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REVIEWS AND COMMENTARY • SPECIAL REPORT

The Current Status of AI-accelerated MRI Techniques in Clinical Use

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Artificial intelligence (AI) tools to accelerate MRI are rapidly entering clinical routine. Several techniques for MRI acceleration already exist, including compressed sensing and parallel imaging. The introduction of AI acceleration tools for MRI is therefore not fundamentally novel. However, the possibility of combining these AI tools with existing MRI acceleration techniques adds potential opportunities and complexity. This article focuses on commercially available AI tools for clinical MRI acceleration. The basic principle of AI-accelerated MRI is to shorten acquisition time—which results in noisier or lower-spatial-resolution images—then recover image quality with AI. The potential advantages of AI-accelerated MRI include increased patient comfort, shorter waiting lists, reduced motion artifacts, economic efficiencies, and environmental benefits. This article first briefly presents fundamental technical aspects of AI acceleration tools, including noise reduction and super-resolution reconstruction, summarizing available evidence. Potential errors and pitfalls, notably hallucinations (ie, invented or disappearing lesions) are serious concerns, yet they remain poorly investigated. The occurrence of hallucinations, however, is probably rare at the acceleration levels recommended for clinical practice. The downstream implications and potential challenges of AI-accelerated MRI are also discussed, including generating too many images and studies for a limited number of radiologists to interpret. Additionally, slight AI-generated modifications of image contrast could lead to systematic bias in analyses that use historical controls, such as brain volume analyses. Also, the critical question of how much acceleration is clinically useful remains unclear and needs further investigation. Finally, the logistics of implementing AI acceleration tools in routine clinical workflow are discussed, including invested time, costs, and essential medicolegal considerations. The scientific community and radiologic societies should endeavor to establish assessment criteria for this new beneficial class of MRI tools that are rapidly entering clinical practice.

Supplemental material is available for this article.

Since the initial demonstrations of MRI, much effort in the field has gone toward reducing acquisition time while preserving diagnostic information. Most recently, artificial intelligence (AI) tools to accelerate MRI acquisition have shown much promise and have rapidly entered clinical use. In general, faster MRI acquisition leads to noisier or lower-spatial-resolution images, as signal is collected during a shorter period of time. Historically, multiple approaches were presented to address this challenge, including different standard spatial imaging filters, such as Gaussian blur, Laplacian, and embossing. Such techniques are not limited to MRI and have been used for other modalities, including CT, radiography, and US. Separate approaches largely specific to MRI have been developed as well, including parallel imaging (1,2) and compressed sensing (3,4). Most recently, MRI acceleration using deep learning–based AI tools has been developed and can be combined with existing tools, adding levels of complexity. Table 1 presents an overview of various techniques for MRI acceleration along with their advantages and disadvantages.

Obvious advantages of faster MRI acquisitions include increased patient comfort (particularly for patients who cannot tolerate standard full-length MRI protocols), shorter waiting lists, reduced motion artifacts, economic efficiencies, and environmental benefits (due to less MRI machine time needed per examination) (5). Moreover, AI-accelerated MRI is a general process that can be applied to basically all MRI sequences, body regions, and diseases. The current article focuses on commercially available AI tools for MRI acceleration in clinical use. Basic methodologic aspects and the current evidence for clinical use are first discussed, followed by potential artifacts, including hallucinations. Downstream effects related to AI-accelerated MRI reconstructions are also presented, including an increased volume of MRI studies and corresponding demands on radiologists for interpretation. Additionally, AI-accelerated MRI results in subtle modifications of image contrast, which may, for example, bias the results of automatic volumetric tools. Finally, the article discusses how much acceleration is clinically useful, and what medicolegal questions might need to be addressed.

Technical Aspects of AI-accelerated MRI

In general, faster MRI acquisition leads to noisier or lower-spatial-resolution images. Thus, the most common use of AI tools for MRI acceleration is to reduce the noise to recover quality (6). AI enhancement can be implemented in the sensor space (k-space), image space, or both. There are trade-offs associated with each of these approaches. The backbone of most such algorithms is a U-Net encoder-decoder generator with skip connections, which is a robust method for image-to-image transformation (7). Both iterative and noniterative approaches have shown success, while models that use a data consistency term in the loss function during training demonstrate further robustness (8). Unfortunately, given the competitive landscape, little detail is provided for commercially available AI acceleration products. These products have typically enabled twofold to fourfold acceleration for most available sequences and cover most body parts. The development of more complex models that address time-resolved imaging is beyond the scope of this article. Some vendors offer various strengths of denoising settings that the user can customize during a trial phase. This choice is not trivial and may depend on MRI sequence, body region, or vendor.

Abbreviation

AI = artificial intelligence

Summary

With the rapid dissemination of artificial intelligence acceleration tools for MRI, individual radiologists and health systems should critically and objectively evaluate the effectiveness of their use in clinical practice.

Essentials

- Artificial intelligence (AI)–accelerated MRI algorithms can be used to accelerate image acquisition, improve image quality, or both.
- Advantages include increased patient comfort, shorter waiting lists, reduced motion artifacts, economic efficiencies, and environmental benefits.
- At very high acceleration rates, hallucinations (invented or disappearing lesions) are possible.
- Hallucinations introduced by AI-accelerated MRI algorithms remain poorly investigated but are probably rare at acceleration levels recommended for clinical practice.
- Downstream effects related to AI-accelerated MRI algorithms include increased numbers of images, with associated demands on radiologists for interpretation, and subtle changes in image appearance.

Another way to reduce imaging time is to acquire lower-spatial-resolution images. The aim of AI super-resolution reconstruction is to increase spatial resolution to better delineate diagnostically relevant structures. To learn how to upscale images effectively, AI models are typically trained on extensive datasets of both low- and high-spatial-resolution images. The ability to perform super-resolution reconstruction is important because some sequences do not use signal averaging, so acceleration via reducing the number of signal averages is not possible. Both in-plane and through-plane implementations have been described (9,10). Super-resolution reconstruction can be combined with noise reduction, but this feature is currently available only from selected vendors.

Emerging from this technology are self-supervised multicontrast reconstruction techniques. These techniques not only expedite the acquisition process by using undersampled data and reference contrast images but also enhance the detailing of anatomic features, leveraging shared information from multiple MRI sequences for improved image quality (11). This is achieved through a self-supervised learning approach that emphasizes consistency across different domains (12). Such methods have also been used to replace motion-degraded images or images that were not acquired because the patient could no longer tolerate the scanning process (13).

Sensor-Space versus Image-Space Acceleration

AI-accelerated MRI can be performed in sensor space (k-space) or image space (after reconstruction) or using a hybrid approach.

k-Space acceleration

Typically, k-space acceleration has the advantage of accessing both magnitude and phase information, which may be valuable as inputs to the enhancement network. Often, a k-space tool is directly installed on the MRI scanner platform by the vendor, which can simplify the workflow for sites. The vendor applies for regulatory clearance (Food and Drug Administration or Conformité Européenne) for the tool as a new “sequence” for the imaging system. The downside to this approach is the potential lack of transparency about whether image enhancement is being applied. Such tools are often available only on newer scanners or newer software platforms, necessitating upgrades or

Table 1: Summary of Methods for MRI Acceleration

Method	Advantages	Disadvantages
Non-AI methods		
Abbreviated protocols	Fewer sequences; faster for radiologists to read; can be used with all scanners	Missing sequences may lead to incorrect diagnosis
Lower-spatial-resolution or noisier image acquisition	Faster acquisition; easy to implement; can be used with all scanners	Poor spatial resolution or increased noise may lead to incorrect diagnosis; image quality may not be acceptable to radiologists
Multicontrast sequences	Many image types acquired with a single prescan and acquisition	Compromises in spatial resolution and noise; longer time to reconstruct; may not be available on older scanners
Parallel imaging	Faster acquisition; reduced specific absorption rate	Motion and coil sensitivity map errors; lower signal-to-noise ratio; g-factor noise; higher reconstruction complexity; may not be available on older scanners
Compressed sensing	Faster acquisition; reduced motion artifacts; reduced specific absorption rate	Assumptions about image sparsity; increased noise; nonlinear, computationally intensive reconstruction methods; not available on older scanners
AI methods		
Deep learning using k-space inputs	Faster acquisition via removing k-space lines; uses both magnitude and phase of the signal; can be combined with non-AI methods	Proprietary k-space format; not available on older scanners; hallucinations possible at high acceleration factors
Deep learning using image-space inputs	Faster acquisition via noisier or lower-spatial-resolution imaging; can be combined with non-AI methods; compatible with all scanners	Uses only magnitude of images; maximum accelerations may be lower than for k-space methods; hallucinations possible at high acceleration factors

Note.—AI = artificial intelligence.

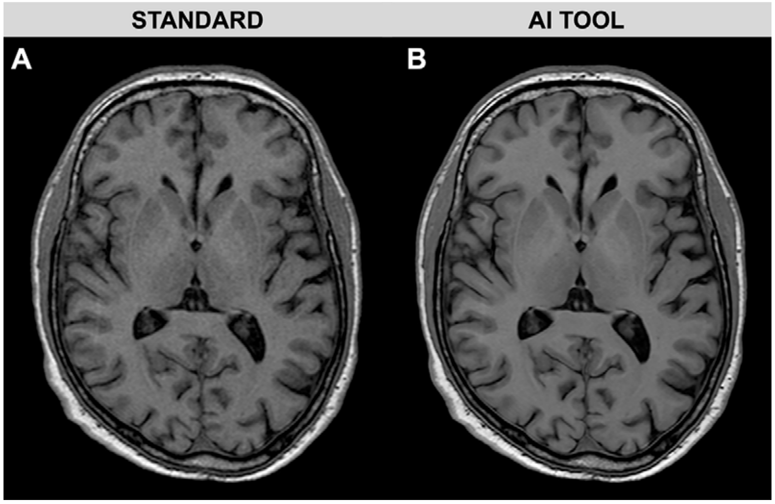

Figure 1: Brain MRI scans acquired with a 19-year-old 1-T open-bore MRI scanner. **(A)** Standard-of-care axial T1-weighted image. **(B)** The same image was postprocessed with a Food and Drug Administration–certified artificial intelligence (AI) image postprocessing tool that was intended for image acceleration but was "misused" to improve image quality, as a software upgrade of the old MRI scanner. This figure highlights that AI acceleration techniques can be used to accelerate image acquisition, improve image quality, or both.

new scanner purchases in order to use them. Finally, if a site has scanners from multiple vendors, multiple AI software solutions need to be negotiated and implemented, which can increase costs and complexity.

Image-space acceleration

As another approach, images can be enhanced after the reconstruction process. This method shares similarities with natural image enhancement, a large field with many described methods that can be leveraged. The most noteworthy among these AI tools are convolutional neural networks and transformers, which have shown success across many applications. One additional advantage of these AI image postprocessing tools for MRI acceleration is the possibility of "soft-upgrading" older MRI scanners (Fig 1). This approach is, in principle, less costly and more sustainable than buying and siting a new MRI scanner, while also avoiding downtime. Furthermore, such methods are vendor-agnostic, allowing implementation and maintenance at sites with scanners from multiple vendors. Finally, because image-space acceleration tools are postprocessing tools, the unenhanced images can be reviewed in conjunction with the enhanced images, which may foster more confidence in the process.

Vendor-specific versus vendor-independent AI acceleration tools

The currently available research that directly compares the performance of k-space versus image-space AI acceleration tools is insufficient. Consequently, the selection of vendor-specific versus vendor-independent tools, for the best possible AI acceleration effect and better workflow integration, might depend on the individual setting. For example, vendor-specific tools might be the best approach for a small imaging center with only one or a few new MRI machines, all from the same vendor and all with available vendor-specific tools. Conversely, a vendor-independent approach might be the best approach for a large imaging center with many MRI scanners from different vendors, some of which might be too old for vendor-specific solutions. In this setting, a vendor-independent approach has the advantage of uniform acceleration across all MRI systems. Many use cases will fall between these two ends of the spectrum. Consequently, the best choice will require balancing advantages versus disadvantages.

Summary of the Available Evidence

As the current article focuses on certified and commercially available tools, we asked vendors to provide any peer-reviewed and published scientific studies using their technologies, and thus compiled 82 studies of vendor-specific tools (Table S1) and 11 studies of vendor-independent tools (Table S2) at the time of writing, summarized in Table 2. These studies span a wide variety of domains and organs. Consequently, the number of studies per domain is limited. For example, for vendor-specific tools, there were seven studies in adult neuroradiology (14–20), four of which involved pituitary gland imaging (17–20), and there were three studies in pediatric neuroradiology (21–23). For vendor-independent tools, eight studies were in the domain of the brain (10,13,24–31). Across both vendor-specific and vendor-independent tools, most studies focused on T2-weighted imaging (52%), followed by diffusion-weighted imaging (15%) (Table 2), while other sequences, such as T1-weighted, were less commonly investigated. Peer-reviewed literature on MRI acceleration for other types of imaging—including T2*-weighted imaging, susceptibility-weighted imaging, MR angiography, MR venography, and perfusion-weighted imaging—is currently lacking.

Most studies compared AI-accelerated versus nonaccelerated MRI (83%), while the rest retrospectively simulated reduced imaging time and applied the AI algorithm (17%) (Table 2). Studies using 3 T were more common (76%) than those using 1.5 T (26%). Most studies used two-dimensional MRI (88%). Retrospective studies (53%) were more common than prospective studies (44%), and the remaining 3% of studies did not specify this aspect. Almost all studies included visual image quality assessment (94%) and analysis of signal-to-noise ratio or contrast-to-noise ratio for large regions of interest (90%). Although the detection of small pathologic lesions is clinically relevant, this important aspect was clearly assessed in only 22% of studies of vendor-specific AI tools and 82% of studies of vendor-independent AI tools. It was unclear whether this was assessed in 44% and 9% of studies, respectively, while it was not assessed in the remaining 34% and 9% of studies, respectively (Table 2; details in Tables S1 and S2). Instead, most studies assessed some form of diagnostic performance, an approach that indirectly assesses lesion detection. However, we can assume that small lesions are more difficult to detect and might be more strongly influenced by image contrast. Specific assessment of small lesions was performed in a minority of studies. For example, one prospective study (involving 3-T two-dimensional T2-weighted imaging in 152 patients) specifically assessed small liver lesions, comparing single-breath-hold AI-accelerated MRI versus multi-breath-hold nonaccelerated MRI (32).

Another recent study evaluated the performance of AI-accelerated MRI for brain metastasis detection in 33 patients

Table 2: Studies of Vendor-Specific and Vendor-Independent AI Acceleration Tools for MRI

Variable	Studies of Vendor-Specific AI Tools (n = 82)*	Studies of Vendor-Independent AI Tools (n = 11)†	All Studies (n = 93)
Field of study			
Adult neuroradiology	7 (9)‡	8 (73)	15 (16)
Pediatric neuroradiology	3 (4)	3 (27)	6 (6)
Type of imaging			
T2-weighted imaging	41 (50)	7 (64)	48 (52)
Diffusion-weighted imaging	14 (17)	0 (0)	14 (15)
Field strength			
1.5 T	18 (22)	6 (55)	24 (26)
3 T	63 (77)	8 (73)	71 (76)
Imaging dimensionality			
Two-dimensional	78 (95)	4 (36)	82 (88)
Three-dimensional	3 (4)	7 (64)	10 (11)
Type of study			
Prospective	34 (41)	7 (64)	41 (44)
Retrospective	45 (55)	4 (36)	49 (53)
Not specified	3 (4)	0 (0)	3 (3)
No. of cases			
No. of controls	303	0	303
No. of patients	10 963	1214	12 177
Analysis components			
Visual image quality assessment	77 (94)	10 (91)	87 (94)
Large region-of-interest SNR or CNR	77 (94)	7 (64)	84 (90)
Dedicated analysis of small pathologic lesions			
Yes	18 (22)	9 (82)	27 (29)
No	28 (34)	1 (9)	29 (31)
Unclear	36 (44)	1 (9)	37 (40)
Study approach			
Direct comparison of AI-accelerated vs nonaccelerated MRI	66 (80)	11 (100)	77 (83)
Retrospective reduction of image time and application of AI algorithm	16 (20)	0 (0)	16 (17)

Note.—Except where indicated, data are numbers of studies, with percentages in parentheses. All included AI tools had Food and Drug Administration or Conformité Européenne certification. Details of the summarized studies are provided in Tables S1 and S2. AI = artificial intelligence, CNR = contrast-to-noise ratio, SNR = signal-to-noise ratio.

* Vendor-specific tools are MRI acceleration tools provided by vendors of MRI scanners and are typically installed on the MRI console.

† Vendor-independent tools are MRI acceleration postprocessing tools that are applied to images in image space regardless of the MRI system vendor.

‡ Includes four studies of the pituitary gland.

with 94 brain metastases and found a sensitivity of 92% for AI-accelerated MRI (26). Lesions less than 4 mm with lower enhancement were more likely to be missed. In particular, five of 94 lesions were missed on the accelerated images. However, this study used an uncommon fast imaging protocol, in which acquisitions in both the frequency- and phase-encoding directions were reduced, even though reducing the spatial resolution by changing the frequency acquisition duration does not produce time savings. This finding speaks to the importance of proper protocol selection. Despite this, the authors found no evidence of a difference in the volumes of interest drawn by the radiation oncologists on accelerated versus nonaccelerated images (26). Although it might be of limited clinical relevance to miss one additional micrometastasis in a patient with multiple known metastases of larger size, it might be relevant to miss a micrometastasis in a patient without known metastasis. Likewise, missing one small lesion at contrast-enhanced MRI in multiple sclerosis might impact treatment decisions. When considering such issues, radiologists should recognize that more lesions may also be seen with higher doses of MRI contrast agents (double dose), higher-relaxivity contrast agents, longer-duration imaging, or higher field strength. Ideally, future studies evaluating AI-accelerated MRI should be multicenter, multivendor prospective studies that include multiple MRI sequences and multiple body regions and assess the detection of small lesions and artifacts.

Potential Pitfalls

Artifacts refers to features on radiologic images that do not correspond to actual anatomic structures, but rather are "invented" by the imaging technique. In the context of AI image reconstruction, *hallucination* refers to the invention of lesions that do not exist or the removal of true lesions by the AI tool. In this sense, hallucinations are a new type of MRI artifact. However, there

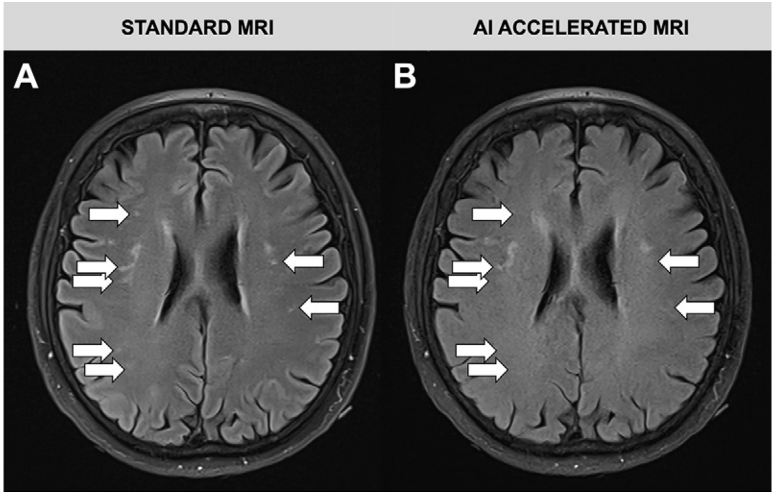

Figure 2: **(A)** Standard-of-care axial two-dimensional T2-weighted fluid-attenuated inversion-recovery MRI scan (acquisition duration, 3 minutes 38 seconds) shows several white matter hyperintensities (arrows). **(B)** When a commercial artificial intelligence (AI) acceleration method was applied, with approximately fivefold acceleration (acquisition duration, 45 seconds), the contrast of the image is different, and multiple small lesions are less conspicuous (arrows) and could potentially be missed during image interpretation.

are concerns that radiologists do not have experience recognizing hallucinations or that hallucinations are too subtle for radiologists to identify. Such concerns parallel those raised at the introduction of other undersampling techniques, such as compressed sensing (4), which initially also created a fear of potential artifacts. These undersampling techniques were rapidly integrated into clinical practice and are standard and largely noncontroversial today.

Hallucinations include invented lesions that do not exist. In some instances, these invented lesions are obviously artificial and are easily detected by the radiologist. Lesions may also disappear (Figs 2, 3). Another form of hallucination could be a change in image appearance that might, for example, mimic pathology (Fig 4). Such potential hallucinations are a concern when applying AI acceleration tools in clinical routine. Few scientific studies exist in this domain, despite the frequent discussion and obvious concern about this issue, perhaps because most clinical applications have used relatively low acceleration factors,

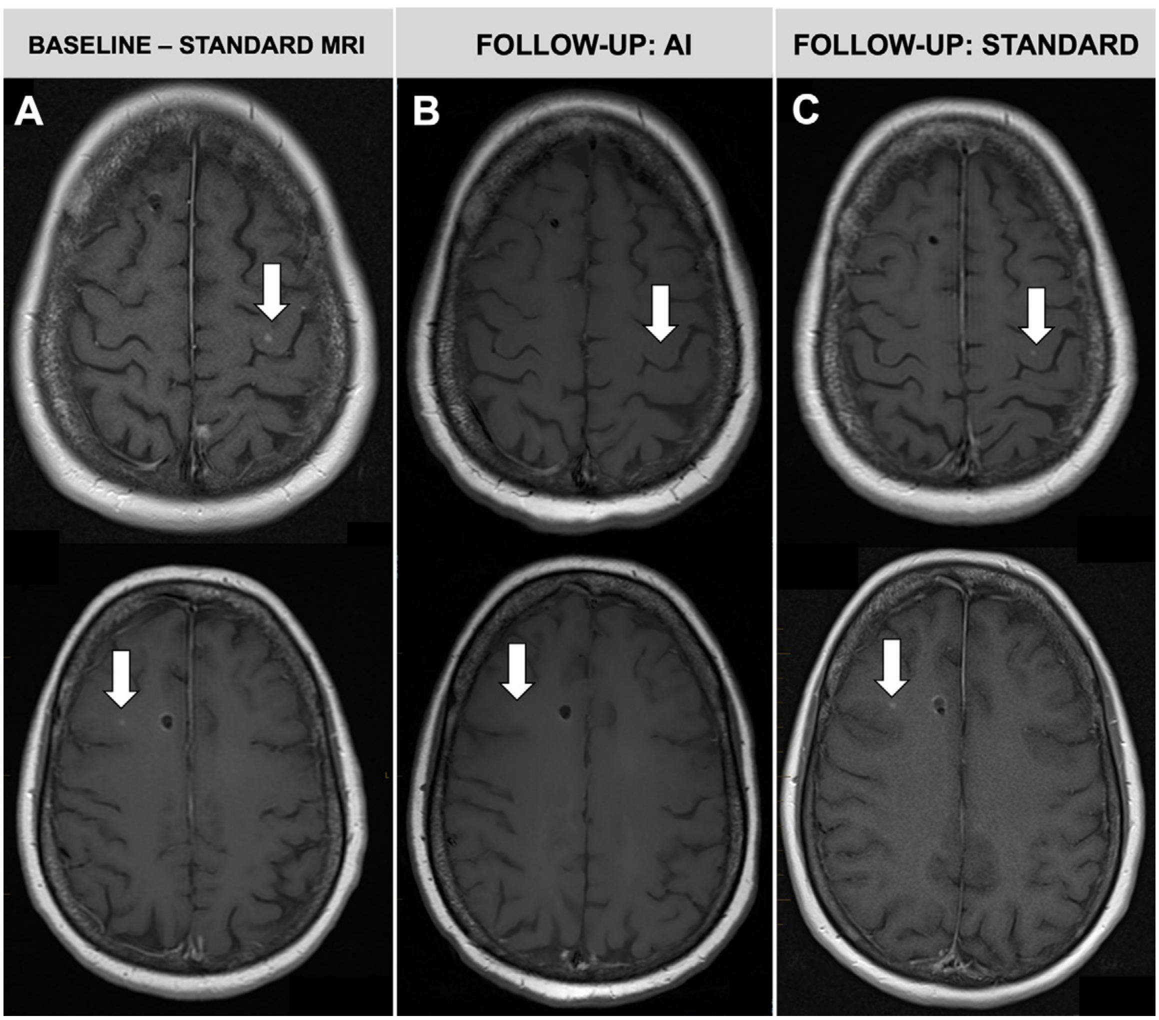

Figure 3: **(A)** Baseline standard-of-care axial contrast-enhanced T1-weighted MRI scans show probable intra-axial micrometastases (arrows). **(B)** Follow-up MRI scan acquired with a commercial artificial intelligence (AI) acceleration method suggests that those micrometastases have disappeared (arrows). **(C)** Subsequent follow-up standard-of-care MRI scan still demonstrates the known lesions (arrows). We paid careful attention that this difference was not due to small differences in section position and image orientation. Such findings suggest that attention should be paid to small lesion visualization when using AI-accelerated MRI. Images courtesy of Laughlin Dawes, MIT, University of New South Wales.

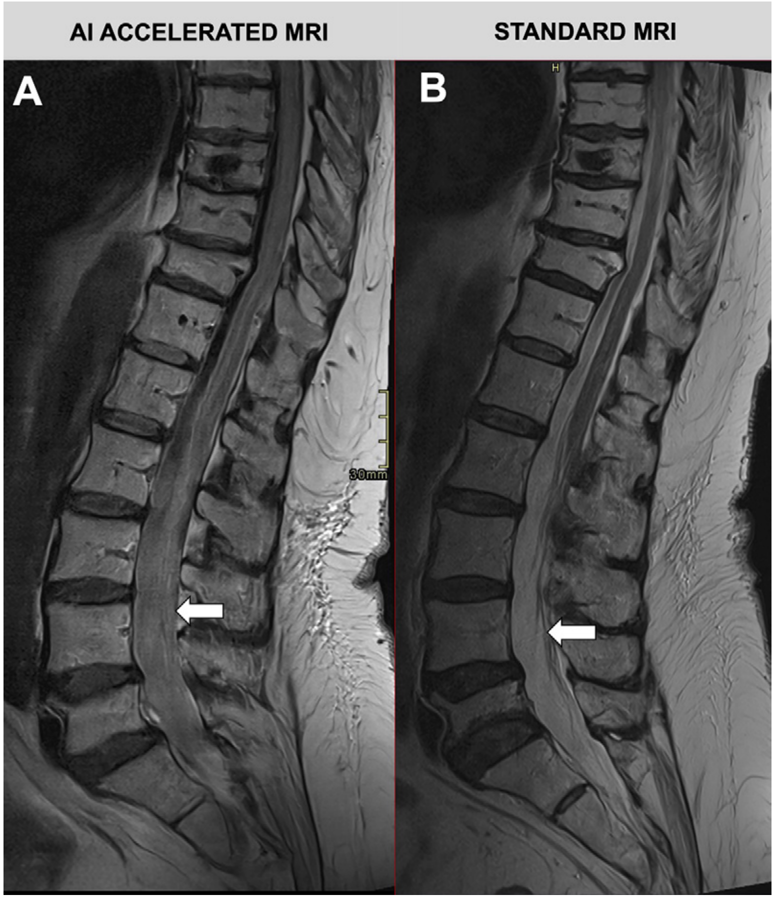

Figure 4: **(A)** Sagittal T2-weighted MRI scan of the lumbar spine acquired with a commercial artificial intelligence (AI) acceleration method shows intradural signal intensity heterogeneity (arrow), possibly mimicking an intradural tumoral process. **(B)** Standard-of-care sagittal T2-weighted MRI scan obtained several days later shows normal intradural signal intensity (arrow). One possible explanation for these disparate findings is that modifying the parameters of the underlying sequence so that it is acquired in a shorter time (ie, accelerated MRI) could affect the imaging contrast, including possible changes in the signal intensity of the cerebrospinal fluid flow. An alternative explanation is that a reduction in repetition time could cause less fluid signal recovery. Attention to how protocols are shortened as part of the implementation of AI-accelerated MRI methods is required to verify that the desired contrast is not altered during this process.

for which such artifacts are uncommon. Another concern has been the potential instability of AI-accelerated MRI reconstructions. One study showed that precisely defined "noise" added to an input image could result in macroscopic image change (33). However, in real life, such tailored noise profiles are vanishingly unlikely to occur, and other studies have shown that deep learning–based reconstructions tend to be robust against such adversarial manipulations (34).

Finally, it is likely that radiologists can use several techniques to identify hallucinations, should they occur. First, they can examine the morphologic features of suspected hallucinations, which may be nonanatomic. Next, they might identify inconsistencies on different image sections and image types. If a structure is present on only a single image section or image type, radiologists are likely to consider the possibility of an artifact. This understanding, combined with the extremely low frequency of hallucinations, suggests that hallucinations may not be problematic for the typical acceleration factors (2× to 4×) in current use. However, consideration should be given to how to design a study to test this hypothesis.

Potential Downstream Considerations

Increasing numbers of images and studies for interpretation

In many countries, there is a shortage of radiologists for the amount of work. This shortage is projected to become even more pronounced in the future, given the steady increase in medical imaging and the essentially flat supply of radiologists (35). AI-accelerated MRI will produce more images per scan time and MRI machine, regardless of whether AI acceleration is used with the aim of producing more images per patient, imaging more patients per unit time, or a combination of both. Although the problem of increasing numbers of images to be interpreted predates AI-based acceleration, and MRI is only one of many imaging modalities, it can still be expected that the increased number of images per unit time due to AI acceleration methods will further increase demands for image interpretation. The extent of the increase in workload, and how to handle it, is largely an unexplored topic.

Effect of AI acceleration on visual analysis and lesion quantification

AI-accelerated MRI scans may have a different image appearance compared with standard (non–AI-accelerated) MRI scans. This difference could reduce lesion conspicuity and with it diagnostic confidence, necessitating longer image interpretation times per case. Of note, there is currently no evidence or systematic scientific assessment of such a potential effect. Future studies might consider addressing this potentially important issue.

Even subtle changes in image appearance with AI-accelerated MRI may be cause for concern. Most currently available postprocessing tools (including brain MRI volumetry, lesion detection tools, and lesion segmentation tools) were developed and certified by the Food and Drug Administration or European Union (Conformité Européenne marking) based on their performance on standard (non–AI-accelerated) MRI scans. Consequently, a potential bias could arise when AI-accelerated MRI scans are postprocessed using existing tools. Few data are currently available on this topic. One publication demonstrated overall similar performance of brain cortical segmentation with image-based AI acceleration of 60% (10). Another study, in patients with multiple sclerosis, found a small but statistically significant mean difference of −0.9% in normalized global brain volume, and a more pronounced mean regional effect of +4% in normalized thalamic volume, with AI-accelerated MRI versus standard MRI (25). Such potential effects should be considered in the clinical context. For reference, average annual brain volume reduction is in the range of 1% for controls and 3% for patients with Alzheimer disease (36). Consequently, a methodologic misestimation of 1%–2% might be relevant in this context. Again, this issue is not novel (radiologists are familiar with variability in measurements based

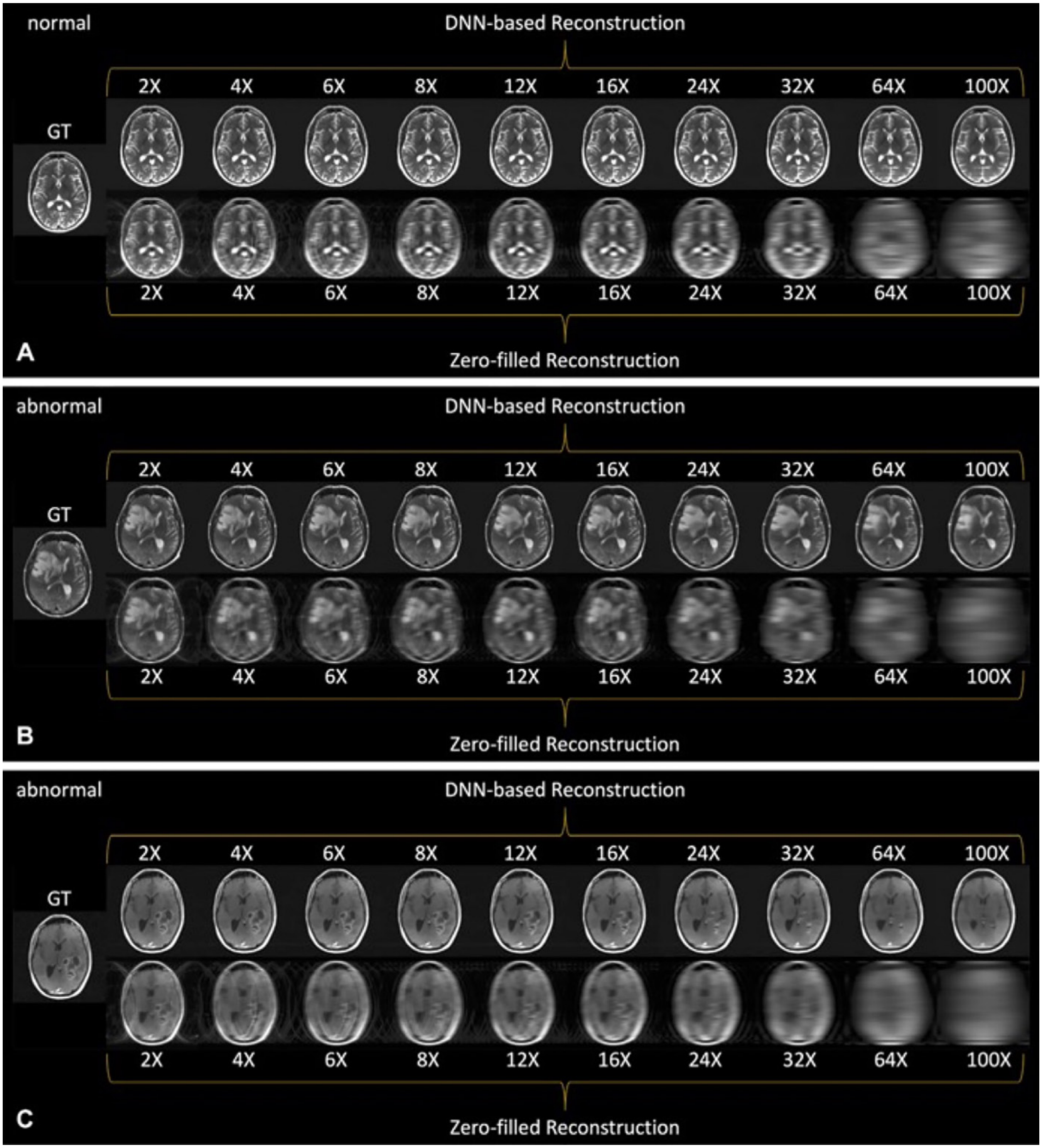

Figure 5: Axial brain MRI scans at various acceleration factors in **(A)** normal and **(B, C)** abnormal cases. In each panel, the standard MRI scan (ground truth [GT]) is shown on the left, and a series of deep neural network (DNN)–based reconstructions (above) and zero-filled reconstructions (below) are shown on the right. These series illustrate how artificial intelligence–accelerated MRI scans change with increases in acceleration factor, showing that pathologic features can become less evident and eventually may be lost, though this is largely limited to very high acceleration factors above 24-fold. Most commercially available algorithms work in the twofold to fourfold acceleration range, which is possibly why images like those further to the right are not typically seen using commercial implementations. Reprinted, with permission, from reference 38.

on MRI scanner vendors, individual scanners, sequences, field strength, and postprocessing tools) (37), yet the introduction of AI-accelerated MRI adds complexity. Eventually, normative cohort datasets should include images from scanners using AI acceleration if this technology becomes widespread, obviating any potential biases or misdiagnoses.

How Much Acceleration Is Clinically Useful?

Generally speaking, the higher the acceleration factor, the higher the beneficial effects, at the cost of potentially decreased image quality and increased risk of artifacts or hallucinations. Already for standard MRI sequences, faster imaging can be performed at the cost of decreased spatial resolution, decreased section

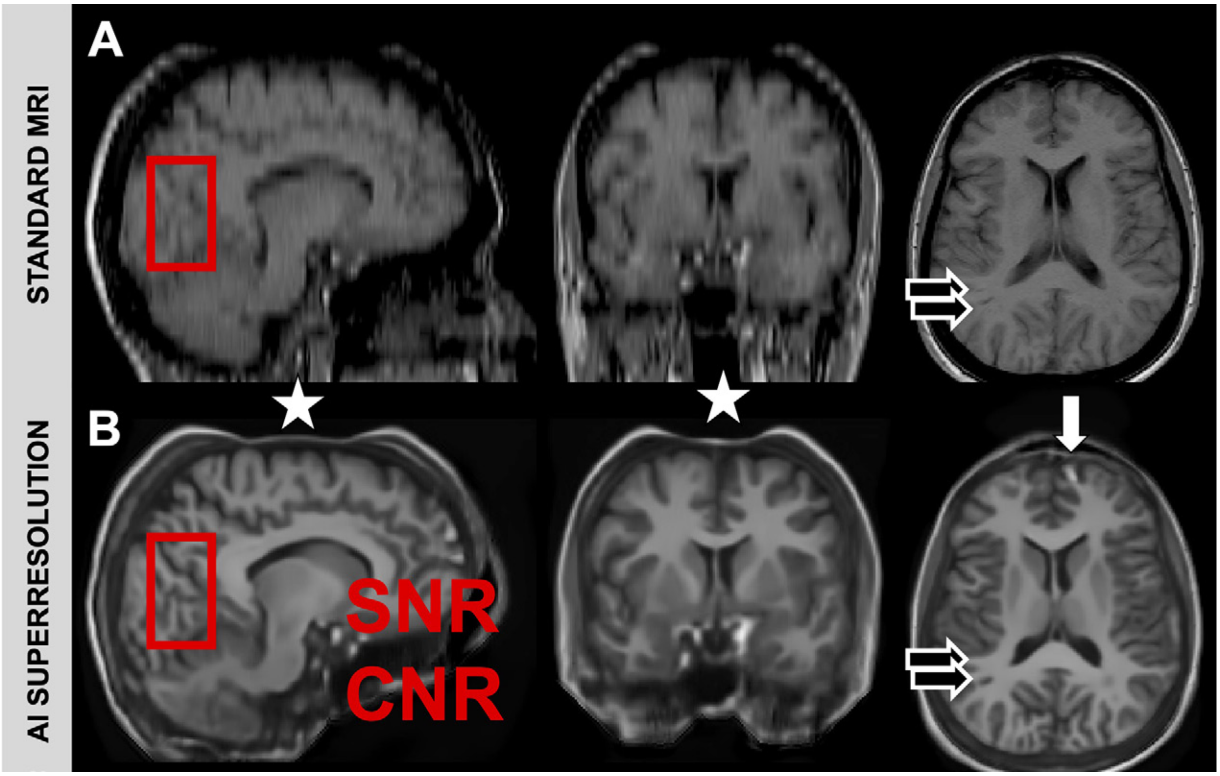

Figure 6: Example of hallucinations after the application of a noncommercial experimental artificial intelligence (AI) super-resolution algorithm. **(A)** Standard-of-care three-dimensional T1-weighted brain MRI scans acquired on an open-bore 1-T MRI machine. **(B)** Images after application of the AI super-resolution algorithm. The gray matter–white matter contrast is notably improved on the coronal and sagittal reconstructions, and the definition of the basal ganglia is markedly improved on the axial section. However, the reconstructions show induced geometric distortion at the vertex (stars in **B**) and hallucinations. One pseudolesion is invented at the left frontal gray matter–white matter junction (white arrow in **B**). One dilated perivascular space in the parietal region is increased in size, while another adjacent, smaller dilated perivascular space has disappeared (black arrows). The signal-to-noise ratio (SNR) or contrast-to-noise ratio (CNR), which is typically measured in a large region of interest (red box), may be increased with this AI super-resolution algorithm, but the AI postprocessed image is less diagnostic because of the described hallucinations and geometric distortion. Note: This AI tool for super-resolution reconstruction is a research product and not certified or commercially available. These images illustrate the potential effect of AI super-resolution reconstruction when applied under extreme conditions.

thickness, and/or increased noise. The balancing of acquisition time versus image quality or risk of artifacts is therefore not new. AI acceleration tools add another dimension to consider in terms of trade-offs, with accompanying levels of complexity. On the one hand, faster access to MRI may provide earlier diagnosis, with subsequent potential benefits to the patient. On the other hand, lower image quality or higher risk of artifacts or hallucinations increases the risk of incorrect diagnosis, with the attendant potential harms. Moreover, the optimal trade-off might depend on the clinical context. For example, imaging in a screening setting and imaging for detailed preinterventional planning might have different demands for image quality. As it is virtually impossible to accurately quantify the risks or benefits of AI acceleration tools, this discussion remains speculative. This basic dilemma is similar to that for other imaging modifications such as CT dose reduction. Although the objective of CT dose reduction is different (reduced radiation dose rather than faster imaging), the basic trade-off between the objective and image quality is similar.

Increased artifacts and hallucinations are certainly a concern for the application of AI acceleration tools in clinical routine. In general, clinically relevant hallucinations are more likely when the AI acceleration factor is high (38,39). At very high acceleration factors (up to 100×), even large, aggressive intra-axial lesions may disappear (Fig 5). Likewise, excessive application of super-resolution reconstruction—that is, pushing the image spatial resolution substantially beyond the actual acquisition spatial resolution—may also result in hallucinations (Fig 6). Future studies should address the effect of acceleration factor on the resulting image quality and the occurrence of artifacts and hallucinations.

Costs of Implementing AI Acceleration Methods

AI acceleration tools are associated with cost, typically either a fixed expense or yearly subscription license fee. AI acceleration saves imaging time, but it also requires information technology resources to install and maintain. The time needed for updates and workflow integration should also be considered. Moreover, when weighing how AI acceleration tools might improve efficiency, practices should consider the time for patient positioning, scan preparation, and room turnover in addition to the time saved during the actual scanning. Because of these factors, the effective real-world clinical time saving is less than the reduction in acquisition time. A retrospective real-world clinical study of two acceleration tools used in 7346 examinations on 10 clinical MRI scanners showed the variable effect of AI acceleration tools (40). Interestingly, the vendor-independent tool was more efficient, reducing scan time by up to 53% and room time by up to 41%. In contrast, the k-space tool reduced scan time only up to 27%, without a substantial reduction in room time (40). Concerning finances, the value of the reduced scan time with AI acceleration tools should be compared with the cost of those tools. Identifying break-even points or return on investment is critical for imaging centers in deciding whether such AI acceleration tools are worthwhile for them, yet most scientific studies and marketing documentation tend to neglect these factors.

Medicolegal Considerations

Most currently available AI tools, such as for lesion detection or lesion quantification, are based on standard MRI sequences. The clinical radiologist can evaluate the added value of the output of such tools via comparison with standard radiologic evaluation. For AI-accelerated MRI sequences, the situation is different as these sequences typically replace the previously implemented sequences. Consequently, the images from the non–AI-accelerated MRI sequence are no longer available for clinical comparison. This presents a dilemma, notably as most of the AI-accelerated sequences are classified as Food and Drug Administration class II or Conformité Européenne class IIa (41). This suggests that the radiologist might be held responsible for evaluating the AI acceleration tools despite the lack of clarity on how this should be done in the absence of the non–AI-accelerated sequences.

Vendor-specific AI acceleration tools for MRI are often embedded in the architecture of the MRI platform. In this case, the regulatory approval of the MRI platform is usually amended, and the enhanced sequences may substitute for the previous standard, with the user having no access to the acquired data that are used as input to the models. This contrasts with image-space AI acceleration approaches, in which the input images are available to the radiologist, who can in principle compare the two images directly. However, in both cases, the radiologist no longer has non–AI-accelerated, longer-acquisition sequences available for comparison.

In the United States, the American College of Radiology MRI Accreditation program sets requirements for imaging quality for outpatient studies. However, in many countries, there are no clear rules on the expected image quality for a given indication, nor standards for the acceptable number of artifacts per patient scan. The radiologist must determine whether to perform faster scans or higher-quality scans to reduce the risk of missed diagnosis and for precise interventional planning. This issue already existed before AI acceleration tools, such as with lower-spatial-resolution standard MRI sequences in abbreviated imaging protocols. However, the use of AI acceleration tools, especially combined with existing tools, adds a level of complexity. It is obviously difficult to provide guidelines and recommendations for this complex issue.

Conclusion

Artificial intelligence acceleration tools for MRI have already been adapted in clinical practice. Both vendor-specific and vendor-independent tools are available. The advantages of faster scanning include increased patient comfort, reduced motion artifacts, shortened waiting lists, economic value, and potential environmental advantages. These advantages come at the potential cost of reduced image quality and hallucinations, although these issues have not been reported with commercial tools using recommended protocols. Possible downstream effects include an increased number of scans to be read by a limited number of radiologists, as well as potential bias in both visual and automatic image interpretation. Generally, the stronger the acceleration factor, the greater the benefits and the potential adverse effects. Prospective, well-designed studies to inform radiologists on how to balance these factors will be valuable and should be prioritized by the scientific community.

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