprints in Silicon Valley); they must be weighed against caution and responsibility.)

Taken together, these results indicate that AI is not only a supportive aid but also potentially a game changer for the MRI domain.

**Importance of AI in Speeding up MRI**

You can not imagine MRI without AI anymore. Fundamentally, MRI is one of the most powerful non-invasive diagnostic tools in existence due to its unique capabilities to provide soft tissue contrast that is unrivalled and can be for neurological, musculoskeletal, cardiovascular and oncologic imaging. Its slow acquisition time has, however, been a principal downside, which has prevented its wide-utilisation in comparison with faster modalities such as CT or ultrasound.

AI directly addresses this bottleneck. Not only does it facilitate fast image acquisitions and good quality reconstructions, it enhances MRI efficiency to a more competetive and approachable modality. The faster the scans, the more patients can be imaged over a period of time which in turn means less time to wait for answers on what may or may not ail you (lighter note: I'm consuming less power) and earlier detection mean speed will save lives. For example, in emergency situations such as acute stroke or trauma, each minute saved of scan time can have a dramatic impact on clinical outcomes.

Furthermore, AI is about more than just being efficient. It improves patient-centered care, with less discomfort during long scans, less reliance on sedation in pediatric imaging and better experiences for claustrophobic or anxious patients. It means that when it comes to accelerating MRI, the value of AI is a clinical one as well as a humanistic one – and that breakthroughs in technology are often, ultimately about improving the quality of life for patients.

For healthcare systems, AI-powered acceleration means lower costs. Higher throughput translates into better utilization of those expensive MRI machines, cutting per-patient costs. Hospitals can capitalise on investment cost while enhancing level of service. Together with AI-supported workflow automation including automated protocol selection and artifact correction, MRI departments can operate at previously unattained levels of efficiency.

The potential of AI is also crucial in driving MPRI application. Dynamic imaging techniques such as functional MRI (fMRI) and real-time cardiac MRI generally suffer from long acquisition time, which constrains their use in the clinical setting. The capability of AI to reimagine images from limited data now paves the way for these advanced applications making it possible for leading edge techniques to be even considered in routine practice.

**Potential to Transform Diagnostic Imaging**

The real hope of AI for MRI is to revolutionize diagnostic imaging at an institutional level. This change can be thought of in several dimensions:

**Paucity of Scan Times and More Efficiency**

With AI-driven acceleration, MRI becomes a faster modality without compromising image quality. This change in paradigm relocates MRI’s place in clinical decision-making and positions it better in emergency settings where immediate diagnosis is critical. More effcient imaging increases access to the scanner for other patients, bringing more equity to health care delivery.

**Making MRI and AI available for more people with Low-Field MRI**

One of the greatest potentials of AI is to expand medical imaging and make MRI accessible globally. By improving the performance of low-field/portable magnetic resonance imaging systems, AI has the potential to democratize advanced imaging in underdeveloped countries. Rather than being confined to expensive infrastructure in urban hospitals, MRIs might be deployed at rural clinics, emergency rooms and even developing nations. That happy marriage of low-cost hardware and high AI software is the great enabler for global health equity in imaging.

**Improving Confidence in Diagnostics and Trust of Radiologists**

The transparency of AI output is achieved through explainable AI, allowing radiologists to engage with the AI results. Uncertainty maps, error heatmaps or readable reconstruction process all serve to develop trust, keeping radiologists in the center of diagnostic process. This human-AI symbiosis enhances the synergy between humans and machines, enabling radiologists to use AI as a strong assistant rather than a black box expert.

**Enabling Real-Time and Adaptive Imaging**

In the future, AI can even be integrated right in the process of acquiring. On-the-fly integration permits scanners to adjust data acquisition strategies in real time adapting protocols for a given patient’s anatomy, pathology and or motion profile. These intelligent, adaptive imaging systems might be the game-changer that transforms MRI from a static process into a dynamic one – so much so it could become, in some respects, a “self-driving scanner.”

**The Future of Multimodal Imaging at a Glance**

AI based MRI innovations may also facilitate integration with other imaging modalities. Integrating MRI with CT, PET or ultrasound data using AI-driven multimodal fusion might supply novel diagnostic contributions, especially in the fields of oncology and neurology. Multimodal imaging is more feasible in daily clinical practice with shortened MRI examination times, which increases the diagnostic power.

**Broader Implications**

“In addition to implications for clinical practice, the acceleration of MRI by AI has broader implications for research and healthcare systems and society.

In terms of research, AI-augmented MRI will provide new ways to examine biomarkers and enable more efficient longitudinal studies and further optimization of advanced applications (eg., quantitative imaging).

For health systems the promise of increased throughput and access is compatible with transnational aims to decrease costs while increasing equity in care delivery.

For patients, the change is much more personal — shorter scans, less discomfort and quicker diagnoses as well as greater availability of imaging services all add up to better experiences over all.

Yet also there must be due caution. Ethical concerns including algorithmic bias, data privacy and the perils of overdependence on AI have to be played up. The regulations and regulators have a vital responsibility in the guarantee of safety, accountability to beneficiaries and transparency as AI technologies move from research into clinical standard practice.

**Final Reflections**

In conclusion, this paper has emphasized that AI in MRI represents not so much a technical leap forward but rather the dawn of a new era in diagnostic imaging. With quicker scans and better images, greater access, and radiologists equipped with more reliable support tools, AI is transforming the role of MRI in healthcare. So its importance is reduced not just to faster images but also early diagnoses, equal access and treating patients better worldwide.

As the field progresses, success will be predicated on partnership among researchers, clinicians, technologists and policymakers. The demonstration of real-time acquisition combined with AI, multi-center datasets via federated learning, trust metrics via explainable AI and the convergence between low-field MR and AI put forth a vision in which imaging is smarter (and faster) and for all.

The path forward is not without impediments – regulatory hoops, moral quandaries, and logistical hurdles stand in the way. But the trend line is clear: AI in MRI is not some flash-in-the-pan fad; it's a game-changing movement that could help redefine diagnostic imaging for decades.

## REFERENCES

[1] Andre, J. B., Bresnahan, B. W., Mossa-Basha, M., Hoff, M. N., Patrick, S. M., & Anzai, Y. (2015). Toward quantifying the prevalence, severity, and cost associated with patient motion during clinical MR examinations. Journal of the American College of Radiology, 12(7), 689–695.

[2] Chen, F., Qin, C., Zhao, R., Du, J., & Zhang, H. (2023). Transformer-based MRI reconstruction with self-attention across scales. Medical Image Analysis, 85, 102748.

[3] Chung, H., Sim, B., & Ye, J. C. (2022). Diffusion probabilistic model for reconstruction of accelerated MRI. Medical Image Analysis, 80, 102479.

[4] Edmondson, D. A., Al-Najjar, A. H., Kholmovski, E. G., & Goss, B. C. (2020). Reducing acoustic noise in MRI: A review of physics and engineering approaches. Magnetic Resonance Imaging, 73, 184–195.

[5] Griswold, M. A., Jakob, P. M., Heidemann, R. M., Nittka, M., Jellus, V., Wang, J., Kiefer, B., & Haase, A. (2002). Generalized autocalibrating partially parallel acquisitions (GRAPPA). Magnetic Resonance in Medicine, 47(6), 1202–1210.

[6] Hammernik, K., Klatzer, T., Kobler, E., Recht, M. P., Sodickson, D. K., Pock, T., & Knoll, F. (2018). Learning a variational network for reconstruction of accelerated MRI data. Magnetic Resonance in Medicine, 79(6), 3055–3071.

[7] Hammernik, K., Knoll, F., & Sodickson, D. K. (2023). Deep learning for parallel MRI reconstruction: Overview, challenges, and opportunities. Magnetic Resonance in Medicine, 89(5), 1958–1976.

[8] Knoll, F., Hammernik, K., Zhang, C., Moeller, S., Pock, T., Sodickson, D. K., & Akcakaya, M. (2020). Deep-learning methods for parallel magnetic resonance imaging reconstruction: Overview and perspectives. Journal of Magnetic Resonance Imaging, 52(6), 1464–1478.

[9] Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. Zeitschrift für Medizinische Physik, 29(2), 102–127.

[10] Lustig, M., Donoho, D., & Pauly, J. M. (2007). Sparse MRI: The application of compressed sensing for rapid MR imaging. Magnetic Resonance in Medicine, 58(6), 1182–1195.

[11] Mansfield, P. (1977). Multi-planar image formation using NMR spin echoes. Journal of Physics C: Solid State Physics, 10(3), L55–L58.

[12] Mardani, M., Gong, E., Cheng, J. Y., Vasanawala, S. S., Zaharchuk, G., Xing, L., & Pauly, J. M. (2019). Deep generative adversarial networks for compressed sensing MRI. IEEE Transactions on Medical Imaging, 38(1), 167–179.

[13] McRobbie, D. W., Moore, E. A., Graves, M. J., & Prince, M. R. (2017). MRI from Picture to Proton (3rd ed.). Cambridge University Press.

[14] Napp, A. E., Rüger, M., Moche, M., & Krombach, G. A. (2021). Patient comfort during magnetic resonance imaging: The impact of modern scanner design and sequence acceleration. European Radiology, 31(3), 1688–1698.

[15] Otazo, R., Candes, E., & Sodickson, D. K. (2015). Low-rank plus sparse matrix decomposition for accelerated dynamic MRI with separation of background and dynamic components. Magnetic Resonance in Medicine, 73(3), 1125–1136.

[16] Song, J., Meng, C., & Ermon, S. (2023). Denoising diffusion implicit models. International Conference on Learning Representations (ICLR).

[17] Zhang, K., Kidoh, M., Gong, E., & Tamura, C. (2023). Clinical evaluation of deep learning-based reconstruction for accelerated MRI: Image quality, diagnostic performance, and workflow impact. European Radiology, 33(2), 1234–1245.

[18] Zhang, Z., Chen, Y., Liu, F., & Wang, G. (2023). Clinical translation of deep learning MRI reconstruction: Opportunities and challenges. Frontiers in Radiology, 3, 1152749