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Optimization of Prostate T2-Weighted Imaging Using AI-Assisted Compressed Sensing Combined with Deep Learning Reconstruction: A Prospective Study

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Author Contributions Statement:

A(Zuonian Hu): study design, data acquisition, objective measurements, manuscript drafting.

B(Shiwei Lai): study design, objective measurements, literature search, statistical analysis, manuscript revision.

C(Shaoxin Xiang): study design, critical revision.

D(Yixin Emu): study design, manuscript review and revision.

E(Yong Xiang): data collection, subjective image assessment.

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Ethical Statement:

Informed consent was obtained from all individual participants included in the study.All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.This study was approved by the Ethics Committee/Institutional Review Board of Guiqian International General

Hospital. This study was approved by the Ethics Committee/Institutional Review Board of Guiqian International General Hospital (IRB Approval No.:GQ-EC-20260327-01).

Clinical Trial Registration:

This study is a non-interventional diagnostic accuracy study evaluating an accelerated MRI technique. No clinical trial registration is required as it does not involve patient interventions, treatment allocation, or alterations to clinical care. As requested.

Clinical trial number: not applicable.

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Abstract

Purpose:

To evaluate the value of artificial intelligence-assisted compressed sensing (ACS) combined with deep learning reconstruction (DLR) in high-resolution prostate T2-weighted imaging (T2WI), with the aim of shortening scan time while improving image quality.

Materials and Methods:

A total of 77 patients suspected of prostate disease based on clinical findings underwent MRI examination, of whom 60 (mean age 65.0 ± 13.9 years, range 28–86 years) completed the full scanning protocol and were included in the analysis. All patients received axial T2WI sequences using three different acceleration techniques: Group A (control group), accelerated with parallel imaging (PI), NEX = 2; Group B, accelerated with ACS, NEX = 2; Group C, accelerated with ACS combined with DLR, NEX = 1.5. Objective evaluation metrics included signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR), measured separately in the peripheral zone (PZ) and transition zone (TZ). Two radiologists independently assessed overall image quality, image artifacts, and diagnostic confidence using a 5-point Likert scale. Scan times were recorded and compared across groups.

Results:

The scanning time in Group C was reduced by 47.2% compared with Group A, from 127 s to 67 s. Compared with Groups A and B, Group C showed significantly higher PZ-SNR, TZ-SNR, and CNR values (all corrected $P < 0.017$; for CNR, C vs A: $P < 0.001$ and C vs B: $P = 0.002$). Group C also

demonstrated significantly better subjective scores in all three categories—overall image quality, image artifacts, and diagnostic confidence—compared with Groups A and B (all corrected $P < 0.017$).

Conclusion:

The synergistic application of ACS acquisition acceleration and DLR optimization achieves substantial scan acceleration in prostate T2WI while effectively improving image quality and diagnostic confidence. This combined strategy offers a promising approach for optimizing prostate MRI workflows.

Keywords: prostate; magnetic resonance imaging; artificial intelligence; deep learning

1.Introduction

Prostate cancer is the second most common malignancy among men worldwide, with its incidence continuously rising and posing a serious threat to men's health [1]. Multiparametric magnetic resonance imaging (mp-MRI), particularly T2-weighted imaging (T2WI), plays an irreplaceable role in the detection, localization, staging, and active surveillance of prostate cancer [2,3]. However, conventional T2WI sequences usually require a long acquisition time, which not only compromises patient comfort and increases the risk of motion artifacts but also limits departmental examination efficiency [4].

To accelerate MRI acquisition, techniques such as parallel imaging (PI) and compressed sensing (CS) have been widely adopted [5,6]. However, these traditional acceleration methods often lead to reduced signal-to-noise ratio (SNR) and increased artifacts when the acceleration factor is increased [7]. In recent years, artificial intelligence (AI), has brought breakthrough advances in MRI acceleration and image reconstruction [8]. In the field of prostate MRI, multiple studies have demonstrated its value. For instance, the C-SENSE AI framework achieved accelerations of 58% and 47% in prostate T2WI and DWI, respectively, while significantly improving both image quality and tumor detection capability [9]. AI-based reconstruction can effectively enhance image quality in T2WI obtained with markedly reduced acquisition times, while maintaining detection performance for prostate cancer that is not significantly compromised.[10]. Nevertheless, the impact of AI-based reconstruction on radiomic features should be noted; studies have shown that over 90% of radiomic features extracted from AI-based reconstruction images differ significantly from those in conventionally reconstructed images [11].

Among these, artificial intelligence-assisted compressed sensing(ACS) and deep learning reconstruction(DLR) are two key technologies that enable MRI acceleration while preserving or even enhancing image quality. AI-assisted compressed sensing (ACS) is an acceleration solution implemented at the acquisition end. Previous studies have shown that ACS technology demonstrates promising application prospects in MRI of the spine , heart , and knee [12,14].DLR improves image quality by reconstructing high-resolution, high-SNR images from low-resolution, low-SNR k-space data while preserving anatomical fidelity, a capability that has demonstrated potential in rectal, musculoskeletal, and renal imaging. [15–17]. A recent feasibility study using 5.0T MRI confirmed the combined value of ACS and DLR for accelerating brain T2-weighted imaging [25]. However, the clinical utility of combining ACS with DLR in high-resolution prostate T2WI remains insufficiently evaluated.

Therefore, the purpose of this study was to prospectively evaluate the application effect of ACS acquisition acceleration combined with DLR in prostate T2WI, and to investigate whether it can maintain or even further improve image quality while shortening scan time, thereby providing a basis for optimizing clinical workflows.

2. Materials and Methods

2.1 Study Subjects

This study was approved by the institutional ethics committee (approval number: GQ-EC-20260327-01), and all participants provided written informed consent. Patients who underwent prostate MRI for clinically suspected prostate lesions between April 2026 and July 2026 were prospectively and consecutively enrolled. Exclusion criteria were as follows: (1) contraindications to MRI (e.g., claustrophobia, incompatible implants); (2) prior prostate surgery or radiotherapy; and (3) receipt of endocrine therapy or chemotherapy prior to enrollment. A total of 77 patients were initially screened, of whom 17 were excluded based on the above criteria. Ultimately, 60 patients completed all three sequence scans and were included in the final analysis (Figure 1). All 60 patients were men, with a mean age of 65.0 ± 13.9 years (range, 28-86 years).

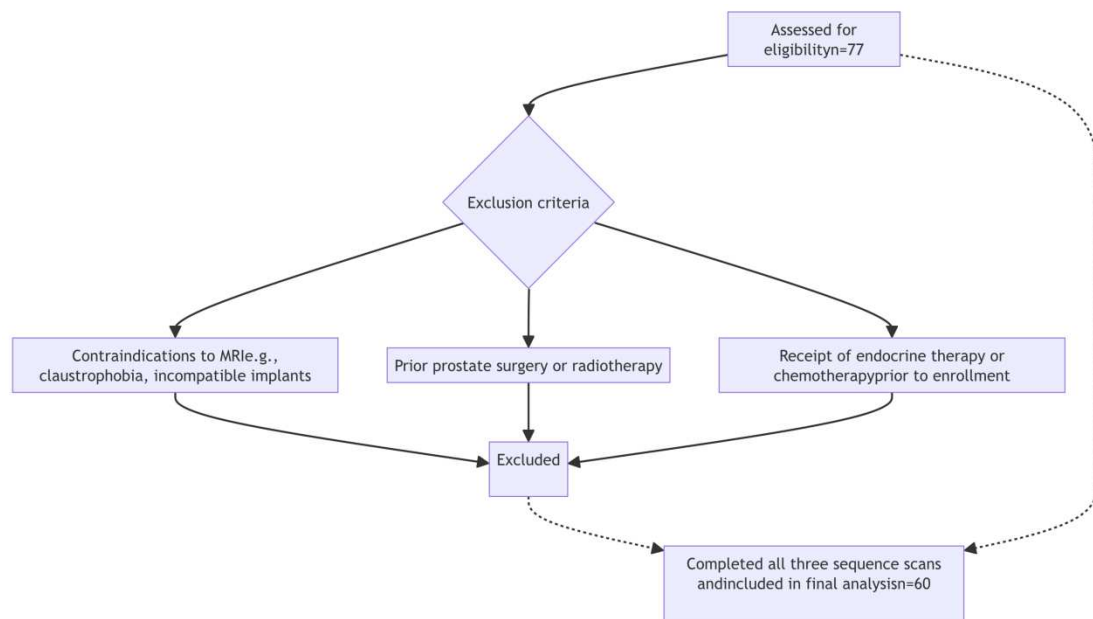


Figure 1. Flowchart of participant inclusion and exclusion criteria.

2.2 MRI Scanning Protocol

All examinations were conducted on the United Imaging uMR 880 3.0T superconducting MR scanner, using a 24-channel body phased-array coil and a spinal coil. Each patient underwent the following three axial T2WI scans:

- Group A (PI group): Conventional parallel imaging (PI) acceleration with a number of excitations (NEX) = 2, serving as the control group.
- Group B (ACS group): ACS acceleration with NEX = 2.
- Group C (ACS + DLR group): ACS acceleration with NEX = 1.5, with DLR applied during the reconstruction process.

The remaining scan parameters (e.g., repetition time [TR], echo time [TE], field of view [FOV],

matrix, and slice thickness) were kept consistent across the three sequences to ensure comparability. Detailed scan parameters are listed in Table 1. The scan time of each sequence was recorded.

Parameters	A	B	C
TR (ms)	3727	3727	3727
TE (ms)	131.1	131.1	131.1
Slice thickness (mm)	3	3	3
Slice gap (mm)	0.3	0.3	0.3
FOV (mm ²)	200*200	200*200	200*200
Matrix	288*288	288*288	288*288
Number of slices	25	25	25
NEX	2	2	1.5
Echo Train Length	27	27	27
Acceleration method and factor	PI:3	ACS:5	ACS:5
Deep-learning reconstructed	No	No	Yes
Scan time(s)	127	82	67

Table 1. Main scan parameters of the three T2WI sequences

2.3 Image Acquisition and Reconstruction Techniques

Both of them were provided by the United Imaging Healthcare (Shanghai, China).

The ACS intelligent optical shuttle imaging technology from United Imaging was adopted. Its core principle is the integration of a deep convolutional neural network (CNN) into the iterative reconstruction framework of CS as a regularization constraint. Trained on millions of fully sampled images, the network can intelligently recover image information from undersampled K-space data, thereby accelerating scanning while effectively suppressing noise and artifacts [19,20].

The DLR approach utilizes a compact convolutional neural network that integrates several enhancement modules and connection layers. In addition, a data-fidelity component incorporating k-space loss is embedded to preserve anatomical fidelity. After being trained on a large dataset comprising millions of multi-contrast and multi-anatomy cases, the DLR is capable of intelligently transforming k-space data with low resolution and low signal-to-noise ratio (SNR) into images of high resolution and high SNR, with greater detail.

2.4 Image Analysis

2.4.1 Objective Image Quality Assessment

Objective image quality measurements were independently performed by two radiologic technologists with 7 years and 8 years of experience, respectively (hereinafter referred to as Technologist 1 and Technologist 2). Both technologists performed region-of-interest (ROI)

delineation and signal intensity measurements on all images on a uWS-MR workstation while blinded to the sequence grouping.

The measurement criteria were as follows: circular ROIs with an area of approximately 20 mm² were placed in the peripheral zone (PZ) and transition zone (TZ) of the prostate on the axial images of each sequence. ROI placement carefully avoided vessels, the urethra, and areas of prostatic calcification or cystic change. Meanwhile, the standard deviation (SD) of background noise was measured in the four corner regions (avoiding anatomical structures) on the same image slice, and the average value was taken as the background noise SD. The signal intensity (SI) and its SD were recorded for each ROI. Based on these measurements, the signal-to-noise ratio (SNR) and contrast-to-noise ratio (CNR) were calculated using the following formulas:

- $SNR = \frac{\mu_{tissue}}{\sigma_{noise}}$
- $CNR = |(\mu_{tissue1} - \mu_{tissue2})| / \sqrt{\sigma_{tissue1}^2 + \sigma_{tissue2}^2}$

To assess the consistency between the two technologists' measurements, the intraclass correlation coefficient (ICC) was used for inter-observer agreement analysis. The objective data used for the final statistical analysis in this study were the average measurements of the two technologists. The results of the consistency analysis are detailed in the Results section (3.4).

2.4.2 Subjective Image Quality Assessment

Two radiologists with 8 and 10 years of experience, respectively, independently and blindly evaluated all images without knowledge of the sequence grouping. A 5-point Likert scale was used to score the following three items:

- Overall image quality: 1 point (non-diagnostic) to 5 points (excellent).
- Image artifacts: 1 point (severe artifacts) to 5 points (no artifacts).
- Diagnostic confidence: 1 point (no confidence) to 5 points (extremely high confidence).

2.5 Statistical Analysis

Statistical analyses were performed using SPSS 27.0. The Shapiro-Wilk test was used to assess normality of continuous variables (SNR and CNR). Normally distributed data were expressed as mean $\pm$ standard deviation and compared using repeated-measures ANOVA with Bonferroni-adjusted post-hoc pairwise comparisons. Non-normal data were presented as median (interquartile range) and compared using the Friedman test followed by Bonferroni-corrected Wilcoxon signed-rank pairwise comparisons (corrected $\alpha' = 0.017$). Scan times were only descriptively reported and not subjected to statistical testing.

Ordinal subjective scores (overall image quality, image artifacts, diagnostic confidence) were reported as median (interquartile range) and analyzed with the Friedman test and

Bonferroni-adjusted Wilcoxon signed-rank post-hoc tests.

Inter-observer agreement for objective SNR/CNR measurements (two radiologic technologists) and subjective image scores (two radiologists) was evaluated using ICC(2,1) (two-way random-effects, absolute agreement, single measurement) according to the Shrout and Fleiss classification. ICC values with their 95% confidence intervals were reported. Agreement thresholds were defined as good for ICC >0.75 and excellent for ICC >0.90. A P value <0.05 was considered indicative of statistical significance.

3. Results

3.1 Patient Baseline Characteristics

A total of 60 patients (all men) with a mean age of 65.0 ± 13.9 years (range: 28–86 years) and a mean Body Mass Index(BMI) of 25.6 ± 3.4 kg/m² (range: 17.8–32.4 kg/m²) completed all scans and were included in the final analysis.

3.2 Scan Time

The scan times for groups A, B, and C were 127 s, 82 s, and 67 s, respectively. Compared with group A, the scan times of groups B and C were reduced by 35.4% and 47.2%, respectively; group C was further shortened by 18.3% relative to group B.

3.3 Objective Image Quality Assessment

The objective image quality metrics, calculated as the average of measurements from the two radiologic technologists, are summarized as follows. The Shapiro–Wilk test was used to assess normality. For PZ-SNR, the distributions deviated significantly from normality in at least one group ($P < 0.05$), whereas SNR TZ and CNR were not normally distributed in any of the three groups (all $P < 0.05$). Accordingly, intergroup comparisons were performed using the Friedman test, and post hoc pairwise comparisons were conducted using the Wilcoxon signed-rank test with Bonferroni correction (corrected $\alpha' = 0.017$). All three metrics (PZ-SNR, SNR TZ, and CNR) are expressed as median (interquartile range, IQR).

PZ-SNR: The PZ-SNR values for groups A, B, and C were 47.23 [26.03], 56.89 [28.48], and 67.74 [38.53], respectively (median [IQR]). The Friedman test revealed significant intergroup differences ($\chi^2 = 52.23$, $P < 0.001$). Post hoc pairwise comparisons with Bonferroni correction demonstrated that PZ-SNR in group C was significantly higher than that in both group A and group B (both $P < 0.001$), and PZ-SNR in group B was also significantly higher than that in group A ($P < 0.001$).

TZ-SNR: The TZ-SNR values for groups A, B, and C were 41.69 [13.17], 50.38 [14.96], and 55.10 [22.07], respectively (median [IQR]). The Friedman test revealed significant intergroup differences ($\chi^2 = 64.30$, $P < 0.001$). Post hoc pairwise comparisons with Bonferroni correction

showed that TZ-SNR in group C was significantly higher than that in both group A and group B (both $P < 0.001$), and TZ-SNR in group B was also significantly higher than that in group A ($P < 0.001$).

CNR: The CNR values for groups A, B, and C were 11.47 [14.45], 13.60 [11.41], and 14.95 [12.81], respectively (median [IQR]). The Friedman test revealed significant intergroup differences ($\chi^2 = 21.90$, $P < 0.001$). Post hoc pairwise comparisons with Bonferroni correction (corrected $\alpha' = 0.017$) demonstrated that CNR in group C was significantly higher than that in group A ($P < 0.001$) and group B ($P = 0.002$), whereas the difference between groups A and B did not reach statistical significance after Bonferroni correction (corrected $\alpha' = 0.021$, $P > 0.017$). Detailed comparisons of objective image quality among the three groups are presented in Figure 2.

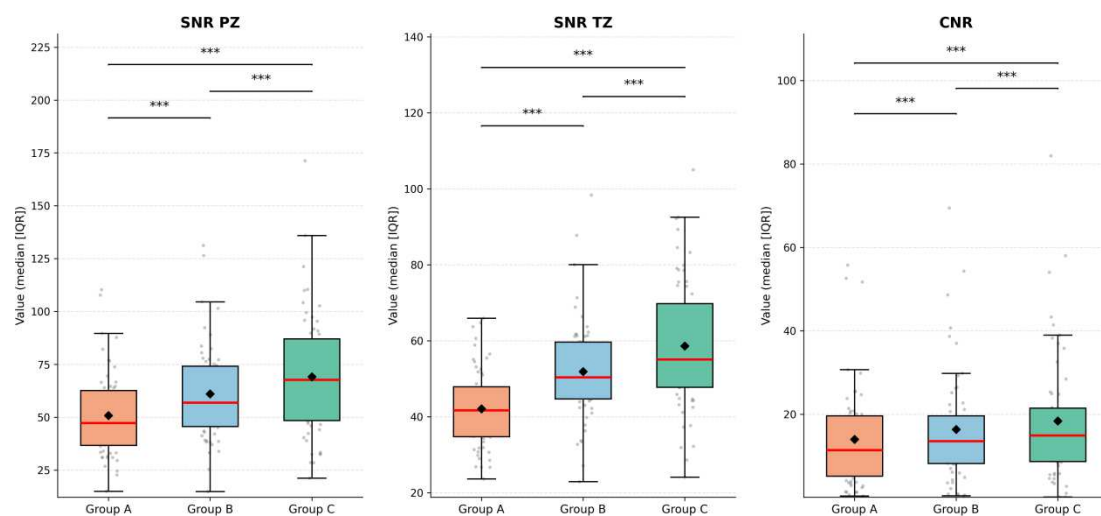


Figure 2. Comparison of objective image quality among the three T2WI sequences. A = PI (NEX 2); B = ACS (NEX 2); C = ACS + DLR (NEX 1.5).

3.4 Comparisons of Subjective Scores Among Groups

The comparisons of subjective scores among the three groups are summarized as follows (Figure 3):

For overall image quality, the scores for groups A, B, and C were 2.50 [0.50], 3.50 [1.00], and 4.50 [0.50], respectively (median [IQR]). Group C achieved significantly higher scores than group B and group A, and group B also scored significantly higher than group A (all corrected $P < 0.017$).

For image artifacts, the scores for groups A, B, and C were 3.00 [1.00], 3.50 [1.00], and 4.50 [0.50], respectively (median [IQR]). Group C demonstrated significantly better scores than group B and group A, and group B was significantly superior to group A (all corrected $P < 0.017$).

For diagnostic confidence, the scores for groups A, B, and C were 3.00 [0.50], 3.50 [0.50], and 4.50 [0.50], respectively (median [IQR]). Group C showed significantly higher scores than group B and group A, and group B also scored significantly higher than group A (all corrected $P < 0.017$).

Detailed comparisons of subjective scores among the three groups are presented in Figure 3, and representative images from each group are shown in Figure 4.

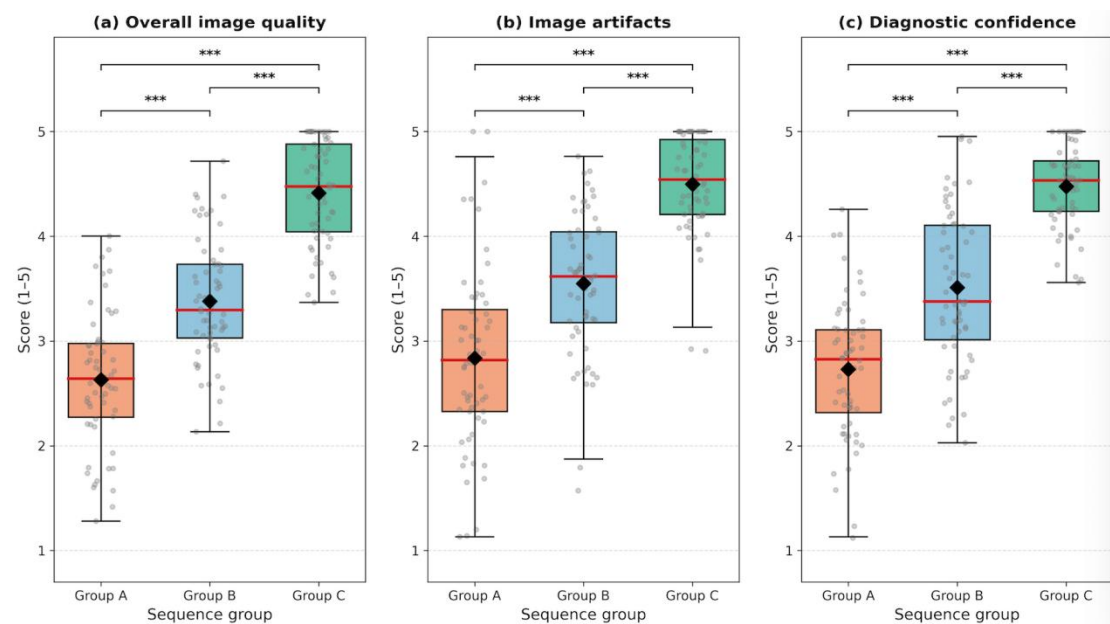


Figure 3. Comparison of subjective scores among the three T2WI sequences. A = PI (NEX 2); B = ACS (NEX 2); C = ACS + DLR (NEX 1.5).



Figure 4. A 68-year-old male patient: comparison of images from the three T2WI sequences. In group A, marked motion artifacts are visible and the boundary between the peripheral zone and the transition zone is blurred; in group B, artifacts are reduced but improvements in SNR and resolution are limited; in group C, image clarity and tissue contrast are optimal, and the hypointense foci in the peripheral zone are clearly delineated.

3.5 Inter-Observer Agreement and Subjective Image Quality Assessment

Inter-Observer Agreement Analysis

For objective measurements, the inter-observer ICC values between the two radiologic technologists for PZ-SNR, TZ-SNR, and CNR were 0.97 (95% CI: 0.95–0.98), 0.95 (95% CI: 0.92–0.97), and 0.93 (95% CI: 0.89–0.96), respectively, all exceeding 0.90 and indicating excellent agreement for the objective measurements.

For subjective scores, the inter-observer ICC values between the two radiologists for overall image quality, image artifacts, and diagnostic confidence were 0.80 (95% CI: 0.68 – 0.87), 0.83 (95% CI: 0.72 – 0.89), and 0.81 (95% CI: 0.71 – 0.88), respectively, all exceeding 0.75 and indicating good to excellent agreement for the subjective assessments.

4. Discussion

This study evaluated the clinical utility of ACS acquisition acceleration combined with DLR in high-resolution prostate T2WI. Our results demonstrated that the ACS+DLR group reduced scan time by 47.2% (from 127 s to 67 s), with significant improvements in PZ-SNR, TZ-SNR, CNR, and all three subjective scores compared with PI and ACS alone (all $P < 0.001$). These findings confirm that the synergistic application of ACS and DLR can overcome the inherent trade-off between scan speed and image quality in prostate MRI.

The clinical value of this strategy is threefold. First, the 67-s acquisition time improves patient tolerance and reduces motion artifacts. Second, the significantly improved SNR and CNR facilitate clear delineation of prostatic zonal anatomy and lesion margins. Third, ACS+DLR group achieved the highest scores in overall image quality, image artifacts, and diagnostic confidence (all $P < 0.001$), substantially strengthening radiologists' diagnostic confidence.

The synergistic effect of ACS and DLR is central to achieving simultaneous acceleration and improved image quality. ACS embeds a deep CNN as a regularization constraint into the CS iterative reconstruction framework, enabling efficient acceleration with noise suppression at the acquisition stage[19-21]. DLR then further performs dual-domain denoising across image and k-space domains, compensating for noise elevation induced by reduced NEX and enhancing anatomical details[22]. This cascade of acquisition acceleration and reconstruction-based denoising provides full-chain optimization. To our knowledge, this is the first study to combine ACS-based acquisition acceleration with DLR-based reconstruction in high-resolution prostate T2WI, providing preliminary evidence for full-chain acceleration approach in this field.

Compared with previous studies, the novelty lies in both technical pathway and experimental design. Prior DL-accelerated T2WI studies mostly relied on a single acceleration technique[23-24], without systematically evaluating the synergistic effect of acquisition-end ACS and reconstruction-end DLR. By incorporating an intermediate ACS-only control group (group B), our stratified design parsed the respective contributions: group B achieved 35.4% acceleration with modest image-quality gain, whereas group C successfully compensated for quality degradation through DLR. Additionally, our simultaneous reporting of PZ/TZ SNR, CNR, and three subjective scores with ICC-verified inter-observer agreement provides a comprehensive evaluation framework.

Several limitations should be acknowledged. First, clinical variables including PSA, body weight, and prostate volume were not prespecified for collection, and the sample size is relatively

modest. Second, diagnostic performance was not validated against PI-RADS and histopathological standards. Third, DLR denoising parameters may require further fine-tuning for different sequences. Moreover, previous studies have shown that over 90% of radiomic features extracted from DLR-reconstructed images differ significantly from those in conventionally reconstructed images[25], warranting cautious interpretation in quantitative radiomic analyses. Future studies may extend this strategy to 3D isotropic T2WI and other mp-MRI sequences.

In conclusion, ACS combined with DLR delivers efficient full-chain acceleration for high-resolution prostate T2WI. It markedly shortens scan duration and improves both objective and subjective image metrics, showing promising potential for clinical translation.

5. Conclusion

The synergistic application of ACS and DLR achieves substantial scan acceleration in high-resolution prostate T2WI, while improving image SNR, CNR, subjective image quality, and diagnostic confidence. This combined strategy offers a novel and effective approach for optimizing prostate MRI workflows, enhancing patient experience, and improving diagnostic efficiency.

Competing interests

The authors declare no competing interests.

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Data Availability Statement

The raw imaging datasets generated and/or analysed during the current study are not publicly available due to patient privacy and institutional data protection policies. However, the de-identified objective measurement data (e.g., SNR, CNR, and scan time values) are included in this published article and its Supplementary Information files. The raw imaging data are available from the corresponding author on reasonable request, subject to ethical and institutional approval.

Abbreviations:

ACS: AI-assisted compressed sensing

AI: Artificial Intelligence
ANOVA: Analysis of Variance
BMI: Body Mass Index
CNN: Convolutional Neural Network
CNR: Contrast-to-Noise Ratio
CS: Compressed Sensing
DLR: Deep Learning Reconstruction
DWI : Diffusion-Weighted Imaging
FOV : Field of View
ICC: Intraclass Correlation Coefficient
mp-MRI: multiparametric Magnetic Resonance Imaging
MRI : Magnetic Resonance Imaging
NEX: Number of Excitations
PI: Parallel Imaging
PI-RADS: Prostate Imaging Reporting and Data System
PZ: Peripheral Zone
ROI: Region of Interest
SD: Standard Deviation
SI: Signal Intensity
SNR: Signal-to-Noise Ratio
TE: Echo Time
TR: Repetition Time
TSE : Turbo Spin Echo
TZ: Transition Zone
T2WI: T2-Weighted Imaging

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [QuantitativemeasurementdataReader1.xls](#)
- [QuantitativemeasurementdataReader2.xlsx](#)