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Thesis

**Measurement of the Impact of Artificial Intelligence on the
MRI Workflow**

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1.Summary

Rationale

Magnetic resonance imaging (MRI) is a key diagnostic modality that provides high-resolution, non-invasive imaging without ionizing radiation. Despite its clinical value, conventional MRI scans are limited by long acquisition times, sensitivity to patient motion, high operational costs, and reduced patient comfort. These limitations can affect both workflow efficiency and diagnostic reliability, particularly in busy clinical environments. In recent years, artificial intelligence (AI)-based reconstruction methods have been introduced with the aim of reducing scan time while maintaining acceptable image quality under appropriate clinical supervision.

Study Design

This prospective experimental study was conducted between January and March 2025 and included 20 patients undergoing routine MRI examinations across multiple anatomical regions, including the brain and spine, abdominal and pelvic organs, the musculoskeletal system, the breast, and the whole body. Conventional MRI sequences were compared with AI-assisted sequences using Siemens Deep Resolve Pro technology (Gain, Sharp, Boost). Workflow efficiency was evaluated by comparing acquisition times, while image quality and economic impact were assessed in a subset of representative cases.

Results

A weighted mean reduction in scan duration of 32.2% was observed with AI-assisted reconstruction, with reductions ranging from 68% in small joints to 7.6% in pancreatic imaging. In addition to shorter acquisition times, AI-enhanced sequences demonstrated reduced image noise and improved tissue contrast compared with conventional images. These improvements supported image interpretation without compromising diagnostic confidence.

Conclusion

AI-assisted MRI significantly improves imaging efficiency and workflow performance by substantially reducing acquisition time while preserving diagnostic usability. However, continued radiologist oversight, appropriate training, and ongoing algorithm refinement remain essential. Further validation using larger and more diverse datasets is required to support the safe, accurate, and effective implementation of AI-based reconstruction in routine clinical practice, particularly in high-volume radiology departments.

2. Introduction

2.1. Background

Magnetic Resonance Imaging (MRI) is a fundamental tool in modern medical diagnostics, offering high-resolution, non-invasive visualization of soft tissues, functional organ systems, and vascular structures. Unlike computed tomography (CT) or X-ray, MRI does not employ ionizing radiation, rendering it suitable for repeated imaging and long-term patient monitoring. MRI is based on the principles of nuclear magnetic resonance (NMR), wherein hydrogen protons align with an external magnetic field and emit signals in response to radio-frequency (RF) pulses. These signals are spatially encoded through magnetic field gradients and reconstructed using Fourier transform algorithms, yielding detailed anatomical and functional images [5,18]. This versatility supports a broad range of clinical applications, including neurology, oncology, cardiology, musculoskeletal medicine, and abdominal imaging.

In neurology, MRI allows detailed examination of brain morphology, cerebrovascular integrity, demyelinating disorders, and acute ischemic events. Standard T1- and T2-weighted scans distinguish tissues based on relaxation times, while fluid-attenuated inversion recovery (FLAIR) reduces cerebrospinal fluid signal to improve lesion detection. Diffusion-weighted imaging (DWI) can detect ischemic strokes at an early stage, while functional MRI (fMRI) shows brain activity during thinking or movement, which helps with surgical planning and rehabilitation. Modern software tools provide additional support by automatically segmenting lesions, measuring lesion volumes, and tracking changes over time, thereby enhancing diagnostic accuracy for conditions such as multiple sclerosis and brain tumors [2]. Volumetric measurements are also more consistent and reliable than traditional methods, for example, helping to distinguish different Parkinsonian syndromes [4].

MRI is also highly valuable in oncology. Multiparametric imaging, which combines anatomical, diffusion, perfusion, and spectroscopic sequences, offers comprehensive insights into tumor biology. Dynamic contrast-enhanced imaging evaluates vascular perfusion and angiogenesis,

diffusion sequences quantify cellular density, and MR spectroscopy differentiates benign from malignant lesions.

Recent studies indicate that predictive models using imaging data can accurately forecast disease recurrence, including biochemical relapse in prostate cancer, without requiring invasive biopsy [6,19]. Advanced reconstruction approaches enhance the visualization of myocardial structure, cartilage, ligaments, tendons, and joint integrity in cardiovascular and musculoskeletal imaging [1]. Neurology and oncology imaging are highlighted as representative MRI applications, as they comprise the most extensively studied and technically demanding domains in AI-assisted research [8,17].

Despite its benefits, conventional MRI still has drawbacks. High-resolution and multi-sequencing examinations typically take 20 to 60 minutes, increasing the risk of motion artefacts and patient discomfort. Children, the elderly, and patients in critical condition are among the vulnerable groups that are most susceptible to motion, which may mask subtle pathologies. Variability in expertise results in inconsistent image quality, repeated scans, delayed diagnosis, and higher operational costs [14,18]. Prolonged scan duration induces anxiety or claustrophobia, occasionally requiring sedation and additional resources [5]. These difficulties highlight the need for methods that improve effectiveness, consistency, and patient satisfaction.

Artificial intelligence (AI) has emerged as an effective approach to address these challenges. Machine learning models, including convolutional neural networks (CNNs) and generative adversarial networks (GANs), have demonstrated high accuracy in image classification, segmentation, denoising, super-resolution reconstruction, and artefact correction [8]. AI also enables optimization of acquisition parameters, such as repetition time, echo time, and flip angles, thereby speeding up scan procedures while preserving diagnostic quality. Techniques like compressed sensing, augmented by AI, have significantly reduced scan time without compromising reliability, especially in musculoskeletal imaging [1].

In addition to technical advancement, artificial intelligence promotes workflow standardization and improves operational efficiency. Automated quality assurance systems detect suboptimal images in real time, thereby reducing repeat scans and increasing departmental throughput [5]. Integrating imaging with laboratory, genomic, and clinical data enhances the accuracy of predictions regarding disease progression, treatment response, and patient prognosis, advancing

precision medicine in neurology, oncology, and multisystem applications [6,9]. This approach lowers inter-operator variability, minimizes discrepancies across scanners and institutions, and allows radiologists to focus on complex diagnostic tasks [7,8].

However, variability in scanner hardware, acquisition protocols, and patient populations remains a significant challenge to the generalisability of AI models across institutions. The successful implementation of these technologies requires a human-centered approach. Patient acceptance relies on transparency and interpretability, whereas technologists' adoption depends on confidence in system reliability and adequate training [13,14,15]. Ethical considerations, including algorithmic bias, accountability, and patient trust, emphasize the importance of human oversight and rigorous evaluation [16,17]. Standardizing sequence naming across scanners improves consistency and supports transferable learning in AI models [23].

These limitations continue to affect workflow efficiency, image consistency, and patient experience in routine clinical MRI. Artificial intelligence (AI) offers potential solutions by improving image acquisition, reconstruction, diagnostic accuracy, and patient-centered care. This thesis evaluates the effects of AI integration on scan length, image quality, and workflow efficiency through a quantitative comparison of AI-assisted and traditional MRI acquisitions. It presents empirical evidence on the feasibility and clinical value of AI-enhanced reconstruction in routine practice by examining its effects on MRI performance, workflow processes, and patient care, its current limitations, and potential areas for further development. It also discusses implementation requirements, including training, governance, and quality assurance.

2.1.1 Historical Evolution of MRI Acceleration Strategies

Magnetic resonance imaging has long involved a trade-off between image quality, spatial resolution, and acquisition time. High spatial resolution requires dense k-space sampling, which inevitably leads to longer scan durations. As MRI protocols became more complex, incorporating multiple sequences and multiparametric acquisitions, particularly in neurology, oncology, and musculoskeletal imaging, the overall examination time increased substantially. Longer scans can negatively affect patient comfort, increase vulnerability to motion artefacts, reduce scanner

availability, and limit clinical throughput [5,8,18]. These practical issues have consistently motivated efforts to shorten MRI acquisition times while preserving diagnostic image quality. Initial MRI acceleration efforts concentrated on hardware enhancements. Improvements in gradient systems and multi-channel receiver coils facilitated faster signal acquisition and enabled advanced reconstruction techniques. A significant advancement in parallel imaging methods, such as sensitivity encoding (SENSE) and generalized autocalibrating partially parallel acquisitions (GRAPPA), has occurred. These approaches exploit spatial sensitivity across multiple coils to reduce the number of phase-encoding steps, enabling controlled k-space undersampling that achieves moderate acceleration while maintaining acceptable image quality. However, noise amplification and reconstruction artifacts constrain their effectiveness at higher acceleration factors, limiting their application in demanding or high-resolution clinical protocols [18].

Compressed sensing represented a further step forward by exploiting sparsity in medical images. This approach is based on the observation that MRI data often contain redundant information and can be efficiently represented in suitable transform domains. By combining incoherent k-space undersampling with iterative reconstruction algorithms, compressed sensing enables images to be reconstructed from far fewer data points than conventional sampling strategies require. Clinical studies demonstrate that this technique significantly reduces acquisition times, especially in musculoskeletal and oncologic imaging, while preserving acceptable diagnostic quality [1,21]. However, at higher acceleration levels, residual artefacts, image blurring, and reconstruction instability can occur, particularly in anatomically complex regions or in the presence of patient motion [5,18].

Despite these advances, both parallel imaging and compressed sensing encountered practical limits in routine clinical use. Beyond certain acceleration thresholds, image quality often deteriorated due to reduced signal-to-noise ratio, compromised contrast resolution, or loss of spatial fidelity. These constraints highlighted the need for new reconstruction strategies capable of handling highly undersampled data without undermining diagnostic reliability. Artificial intelligence and deep learning have shifted reconstruction methods toward data-driven approaches. Unlike traditional methods that rely on predefined physical models, AI techniques learn reconstruction patterns from large datasets of paired, fully sampled, and undersampled images. AI-assisted reconstruction

naturally extends earlier acceleration strategies by building on physical principles and addressing their limitations [1,18].

2.2. Literature Review

Advancements in magnetic resonance imaging (MRI) technology have enabled the development of artificial intelligence (AI) algorithms that improve image quality, scanner performance, and operational efficiency. Traditionally, AI applications in radiology have concentrated on post-processing tasks, including lesion detection, classification, and segmentation. Recent progress has expanded AI applications to MRI acquisition and reconstruction, leading to reduced scan times, enhanced image quality, and fewer artefacts. For example, artificial compressed sensing (ACS) has demonstrated a nearly 50% reduction in acquisition time for head and neck cancer MRI without compromising image quality [1,8,21], showing the potential of AI-based methods to accelerate imaging workflows.

These algorithms enable either enhanced spatial resolution without prolonging acquisition time or accelerated scans without compromising diagnostic quality. By improving the trade-off between scan duration and image resolution according to protocol configuration, artificial intelligence improves the adaptability and efficiency of magnetic resonance imaging operations. Commercial applications of AI-based reconstruction, such as the Deep Resolve Pro in modern MRI systems, have demonstrated significant technological advancement. These tools are increasingly integrated into routine vendor workflows, allowing acceleration without altering established clinical protocols or reporting practices.

These algorithms use deep learning networks trained on extensive datasets to reconstruct high-quality images from undersampled raw data. Deep Resolve Gains reduces spatially variable noise by generating position-specific noise maps directly from raw acquisition data, enabling targeted denoising without increasing scan time. Deep Resolve Sharp increases spatial resolution by increasing the in-plane matrix size through neural network-based super-resolution techniques, improving image sharpness without prolonging acquisition. Deep Resolve Boost further optimizes highly accelerated sequences by reconstructing images with a high signal-to-noise ratio (SNR) from sparse data sampling. These reconstruction methods collectively enable significant

reductions in scan time while maintaining or improving diagnostic image quality, particularly in anatomically complex regions such as the brain, liver, prostate, and musculoskeletal system.

The application of artificial intelligence (AI) to magnetic resonance imaging (MRI) shows potential for enhancing patient-centered care, operational effectiveness, and diagnostic precision. However, routine AI deployment in MRI confronts significant technical, financial, and organizational obstacles that limit its mainstream adoption, even in the face of rapid technological advancements.

To ensure that AI delivers genuine clinical benefit rather than remaining theoretical, it is essential to identify and analyze these challenges. Most AI-assisted MRI research focuses on tasks such as lesion detection, segmentation, and image reconstruction. While these improve image quality, speed, and signal-to-noise ratio, their generalizability across organ systems and clinical settings remains uncertain [1,18]. This uncertainty persists because AI models are typically trained on retrospective datasets collected from controlled environments using uniform, high-quality imaging protocols. Variations in scanner hardware, imaging protocols, patient anatomy, and motion artifacts significantly affect AI performance [7,8].

These inconsistencies across institutions may diminish diagnostic confidence and restrict the clinical applicability of AI beyond its initial validation. A major technical challenge concerns dependency on operators and workflows. While AI can standardize image reconstruction and optimize protocols, its implementation needs careful integration into existing workflows. Radiology personnel must be proficient in configuring AI-enhanced sequences, monitoring algorithm outputs, and identifying limitations. Improper use or excessive reliance on AI may result in suboptimal images, misdiagnosis, or inefficient scanner utilization. Research indicates that successful AI deployment depends on the acceptance and training of technologists; however, many institutions have not yet developed adequate operational or instructional frameworks [8,14].

The opacity of deep learning models, sometimes known as "black boxes," complicates clinical interpretation, accountability, and informed consent. Assigning responsibility for diagnostic errors, whether to the AI system, the radiologist, or the institution, remains a significant,

unresolved legal and ethical challenge [16]. The human-in-the-loop model addresses these concerns by positioning AI as a decision-support tool while radiologists retain final interpretive authority. This model reduces over-reliance on AI, preserves professional accountability, and enables contextual evaluation of AI outputs [6,13]. However, clear governance frameworks, standardized procedures, and comprehensive training for human-in-the-loop workflows remain insufficient. This limitation leads to variability in AI adoption and uncertainty about best practices for clinical integration.

Routine clinical integration encounters difficulties such as limited real-world evaluation, ethical issues, financial obstacles, and technical constraints [5,8,16]. Addressing these requires comprehensive research assessing AI performance across various organ systems, patient populations, and healthcare settings [7,12,18]. This research requires rigorous evaluation of algorithmic accuracy and reliability [9,10], strategic integration into clinical workflows to improve efficiency and reduce operator dependency [8], analysis of cost-effectiveness and resource use [5,20], consideration of ethical governance and accountability [16,17], and assessment of patient acceptability and satisfaction [13,15]. Together, these findings indicate that careful clinical validation and structured implementation are essential for responsible integration of AI into MRI practice [5,8,13].

Multiple studies have evaluated the impact of artificial intelligence (AI) on magnetic resonance imaging (MRI) workflows in clinical settings, with emphasis on technical performance and practical applicability. These investigations have explored the effects of AI-assisted MRI on scan efficiency, image quality, and diagnostic confidence, while addressing operational [5,8] and ethical considerations [16,17]. The literature provides insights into the feasibility and clinical value of integrating AI into routine MRI practice [1]. AI has been shown to reduce scan times, minimizing patient discomfort and motion artifacts while enhancing workflow efficiency [1,18,20]. While preserving or improving diagnostic reliability, improvements in image quality have also been shown, based on objective metrics including signal-to-noise ratio, contrast-to-noise ratio, and artefact reduction [1,5,18]. The clinical benefit of AI-assisted decision support has also been highlighted by earlier research examining radiologists' confidence and inter-reader consistency in interpreting AI-enhanced images [10,12].

Beyond technical and clinical performance, integrating AI has potential economic benefits, including increased patient throughput and optimized resource utilization [5,20]. Prior research has examined the ethical and patient-centered factors, such as patient acceptance and the role of human supervision in AI-driven workflows [13,15,16].

3. Thesis Objective

The primary goal of this thesis is to systematically evaluate the impact of artificial intelligence (AI) on magnetic resonance imaging (MRI) workflow. Specifically, this study assesses how AI-driven reductions in scan time affect clinical efficiency, diagnostic performance, and resource utilization. To achieve this aim, the research focuses on the following four objectives:

1. Quantitative Evaluation of Workflow Efficiency

To quantify the reduction in acquisition times enabled by AI-enhanced protocols compared to conventional MRI across various anatomical regions.

2. Analysis of Diagnostic Quality and Operational Impact

To evaluate the correlation between AI-accelerated scan times and image quality, as well as assess the subsequent impact on patient throughput and scanner utilization rates.

3. Ethical and Clinical Implementation

To analyze the ethical and clinical challenges associated with AI integration, including human oversight, transparency, and accountability in clinical practice.

4. Recommendations for Clinical Implementation

To propose evidence-based guidelines for the adoption of AI, identify requirements for multicenter validations, and outline strategies for integrating AI into standard radiological practices.

4. Materials and Methods

4.1 Study Design

This prospective, experimental study evaluated the feasibility and operational impact of AI-assisted MRI workflows compared with conventional workflows. It assessed workflow efficiency, operator workload, and resource utilization within a clinical environment.

The study was conducted from January to March 2025 at the Radiology Department of Vercelli Hospital. Twenty consecutive patients were prospectively enrolled, with examinations covering distinct anatomical regions. All patients underwent routine MRI examinations based on clinical diagnosis, with inclusion criteria aligned with standard clinical practice rather than research-specific selection. No additional interventions or invasive procedures were performed beyond routine MRI scans. The study included various clinical scenarios, including neuroimaging, musculoskeletal, abdominal, and cardiac MRI. Both non-contrast and contrast-enhanced sequences were incorporated to thoroughly evaluate AI performance across standard clinical applications, covering routine and complex imaging protocols.

The pilot nature of this study is reflected in the sample size of 20 patients. Rather than generating conclusive estimates of diagnostic accuracy, the study aimed to explore the practical integration of AI, assess workflow feasibility, and highlight challenges in clinical implementation. Each anatomical region was represented by a single patient to allow a broad assessment across multiple MRI applications. This approach reflected diversity in patient anatomy, clinical indications, scan complexity, and sequence types, thereby establishing a reliable foundation for subsequent larger-scale studies. Patient confidentiality and data protection were maintained throughout the study.

Ethical Considerations: This study was conducted in accordance with institutional guidelines and the Declaration of Helsinki. All MRI examinations were performed as part of routine clinical care. Anonymized imaging data were used for analysis, and no additional procedures or interventions were required.

4.2 Integration of Artificial Intelligence into the MRI Workflow

Artificial intelligence was integrated into the MRI workflow in image acquisition, post-processing, and automated workflow management. The aim was to determine whether AI could reduce scan times, limit operator intervention, and standardize protocol execution across different clinical settings and anatomical regions. This implementation enabled a direct comparison of conventional MRI protocols with AI-enhanced sequences in order to assess their impact on functional viability, workflow efficiency, and image quality.

It is critical to differentiate between acquisition and the broader workflow that controls throughput and staff burden in order to understand how AI affects MRI operations. Patient registration, safety screening (metallic implants, renal function when contrast is planned), coil selection, localiser acquisition, protocol sequence execution, contrast injection, post-processing and image transfer to PACS, and, finally, radiologist interpretation and reporting.

The operational benefit of AI-assisted MRI depends on how time savings interact with subsequent processes, even though this study measured acquisition time. Longer scans in a traditional workflow raise the risk of patient tiredness and movement. Variability between examinations and operators may result from repeated sequences, extra patient communication, and protocol disruptions. Longer acquisition windows further raise the possibility of timing mistakes during dynamic periods in contrast-enhanced experiments, particularly when breath-hold compliance is restricted.

Although AI-assisted reconstruction may indirectly affect the entire workflow, it primarily targets the acquisition and reconstruction components. Shorter scans may increase patient compliance while lowering the possibility of motion artefacts and the requirement for repetitions. Time predictability is enhanced by faster scheduled scan completion, which facilitates more seamless scheduling and lessens "cascading delays" throughout the day.

Furthermore, standardised reconstruction helps provide radiologists with more uniform output, which enhances interpretation efficiency, and lessens unpredictability caused by manual parameter adjustment. Scan-time reduction was evaluated as the primary quantitative parameter in this study,

and its operational implications were interpreted from the perspective of the entire MRI workflow. In high-volume departments, where acquisition time is the greatest adjustable component and fixed tasks like screening, positioning, and coil setup stay constant, the process mapping explains why even small savings may have significant operational impact.

4.2.1 Image Acquisition

In this study, AI-assisted image acquisition optimized scan parameters, accelerated sequences, and adapted protocols to patient-specific factors, reducing scan time while maintaining diagnostic quality and workflow efficiency. Scan parameter optimization was performed using AI algorithms to automatically adjust factors such as repetition time (TR), echo time (TE), slice thickness, and field of view (FOV). These adjustments reduced redundant or suboptimal sequences, ensuring each scan achieves sufficient image quality for clinical interpretation while minimizing acquisition time. In addition, deep learning-enhanced parallel imaging techniques were applied to accelerate data acquisition, reducing scan time while preserving signal-to-noise ratio and anatomical detail for high-quality imaging.

Reinforcement learning-inspired sequence selection was used to support adaptive protocol execution, enabling the identification of suitable sequences based on patient factors such as breath-hold compliance, anatomical variability, and clinical indication. This adaptive approach reduced scan time and the need to repeat sequences, improving workflow efficiency. Adaptive protocol timing optimizes sequence order and duration to enhance patient comfort, minimize motion artefacts, and support high-throughput operation. Artificial intelligence, when clinically appropriate, was used to reduce the number of breath-hold sequences for patients with limited compliance and reordered sequences to reduce idle scanner time, ensuring more efficient use of MRI resources.

4.2.2 Reconstruction and Post-Processing

AI-assisted reconstruction was used to standardize image output, ensure consistent diagnostic quality across various anatomical regions and sequence types, and reduce operator effort. By automating complex reconstruction processes, AI reduced operator variability, minimized manual interventions, and accelerated image availability for clinical interpretation. These improvements

sustained diagnostic confidence across multiple tests, enhanced patient throughput, and increased overall workflow efficiency.

In this study, artificial intelligence algorithms analyzed raw k-space data to automatically generate reconstructed images, eliminating the need for numerous manual modifications by MRI specialists. This automation ensured consistent image quality across examinations and anatomical regions, reduced operator workload, and decreased post-processing time. Standardizing automated reconstruction minimized errors associated with human-dependent parameter adjustments, enabling repeatable, reliable imaging results and supporting timely clinical decision-making.

AI-assisted reconstruction was fully integrated into the MRI system, enabling seamless application of optimized sequence settings during routine examinations. Radiologists reviewed all reconstructed images before interpretation, preserving a human-in-the-loop approach. This integration improved workflow efficiency while preserving patient safety, diagnostic accuracy, and clinical accountability, reduced scanner idle time, and supported more efficient use of MRI resources.

Deep learning–based reconstruction with the Deep Resolve Pro package

Image reconstruction was performed on a Siemens MRI system integrated with the Deep Resolve Pro Package, which includes three deep learning algorithms: Deep Resolve Gain, Deep Resolve Sharp, and Deep Resolve Boost. Deep Resolve Gain improves the signal-to-noise ratio (SNR) by applying spatially adaptive denoising. Instead of standard global filters, it produces localized noise maps from raw k-space data, allowing noise reduction in low-SNR areas while preserving anatomical details in high-SNR regions. This approach maintains high image quality across various sequences and anatomical regions, facilitating image interpretation.

Deep Resolve Sharp improves spatial resolution using neural network reconstruction, increasing the effective in-plane acquisition matrix and enhancing edge definition without extending scan time. It was applied to high-resolution neuroimaging and musculoskeletal sequences to visualize fine anatomical structures without increasing acquisition time.

Deep Resolve Boost enables reconstruction from under-sampled data, accelerating scans without compromising image quality. When combined with Deep Resolve Sharp, it enhances both signal

quality and spatial resolution, improving workflow reliability and diagnostic efficiency. Deep Resolve algorithms are compatible with standard coil configurations and operate automatically within routine MRI protocols. Reconstruction settings are standardized to reduce operator variability. Radiologists verified each image to ensure clinical accuracy before interpretation.

4.3 Data Collection Methods

The data collection aimed to ensure consistent results across different anatomical regions and MRI sequence types, enabling comparison between conventional and AI-assisted MRI protocols.

4.3.1 Efficiency Metrics

Scan duration: Traditional and AI-assisted MRI sequences were compared by recording total acquisition times for each anatomical region. Efficiency gains were quantified by calculating the percentage reduction in scan time between conventional and AI-assisted MRI protocols, indicating significant time savings that may enhance patient comfort and reduce motion artefacts.

Patient throughput: Scan duration data were used to assess scanner utilization and average time per patient. These measures were collected to support the evaluation of workflow efficiency in routine clinical practice. Reductions in scan times may increase the number of patients served daily.

4.3.2 Workflow Standardization

AI-assisted MRI protocol adherence was evaluated by assessing consistency in sequence selection and parameter settings relative to institutional guidelines. Variations related to operator handling and anatomical regions were recorded to assess the impact of AI integration on protocol standardization and workflow consistency.

4.4 Data Analysis

Statistical analyses were conducted using SPSS version 27.0. Differences in continuous variables, including overall scan time and percentage scan time reduction between conventional and AI-assisted MRI sequences, were assessed using paired t-tests. Statistical significance was defined as

$p < 0.05$. Normality was checked visually to confirm the appropriateness of parametric testing. The analysis focused exclusively on objective, quantitative outcomes related to scan duration, workflow efficiency, and operational performance.

4.5 Rationale for the Pilot Study Design

The pilot study design enabled a controlled evaluation of the feasibility of artificial intelligence across multiple anatomical regions. MRI examinations were performed on a representative cohort of 20 patients including the brain and spine, abdominal and pelvic organs, musculoskeletal system, breast, and whole-body imaging. In a real-world clinical setting, the study identified technical and workflow challenges, including sequence optimization, operator adaptability, and protocol integration. This study lays the foundation for larger multicenter trials by emphasizing objective measures of efficiency and standardization. Future research should broaden evaluation to include clinical outcomes, diagnostic accuracy, and economic impact, thereby providing additional evidence to support the integration of artificial intelligence in standard MRI procedures. This design also allowed early identification of workflow bottlenecks and integration challenges prior to large-scale deployment.

5. Results

AI-enhanced Deep Resolve sequences consistently reduced MRI acquisition times across all anatomical regions examined compared with conventional MRI protocols (**Table 1**). A paired t-test demonstrated a statistically significant reduction in acquisition time with Deep Resolve compared with standard imaging ($t(19) = 9.22$, $p < 0.001$). Detailed acquisition times for each examination, along with the corresponding percentage reductions, are provided in **Table 2**.

AI-assisted reconstruction demonstrated significant efficiency gains across different MRI applications, including neuroimaging, musculoskeletal imaging, cardiovascular imaging, and abdominal imaging. These reductions occurred in both non-contrast and contrast-enhanced examinations, suggesting that AI acceleration is broadly applicable across various protocol types and clinical indications.

All AI-assisted sequences complied with the protocol, and all required diagnostic sequences were successfully acquired. No AI-enhanced examination required protocol interruption or repetition due to reconstruction failure, image artefacts, or inadequate image quality. This protocol compliance was observed consistently across all anatomical regions examined.

5.1 Scan-Time Reduction Across Anatomical Regions

In neuroimaging, total brain MRI acquisition time decreased from 19:56 min to 15:03 min, corresponding to a 24.5% reduction. Spinal MRI demonstrated progressively greater efficiency gains with increasing sequence complexity: acquisition time was reduced by 25.0% in cervical spine imaging, 36.0% in dorsal spine imaging, and 44.0% in lumbar spine imaging. When spinal imaging was considered as a complete examination, total acquisition time decreased from 27:44 min to 18:31 min, representing a 33.0% reduction. Head and neck MRI protocols showed a 25.4% reduction in acquisition time. Abdominal imaging demonstrated variable but consistent time savings: upper abdominal liver protocols were reduced by 27.0%, cholangiographic examinations by 23.3%, and pancreatic MRI by 7.6%, reflecting the more limited acceleration potential of already short, motion-sensitive sequences. Pelvic organ imaging showed a 16.6% reduction, while rectal MRI demonstrated a substantial 52.4% reduction in acquisition time. Multiparametric prostate MRI protocols were shortened by 30.2% while maintaining full diagnostic sequence coverage.

Musculoskeletal imaging exhibited the most pronounced reductions. Pelvic bone MRI acquisition time decreased by 32.9%, shoulder MRI by 49.7%, knee MRI by 43.0%, and foot MRI by 46.0%. Small joint imaging showed the greatest relative benefit, with acquisition time reduced by up to 68.0%. Breast imaging protocols also benefited substantially, with scan-time reductions of 46.0% in clinical breast MRI and 28.6% in breast prosthesis evaluation.

Whole-body MRI acquisition time was reduced from 31:55 min to 23:33 min, corresponding to a 26.0% reduction. Across all anatomical regions combined, total acquisition time decreased from 5 hours 29 minutes to 3 hours 43 minutes, yielding a weighted mean scan-time reduction of 32.2%.

5.2 Image Quality Assessment

In addition to quantitative reductions in scan time, qualitative improvements in image quality were observed. Figure 1 illustrates a comparison of axial T2 TSE brain sequences, where AI-enhanced reconstruction demonstrates reduced noise, improved signal uniformity, and greater anatomical delineation compared with standard acquisition. Motion-related artefacts were visibly reduced, improving structural clarity.

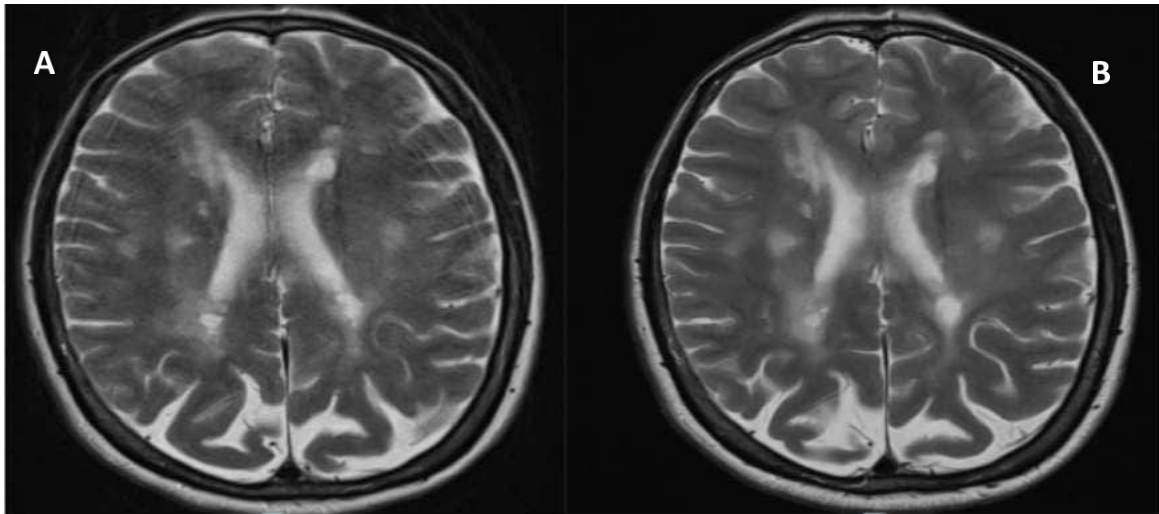


Figure 1. T2 TSE axial brain sequence in a 58-year-old female patient with multiple sclerosis.

(A) Standard MRI without AI reconstruction demonstrating motion artefacts and reduced structural clarity.

(B) AI-enhanced reconstruction showing reduced noise, improved signal uniformity, and clearer anatomical delineation.

Similarly, **Figure 2** demonstrates the impact of AI-assisted reconstruction on diffusion-weighted breast imaging. The AI-enhanced images show reduced background noise, improved tissue contrast, and clearer delineation between fibroglandular and adipose tissue, resulting in improved lesion conspicuity. No AI-enhanced images were judged to be diagnostically inferior to their conventional counterparts.

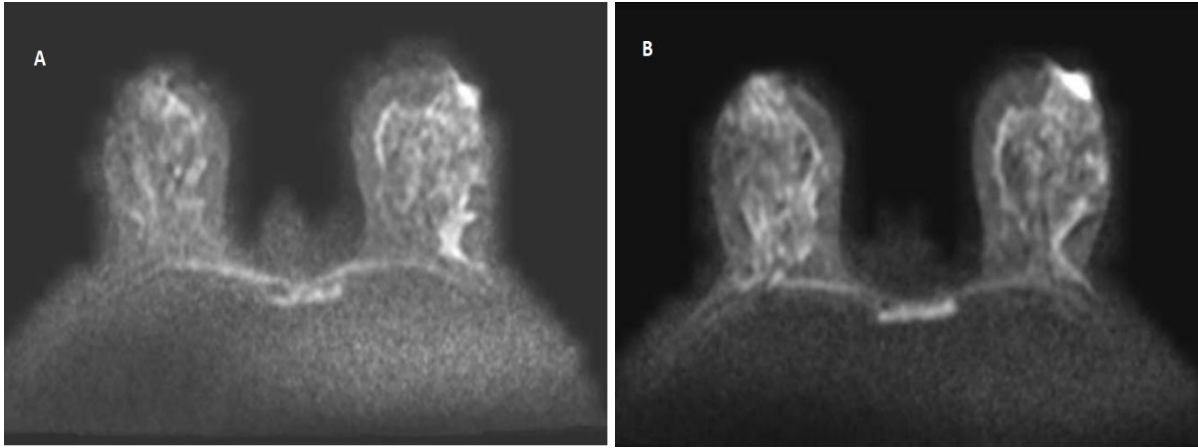


Figure 2. Diffusion-weighted imaging (DWI) sequence (b-value = 800 s/mm²), axial plane, in a 62-year-old female patient with breast cancer.

(A) Standard acquisition without AI reconstruction. The glandular tissue appears relatively granular, with noticeable background noise. Anatomical structures, including the skin, fibroglandular parenchyma, and adipose tissue, demonstrate less well-defined margins and reduced overall sharpness.

(B) AI-enhanced reconstruction. The image demonstrates a clearer and more homogeneous appearance, with substantial reduction in background noise. Structural boundaries are more sharply defined, and contrast between fibroglandular and adipose tissues is enhanced.

5.3 Operational and Economic Assessment

Reduced MRI acquisition times achieved through AI-assisted sequences were associated with operational and economic impacts on radiology departments. Reducing scan durations through AI may enhance scanner availability and enable more examinations to be completed within existing operating hours by addressing limited MRI capacity and reducing scheduling bottlenecks.

Workflow timing analysis suggests that these efficiency improvements could lead to an increase in daily patient throughput. These efficiency gains were achieved without extending operating hours or adding MRI systems, suggesting that AI may optimize existing infrastructure. By reducing patient rescheduling, overtime staffing, and inefficiencies related to delayed clinical decision-making, shorter scan times may help reduce downstream expenses.

Shorter acquisition times may increase labour efficiency by lowering technologist interventions, such as manual sequence adjustments, protocol interruptions, and repeat acquisitions due to patient movements or fatigue. Both operational performance and patient satisfaction may be indirectly supported by increased patient tolerance and improved examination completion. A three-year Net Present Value (NPV) study was conducted to assess the long-term financial implications of AI integration. The NPV analysis was based on modeled operational cost savings and throughput assumptions derived from observed scan-time reduction.

The assessment considered the initial and ongoing costs of operational expenses. The economic assessment yielded a positive net present value, indicating recovery of initial and ongoing costs within the projected time frame. These findings suggest that AI-assisted MRI may represent a financially viable approach to improve scanner utilization and departmental efficiency in modern radiology practice.

5.4. Tables of Results

Table 1. Comparison of total MRI acquisition times between standard protocols and AI-assisted Deep Resolve sequences across anatomical regions.

MRI Type	Standard (min)	Deep Resolve (min)	Reduction (%)
Brain	19:56	15:03	24.5%
Cervical Spine	12:14	9:11	25.0%
Dorsal Column	11:38	7:27	36.0%
Lumbar Spine	12:07	6:47	44.0%
Total (Spinal Column)	27:44	18:31	33.0%
Standard Neck	27:58	20:51	25.4%
ADD SUP Liver	9:18	6:47	27.0%
Cholangio	7:53	6:03	23.3%

Pancreas	14:07	13:03	7.6%
Pelvis (organs)	15:28	12:54	16.6%
Rectum	9:40	4:36	52.4%
Prostate	23:32	16:25	30.2%
Pelvic Bones	12:06	8:07	32.9%
Shoulder	13:07	6:36	49.7%
Knee	15:05	8:36	43.0%
Small Joints	3:02	0:59	68.0%
Foot	18:07	9:45	46.0%
Clinical Breast	19:48	10:39	46.0%
Prosthesis Breast	23:52	17:02	28.6%
Whole Body	31:55	23:33	26.0%
Overall (all regions)	328:37(~5h29m)	222:55(~3h:43m)	32.2%

Table 2. Detailed sequence-level comparison of standard and AI-enhanced Deep Resolve acquisition times.

CATEGORY	SEQUENCE	STANDARD	DEEP RESOLVE
STANDARD BRAIN	AX T2	4:14	1:12
	AX T1	2:31	2:03
	SAG T2	2:36	0:55

	DIFF	0:50	1:08
	SAG FLAIR	5:25	5:25
	AX 3D MDC	4:20	4:20
	TOT	19:56	15:03
CERVICAL SPINE			
	SAG T2	2:45	0:51
	SAG T1	1:59	1:08
	AX GRA	4:50	4:50
	SAG STIR	2:40	2:22
	TOT	12:14	9:11
DORSAL COLUMN			
	SAG T2	2:52	1:14
	SAG T1	2:40	1:46
	AX T2	2:19	2:05
	SAG STIR	3:47	2:22
	TOT	11:38	7:27

LUMBAR SPINE	SAG T2	2:52	1:23
	SAG T1	2:40	1:19
	AX T2	2:48	2:05
	SAG STIR	3:47	2:00
	TOT	12:07	6:47
COLUMN IN TOTAL	SAG T2	5:33	2:28
	SAG T1	4:49	3:32
	SAG STIR	6:57	4:44
	AX T2 GRE CERV	2:10	2:10
	AX T2 LOMB	3:26	2:05
	SAG T1 MDC	4:49	3:32
	TOT	27:44	18:31
STANDARD NECK	AX T1	3:34	1:54
	AX T2	4:00	2:07
	COR STIR	3:14	2:16

	COR T1	2:58	2:02
	SAG T2	4:08	2:28
	AX DWI	5:33	5:33
	T1 VIBE SAG MDC	4:31	4:31
	TOT	27:58	20:51
ADD SUP LIVER	AX T2 FS	0:53	0:40
	AX T1 DIXON	0:18	0:18
	AX DWI	3:09	2:11
	COR T2	1:38	0:36
	T1 AX 3D PRE	0:18	0:18
	CARE BOLUS SAG	1:14	1:14
	T1 AX 3D ART	0:18	0:18
	T1 AX 3D VEN	0:18	0:18
	T1 AX 3D EQUIL	0:18	0:18
	T1 AX 3D 5 MIN	0:18	0:18
	T1 AX 3D 10 MIN	0:18	0:18
	T1 AX 3D 20 MIN	0:18	0:18

	TOT	9:18	6:47
COLANGIO	AX T2 FS	1:28	0:40
	COR T2	1:38	0:36
	RADIALE	1:01	1:01
	3D MRCP	3:46	3:46
	TOT	7:53	6:03
PANCREAS	COR T2	1:38	0:36
	AX T2 FS	1:28	0:40
	AX T2 MIRATA TRIG	3:13	3:13
	AX T1 MIRATA APNEA	0:49	0:49
	AX T1 DIXON MIRATA	0:18	0:18
	AX T2 3MM	0:48	0:32
	DWI AX	3:09	2:11
	T1 AX 3D PRE	0:18	0:18
	CARE BOLUS SAG	1:14	1:14
	T1 AX 3D ART	0:18	0:18
	T1 AX 3D VEN	0:18	0:18

	T1 AX 3D EQUIL	0:18	0:18
	T1 AX 3D 5 MIN	0:18	0:18
	TOT	14:07	13:03
PELVIS	SAG T2	2:51	1:46
	AX T2 FS	2:47	1:18
	AX DIFF	2:28	2:28
	T1 3D DIXON PRE	3:41	3:41
	T1 3D DIXON MDC	3:41	3:41
	TOT	15:28	12:54
RECTUM	COR T2	3:34	1:39
	AX T2	3:00	1:28
	SAG T2	3:06	1:29
	TOT	9:40	4:36
PROSTATE	AX T1	3:01	1:03
	SAG T2	3:46	1:57
	COR T2	3:39	1:57

	AX T2	4:14	2:36
	DIFF	4:41	4:41
	AX T1 DINAM MDC	4:11	4:11
	TOT	23:32	16:25
PELVIS	T2 STIR COR	3:48	1:57
	T1 COR	2:18	1:28
	T2 AX	2:33	1:34
	T1 AX	1:59	1:57
	T2 SAG	1:28	1:11
	TOT	12:06	8:07
SHOULDER	AX T2	3:30	1:58
	SAG T1	2:50	1:33
	COR T2	3:30	1:25
	COR STIR	3:17	1:40
	TOT	13:07	6:36

KNEE	SAG T1	3:02	1:21
	SAG T2 STIR	3:56	1:48
	AX T2	3:55	1:40
	COR T2 GRE	4:12	3:47
	TOT	15:05	8:36
SMALL JOINTS	SAG STIR	3:02	0:59
FOOT	SAG T1	2:45	1:12
	AX STIR	3:53	4:17
	AX T2	3:06	1:17
	COR STIR	3:18	1:17
	COR T1	2:03	0:43
	TOT	18:07	9:45
BREAST	STIR AX	3:51	1:35
	T2 AX	3:55	1:27
	DIFF STIR AX	4:01	4:01
	T1 3D SPAIR AX MDC	8:01	3:36
	TOT	19:48	10:39

PROSTHESIS BREAST	AX T2 DIXON	3:46	1:27
	STIR SILICON ONLY	4:36	2:36
	STIR WATER ONLY	5:07	2:36
	DIFF SPAIR	2:20	2:20
	T1 3D SPAIR AX MDC	8:03	8:03
	TOT	23:52	17:02
WHOLE BODY	DIFF STIR	12:10	10:10
	T1 VIBE DIXON AX	1:40	1:40
	T2 HASTE AX	6:01	3:09
	T1 VIBE POLM	0:18	0:18
	SAG T1 COLONNA	4:49	3:32
	SAG STIR COLONNA	6:57	4:44
	TOT	31:55	23:33

6. Discussion

6.1 Quantitative and Clinical Impact

In this work, AI-assisted MRI reconstruction was associated with a weighted mean reduction in acquisition time of 32.2% across routine clinical protocols. The degree of acceleration varied according to anatomical region and sequence complexity, with reductions ranging from 7.6% in pancreatic imaging to as much as 68% in high-resolution musculoskeletal examinations. This variability reflects the dependence of AI-driven acceleration on baseline acquisition duration, spatial resolution requirements, and sensitivity to motion. Sequences with long acquisition times and high spatial resolution demands demonstrated the greatest benefit from AI-assisted reconstruction.

These efficiency gains were achieved using the vendor-integrated Deep Resolve Pro reconstruction pipeline (Deep Resolve Gains, Sharp, and Boost; Section 4.2.2), which enables accelerated acquisition while preserving signal-to-noise characteristics and perceived image sharpness under radiologist supervision. These findings are consistent with previous reports. A 2024 systematic review by **Priyanka et al.** evaluated the impact of AI-assisted compressed sensing in musculoskeletal MRI and reported consistent scan-time reductions across multiple joint protocols while maintaining or improving perceived image quality and diagnostic usability [1]. The authors highlighted that musculoskeletal sequences are particularly well suited to AI-based acceleration due to high signal redundancy and relatively low motion susceptibility. This observation closely mirrors the findings of the present study, in which the largest scan-time reductions were observed in high-resolution musculoskeletal imaging.

Comparable results have been reported in neuroimaging. A comprehensive review by **Yang et al.** described the application of artificial intelligence in MRI acquisition and demonstrated that deep learning-based reconstruction enables accelerated T2-weighted and diffusion-weighted brain imaging while preserving signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR) [18]. These findings are supported by a feasibility study by **Wen et al.**, who demonstrated that AI-assisted compressed sensing combined with deep learning reconstruction at 5.0 T significantly reduced brain T2-weighted acquisition times without compromising quantitative image quality

metrics or diagnostic interpretability [22]. The preserved image clarity and radiologist confidence observed here are consistent with these reports.

Evidence from prostate MRI further supports the quantitative and clinical feasibility of AI-assisted acceleration. A systematic review by **Reinhardt et al.** concluded that AI-accelerated prostate MRI protocols can reduce examination time while maintaining diagnostic performance, particularly when AI reconstruction is integrated into standardized workflows [20]. In addition, **Yu et al.** introduced a human-in-the-loop AI framework (PI-RADSAI) for prostate cancer diagnosis, demonstrating that AI-assisted MRI improves efficiency while preserving diagnostic accuracy when radiologists retain final interpretive responsibility [6]. These findings align with this study, in which AI was used exclusively as a reconstruction and workflow-support tool under radiologist supervision.

Real-world clinical validation studies further support the importance of supervised AI deployment. **Barnett et al.** evaluated AI-based MRI monitoring in multiple sclerosis and demonstrated reliable longitudinal lesion assessment in routine clinical practice when AI outputs were reviewed by experienced radiologists [3]. Similarly, a narrative review by **Nair et al.** reported that AI-assisted MRI improves radiologist productivity and scanner utilization without replacing clinical judgment, particularly when used as a decision-support tool rather than an autonomous system [8]. Together, these studies support the human-in-the-loop approach adopted in the present work.

From a technical perspective, AI-based reconstruction has been shown to improve image quality parameters relevant to diagnostic confidence. **Melazzini et al.** reported that AI-driven reconstruction techniques can reduce image noise, enhance contrast resolution, and decrease motion-related artefacts, thereby improving image quality and patient safety while reducing the need for repeat examinations [5].

These qualitative improvements are visually demonstrated in the comparison of T2-weighted brain sequences shown in **Figure 1**, where AI-assisted reconstruction provides reduced noise and improved tissue contrast compared with conventional acquisition. In musculoskeletal imaging, enhanced visualization of cartilage, ligaments, tendons, and bone interfaces facilitates clearer visualization for assessment of degenerative changes, ligament injuries, and cartilage defects,

particularly when high-resolution accelerated protocols are applied. Similar qualitative improvements in diffusion-weighted breast MRI are demonstrated in **Figure 2**.

Despite these advantages, limitations remain. Studies focusing on lesion detection have shown that AI-assisted acceleration does not fully overcome intrinsic spatial resolution constraints. **Schlaeger et al.** demonstrated that although AI-based methods improve lesion conspicuity in multiple sclerosis, the detection of very small lesions particularly those smaller than 5–5.5 mm remains challenging due to partial-volume effects and anatomical complexity [10]. Similar limitations were observed in this cohort, especially in anatomically complex regions such as the spine and abdomen, indicating that caution is warranted when evaluating extremely small abnormalities using highly accelerated protocols.

Scan-time reduction varied by sequence complexity and clinical indication. Protocols with longer acquisition times, including high-resolution musculoskeletal imaging and multiphase abdominal examinations, exhibited the greatest absolute reductions. This observation is consistent with previous reports showing that AI-based acceleration provides the greatest efficiency gains in lengthy or high-resolution protocols [1,18,20]. Even modest reductions in acquisition time may have meaningful clinical impact. Shorter examinations improve scheduling flexibility, increase patient throughput, and reduce workflow variability, thereby enhancing operational efficiency in high-volume imaging environments [8].

Importantly, accelerated acquisition did not appear to reduce radiologists' confidence in image interpretation in the present study. Radiologists reported that image appearance remained familiar, with no need for changes in reporting criteria or interpretive approach during routine clinical reading. This finding aligns with previous reports indicating that AI-assisted MRI preserves diagnostic reliability when implemented within a supervised clinical framework [6,8,16]. Maintaining radiologist oversight ensures professional accountability, supports quality assurance, and mitigates risks associated with algorithmic bias or unexpected reconstruction.

Overall, the quantitative findings of this study are consistent with existing evidence indicating that AI-assisted MRI enables substantial reductions in acquisition time without compromising image quality or diagnostic usability. When implemented in routine clinical workflows under a human-

in-the-loop framework, AI-based reconstruction supports clinically relevant efficiency gains and operational improvements, particularly in high-volume radiology settings where reliability, consistency, and diagnostic confidence are critical.

6.2 Workflow Efficiency and Operational Impact

Artificial intelligence (AI) affects MRI workflow primarily by reducing acquisition time and simplifying technical steps during image reconstruction. In routine clinical practice, AI-assisted reconstruction reduces the need for repeated manual adjustments by technologists, which decreases operator-dependent variability and improves consistency across scanners and institutions. This standardization is particularly relevant in high-volume imaging environments, where small inefficiencies accumulate and directly influence throughput and service delivery.

Previous literature supports these observations. In a narrative review focused on radiologist productivity, **Nair et al.** reported that AI-assisted MRI reconstruction shortens examination times and reduces workflow interruptions, allowing radiologists and technologists to concentrate on image interpretation, patient management, and quality control rather than technical optimization of sequences [8]. Similarly, **Denck et al.** highlighted that automated protocoling and standardized reconstruction reduce variability between operators and scanners, leading to more predictable workflows and improved operational reliability in daily MRI practice [23].

One of the most tangible operational benefits of AI-assisted MRI is increased scanner throughput. Shorter acquisition times allow imaging units to perform more examinations per day without extending operating hours or increasing staffing levels. Although the exact throughput gain depends on baseline protocol duration, scanner configuration, and institutional organization, systematic evaluations indicate that scan-time reductions ranging from approximately 19% to over 70%, depending on anatomical region and sequence type, translate into meaningful capacity increases when applied across routine workflows [1,8]. In practical terms, this may help alleviate scheduling bottlenecks, reduce waiting lists, and improve patient access to MRI services in high-demand settings.

Standardization of reconstruction and acquisition strategies also has important implications for longitudinal imaging and research. Consistent reconstruction algorithms reduce inter-scan

variability, which is essential for follow-up examinations, multicenter trials, and quantitative imaging applications such as volumetric assessment, tissue segmentation, and radiomics. In a multicenter study of whole-body MRI, **Lavdas et al.** identified protocol heterogeneity and workflow variability as major operational challenges, particularly when machine learning tools are introduced across different sites [7]. These findings reinforce the value of AI-assisted standardization in supporting reproducible imaging and efficient workflow at both institutional and multicentre levels.

Workflow improvements also extend to patient experience, which indirectly affects operational efficiency. Shorter examinations reduce discomfort, fatigue, and anxiety, particularly in pediatric, geriatric, and claustrophobic patients. Improved tolerance enhances patient cooperation, which reduces motion-related artifacts and lowers the risk of incomplete or repeated scans. This, in turn, improves image quality and reduces inefficiencies associated with repeat acquisitions. Patient surveys have shown that acceptance of AI in medical imaging is generally higher when AI contributes to shorter scan times and is used as a supportive tool under professional supervision rather than as an autonomous system [13,15].

Staff acceptance plays an equally important role in realizing workflow benefits. In a survey of MRI technologists, **Abuzaid et al.** reported higher willingness to adopt AI systems when these tools simplified examination workflows, reduced scan complexity, and supported existing professional roles rather than replacing them [14]. This finding is operationally relevant, as workflow efficiency gains are unlikely to be sustained if AI tools are not consistently adopted or trusted by frontline staff.

Reducing the frequency of repeat scans represents another important operational advantage. Conventional MRI examinations may need to be repeated due to motion artifacts, poor image quality, or incomplete acquisitions, leading to increased scanner time, staff workload, and patient burden. AI-assisted reconstruction mitigates these issues by producing diagnostically acceptable images within shorter acquisition windows. A recent systematic review and meta-analysis by **Safari et al.** demonstrated that AI-driven motion artifact detection and correction significantly reduce motion-related image degradation, supporting more reliable acquisitions and fewer repeat examinations in routine practice [24].

From an economic perspective, workflow efficiency improvements are closely linked to cost containment. Reduced acquisition times lower indirect labor costs by improving staff time allocation and minimizing workflow interruptions. Increased throughput improves scanner utilization, allowing departments to meet growing imaging demand without immediate investment in additional equipment. Energy consumption is another operational consideration. MRI systems are energy-intensive, particularly during long, high-resolution sequences that require sustained gradient activity and cooling. Shortening scanner active time through AI-assisted acceleration can reduce electricity consumption and associated operational costs.

Although this study did not include a formal cost-effectiveness or energy analysis, previous evaluations suggest that cumulative efficiency gains from reduced scan duration and fewer repeat examinations may contribute to favorable long-term economic outcomes in high-volume centers [8]. At the healthcare system level, improved MRI efficiency increases patient access to diagnostic imaging, particularly in institutions with limited scanner availability. Shorter scan durations and improved scheduling flexibility may reduce waiting times and scheduling delays, which is especially important in clinical areas such as oncology, neurology, and musculoskeletal medicine, where imaging findings often guide treatment decisions and follow-up strategies. By improving workflow predictability and reducing operational variability, AI-assisted MRI supports more sustainable imaging services.

Despite these advantages, workflow benefits are context-dependent. The magnitude of efficiency gains depends on baseline protocol length, patient population, scanner hardware, and institutional organization. Initial investments related to software integration, staff training, and system maintenance must also be considered. Moreover, while AI-assisted MRI reduces indirect operational costs, the present study did not include a detailed cost-benefit or return-on-investment analysis. Future studies should incorporate structured economic evaluations to quantify long-term financial impact across different healthcare settings.

Together with existing literature, the results of this study show that AI-assisted MRI improves workflow by shortening examinations, standardizing reconstruction, and limiting repeat scans. These changes allow higher throughput, better use of scanner capacity, improved patient comfort, and more reliable image quality. When applied within routine clinical workflows under

professional supervision, AI-based reconstruction represents a practical way to meet the growing operational demands of MRI services without reducing diagnostic performance.

6.3 Clinical Performance and Diagnostic Implications of AI-Assisted MRI

Recent literature consistently supports the clinical value of AI-assisted MRI in reducing acquisition time while preserving diagnostic usability across a wide range of imaging applications. A systematic review by **Priyanka et al.** demonstrated that AI-assisted compressed sensing techniques in musculoskeletal MRI achieve substantial scan-time reductions often exceeding 40–60% for high-resolution protocols while maintaining image quality. Radiologist confidence was preserved, particularly for joint and cartilage-focused imaging [1]. Comparable findings have been reported in neuroimaging, where AI-accelerated T2-weighted acquisitions preserved contrast and signal characteristics despite shorter scan durations, supporting the feasibility of accelerated protocols in routine clinical practice [18,22].

Beyond acceleration, several studies emphasize the reliability of AI when integrated into real-world workflows. **Barnett et al.** validated AI-based MRI monitoring in multiple sclerosis using routine clinical data, demonstrating that AI-supported assessments can be implemented without disrupting diagnostic workflows or reducing clinical confidence [3]. Similarly, comparative volumetric studies in Parkinsonian syndromes found no clinically meaningful differences between AI-assisted and conventional methods when appropriate validation and quality control were applied [4]. These results suggest that AI can support longitudinal and quantitative imaging tasks when embedded within standardized imaging protocols.

Despite these benefits, the literature highlights important diagnostic limitations. Studies focusing on lesion detection in multiple sclerosis have shown that while AI can improve sensitivity for contrast-enhancing lesions, performance decreases for very small abnormalities and in anatomically complex regions [10]. In oncology imaging, **Alves et al.** reported that AI performance varies across scanners, acquisition settings, and patient populations, emphasizing the need for cautious interpretation and continuous validation in clinical practice [9]. Reviews of AI-assisted neuro MRI acquisition similarly stress that acceleration benefits must be balanced against

spatial resolution and signal-to-noise constraints, particularly for subtle or early-stage pathology [18].

Human supervision remains a key factor influencing clinical effectiveness and acceptance. The PI-RADSAI framework introduced by **Yu et al.** demonstrated that human-in-the-loop approaches improve diagnostic consistency and clinical usability in prostate MRI, outperforming fully automated strategies in real-world settings [6]. Patient-focused surveys further support this model, with higher acceptance and trust reported when AI outputs are reviewed by radiologists rather than used autonomously [13,15]. These findings reinforce the role of AI as a supportive tool that enhances, rather than replaces, expert clinical judgment.

Workflow and productivity improvements associated with AI-assisted MRI also have direct clinical implications. Studies in whole-body MRI and high-volume imaging environments report reduced radiologist workload, improved scanner utilization, and more consistent imaging outputs when AI-assisted reconstruction and protocol optimization are applied [7,8]. Cross-site validation studies in breast MRI demonstrate that AI-based harmonization and segmentation improve reproducibility across scanners and institutions, supporting multicenter research and standardized follow-up imaging [12]. Automated protocoling further contributes to consistency and efficiency, particularly in complex or time-intensive examinations [23].

Motion-related artefacts remain a significant challenge in conventional MRI, particularly in elderly, pediatric, or uncooperative patients. Meta-analyses of AI-driven motion artifact detection and correction show that reduced acquisition times decrease motion susceptibility and improve overall image interpretability, while motion-related limitations are not fully eliminated [24]. These improvements are clinically relevant, as they reduce repeat scans and improve diagnostic confidence in vulnerable patient populations.

Available evidence indicates that AI-assisted MRI can improve clinical efficiency while preserving diagnostic reliability when applied within validated and supervised workflows. Limitations remain, particularly in the assessment of very small lesions and in anatomically complex regions; however, published studies consistently describe AI-based reconstruction as a supportive addition to conventional MRI rather than a replacement. When combined with

standardized acquisition protocols and expert oversight, AI-assisted approaches contribute to more consistent image quality, facilitate advanced post-processing analyses, and support broader access to high-quality MRI across different clinical contexts. These observations provide a basis for further examination of the clinical and operational implications of AI integration in routine practice.

6.4 Patient-Centered, Economic, and Ethical Considerations

Several studies in the literature emphasize that one of the most tangible patient-centered benefits of AI-assisted MRI is the reduction in acquisition time, which directly influences patient comfort and examination tolerability. In their systematic review of AI-assisted compressed sensing in musculoskeletal MRI, Priyanka et al. reported consistent reductions in scan duration while maintaining diagnostic image quality, noting that shorter examinations reduced patient discomfort and motion-related degradation, particularly in painful or mobility-limited patients [1]. These findings are clinically relevant for musculoskeletal imaging, where prolonged positioning often contributes to motion artifacts and incomplete studies.

Beyond musculoskeletal applications, Melazzini et al. highlighted that AI-based reconstruction techniques improve image quality while supporting patient safety by reducing scan duration and minimizing the need for repeat acquisitions in both CT and MRI [5]. Their review underscored that shorter examinations are particularly beneficial for pediatric and elderly populations, in whom prolonged scans are associated with increased anxiety and, in some cases, sedation requirements. This aligns with broader clinical experience suggesting that faster MRI protocols may improve patient compliance without compromising diagnostic reliability.

Patient perception and acceptance of AI-assisted MRI have been directly explored in several studies. Fransen et al. examined patient perspectives on AI use in prostate MRI and found that acceptance was high when AI was used to support radiologist interpretation rather than operating autonomously [13]. Patients reported greater confidence in AI-assisted imaging when they were informed that final decisions remained with the radiologist and when AI use contributed to shorter scan times or improved image clarity. Similarly, McGhee et al. reported that patients generally

prefer AI systems that enhance efficiency and comfort while preserving physician oversight, reinforcing the importance of transparency and communication in AI deployment [15].

AI-assisted MRI also contributes to patient-centered care by enabling more personalized diagnostic strategies. In prostate cancer imaging, Hou et al. demonstrated that AI-assisted MRI could predict biochemical recurrence without the need for invasive biopsy, supporting individualized risk stratification and follow-up planning [19]. In neuroimaging, Barnett et al. provided real-world validation of AI-based MRI monitoring in multiple sclerosis, showing that AI-supported quantitative analysis improved consistency in lesion assessment and longitudinal disease monitoring without increasing patient burden [3]. These studies illustrate how AI-assisted MRI can support precision medicine by facilitating non-invasive, reproducible, and patient-specific imaging assessments.

Economic considerations represent a second critical dimension of AI integration. Reduced acquisition times and fewer repeat scans translate into indirect cost savings through improved scanner utilization and reduced staff workload. In their narrative review, Nair et al. reported that AI-assisted MRI may improve departmental efficiency by allowing radiologists and technologists to focus on interpretation and patient care rather than repeated technical adjustments, thereby improving productivity without increasing staffing levels [8]. While direct cost analyses remain limited, these efficiency gains are consistently described as economically advantageous in high-volume imaging environments.

However, several studies caution that economic benefits depend heavily on implementation context. Lavdas et al., in a multicenter whole-body MRI study, identified variability in scanner hardware, protocol standardization, and institutional workflows as major challenges that can limit the scalability and cost-effectiveness of AI tools across sites [7]. These findings highlight that initial investments in AI-capable software, staff training, and IT infrastructure must be carefully weighed against expected long-term efficiency gains, particularly in resource-constrained healthcare settings.

Staff acceptance also plays an important economic and operational role. Abuzaid et al. found that MRI technologists were more willing to adopt AI systems when these tools simplified workflows,

reduced scan complexity, and supported existing professional roles rather than replacing them [14]. This is particularly relevant because resistance to adoption can undermine potential efficiency and cost benefits, regardless of technical performance.

Ethical considerations are closely linked to both patient trust and clinical reliability. Nouis et al. reported that healthcare professionals express concerns regarding accountability, transparency, and potential bias in AI-assisted decision-making, particularly when algorithmic behavior is not easily interpretable [16]. Norori et al. further emphasized that bias may arise when AI models are trained on non-representative datasets, potentially leading to unequal diagnostic performance across different patient populations [17]. These concerns are especially relevant in MRI, where subtle anatomical and demographic differences may influence AI outputs.

Importantly, several studies suggest that ethical risks are mitigated when AI systems are implemented within supervised clinical frameworks. Yu et al. demonstrated that a human-in-the-loop AI model for prostate MRI preserved diagnostic accuracy while maintaining clinician accountability and patient trust [6]. This approach aligns with patient preference data and supports the view that ethical integration of AI in MRI depends on preserving radiologist oversight rather than replacing clinical judgment.

Despite growing evidence, the literature remains limited in its evaluation of patient-centered outcomes, long-term economic impact, and ethical governance in routine clinical practice. Many studies focus on technical feasibility or specific anatomical regions, with fewer addressing sustained real-world implementation. This gap underscores the need for prospective studies that assess patient experience, staff adaptation, cost-effectiveness, and ethical monitoring alongside technical performance. In particular, standardized outcome measures and harmonized study designs are needed to allow meaningful comparison across institutions and healthcare systems.

Evidence from the referenced literature indicates that AI-assisted MRI offers meaningful patient-centered and economic benefits when implemented with appropriate professional oversight. Shorter scan times, improved image consistency, and enhanced quantitative analysis support better patient experience and more efficient service delivery. However, ethical governance, transparency,

and context-specific evaluation remain essential to ensure equitable and sustainable adoption of AI-assisted MRI in routine clinical practice.

6.5 Operational Recommendations for Healthcare Operators

Healthcare institutions introducing AI-assisted MRI should adopt practical measures that address patient care, costs, and ethical responsibilities, in line with current European regulatory frameworks, including the EU Artificial Intelligence Act [25]. A structured and well-documented approach helps ensure safe clinical use and long-term sustainability.

1. Applicability screening: Institutions should first assess whether the AI systems in use fall under the scope of the GDPR and the AI Act. This assessment should be documented and should consider the intended clinical purpose of the system and its role within diagnostic decision making pathways. AI tools that support diagnosis or treatment decisions require particular attention, as they are generally classified as high-risk under current regulations.

2. Internal mapping of AI systems: An internal overview of all AI applications used within MRI services should be maintained. Each system should be described according to its clinical function, level of risk, and potential impact on patient care to support traceability and internal audit processes. This overview supports accountability and helps institutions manage and monitor AI use in a consistent way.

3. Transparency and patient communication: Patients should receive clear information about the use of AI-assisted MRI. This includes explaining how AI is used during image reconstruction, what benefits it may offer, and what its limitations are using language appropriate to patient understanding. Clear communication supports informed consent and reassures patients that AI does not replace the radiologist's role in image interpretation.

4. Technical and organizational measures: AI systems should be regularly checked to ensure stable performance. Routine software updates, quality controls, and monitoring for unexpected changes in output are necessary to detect performance drift over time. At the organizational level, responsibilities should be clearly defined, and data protection measures such as anonymization and secure storage should be consistently applied.

5. Staff training and oversight: Radiologists and MRI technologists should receive appropriate training on AI-assisted reconstruction. Training should focus on understanding system outputs, identifying potential artifacts, and integrating AI-assisted images into standard reporting workflows without increasing cognitive workload. Clinical responsibility should remain with trained professionals, maintaining a human-in-the-loop approach.

6. Regulatory monitoring: Because regulations related to AI are evolving, healthcare providers should stay informed about updates to the AI Act and related guidance [25]. Regular review of regulatory requirements allows institutions to adapt internal procedures when needed and reduce compliance risks.

7. Ongoing governance and monitoring: Ethical aspects should be addressed as part of routine clinical governance, integrated into existing quality assurance and risk management frameworks. This includes attention to potential bias, consistent performance across patient groups, and transparency in AI use. Ongoing review and professional oversight help maintain patient trust and support responsible use of AI-assisted MRI. Regular auditing and documenting performance reporting further strengthen accountability and regulatory compliance.

By applying these measures, healthcare institutions can integrate AI-assisted MRI into routine practice in a controlled and responsible manner. A clear operational framework supports patient safety, professional accountability, and compliance with regulatory requirements while allowing institutions to benefit from improvements in image quality and examination efficiency [25].

6.6 Limitations and Future Directions

6.6.1 Technical and Diagnostic Limitations

Despite the demonstrated advantages of this study, including a 32.2% reduction in weighted mean scan time, several technical limitations remain. Although AI-enhanced reconstruction improved noise suppression and overall image clarity, the detection of very small lesions continues to be challenging. Partial-volume effects may limit the visibility of lesions smaller than approximately 5–5.5 mm in accelerated acquisitions, particularly when voxel dimensions approach lesion size. Even with AI-based denoising, signal averaging can reduce lesion conspicuity in anatomically

complex regions such as the spine and abdomen. This is particularly relevant for disease detection and follow-up, where subtle interval changes may have important clinical significance.

Motion-related artefacts and subtle signal inhomogeneities may also persist in highly accelerated protocols. While AI-assisted reconstruction improves perceived sharpness and contrast, it cannot fully overcome the intrinsic spatial resolution constraints imposed by acquisition parameters. These findings indicate that AI-assisted MRI enhances efficiency while preserving diagnostic quality in most routine applications; however, caution remains necessary when evaluating very small abnormalities in complex anatomical regions.

6.6.2 Study Design and Generalizability

This pilot feasibility study included 20 patients, with examinations distributed across multiple anatomical regions. While this approach is appropriate for an initial feasibility assessment, it significantly limits statistical power for any specific diagnostic category. Observed reductions in scan time and improvements in image quality may have been influenced by individual patient factors, including body habitus, ability to remain motionless, or the specific underlying pathology. As a result, the findings cannot fully capture the range of anatomical variability or lesion characteristics present in broader clinical populations, which are more appropriately addressed in targeted, hypothesis-driven validation studies.

Although this design allowed evaluation across neuroimaging, musculoskeletal, abdominal, and spinal protocols, it restricted generalizability for specific diseases. The primary aim of the study was to assess workflow integration and practical performance in a real clinical setting rather than to establish definitive diagnostic accuracy metrics.

The study was conducted at a single institution using Siemens Healthineers MRI systems with proprietary AI-based reconstruction software (Deep Resolve). Reconstruction behaviour and acceleration performance may vary depending on scanner manufacturer, magnetic field strength, software version, and hardware configuration. Consequently, the observed reductions in acquisition time and preservation of image quality may not be directly reproducible across all MRI environments. Multicenter studies using diverse scanner platforms are therefore required to validate broader applicability. Projected increases in daily patient throughput were estimated

through workflow modeling, suggesting potential gains in the range of approximately 25–35% based on workflow modeling and short-term observations. Long-term validation in high-volume clinical settings is needed to determine whether these efficiency gains can be sustained without compromising diagnostic quality [5,8,23].

6.6.3 Scope of Measured Outcomes and Workflow Metrics

Due to its direct measurability and comparability across protocols, acquisition time was selected as the primary objective workflow metric in this study. However, several important components of the MRI workflow were not quantitatively recorded, including patient preparation, coil setup, examination room turnover, and reporting time. These elements play a substantial role in real-world throughput and may influence how scan time reductions translate into increased appointment capacity in routine clinical practice.

In addition, the study did not document patient-reported comfort, sedative use, or repeat-scan frequency, all of which are clinically relevant outcomes, particularly in vulnerable patient groups such as pediatric, elderly, or claustrophobic patients. Although shorter acquisition times are expected, based on prior evidence, to indirectly improve these factors, their omission limits the ability to fully characterize the patient-centered impact of AI-assisted MRI. The direct effect on radiologist workload, reporting efficiency, and downstream clinical decision-making was not formally assessed and should be evaluated in future studies.

Future studies should therefore include prospective time–motion analyses, repeat-sequence tracking, and structured patient experience assessments. Integrating these endpoints would allow modelling of the entire examination duration, more precise estimation of workflow efficiency, and a more comprehensive evaluation of clinical value beyond acquisition efficiency alone.

6.6.4 Ethical Considerations and Interpretability

Beyond technical and methodological constraints, ethical considerations remain central to the responsible use of AI-assisted MRI. Patient privacy and data governance are essential ethical issues. Large amounts of imaging data, often obtained from standard clinical practice, are necessary for AI models to function. Strong anonymisation, safe data processing, and adherence

to data protection laws are necessary to protect patient privacy and prevent misuse of sensitive health data.

Algorithmic bias represents a key concern, as models trained on non-representative datasets may demonstrate variable performance across patient populations. Differences in age, sex, ethnicity, and disease prevalence can influence model behaviour and may contribute to disparities in diagnostic outcomes. Continuous validation using heterogeneous datasets and ongoing performance monitoring are therefore essential. Failure to address such bias may undermine trust and equitable clinical deployment of AI system.

The integration of AI into diagnostic imaging also raises concerns regarding clinical accountability and liability. AI-assisted reconstruction is not a self-diagnostic system; rather, it should be considered a decision-support tool embedded within established clinical reporting workflows. The radiologist must still have ultimate authority over image interpretation, highlighting the necessity of clear accountability frameworks in clinical procedures aided by AI to define responsibility in case of diagnostic error. Clear institutional policies are therefore necessary to support safe clinical adoption.

Interpretability also remains a challenge. Many deep learning systems function as “black-box” models, generating outputs without transparent reasoning. This lack of explainability may complicate communication between clinicians and patients. Furthermore, limited transparency may contribute to automation bias, where clinicians place excessive trust in AI-generated outputs. Without critical appraisal, such reliance could increase the risk of overlooked findings or reduced diagnostic vigilance.

In this study, a human-in-the-loop approach was ensured by requiring radiologists to examine all AI-reconstructed images before they were interpreted as part of routine diagnostic practice. Professional accountability is maintained and patient confidence is upheld by utilizing AI-supported process improvements under continuous clinical oversight. Transparency and clinician confidence may be further enhanced by future developments in explainable AI and uncertainty-aware reconstruction. Equitable access to AI-enabled MRI technologies should be considered

during implementation to avoid widening disparities between high- and low-resource healthcare settings.

6.6.5 Future Directions and Conclusions

Future studies will need to include larger, multicenter cohorts covering different anatomical regions to address the limited sample size and improve generalisability. Using prospective designs would allow observation of how AI-assisted MRI performs in everyday clinical practice and would reduce the risk of selection bias. From a technical perspective, further work is needed to improve reconstruction stability in artefact-prone areas, increase sensitivity to small lesions, and refine acquisition parameters across different field strengths. It will also be important to test this approach on MRI systems from different vendors and with different protocol settings to better understand how broadly these results can be applied.

Making AI systems easier to understand would help clinicians feel more comfortable using them in daily practice, as reconstruction results would be clearer and easier to assess. Longer follow-up studies are also needed to check whether the advantages of AI-assisted MRI last over time, not only in terms of scan duration, but also for diagnostic accuracy, patient outcomes, costs, and everyday workflow. If these systems continue to be carefully validated and used under radiologist supervision, AI-assisted MRI may gradually become part of routine diagnostic work in selected clinical settings rather than remaining only a tool for speeding up examinations. Any implementation should be cautious, so that gains in efficiency actually translate into measurable and consistent improvements in patient care.

This thesis examined the use of AI-assisted MRI reconstruction in routine clinical practice, focusing on scan time, image quality, and workflow. When Siemens Deep Resolve Pro was used in routine MRI protocols, scan duration was reduced, with an average reduction of 32%. The amount of time saved was not the same for all examinations. Short abdominal studies showed smaller changes, while high-resolution musculoskeletal scans showed the largest reductions.

Qualitative image assessment showed that AI-enhanced reconstructions generally exhibited lower noise and improved tissue contrast compared with conventional images. Importantly, none of the AI-enhanced images were considered diagnostically inferior to standard acquisitions. This

indicates that accelerated imaging was achieved without compromising diagnostic usability when images were reviewed by radiologists under clinical supervision.

From an operational perspective, shorter scan durations may improve scanner availability, reduce workflow interruptions, and increase patient throughput within existing operating hours. Reduced motion-related artifacts and fewer repeat acquisitions also have the potential to improve examination reliability and patient tolerance, particularly in vulnerable patient groups.

This study has limitations related to its pilot design, single-center setting, and limited sample size, with one patient representing each anatomical region. Nevertheless, the findings provide practical evidence that vendor-integrated AI reconstruction can be safely implemented in routine MRI workflows when used as a decision-support tool within a human-in-the-loop framework. Future studies should focus on multicenter prospective validation, include broader workflow and patient-reported outcomes, and assess long-term clinical and economic impact.

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