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**Diffusion-Weighted Magnetic Resonance Imaging of the Pancreas: A Narrative
Review**

DWI of pancreas

Qing-Yu Gao, Li-Jia Wang, Chao Ma

Abstract

Diffusion-weighted magnetic resonance imaging (DWI) has become an essential tool in the field of pancreatic MRI, enabling the detection, characterization, prediction, and evaluation of pancreatic diseases. In this article, we review the acquisition parameters, postprocessing techniques, and quantitative methods utilized in pancreatic DWI. Various postprocessing models, including monoexponential, biexponential, stretched exponential and non-Gaussian kurtosis models, as well as deep learning networks, have been used to assess their clinical utility in diagnosing pancreatic diseases. The single-shot echo-planar imaging (SS-EPI) sequence is the commonly used sequence for DWI data acquisition in clinical settings, and the apparent diffusion coefficient (ADC) calculated using the mono-exponential model is the most widely used quantitative parameter in clinical practice. The repeatability threshold for ADC of normal pancreas is 37% for test-retest scans, while the repeatability threshold for pancreatic tumors needs to be further investigated. Complex postprocessing models exploring new DWI-based biomarkers beyond ADC to assess histological features, and artificial intelligence in DWI postprocessing and data analyses hold promise in the diagnosis of pancreatic diseases. Future work should focus on standardizing protocols, conducting multicenter studies, and exploring variety of methods to improve the accuracy of DWI quantitative results to increase the clinical effectiveness of DWI in patients with pancreatic diseases.

Key Words: Diffusion-weighted imaging; Pancreas; Magnetic resonance imaging; Model; Artificial intelligence

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Core Tip: The development of diffusion-weighted magnetic resonance imaging (DWI) has been pivotal in propelling the progress of pancreatic MRI. In this article, we offer a narrative review of the utilization of both foundational DWI techniques and deep

learning algorithms in the diagnosis of pancreatic disorders. Additionally, we delve into the possible advantages of employing sophisticated models in DWI data analysis for the detection and diagnosis of pancreatic diseases.

INTRODUCTION

Diffusion-weighted **magnetic resonance** imaging (DWI) is a quantitative MRI technique that uses gradient pulses to detect and measure the diffusion of water molecules in tissues. DWI has applicability across various organs, in both tumor and nontumor environments, for the qualitative and quantitative assessment of various pathological conditions[1]. Currently, the ⁸ **single-shot echo-planar imaging (SS-EPI)** sequence is one of **the most used DWI acquisition techniques in clinical practice**, which offers fast acquisition speed, thus reducing motion artefacts and scanning time, but it is prone to magnetic susceptibility artefacts, leading to limited image spatial resolution. Readout-segmented EPI (rs-EPI) DWI[2] and reduced field-of-view (rFOV) DWI[3,4], **have markedly enhanced spatial resolution in pancreatic imaging.**

Initially, due to the presence of artefacts and pitfalls, DWI was focused primarily on neuroimaging[5]. To date, with the **developments** of methods and advancements in hardware and software, DWI has been extensively studied in various clinical scenarios from head to toe, including identifying benign and malignant lesions, distinguishing different types of malignant tumors, and predicting and evaluating treatment response[6,7]. The Quantitative Imaging Biomarker Alliance (QIBA) has been striving to standardize quantitative imaging biomarkers for both clinical trials and practice[8]. QIBA has provided valuable insights into the acceptable levels of variance. This knowledge is crucial for fully leveraging ADC as a quantitative imaging metric for lesions in the head (8%), liver (27%), breast (27%), and prostate (15%)[9]. However, in pancreatic **imaging**, DWI has certain limitations. Challenges in obtaining high-quality DW images arise from factors such as motion artefacts caused by respiration, peristalsis, and blood flow, as well as difficulties related to fat suppression. Therefore, it is essential

to recognize and address these limitations in pancreatic applications to ensure that DWI can play an optimal role in the diagnosis and assessment of pancreatic diseases.

In this study, we review the acquisition technology of DWI and the application of commonly used postprocessing models in the pancreas and introduces some complex models and deep learning in DWI postprocessing to highlight their potential applications in pancreatic diseases. In conducting this review, we primarily adopted a narrative approach, while also incorporating quantitative data from prior studies. The information pertained to the application of DWI in the pancreas, including specific scanning settings and its role in the diagnosis of pancreatic diseases.

BASIC PRINCIPLES OF DWI

DWI sequences

SS-EPI is widely recognized as the preferred method for integrating DWI with fat-suppression techniques[10]. To minimize the influence of motion artefacts, both breath-hold and free-breathing technologies are utilized alongside diverse signal acquisition strategies, which may include respiratory and/or cardiac triggering. Free-breathing sequences, in particular, provide a superior signal-to-noise ratio (SNR) and accommodate a broader range of b values than their breath-hold counterparts do.

Rs-EPI, a powerful imaging technique, is a multi-shot sequence that has been utilized in some anatomical regions, including the brain[11], breasts[12,13], prostate[14], kidneys[15] and joints[16]. Rs-EPI significantly mitigates susceptibility artefacts and T2* decay-induced blurring, thereby enhancing the quality of DWI images and the reliability of quantitative parameters. However, the prolonged acquisition time required may limit its clinical utility. Advancements in imaging technology have led to the development of rFOV-DWI as an innovative solution. This technique offers improved image quality, superior tissue resolution, and a substantial reduction in artefacts and distortion[4,17]. Therefore, this method presents a promising solution for addressing the constraints associated with conventional full-FOV DWI. rFOV-DWI leverages 2D RF along with 180° pulse-back technology to minimize the signal loss resulting from the

uneven B1 field distribution in the pancreatic region[17]. This approach effectively overcomes resolution challenges while enhancing pancreatic imaging quality. In contrast to other multishot techniques aimed at improving DWI clarity and reducing image distortion, rFOV-DWI avoids complex reconstruction processes[18]. However, its limitation lies in the **small FOV**, which may hinder the evaluation of areas beyond the imaging FOV, such as the lymph node status[19].

Acquisition parameters for DWI

In DWI, an important parameter known as the b value, also known as the diffusion factor, represents the sensitivity of the sequence to diffusion motion and serves as an indicator for detecting the ability to capture diffusion motion. The b value is defined as follows:

(1)

where G represents the magnitude of the diffusion gradient, δ denotes the duration for which the gradient is applied, and Δ signifies the time interval between two diffusion gradients. Given the physical constraints on the maximum achievable diffusion gradient, there is an upper limit to the value of G. Consequently, when G reaches its maximum, the b value can be increased only by adjusting either δ or Δ .

The magnitude of the b value in DWI has a **significant** effect on image quality and lesion detection. Therefore, the selection of appropriate b values tailored to specific anatomical regions is crucial for accurate lesion evaluation. In abdominal DWI, the commonly utilized range for low and high b values is typically between 0-100 s/mm² and 500-1500 s/mm², respectively. **DWI with high b values** tend to reflect restricted diffusion and thus enhance the detectability of lesions in images. Koc *et al.*[20] reported that a high b value of 600 s/mm² at 1.5-T MRI was optimal for distinguishing between benign and malignant lesions in the abdomen. Specifically for the pancreas, Fukukura *et al.*[21] demonstrated that increasing the b value from 500 s/mm² to 1500 s/mm² at 3.0-T MRI can improve the visibility of pancreatic adenocarcinoma. This improvement is attributed to the reduction in the signal from the distal pancreas, whereas the signal

from pancreatic adenocarcinoma remains significantly elevated. However, increasing the b value beyond 2000 s/mm² can degrade the image quality. This decline is attributed to the fact that while higher b values can augment contrast, they also reduce the SNR and increase the susceptibility to artefacts.

DWI models

Numerous models are available for the quantitative assessment of the pancreas *via* DWI, including the monoexponential model, intravoxel incoherent motion (IVIM), stretched exponential model (SEM), diffusion kurtosis imaging (DKI) model, and many others. The most used models for quantitative assessment involve calculating the apparent diffusion coefficient (ADC) *via* a monoexponential model and estimating the derived parameters from the IVIM, which is based on biexponential analyses[22]. The fitting equations for these two models are as follows:

Monoexponential model:

(2)

IVIM:

(3)

In the IVIM, three main parameters are quantified. D^* represents the perfusion information, also known as the perfusion coefficient, which mainly represents the contribution of perfusion to the attenuation of the diffusion image signal. D reflects the true diffusion information, also known as the actual diffusion coefficient, which mainly represents the contribution of true diffusion to the attenuation of the diffusion image signal, and f is the perfusion fraction, reflecting the proportion of perfusion.

The SEM, proposed by Bennett *et al.*[23], is a model that can simultaneously quantify water molecule diffusion capability and voxel heterogeneity[24]. Compared with the traditional exponential decay model, the SEM can better describe complex diffusion processes and tissue heterogeneity. The equation for the SEM is shown in Formula (4):

(4)

(5)

The DKI model can be used to quantify the degree of deviation from the Gaussian distribution[25]. By applying Formula (5), the diffusion kurtosis coefficient (K) can be obtained. K represents the deviation of the diffusion behavior from the Gaussian model and the degree of tissue structure confinement and heterogeneity in the tissue composition. The diffusion coefficient (D) is used to correct for non-Gaussian bias.

These models have been proposed for exploring the microstructural characteristics of tissues and investigating disease diagnosis and efficacy evaluation. Furthermore, with the rapid progression of deep learning technologies, the incorporation of deep neural networks into these foundational models enables improved precision in quantitative parameters estimation. As a result, we can achieve a more comprehensive understanding of the pancreatic microenvironment and design more efficacious strategies for disease diagnosis and treatment by leveraging deep learning techniques to analyze DWI data.

APPLICATION OF DWI IN PANCREATIC DISEASES

The contrast of DWI is related to the tissue cellularity, tissue structure, and cell membrane integrity. The use of the ADC map in differentiating and diagnosing various pancreatic diseases has been reported. Sabry *et al.*[26] measured the average pancreatic ADC values in a small sample of acute pancreatitis patients and healthy controls. They reported that the optimal ADC threshold for distinguishing between the two groups was $1.32 \times 10^{-3} \text{ mm}^2/\text{s}$, with a sensitivity of 81.25%, a specificity of 93.75%, and an accuracy of 91.8%. Several studies evaluating chronic pancreatitis (CP) have reported that the ADC values in patients with CP are lower than those in healthy controls[27,28]. Therefore, DWI can serve as an adjunctive tool in diagnosing pancreatitis. Zhu *et al.* reported that an ADC sensitivity of 83% in differentiating benign and malignant lesions, with a specificity of 87% and an area under the curve (AUC) of 0.92[29]. Several studies have also focused on the use of DWI to discriminate between autoimmune pancreatitis (AIP) and pancreatic ductal adenocarcinoma (PDAC). Given the overlapping clinical and radiological characteristics of mass-forming pancreatitis and PDAC, differentiating

them is difficult. Nevertheless, since the treatment and prognosis of these two diseases are significantly different, it is important to make a correct diagnosis[30]. Several studies[31-35] have reported different ADC cut-off values ranging from 0.88 to 1.26×10^{-3} mm²/s for differentiating mass formation pancreatitis and PDAC. However, Ha *et al.*[36] reported that the ADC was ineffective in differentiating PDAC from mass-forming pancreatitis, and a comparison of ADCs for mass-forming pancreatitis and PDAC in different studies led to conflicting conclusions. Therefore, more advanced models may be needed to be further investigated. In a study by Robertis *et al.*[37], the perfusion fraction (f) led to 100% sensitivity in distinguishing PDAC tissue from normal pancreas tissue and AIP tissue from normal pancreatic tissue. Zeng *et al.*[38] measured IVIM parameters, correlated them with histopathological data, and achieved superior performance in differentiating nonhypervascular pancreatic neuroendocrine tumors (PNETs) and PDAC. Notably, the D was found to be more effective than both the ADC and the perfusion fraction f. Additionally, the ADC has been consistently shown to be significantly correlated with tissue-determined pancreatic fibrosis, as evidenced by studies[39-41]. DWI and corresponding ADC maps of the normal pancreas and nine representative pancreatic pathologies are shown in Figure 1.

DWI can be used to differentiate between benign and malignant tissues, and numerous studies have demonstrated that the ADC and f measurements are the most precise parameters. The IVIM employs a biexponential model to quantify the macroscopic diffusion of water and the microscopic perfusion of blood in capillaries. IVIM DWI can provide more refined tissue characterization and improves the discrimination between benign and malignant tissues[42]. Significant progress has been made in the use of IVIM parameters in the early detection of chronic pancreatitis[43], the prediction of the pathological grade of pancreatic cancer, the determination of lymph node metastasis, and the differentiation of various pancreatic tumor diseases. Liu *et al.*[44] explored the correlation between IVIM parameters and pancreatic fibrosis. Their findings indicated that the D and f values exhibited greater sensitivity and diagnostic performance for grading PDAC. McCullum *et al.*[45] employed histogram

analysis of the median, standard deviation, skewness, kurtosis, and percentile to compare the parameter distributions of patients with pancreatic cancer before and after treatment response by using IVIM DWI and reported that f and D changed substantially, whereas D^* showed no significant correlation in any test. The results of this study imply that the f and D parameters may be potential indicators for evaluating the treatment response of patients with pancreatic cancer. However, Zhu *et al.*[29] systematically evaluated the ability of the IVIM to distinguish between benign and malignant pancreatic lesions. They reported that the IVIM exhibited high sensitivity and specificity (84% and 83%, respectively). The performance in terms of these values was comparable to the performance of the ADC values (83% and 87%, respectively). The multi-b-value IVIM also has challenges because of its high parameter variability and reproducibility, as well as its complexity and prolonged acquisition times. Consequently, although the bi-exponential IVIM model has been extensively investigated, its routine application in diagnosing pancreatic diseases has not yet been established, and there is still a lack of consensus on selecting appropriate b values.

There is limited research on the application of the SEM in pancreatic DWI. Currently, SEM is primarily used to differentiate between different types of pancreatic tumors. Shi *et al.*[46] compared the correlations between different parameters *via* various methods and reported that α has significant potential in distinguishing PDAC from PNET, thus improving the diagnostic accuracy. Li *et al.*[47] conducted volume histogram analysis for each DWI parameter and compared the histogram indices obtained from different tumor parameters. They reported that volume histogram analysis of the SEM could be used to differentiate PDAC from PNET. However, the median f value obtained from IVIM DWI was more valuable than the ADC, D_p , DDC, and α values were. Therefore, the SEM, with its ability to elucidate the intricate tissue characteristics and biological behavior of pancreatic tumors, holds promise for refining early diagnostic procedures and optimizing therapeutic outcomes.

DKI was initially developed for neuroimaging research, and research focused primarily on capturing microstructural information related to the diffusion in grey and

white matter of the brain[48]. This technique examines the degree of diffusion restriction in tissue structures and the components of intra- and extracellular diffusion[49]. The typical b-value range for DKI is between 0 and 3000 mm²/s, with higher b-values often falling within the range of 2000 to 3000 mm²/s[50]. As the application of DKI models continues to expand, there has been significant interest in their use for tumor characterization and grading. Tumor tissue is distinct from neural tissue, leading to variations in scanning protocols and significantly reduced acquisition times. Unlike neural tissues, which exhibit strong anisotropy and require multiple scanning directions or diffusion kurtosis tensor calculations, tumor tissues generally do not require such approaches. In many cases, obtaining the mean diffusion (MD) and mean kurtosis (MK) of tissues can be achieved in much shorter scanning times, as quickly as 12 minutes. DKI has been widely applied to various abdominal organs, including the prostate[51], kidney[52], and cervix[53], demonstrating greater clinical value than traditional DWI techniques do. In the field of pancreatic imaging, a study conducted by Granata *et al.*[54] revealed that the MD can be used to effectively differentiate between pancreatic parenchyma, peritumoral inflammation, and pancreatic tumors. Furthermore, Philipp *et al.* suggested that the DKI-derived parameter D can serve as a noninvasive biomarker for evaluating the composition of stromal tissue in PDAC[55]. In terms of treatment response evaluation, Granata *et al.*[56] reported significant changes in the MD parameter obtained from DKI before and after electrochemotherapy in pancreatic cancer patients, and excellent diagnostic performance was achieved (sensitivity = 0.8, specificity = 1.0, AUC = 0.933). Zhang *et al.*[57] assessed the efficacy of first-line chemotherapy in unresectable pancreatic cancer patients via DKI and reported that the MD (sensitivity = 85.7%, specificity = 85.7%, AUC = 0.898) outperformed the ADC in terms of diagnostic performance. These findings highlight the potential of DKI in characterizing pancreatic lesions, assessing treatment response, and improving diagnostic accuracy.

While focusing on the application of DWI and quantitative parameters, it should be noted that the variability of quantitative parameters is an important consideration.

According to the recommendations of the QIBA, the ADC variation threshold can be calculated using the following formula[8,9]:

$$\text{Scaled percent repeatability coefficient} = 2.77 \times wCV \times 100\%$$

The weighted coefficient of variation (wCV) can be derived from previous studies, computed using the reported sample size for each study as a weighted factor.

(6)

Here, wCV_i represents the weighted coefficient of variation from the i^{th} article out of a total of n articles, and N_i denotes the sample size from the i^{th} study. According to previous research findings[58-60], the repeatability threshold for ADC of the normal pancreas is 37% (38%, 35% and 37% for the head, neck and tail of pancreas, respectively) for test-retest scans. However, there is a paucity of relevant research data for pancreatic tumors. Therefore, the repeatability threshold for pancreatic tumors of ADC and other quantitative parameters requires further investigation.

DEEP LEARNING IN DWI MODELS

The emergence of deep learning has led to significant advancements in the field of medical imaging. Researchers have successfully applied deep neural networks (DNNs) to fit the IVIM, as exemplified by the work of Barbieri *et al.*[61]. By employing unsupervised learning training with DNNs, they generated more detailed parameter maps, reduced noise levels, and accelerated generation speeds compared to conventional methods, such as the least squares trust region algorithm and Bayesian probability-based IVIM fitting. Another noteworthy development by Kaandorp *et al.*[62] involved the utilization of unsupervised physics-informed DNNs (PI-DNNs) for IVIM modelling. By incorporating the consistency between IVIM predictions and measured signals as a loss term in DNNs, they were able to train the unsupervised PI-DNN directly on patient data without the need for ground truth. This approach resulted in the successful development and training of IVIM-NET, a method capable of accurately and independently predicting IVIM parameters in patients with PDAC[63,64]. Building upon this groundwork, Troelstra *et al.*[65] developed an unsupervised physics-informed

deep neural network known as IVIM-NET, which is based on a triple-exponential IVIM. They evaluated the performance of this model in the context of nonalcoholic fatty liver disease (NAFLD) and revealed a strong correlation with histopathology. The performance of this model surpassed that of traditional least-squares (LSQ) methods. Shi *et al.*[66] combined DW images with convolutional neural networks (CNNs) to transform multi-b-value DW images into histogram arrays, which were subsequently employed as inputs for a 2D CNN model. This approach enables the differentiation of various pancreatic tumor types, including PDAC, PNET, and solid pseudopapillary neoplasm (SPN). These studies collectively highlight the profound benefits of integrating deep learning networks into DWI modelling, facilitating more precise and efficient analysis of medical images while enhancing our understanding and diagnostic capabilities across a range of diseases.

DIFFUSION-RELAXATION DWI

Although basic DWI models have been widely used in the clinical monitoring of diseases, they provide limited microstructural information[67,68]. To improve disease diagnosis, researchers have employed hybrid multidimensional MRI techniques to acquire specific parameter maps, which are feasible in terms of imaging time and image quality for the clinical application of abdominal organs. Furthermore, the maps derived from hybrid multidimensional MRI could be used to quantify histological compartments of tumors. Some studies in prostate and other abdominal organ cancers[69-73], where the combination of T2-weighted imaging with DWI data has been shown to increase the diagnostic accuracy[74,75]. This method has demonstrated an overall sensitivity of 76% and a specificity of 82% in prostate cancer detection[76]. Zhang *et al.*[72] utilized *ex vivo* diffusion-relaxation correlation spectroscopic imaging (DR-CSI)[77] to quantify T2 relaxation and diffusion (T2-D) component spectra, which constitute the entire MRI signal in each voxel. By integrating the T2-D spectral peaks on a voxel basis, they generated signalling component fraction maps, characterizing the application value of DR-CSI in the compartmental quantification of *ex vivo* prostate

specimens from prostate cancer patients. DR-CSI employs an improved two-dimensional ss-EPI sequence, simulating the sum of continuous exponential decay functions for each MRI signal voxel by acquiring multiple echo times and corresponding b values. This process enables the characterization of T2 and D as follows:

(7)

where $S(x, y, TE, b)$ represents the measured signal in the voxel for each TE-b data point, while $\omega(x, y, T2, D)$ represents the T2-D spectrum to be reconstructed for the voxel. The Laplace transform is denoted by L . To solve for $\omega(x, y, T2, D)$, a nonnegativity constraint and a regularization term are applied.

(8)

Each peak in the T2-D spectrum represents a separate signalling component, allowing for the calculation of signalling component fractions in voxels or spatial regions.

(9)

Currently, this technique has been extensively studied for organs such as the kidney[78], liver[79], and cervix[80], *et al.* In clinical, it is possible to obtain multi-TEs and multi-b values data associated with each voxel. The following equation is subsequently used to calculate the tissue composition volumes in each voxel:

(10)

where $i = 1, \dots, N$ and represents the position of the i^{th} voxel. P indicates the number of combinations of b , and TE ω_q denotes the density normalization factor associated with the Riemann sum. S represents the signal intensity corresponding to different combinations of TEs and b values, whereas S_0 represents the signal intensity at the lowest echo time and b value. The quantitative T2 and ADC values are obtained by fitting a single exponential decay model. The function represents the two-dimensional diffusion-relaxation correlation spectrum, which provides the volume fraction of different tissue components in each voxel. Chatterjee *et al.*[64] found a strong correlation between tissue composition measured *via* hybrid multidimensional MRI and quantitative histological evaluations. The results for prostate tissue components

(stroma, epithelium, and lumen) *via* these methods exhibit excellent consistency with the pathological results. To date, the application of these complex models to calculate tissue quantification maps and analyze tumor tissue characteristics has been preliminarily explored in conditions such as pituitary adenomas[81] and parotid gland tumors[82]. Nevertheless, research in a specific domain of pancreatic tumors has not yet been undertaken. Consequently, considering the pronounced lumen structure of pancreatic tissue, there is a strong rationale for applying this advanced imaging technique to pancreatic tumors within a murine model. This application warrants a thorough feasibility analysis and could pave the way for novel insights into the intricate microarchitecture and pathological profiles of the abovementioned tumors.

Optimizing post-processing parameters for tumor DWI remains a challenging task, and rigorous validation against histopathology is indispensable for clinical translation. To accelerate the clinical application of diffusion techniques, the development of an open-source tool, community-driven platform is imperative. Such a shared resource would offer researchers and clinicians a standardized framework to implement and optimize DWI postprocessing models, thereby enhancing the accuracy of tumor characterization and guiding personalized therapy.

DISCUSSION

Currently, ¹³ 1.5 Tesla (1.5-T) and 3 Tesla (3.0-T) MRI systems are commonly used in the clinic for examinations across various anatomical regions of patients. A systematic review concluded that the superiority of 3.0-T over 1.5-T for pancreatic DWI had not been proven, due to a lack of published studies[83]. However, in recent years, there has been a significant increase in the clinical application of 3.0-T MRI for pancreatic detection, with the number of studies conducted at ³ 3.0-T being comparable to those at 1.5-T. Therefore, DWI using 3.0-T units clearly enhances the diagnostic performance for pancreatic lesions[29] due to the advantages offered by the 3.0-T system, such as improved SNR[82,84,85]. With the maturation of ultra-high-field technology, feasibility has been established for 5.0-T, 7.0-T, and even 11.7-T. Rosenkrantz[86] found ³ that the

subjective image quality of abdominal DWI at 3.0-T is significantly inferior to that at 1.5-T. However, several studies have demonstrated that when combined with the rFOV-DWI technique, 5.0-T MRI can improve the quality of pancreatic images[82-84]. Zheng *et al.*[87,88] compared the subjective image quality ratings of DW images acquired via the rFOV-DWI technique with 3.0-T MRI and 5.0-T MRI, respectively, and confirmed that the subjective image quality at 5.0-T was significantly greater than that at 3.0-T. Jiang *et al.*[89] measured ADC values in normal pancreatic tissue and reported high stability, repeatability, and consistency, indicating that 5.0-T DWI can be a reliable tool for pancreatic clinical diagnosis and that rFOV-DWI is a feasible quantitative imaging tool for studying pancreatic lesions. 7.0-T MRI is currently a limited choice for high-field MRI in human imaging and is applicable only to the head[90-92] and limbs[93]. The use of ultrahigh-field MRI is limited to preclinical animal experiments. Fujiwara *et al.*[94] evaluated the correlation between IVIM parameters and ischemic changes in the rat cerebral cortex via a preclinical ultrahigh-field 11.7-T MRI scanner. In a study by Zhang *et al.*[95], conventional DWI, IVIM, and DKI were performed to assess pancreatic fibrosis in a rat model of chronic pancreatitis. They validated the effectiveness of diffusion parameters such as the ADC, D, MD, and MK in evaluating the staging of pancreatic fibrosis. In summary, 1.5-T and 3.0-T imaging remain the mainstream choices. In this context, the stability of parameter measurements and the impact of postprocessing algorithms on the results are crucial factors that different research teams are continuously striving to address. Therefore, we recommend the development of an open-source mathematical framework and the open exchange of domain expertise. Such collaborative initiatives will enhance the accuracy and reliability of DWI, ultimately accelerating progress in the diagnosis and treatment of pancreatic disease.

To translate research findings into clinical practice, consideration must be given to postprocessing of DWI data. However, there are still problematic regarding the feasibility of applying complex models from the brain to the abdomen. Consequently, it is valuable to obtain high-quality images, which should not only have high resolution but also minimize negative factors that affect image quality, such as motion artefacts,

cardiac pulsation, and gastrointestinal peristalsis, for conducting clinical validation experiments, designing suitable animal models, and utilizing dedicated imaging instruments. Additionally, animal models can provide detailed pathological information, which is valuable for revealing the potential characteristics of tumors and changes after treatment. Furthermore, certain research groups in the field of prostate studies have provided superior samples, which can serve as valuable references[63-65].

THE CURRENT CHALLENGES AND FUTURE DEVELOPMENT TRENDS

The current challenges in using DWI for pancreatic disease diagnosis are twofold: Image quality and imaging time. The pancreas is particularly prone to artifacts due to its small size and its proximity to the gas- and air-filled structures of the upper gastrointestinal tract. These structures cause motion and susceptibility artifacts, which can degrade image quality and complicate the radiological decision-making process, especially in exams with a high artifact burden. The high susceptibility to artifacts in abdominal DWI may stem from motion caused by gastric and bowel movement, as well as respiratory motion. This can make it difficult to discern small lesions, which are potentially highly relevant for diagnosis. To balance imaging time and image quality, including SNR and spatial resolution, increasing spatial resolution can lead to a rapid decrease in the SNR of DWI. This may result in a noise floor bias in the measurements of quantitative parameters, which in turn limits the application of DWI in pancreatic imaging. Therefore, the development of better MRI hardware facilities, such as more powerful gradients, and advanced imaging methods, including the use of artificial intelligence, to achieve fast and high-quality pancreatic DWI imaging is a constant pursuit of MRI equipment manufacturers, research teams, and clinicians.

Quantitative DWI parameters, including ADC values, may be subject to variations due to biological factors, technical factors, and measurement errors. Establishing reference standards for DWI imaging and quantitative analysis, and promoting them on a global scale, as suggested by organizations like QIBA, is of paramount importance.

Additionally, conducting **multicentre trials** to enhance the applications of DWI in pancreatic diseases is one of the urgently needed tasks.

The clinical application of newly developed high-field MRI systems, such as 5.0-T, in pancreas diagnostics has yet to be fully evaluated, particularly regarding the quality, stability, and repeatability of DWI. **Current reports are limited by small cohorts and an almost exclusive focus on healthy volunteers, leaving the generalizability to pancreatic pathology unknown.** These challenges underscore the need for further advancements in DWI and techniques to improve image quality, reduce artifacts, and enhance the diagnostic accuracy of pancreatic disease diagnosis.

CONCLUSION

DWI is currently the most widely utilized quantitative sequence in pancreatic imaging and has good contrast for visualizing tumors, as it easily captures abnormal tumor regions. However, despite its extensive application in pancreatic imaging, the potential of various quantitative parameters of various DWI models in the pancreas remains largely unexplored. This presents an opportunity for further research and exploration to uncover the potential value of these quantitative parameters in diagnosing and treating pancreatic diseases. Through continued investigation and innovation in image data acquisition, reconstruction, quantitative parameters map generation, quality assurance and interpretation., we anticipate more breakthroughs in pancreatic imaging that will offer enhanced diagnostic accuracy and reliable treatment strategies for clinical practice.

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SIMILARITY INDEX

PRIMARY SOURCES

- 1 www.ncbi.nlm.nih.gov 53 words — 1%
Internet
- 2 Xin Xu, Xuening Zhang. "The Application of Intravoxel Incoherent Motion Diffusion-Weighted Imaging in the Diagnosis of Hilar Obstructive Jaundice", *Journal of Computer Assisted Tomography*, 2019 38 words — 1%
Crossref
- 3 Hiromitsu Onishi. "MR Cholangiopancreatography at 3.0 T", *Investigative Radiology*, 09/2009 28 words — 1%
Crossref
- 4 cancerimagingjournal.biomedcentral.com 28 words — 1%
Internet
- 5 Anoshirwan Andrej Tavakoli, Constantin Dreher, Anna Mlynarska, Tristan Anselm Kuder et al. "Pancreatic imaging using diffusivity mapping – Influence of sequence technique on qualitative and quantitative analysis", *Clinical Imaging*, 2021 20 words — < 1%
Crossref
- 6 ejrnm.springeropen.com 18 words — < 1%
Internet
- 7 Yunfei Zhang, Ruofan Sheng, Chun Yang, Yongming Dai, Mengsu Zeng. "Higher field reduced FOV diffusion-weighted imaging for abdominal imaging at 5.0 Tesla: image quality evaluation compared with 3.0 Tesla", *Insights into Imaging*, 2023 17 words — < 1%

-
- 8 Cicheng Huang, Chenao Zhan, Yiqi Hu, Ting Yin, Robert Grimm, Tao Ai. "Histogram analysis of breast diffusion kurtosis imaging: a comparison between readout-segmented and single-shot echo-planar imaging sequence", *Quantitative Imaging in Medicine and Surgery*, 2022
Crossref 15 words — < 1%
-
- 9 Zhaohuan Zhang, Holden H. Wu, Alan Priester, Clara Magyar et al. "Prostate Microstructure in Prostate Cancer Using 3-T MRI with Diffusion-Relaxation Correlation Spectrum Imaging: Validation with Whole-Mount Digital Histopathology", *Radiology*, 2020
Crossref 15 words — < 1%
-
- 10 Aritrick Chatterjee, Crystal Mercado, Roger M. Bourne, Ambereen Yousuf et al. "Validation of Prostate Tissue Composition by Using Hybrid Multidimensional MRI: Correlation with Histologic Findings", *Radiology*, 2021
Crossref 14 words — < 1%
-
- 11 Sang-Kwon Lee, Juryeoung Lee, Seolyn Jang, Eunji Lee, Chang-Yeop Jeon, Kyung-Seoub Lim, Yeung Bae Jin, Jihye Choi. "Renal Diffusion-Weighted Imaging in Healthy Dogs: Reproducibility, Test-Retest Repeatability, and Selection of the Optimal b-value Combination", *Frontiers in Veterinary Science*, 2021
Crossref 14 words — < 1%
-
- 12 jsurgmed.com
Internet 14 words — < 1%
-
- 13 Luis Flávio Gonçalves, Nicholas C. Rubert. "Chapter 14 Applications of Magnetic Resonance Imaging in the Fetal Heart", *Springer Science and Business Media LLC*, 2025
Crossref 12 words — < 1%

14 Nabil Bachagha, Xinyuan Wang, Lei Luo, Li Li, Houcine Khatteli, Rosa Lasaponara. "Remote sensing and GIS techniques for reconstructing the military fort system on the Roman boundary (Tunisian section) and identifying archaeological sites", Remote Sensing of Environment, 2020 12 words — < 1%

Crossref

15 X.Y. Yang, X. Li, F.H. Ma, H.M. Li, S.H. Zhao, Y.A. Li, J.W. Qiang. "MRI characteristics for differentiating mucinous borderline ovarian tumours from mucinous ovarian cancers", Clinical Radiology, 2021 12 words — < 1%

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