

Article

A Two-Vector Framework for MRI Knee Diagnostics: Fuzzy Risk Modeling, Digital Maturity, and Finite-Element Wear Assessment

Akerke Tankibayeva ¹, Saule Kumargazhanova ¹, Bagdat Azamatov ¹, Zhanerke Azamatova ¹, Nail Beisekenov ² and Marzhan Sadenova ^{1,*}

¹ D. Serikbayev East Kazakhstan Technical University, 19 Serikbayev Str., Ust-Kamenogorsk 070000, Kazakhstan; atankibayeva@edu.ektu.kz (A.T.); saule.kumargazhanova@edu.ektu.kz (S.K.); bazamatov@edu.ektu.kz (B.A.); zhazamatova@edu.ektu.kz (Z.A.)

² Department of Ecology and Conservation Biology, Texas A&M University, College Station, TX 77843, USA; beisekenovnail@tamu.edu

* Correspondence: msadenova@edu.ektu.kz

Featured Application

The framework supports clinical decision-making in knee MRI by jointly quantifying diagnostic risk and departmental digital readiness. A fuzzy-logic module estimates producer's and consumer's error probabilities under measurement/interpretation uncertainty, while a digital-maturity index aggregates six weighted capability agents. In parallel, a finite-element (FE) module evaluates TKA contact mechanics, linking imaging reliability to wear-relevant metrics (peak contact pressure 85.449 MPa; UHMWPE von Mises stress 43.686 MPa under $F = 1150$ N at 0° flexion). Together, the tools help target QA actions, optimize protocols, and guide staffing/IT and implant-configuration decisions.

Abstract

Knee disorders are a major indication for musculoskeletal imaging, yet MRI reliability remains constrained by signal nonuniformity, motion artefacts, protocol variability, and reader-dependent effects. This study presents an integrated two-vector framework that couples (i) a fuzzy diagnostic control-risk model with (ii) a quantitative digital-maturity assessment to strengthen MRI-based diagnosis of knee pathology. The vertical vector characterizes organizational readiness through a weighted fuzzy aggregation of six capability agents (technical, information and analytical, mathematical/model, metrological, human resources, and software support). The horizontal vector estimates producer's and consumer's risks as misclassification probabilities relative to an acceptance boundary, driven by measurement/interpretation uncertainty, variability of the decision threshold, and the ratio of instrumental to physiological dispersion. Simulation results indicate that error probabilities increase sharply when threshold uncertainty exceeds 20–25% and rise by approximately 15–20% as the standard-deviation ratio approaches unity. To connect diagnostic reliability with downstream mechanics, a FE analysis of the tibial insert in TKA under $F = 1150$ N at 0° flexion predicts a peak contact pressure of 85.449 MPa and a maximum UHMWPE von Mises stress of 43.686 MPa, identifying wear-critical contact zones. Overall, the proposed framework provides interpretable quantitative targets for QA, protocol refinement, and resource allocation in radiology services undergoing digital transformation, and offers a reproducible pathway for linking imaging reliability to biomechanical risk.

Academic Editors: Thomas Lindner, Krzysztof Malczewski and Ryszard Kozera

Received: 15 December 2025

Revised: 23 January 2026

Accepted: 30 January 2026

Published: 3 February 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: MRI; knee; fuzzy logic; diagnostic risk; digital maturity; quality assurance; simulation modeling; finite-element analysis; UHMWPE wear; musculoskeletal imaging

1. Introduction

1.1. The Role of MRI in the Diagnosis of Knee Joint Diseases

Magnetic resonance imaging (MRI) is a cornerstone modality in knee diagnostics because it provides high soft-tissue contrast and enables noninvasive assessment of intra-articular structures (menisci, ligaments, cartilage, and synovium). Modern radiomics further demonstrates that substantial quantitative information can be extracted from MR images when texture-based segmentation and advanced feature-learning algorithms are applied [1]. Within the musculoskeletal domain, the knee joint remains among the most frequently injured large joints, with meniscal and ligamentous lesions representing common clinical indications for imaging and treatment planning [2–4].

Despite its established clinical role, MRI-based diagnosis is not error-free. Residual diagnostic errors for intra-articular knee lesions have been reported across a broad range depending on lesion type, imaging protocol, scanner characteristics, reader experience, and reference standards used for verification [5–8]. Conventional imaging methods (e.g., radiography for osseous injury and limited ultrasonography for selected soft-tissue conditions) may be insufficient for many intra-articular pathologies, reinforcing MRI as a principal modality for differential diagnosis and early detection of degenerative changes [5–10]. Under optimized protocols and in well-defined settings, MRI can achieve high diagnostic performance; however, published accuracy and sensitivity estimates vary across studies, reflecting both technical variability and patient-related factors (motion, anatomy, comorbid changes) [9,10].

Recent advances in artificial intelligence (AI) and decision-support systems increasingly aim to improve reproducibility and reduce inter-reader variability. Deep-learning pipelines have been proposed for detection and grading of meniscal and ligament injuries, while reconstruction and acceleration networks target faster acquisition and more stable image quality [11,12]. In parallel, methods addressing intensity non-uniformity and extending MRI to low-field and portable platforms seek to broaden access without compromising clinically relevant image information [13,14]. These developments motivate not only better image analysis, but also more explicit modeling of uncertainty, risk, and organizational factors that shape diagnostic reliability in real clinical environments.

1.2. Literature Review and Problem Formulation

MRI is grounded in nuclear magnetic resonance physics: nuclei absorb and re-emit radiofrequency energy in a magnetic field, producing signals whose contrast depends on tissue composition and microenvironment (e.g., water content and relaxation properties) [9,10]. Because many soft-tissue injuries and inflammatory changes alter tissue hydration and microstructure, MRI is well suited to detecting subtle pathology that may not be visible on other modalities [11,12]. Nevertheless, persistent limitations are widely documented: small or low-contrast lesions, motion artefacts, protocol variability, and reader-dependent interpretation can all contribute to residual diagnostic uncertainty [1–4]. As a result, knee MRI quality assurance increasingly requires a structured view of how multiple error sources interact across the imaging chain.

A useful perspective is to treat diagnostic performance as the outcome of a complex sociotechnical system that includes the scanner, acquisition protocol, post-processing pipeline, reporting workflow, and human interpretation. Approaches such as hazard

analysis and critical control concepts—adapted from engineering practice to technical and medical systems—support the decomposition of overall uncertainty into traceable contributors and help identify high-leverage control points for reducing error [15–20]. A key difficulty, however, is the definition of a trustworthy “norm” or reference baseline: patient-specific pre-injury scans are rarely available, and population databases cannot fully represent individual anatomy or clinical heterogeneity [18]. Data augmentation and synthetic-data methods may improve robustness in learning-based pipelines and support the construction of reference distributions for modeling uncertainty, particularly when longitudinal imaging and outcomes data accumulate [17–19].

From a metrological and risk-management standpoint, diagnostic uncertainty can be formalized using distributional models for the true underlying state and for measurement/interpretation error. In this work, we quantify two complementary risks that arise when decisions are made relative to an acceptance boundary (standard boundary) under uncertainty: producer’s risk (rejecting a conforming case) and consumer’s risk (accepting a nonconforming case) [20–23]. Let S denote a latent (unobserved) true diagnostic-quality parameter and let S_m be its observed/assessed value. We adopt the measurement model $S_m = S + \Delta$, where Δ is an aggregated error term capturing measurement noise and interpretation variability. Let SB denote the acceptance boundary (standard boundary) for decision-making. Then, producer’s risk N_{pr} and consumer’s risk N_{cr} can be expressed as:

$$N_{pr} = \int_{-\infty}^{SB} f_S(s) [1 - F_{\Delta}(SB - s)] ds, \quad (1)$$

$$N_{cr} = \int_{SB}^{+\infty} f_S(s) F_{\Delta}(SB - s) ds, \quad (2)$$

where $f_S(s)$ is the probability density function (pdf) of the true parameter S , and $F_{\Delta}(\cdot)$ is the cumulative distribution function (CDF) of the error Δ . In this formulation, N_{pr} increases when uncertainty causes conforming cases ($S \leq SB$) to be incorrectly classified as nonconforming, whereas N_{cr} increases when uncertainty causes nonconforming cases ($S > SB$) to be incorrectly accepted. This explicit definition ensures that the density/CDF arguments match the intended random variables and avoids ambiguity in notation.

In practice, the uncertainty distribution for MRI-based diagnosis may deviate from classical Gaussian assumptions because the “measurement channel” includes both physical acquisition and human interpretation, and error sources can be bounded, asymmetric, or multimodal depending on workflow and case mix [20–22]. For this reason, we adopt a uniform distribution for selected uncertainty components as a conservative baseline when only plausible bounds can be justified at the outset (i.e., a “maximum ignorance” assumption within known limits). We additionally treat this choice as testable: in the revised manuscript, distributional assumptions are explicitly documented and their influence on N_{pr} and N_{cr} is examined through sensitivity comparisons against alternative distributions when warranted by available data.

Importantly, diagnostic risk is not determined by physics alone. Digital transformation reshapes imaging workflows by changing protocol governance, auditability, metadata completeness, staff training pathways, and the reliability of clinical information exchange. In healthcare settings, the concept of digital maturity is commonly used to denote the extent to which digital capabilities, governance, and workflow integration are institutionalized to support safe and effective care delivery [23–25]. For radiology services, this includes software infrastructure (e.g., scheduling, reporting, QA logging), data interoperability, and organizational readiness for continuous monitoring and improvement. Similarly, “Big Data systems” in this context refer to large-scale, continuously updated

clinical and operational datasets (imaging metadata, QA logs, outcomes, and error reports) that enable iterative refinement of uncertainty models and risk estimates over time [26–28].

These considerations motivate a practical decomposition into two coordinated dimensions: (i) a horizontal vector capturing diagnostic control risk under uncertainty (quantified by N_{pr} and N_{cr}), and (ii) a vertical vector capturing organizational readiness and digital maturity that shapes how uncertainty is generated, detected, and mitigated. In this manuscript, the term two-vector framework is used to denote this conceptual decomposition and its operationalization; it is not intended as a reference to PACS/PISA terminology or other unrelated architectures. Risk terminology and process logic are aligned with ISO 31000:2018 (risk management—guidelines), and algorithmic workflow diagrams follow ISO 5807:1985 (information processing—documentation symbols and conventions) where applicable [29–32].

Section 2 details the proposed two-vector framework, including the digital maturity model, the probabilistic diagnostic-risk formulation, and the computational implementation. Section 3 reports modeling results and sensitivity analyses. Section 4 discusses practical implications, limitations, and actionable recommendations for reducing diagnostic error risk. Section 5 concludes the paper and outlines directions for future validation.

1.3. Purpose, Novelty, and Objectives of the Study

The purpose of this study is to improve the reliability of knee MRI diagnostics by integrating organizational and probabilistic perspectives on uncertainty and risk. Specifically, we propose a two-vector framework that (i) quantifies diagnostic control risk via producer's and consumer's risks under uncertainty and (ii) quantifies the digital maturity of the radiology department using a transparent fuzzy aggregation approach. The framework is designed to support department-level quality assurance decisions and to clarify which organizational levers most efficiently reduce diagnostic error risk.

The methodological contribution of this work is threefold. First, it provides a reproducible definition of diagnostic control risk for knee MRI using explicit probability expressions with clearly defined variables and assumptions. Second, it introduces a digital maturity index tailored to radiology workflow readiness, enabling organizational factors to be represented quantitatively alongside technical and human sources of uncertainty. Third, it couples these components to support scenario-based evaluation of how organizational readiness can change the uncertainty bounds and, consequently, the estimated diagnostic risks; this creates an operational link from management actions to expected reliability outcomes. In addition, the manuscript explores how diagnostic reliability can be related to downstream biomechanical consequences through finite-element (FE) assessment of contact stress and UHMWPE wear indicators as an illustrative application, thereby motivating clinical relevance beyond the imaging decision itself.

The main objectives of the study are as follows:

1. To define and operationalize a two-vector framework consisting of a horizontal diagnostic control-risk vector and a vertical organizational digital-maturity vector.
2. To develop a fuzzy, reproducible digital-maturity assessment model based on six defined agents and transparent weighting/aggregation procedures.
3. To quantify the dependencies of N_{pr} and N_{cr} on statistical control parameters and uncertainty assumptions, including baseline uniform uncertainty modeling and sensitivity considerations.
4. To implement a software module—a self-contained computational program for Monte-Carlo risk evaluation, parameter sweeps, and visualization—and to validate its behavior through a computational experiment.

5. To formulate practical recommendations for reducing MRI diagnostic error risk by translating model outputs into targeted quality-assurance actions (presented in the Discussion section).

2. Materials and Methods

2.1. Methodological Framework and Research Design

This study proposes a two-vector operational framework for improving the reliability of knee MRI diagnostics by explicitly combining: (i) an organizational digital maturity assessment (vertical vector), and (ii) a probabilistic diagnostic control-risk model (horizontal vector). The methodological foundation synthesizes systems integration and quality management principles under digital transformation, with emphasis on reproducibility, auditability, and risk-based decision support in clinical workflows [33–39]. Risk governance terminology and decision logic are aligned with ISO 31000:2018 (risk management—guidelines), while algorithmic diagram conventions referenced in this work follow ISO 5807:1985 [29–32].

The workflow comprises four stages:

1. Vertical vector (V): digital maturity modeling. Organizational and technological readiness of the radiology department is quantified using a weighted fuzzy aggregation model based on six support agents (Y1–Y6).
2. Horizontal vector (L): diagnostic control-risk modeling. Producer’s and consumer’s risks are computed under uncertainty using distribution-based expressions and Monte-Carlo simulation.
3. Coupling ($V \rightarrow L$): maturity-informed uncertainty parameterization. Digital maturity is used to parameterize the uncertainty magnitude in the diagnostic-risk model (measurement/interpretation error and, when relevant, variability in the decision boundary).
4. Biomechanical module (finite element analysis). A finite element (FE) analysis of the tibial assembly in total knee arthroplasty (TKA) is performed as an illustrative application linking reliability considerations to downstream mechanical consequences (contact pressure and stress in UHMWPE).

All computational procedures (risk simulation, parameter sweeps, and visualization) were implemented in a self-contained software module (Section 2.3.7).

2.2. Vertical Vector: Digital Maturity Assessment Using a Fuzzy Aggregation Model

2.2.1. DEFINITION of the Two-Vector Framework and Scope

The clinical–diagnostic system for joint diseases (Figure 1) is interpreted as a two-dimensional operational field:

- The vertical vector (V) reflects strategic and organizational readiness quantified as digital maturity.
- The horizontal vector (L) reflects operational diagnostic control under uncertainty quantified through risk metrics (producer’s and consumer’s risks).

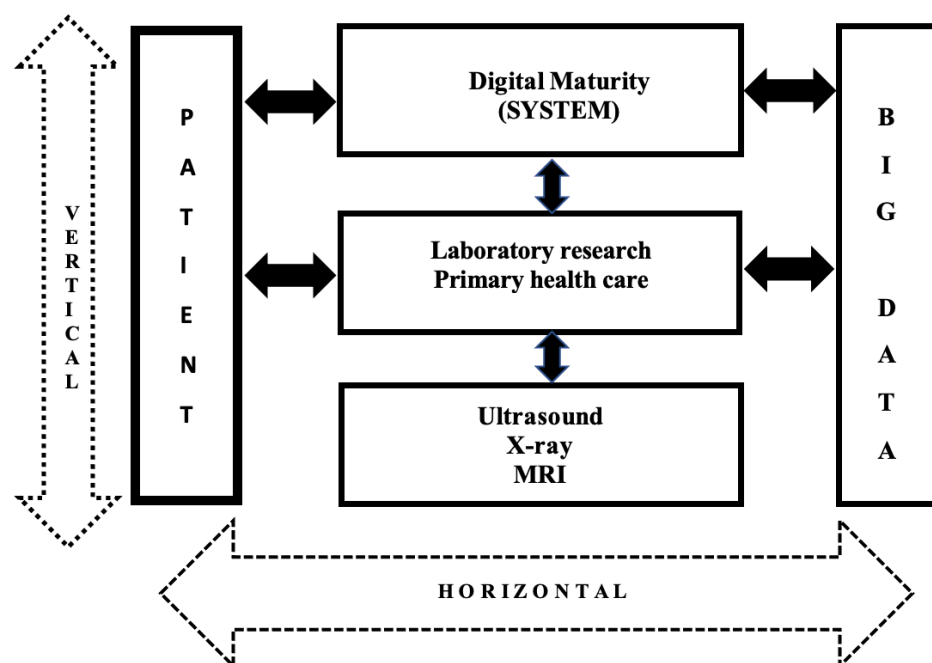


Figure 1. Structural model of the organizational–technical integrated system of diagnostic care for joint diseases.

2.2.2. Digital Maturity Agents (Y1–Y6) and Expert Elicitation

Digital maturity is treated as an aggregate characteristic of organizational and technological capability under digital transformation, capturing the ability to standardize protocols, ensure traceability of decisions, manage data quality, and maintain continuous monitoring and improvement loops using digital tools.

Six maturity support agents are defined:

- Y1 Technical support: scanner uptime, maintenance readiness, coil availability, protocol stability.
- Y2 Information and analytical support: metadata completeness, QA logging, audit trails, analytics dashboards.
- Y3 Mathematical/model support: availability of validated models and documented pipelines for QA metrics and risk computation.
- Y4 Metrological support: calibration routines, measurement traceability, uncertainty documentation, acceptance criteria definition.
- Y5 Human resources support: staff qualification, training, competency assessment, workload control, and double-reading policy.
- Y6 Software support: interoperability, workflow software reliability, protocol versioning, automated QA tools.

Expert panel and weighting procedure. Agent weights were elicited from an expert panel of 5 specialists directly involved in MRI service delivery and quality management: 2 radiologists (musculoskeletal imaging), 2 MRI technologists, 1 departmental quality manager, 1 biomedical engineer, and 1 health informatics specialist. Each expert independently rated the relative importance of Y1–Y6 for diagnostic reliability on a 10-point scale (1 = minimal importance; 10 = maximal importance). Ratings were aggregated using the arithmetic mean and then normalized to enforce $\sum_{i=1}^6 w_i = 1$. Inter-expert agreement was assessed using Kendall's coefficient of concordance, yielding $W = 0.71$, indicating substantial agreement. The resulting expert ratings and normalized weights are provided in Table 1.

Table 1. Results of ranking the system support of quality for the vertical management vector.

Expert Number	Yj					
	Y1	Y2	Y3	Y4	Y5	Y6
1	0.25	0.214	0.357	0.178	0.357	0.357
2	0.241	0.172	0.310	0.275	0.310	0.310
3	0.235	0.264	0.294	0.205	0.294	0.294
4	0.205	0.235	0.264	0.294	0.264	0.264
5	0.2	0.3	0.266	0.233	0.266	0.266
Weight (mi)	0.226	0.237	0.298	0.247	0.357	0.298

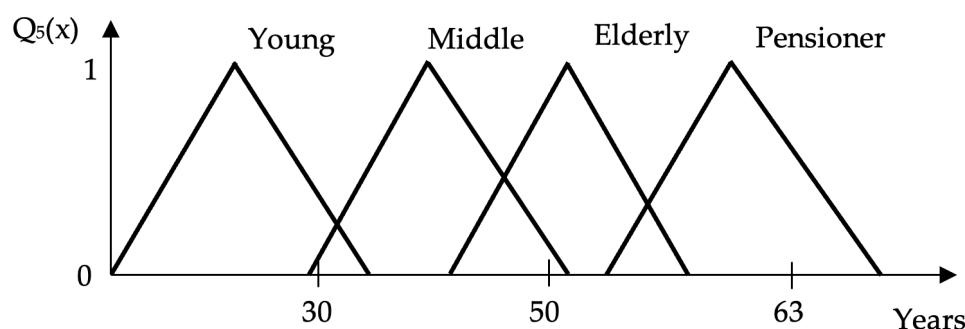
2.2.3. Fuzzification: Linguistic Variables and Membership Functions

To represent maturity on an interpretable continuous scale while preserving linguistic interpretability, fuzzy set theory is applied [33]. Each agent Y_i is represented as a linguistic variable X_i defined on a bounded domain $X_i \in [0, 100]$ (percentage-like score). Each linguistic variable uses four terms: {Poor, Average, Good, High}.

All membership functions are triangular and defined by parameters (a, b, c) with $a < b < c$. The membership function is:

$$\mu(x; a, b, c) = \begin{cases} 0, & x \leq a, \\ \frac{x-a}{b-a}, & a < x \leq b, \\ \frac{c-x}{c-b}, & b < x < c, \\ 0, & x \geq c. \end{cases} \quad (3)$$

Here, x is the crisp input score for an agent, and $\mu(x; a, b, c) \in [0, 1]$ is the membership degree in a linguistic term. For visualization, an example set of membership functions is shown in Figure 2.

**Figure 2.** Membership functions (terms) of the linguistic variable “Human resources support”.

2.2.4. Term Weights, Aggregation, and Normalization

For each linguistic variable X_i , term weights ω_{ij} are used (Table 2), where $j \in \{1, 2, 3, 4\}$ denotes the four terms. For each i , term weights satisfy $\sum_{j=1}^4 \omega_{ij} = 1$, and agent weights satisfy $\sum_{i=1}^6 w_i = 1$.

Table 2. Weights of the linguistic variable (LV) and its terms in the fuzzy model.

Linguistic Variables (LV)	Weight of LV ω_i	Weight of Terms			
		Ki1	Ki2	Ki3	Ki4
Technical support	ω_1	0.053	0.088	0.229	0.306
Information and analytical support	ω_2	0.254	0.362	0.275	0.108

Mathematical support	ω_3	0.060	0.096	0.205	0.310
Metrological support	ω_4	0.051	0.098	0.197	0.339
Staffing	ω_5	0.042	0.090	0.236	0.328
Software	ω_6	0.055	0.098	0.199	0.339

The fuzzy score for each agent is computed as a weighted sum of term memberships:

$$y_i = \sum_{j=1}^4 \omega_{ij} \mu_{ij}(x_i), \quad (4)$$

where x_i is the crisp score of the i -th agent and $\mu_{ij}(x_i)$ is the membership degree of term j .

The overall digital maturity index is then computed as:

$$K_{\text{sum}} = \sum_{i=1}^6 w_i y_i, \quad (5)$$

where $K_{\text{sum}} \in [0, 1]$.

Normalization of raw indicators. When an agent score is derived from raw operational indicators z_i not naturally expressed on a 0–100 scale, min–max normalization is used:

$$x_i = 100 \cdot \frac{z_i - z_i^{\min}}{z_i^{\max} - z_i^{\min}}. \quad (6)$$

Bounds $z_i^{\min}$ and $z_i^{\max}$ are selected from institutional historical QA logs where available, and otherwise from expert-defined operational limits consistent with departmental QA procedures.

2.2.5. Desirability Mapping and Maturity Categories

The quantitative index K_{sum} is mapped to qualitative maturity categories to support managerial interpretation. A Harrington-type desirability categorization is applied to define five maturity levels based on K_{sum} :

- 0.00–0.20: Very poor
- 0.20–0.37: Poor
- 0.37–0.63: Satisfactory
- 0.63–0.80: Good
- 0.80–1.00: Very good

This mapping is used for interpretability and threshold-based action planning, while the quantitative analysis uses the continuous value of K_{sum} .

2.3. Horizontal Vector: Diagnostic Control-Risk Modeling Under Uncertainty

2.3.1. Object of Modeling and MRI-Aligned Scope

The horizontal vector focuses on operational diagnostic control within the Department of Radiological Diagnostics, modeling uncertainty sources relevant to knee MRI, including scanner/protocol variability and interpretation variability. The goal is to quantify how uncertainty influences misclassification relative to an acceptance boundary used in a diagnostic control procedure.

2.3.2. Definitions: Controlled Parameter, Measurement Model, and Standard Boundary (SB)

Let S denote a latent (unobserved) true diagnostic-quality parameter and let S_m denote its observed/assessed value [19]. The measurement model is:

$$S_m = S + \Delta, \quad (7)$$

where Δ is an aggregated error term capturing measurement and interpretation variability.

Let SB denote the standard boundary (acceptance boundary) used for decision-making (e.g., a threshold on a QA metric, diagnostic confidence score, or protocol-specific acceptance criterion). Cases with $S \leq SB$ are conforming, while cases with $S > SB$ are nonconforming.

Let $f_S(s)$ denote the probability density function (pdf) of S , and let $F_\Delta(\cdot)$ denote the cumulative distribution function (CDF) of Δ .

2.3.3. Producer's and Consumer's Risks

Two complementary misclassification risks are quantified [18–20]:

- Producer's risk N_{pr} : rejecting a conforming case due to uncertainty.
- Consumer's risk N_{cr} : accepting a nonconforming case due to uncertainty.

These are computed as:

$$N_{pr} = \int_{-\infty}^{SB} f_S(s) [1 - F_\Delta(SB - s)] ds, \quad (8)$$

$$N_{cr} = \int_{SB}^{+\infty} f_S(s) F_\Delta(SB - s) ds. \quad (9)$$

where S is the latent (true) controlled parameter; S_m is its measured/assessed value; SB is the acceptance boundary (standard boundary); Δ is the aggregated measurement/interpretation error such that $S_m = S + \Delta$; $f_S(s)$ is the pdf of S ; and $F_\Delta(\cdot)$ is the CDF of Δ . Producer's risk N_{pr} corresponds to false rejection ($S \leq SB$ but $S_m > SB$), while consumer's risk N_{cr} corresponds to an undetected defect ($S > SB$ but $S_m \leq SB$).

2.3.4. Distributional Assumptions and Uniform Baseline

MRI diagnostic uncertainty may be non-Gaussian due to bounded errors, protocol variation, and reader-dependent effects [20–22]. When only plausible bounds can be justified at the initial stage, a uniform distribution baseline is adopted as a conservative “maximum ignorance within bounds” model.

A uniform distribution $U(a, b)$ is defined by:

$$f(x) = \begin{cases} \frac{1}{b-a}, & a \leq x \leq b, \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

Uniform distributions are used to model either S or Δ (or both) when only bounds $[a, b]$ or $[e, u]$ are defensible. To assess robustness, additional comparisons against Gaussian and triangular distributions are performed under matched mean and variance where applicable, and the resulting sensitivity of N_{pr} and N_{cr} is reported.

2.3.5. Monte-Carlo Simulation Algorithm and Outputs

Monte-Carlo simulation is used to estimate risk probabilities when analytic evaluation is impractical or when parameter sweeps are required.

Inputs: bounds/parameters for S and Δ , decision boundary SB , and the number of iterations N .

Algorithm: for each iteration $i = 1, \dots, N$, sample $S_i \sim f_S$, sample $\Delta_i \sim f_\Delta$, compute $S_{m,i} = S_i + \Delta_i$, and apply the acceptance rule $S_{m,i} \leq SB$.

Two error events are counted:

- False rejection: $S_i \leq SB$ but $S_{m,i} > SB$ (increment N_{fr}).
- Undetected defect: $S_i > SB$ but $S_{m,i} \leq SB$ (increment N_{ud}).

Estimated risk probabilities are [23]:

$$\hat{N}_{pr} = \hat{P}_{fr} = \frac{N_{fr}}{N}, \hat{N}_{cr} = \hat{P}_{ud} = \frac{N_{ud}}{N}. \quad (11)$$

An operational reliability index is also reported:

$$D = 1 - (\hat{N}_{pr} + \hat{N}_{cr}), \quad (12)$$

where $D \in [0, 1]$.

2.3.6. Coupling: Maturity-Informed Uncertainty Parameterization ($V \rightarrow L$)

To connect organizational readiness to diagnostic control risk, digital maturity is used to parameterize the effective uncertainty magnitude. Let K_{sum} be the digital maturity index from Equation (5) [24]. We model maturity as reducing the effective error bound of Δ by scaling a baseline bound Δ_{max} :

$$\Delta \sim U(-\alpha(K_{\text{sum}}) \Delta_{\text{max}}, \alpha(K_{\text{sum}}) \Delta_{\text{max}}), \quad (13)$$

with a monotone decreasing scaling function:

$$\alpha(K_{\text{sum}}) = \alpha_{\text{min}} + (1 - \alpha_{\text{min}})(1 - K_{\text{sum}}), \quad (14)$$

where $\alpha_{\text{min}} = 0.35$ represents an irreducible uncertainty floor (e.g., physiological and case-mix variability that cannot be eliminated by organizational measures alone). This coupling provides a quantitative operational bridge between maturity improvements (training, QA, software support, protocol governance) and expected reductions in $\hat{N}_{pr}$ and $\hat{N}_{cr}$.

2.3.7. Software Module and Computational Environment

All simulations and parameter sweeps were executed in a standalone software module implemented in Python 3.11 using NumPy 1.26, SciPy 1.11, and Matplotlib 3.8 for visualization. Random sampling used a fixed seed of 20250114 to ensure reproducibility of Monte-Carlo results. The software module accepts distribution choices and parameters $[a, b]$, $[e, u]$, SB , and N , and outputs $\hat{N}_{pr}$, $\hat{N}_{cr}$, D , and graphical summaries.

2.4. FE Analysis of the Biomechanical Behavior of the Tibial Assembly

2.4.1. Model Geometry, Mesh, and Software

To complement the diagnostic reliability analysis with an illustrative downstream biomechanical assessment, a FE analysis of the tibial assembly of a TKA implant was performed. The analysis focuses on contact pressure and stress in UHMWPE as surrogate indicators related to wear risk.

A three-component assembly was modeled: femoral component, UHMWPE tibial insert, and tibial tray. The FE mesh contained 194,683 nodes and 111,309 elements. Geometry and mesh views are shown in Figure 3a,b. The FE model was built and solved using ANSYS Mechanical 2024 R1, and 2D/3D visualizations were generated within the ANSYS post-processing environment.

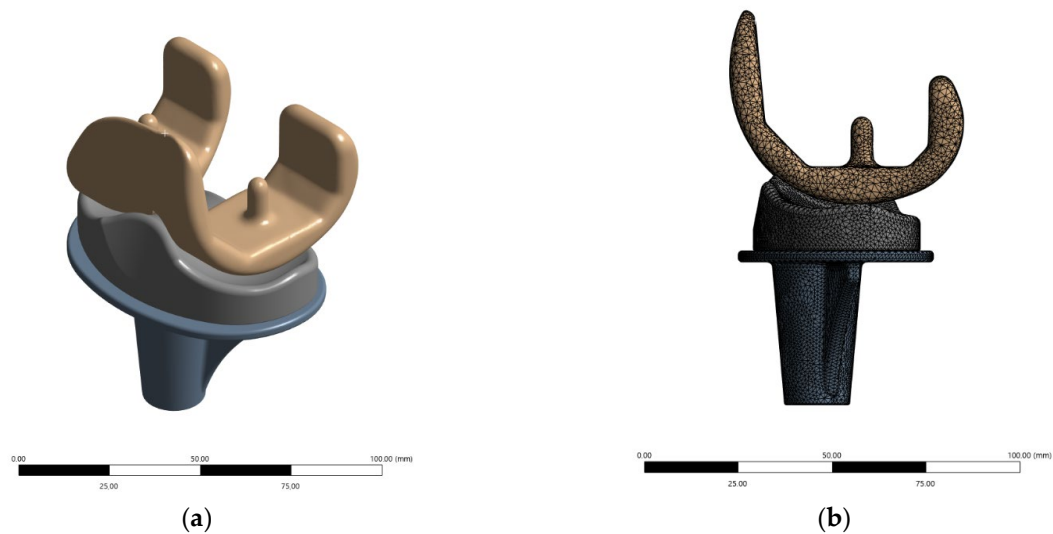


Figure 3. Geometry of the knee joint endoprosthesis assembly (a) and the generated FE mesh (b). The main assembly components are shown: Femoral Component, Tibial Insert, and Tibial Tray.

2.4.2. Material Properties and Contact Definitions

Materials were modeled as isotropic linear elastic solids with standard literature-consistent properties commonly used for comparative contact-stress assessments:

- Femoral component (CoCrMo alloy): $E = 210$ GPa, $\nu = 0.30$.
- Tibial tray (Ti-6Al-4V alloy): $E = 110$ GPa, $\nu = 0.34$.
- UHMWPE insert: $E = 1.0$ GPa, $\nu = 0.40$.

Contact definitions were as follows:

- Femoral component–insert frictional contact with coefficient $\mu = 0.04$.
- Insert–tray: bonded contact (fixed-fit approximation).
- Base of tibial tray: fixed support constraint.

Boundary conditions and contact regions are shown in Figure 4.

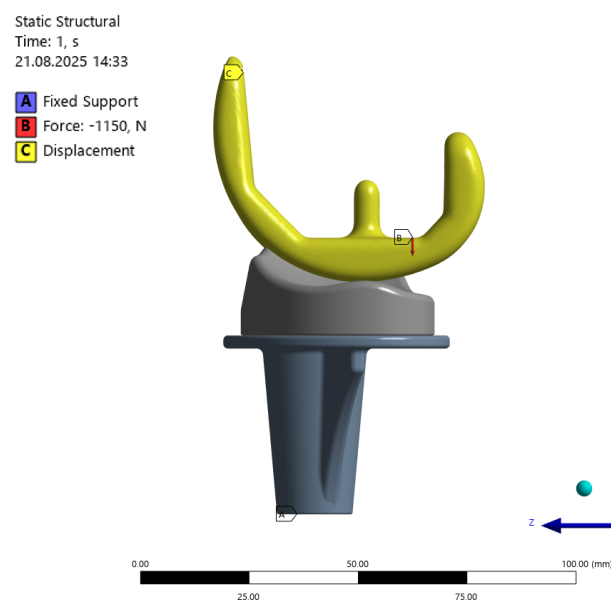


Figure 4. Boundary conditions and loading scheme: Fixed Support at the base of the tibial tray; frictional contact between the femoral component and the insert ($\mu = 0.04$); bonded contact between the insert and the tray; axial compressive force $F = 1150$ N at 0° flexion.

2.4.3. Loading, Solution Controls, and Mesh Convergence

An axial compressive force $F = 1150\text{ N}$ was applied to the articular surface of the femoral component at 0° flexion to represent a stance-phase loading condition. Solution quality was controlled by local mesh refinement in the contact region and monitoring changes in peak contact pressure and von Mises equivalent stress; variations did not exceed 5%, indicating mesh-independent results under the adopted criterion. Detailed stress and pressure fields are reported in the Results section.

3. Results

3.1. Horizontal Vector of the Study

At the second systemic level of care for patients with joint diseases, the diagnostic service portfolio typically includes ultrasound diagnostics, radiography, and MRI. In this study, the horizontal vector (L) focuses on knee MRI as an operational, process-oriented diagnostic system and decomposes the end-to-end workflow into five interacting agents:

- A1—Agent “Scanning”: MRI acquisition and protocol execution (patient positioning, sequence selection, signal capture).
- A2—Agent “3D modeling”: reconstruction of volumetric MR data and creation of a consistent anatomical representation.
- A3—Agent “Slicing”: generation of 2D image planes (sagittal, coronal, axial) and interactive reformatting.
- A4—Agent “Control”: quality control of image adequacy (signal-to-noise, artefacts, protocol completeness) and verification against acceptance criteria.
- A5—Agent “Solution”: clinical interpretation and diagnostic conclusion based on the evaluated image evidence.

A structural–technological model of this workflow is provided in Figure 5, which is used as the operational basis for subsequent uncertainty modeling and risk estimation.

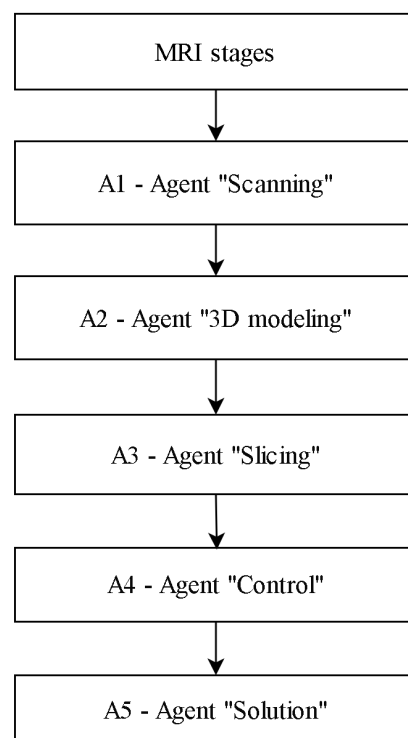


Figure 5. Structural–technological model of magnetic resonance tomographic diagnostics.

3.2. First Stage: Protocolized Patient Pathway and Information Capture

At the first stage, the radiology department operates within a protocolized pathway that begins with patient preparation and administrative intake and proceeds through examination planning and reporting. In the context of a digital workflow modeled using an IDEF0-style representation, the business process is expressed through the following operations: (i) admit the patient, (ii) create or update a medical record, (iii) refer to the radiology department, (iv) prepare the patient for examination, (v) conduct the MRI examination, (vi) prescribe additional examinations if required, and (vii) issue a diagnostic conclusion.

Although radiography may be used upstream as a complementary modality for specific clinical indications, the results presented below focus on MRI-specific stages (A1–A5) and the uncertainty and risk generated within the imaging and interpretation chain.

3.3. Second Stage: DICOM-Based Visual Assessment and ROI Extraction

At the second stage, diagnostic assessment is performed by visual analysis of MRI slices stored in DICOM format [34]. Representative MRI images used for visual assessment of meniscal integrity are provided in Appendix A (Figure A1 for the sagittal view and Figure A2 for the coronal view), illustrating normal and pathological meniscal structures used for comparative evaluation.

The DICOM format supports multiplanar inspection and arbitrary-angle visualization using standard tools, enabling clinicians to interrogate the region of interest (ROI) and to apply routine clinical interpretation procedures. In the proposed workflow, the clinician first identifies an ROI on the original image and maps it to a numerical array X that represents pixel-level intensity values within the selected tissue region.

3.4. Third Stage: Numerical ROI Modeling and Normalization-Based Enhancement

3.4.1. ROI Representation and Interpretation Target

MRI images are represented as grayscale pixel matrices, where each pixel stores an intensity value proportional to the measured signal. In this work, the proposed procedure does not treat “accuracy” as a property of isolated operations; instead, it treats reliability as a system-level outcome that emerges from the interaction of acquisition quality, post-processing, acceptance criteria, and interpretive variability. This motivates the use of explicit uncertainty modeling and risk estimation in later stages.

3.4.2. Normalization Procedures (Row-Wise and Column-Wise)

Formally, for the ROI intensity matrix $X \in \mathbb{R}^{R \times C}$, row-wise normalization is defined as [37]:

$$X_{r,c}^{(r)} = \frac{X_{r,c}}{\max_c (X_{r,c}) + \varepsilon}, r = 1, \dots, R, c = 1, \dots, C, \quad (15)$$

and column-wise normalization as [38]:

$$X_{r,c}^{(c)} = \frac{X_{r,c}}{\max_r (X_{r,c}) + \varepsilon}. \quad (16)$$

Here, ε is a small constant used to avoid division by zero.

These normalized matrices $X^{(r)}$ and $X^{(c)}$ are used (i) to produce the enhanced slices shown in Figure 6 and (ii) to compute the normalized one-dimensional profiles I_{rel} in Section 3.4.3, ensuring comparability of relative contrast patterns across rows/columns regardless of global brightness scaling.

After ROI extraction, the array X is normalized using two complementary procedures to enhance interpretability and reduce certain types of intensity-scale variability:

1. Row-wise normalization: for each row r , all values are divided by the maximum value in that row, producing a normalized row profile that emphasizes within-row relative contrasts.
2. Column-wise normalization: similarly, for each column c , all values are divided by the maximum value in that column, producing a normalized column profile.

These operations function as simple, transparent intensity rescaling filters that can reduce the effect of global brightness variation and highlight internal heterogeneity patterns within the ROI.

The effect of the transformations is shown in Figure 6, where the normalized images provide a clearer delineation of anatomical slice structures compared with the original tomographic slice.

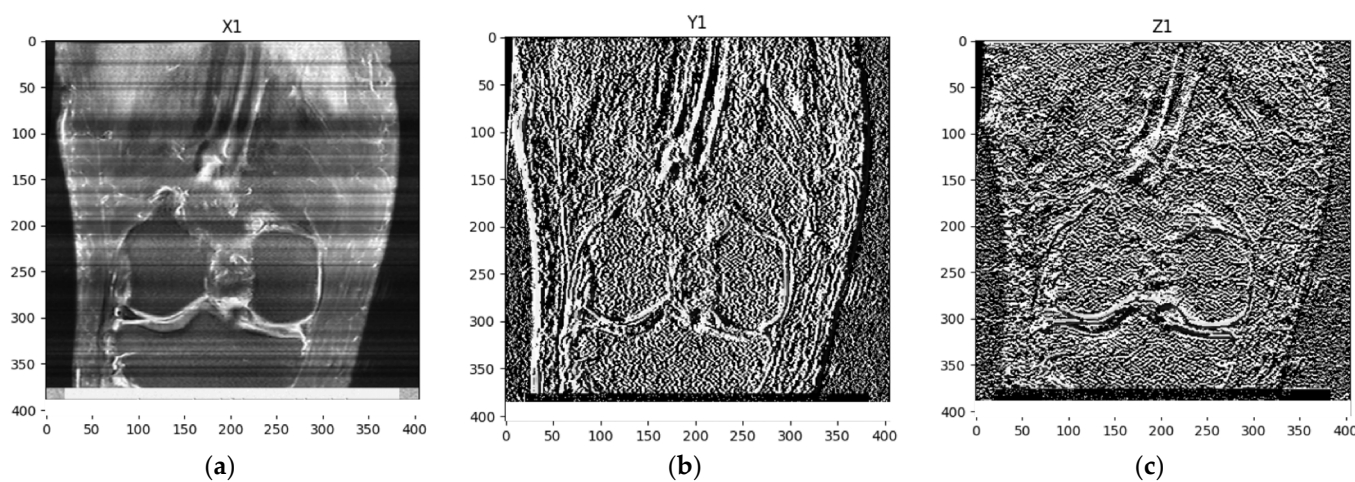


Figure 6. Original and transformed tomographic images of the knee joint, where: (a) the original tomographic slice of the knee joint; (b) the normalized tomographic slice (row-wise normalization); (c) the normalized tomographic slice (column-wise normalization).

3.4.3. One-Dimensional Pixel-Intensity Profiles

To support the clinician's qualitative assessment with an additional quantitative view, pixel-intensity profiles are extracted from selected rows or columns of the ROI. Figure 7 illustrates a representative one-dimensional profile extracted from a single row within Block 1 of the ROI (from the normalized ROI in Section 3.4.2). In this figure, the vertical axis I_{rel} denotes relative pixel intensity (normalized), and M denotes the pixel index along the selected row.

The plot reveals pronounced heterogeneity along the row, consistent with spatial variation in tissue signal intensity, which can be interpreted as a proxy for local differences in water content and tissue structure. Graphical modeling for Figure 8 was performed using Statistica 10. Statistica 10 is a commercial statistical analysis and data visualization software package (TIBCO Software Inc.) used here only to generate the line plot and to export the figure in publication-ready format; no additional statistical inference beyond visualization was performed in Statistica.

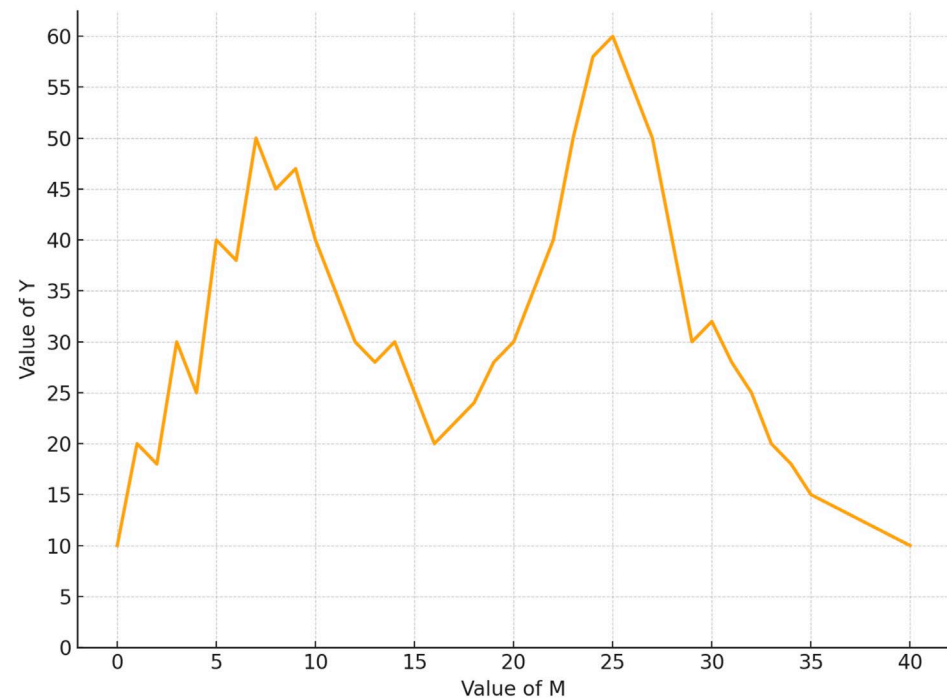


Figure 7. One-dimensional pixel-intensity profile extracted from a single row of the ROI (Block 1), where the vertical axis I_{rel} represents the normalized relative pixel intensity and M denotes the pixel index.

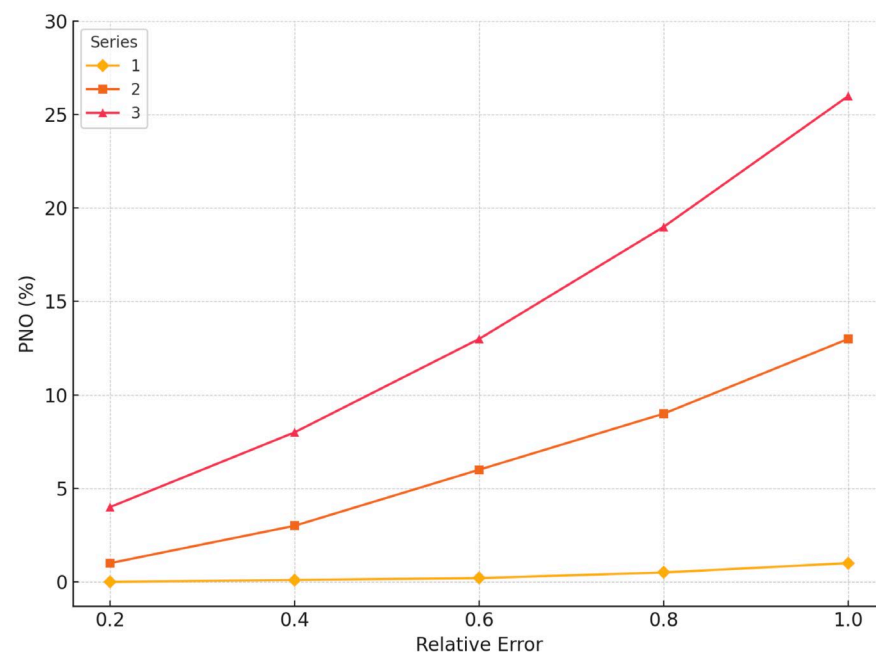


Figure 8. Computer experiment results: dependence of the estimated consumer's risk $\hat{N}_{cr}$ on the ratio σ_{μ}/σ_S under three boundary settings $SB = S_{sr} + \{1,2,3\}\sigma_S$.

3.5. Fourth Stage: Maturity–Risk Computer Experiment (Horizontal Vector Risk Metrics)

3.5.1. Digital Maturity Outcome (Vertical Vector Summary Used for Coupling)

The structural model in Figure 1 assumes operation of the radiology department under digital transformation (Industry 4.0 principles) within an ISO-certified quality management environment. The effectiveness of the vertical vector is quantified by the digital maturity index K_{sum} , computed as a weighted aggregation of six agents (technical,

information–analytical, mathematical/model, metrological, human resources, and software support) as defined in Section 2.2.

For the evaluated department-year scenario (2024), the calculated maturity index was $K_{\text{sum}} = 0.67$, which corresponds to the “Good” maturity category on the adopted desirability scale (0.63–0.80). The maturity value K_{sum} is subsequently used to parameterize uncertainty magnitude in the risk model via the coupling defined in Equations (13) and (14).

3.5.2. Risk Experiment Design and Parameter Definitions

A computer experiment was conducted using the developed software module to investigate how parametric uncertainty affects diagnostic control risks. The modeled quantities were:

- S_{sr} : mean of the controlled parameter S ;
- σ_S : standard deviation of the controlled parameter S ;
- σ_μ : standard deviation of the measurement/interpretation channel error (linked to Δ);
- SB : standard boundary (acceptance boundary) used for the decision rule $S_m \leq SB$ (Section 2.3.2).

Risk probabilities were evaluated as functions of the ratio σ_μ/σ_S while varying the boundary level. For comparability with conventional statistical-control interpretations, the boundary was parameterized as:

- $SB = S_{\text{sr}} + 1\sigma_S$;
- $SB = S_{\text{sr}} + 2\sigma_S$;
- $SB = S_{\text{sr}} + 3\sigma_S$.

In the simulation, the estimated probabilities $\hat{N}_{pr}$ (producer’s risk; false rejection) and $\hat{N}_{cr}$ (consumer’s risk; undetected defect) were computed as defined in Equations (11) and (12).

3.5.3. Risk Curves and Interpretation

The simulation results are summarized in Figure 8, which shows the dependence of the consumer’s risk $\hat{N}_{cr}$ on the ratio σ_μ/σ_S for the three boundary settings defined above.

Figure 8 exhibits three curves. The upper curve corresponds to $SB = S_{\text{sr}} + 1\sigma_S$, indicating the highest consumer’s risk at comparable uncertainty ratios. The second curve corresponds to $SB = S_{\text{sr}} + 2\sigma_S$, showing reduced risk across the examined range. The third curve approaches zero for $SB = S_{\text{sr}} + 3\sigma_S$, indicating that a stricter acceptance boundary substantially suppresses the probability of an undetected defect under the modeled assumptions.

Across scenarios, the risks increase with the uncertainty ratio σ_μ/σ_S , consistent with the interpretation that larger measurement/interpretation variability relative to intrinsic process variability increases misclassification. Because $\hat{N}_{cr}$ corresponds to acceptance of a nonconforming case, it directly relates to patient-facing risk and should, therefore, be prioritized when selecting organizational and technical measures aimed at improving diagnostic reliability.

3.5.4. Clarification of the Control-Error Model Figure and Notation

A graphical interpretation of control error formation under uncertainty is provided in Figure 9. In this representation, S is the controlled parameter with density $f_S(s)$, SB is the decision boundary, and Δ is the measurement/interpretation error with density $f_\Delta(\delta)$. The measured value S_m is generated by $S_m = S + \Delta$. Importantly, the probability density of the error is written as $f_\Delta(\delta)$ with argument δ ; the measured value has density $f_{S_m}(s_m)$ with argument s_m . This consistent notation is used throughout the Results and aligns the variable arguments with the intended random quantities.

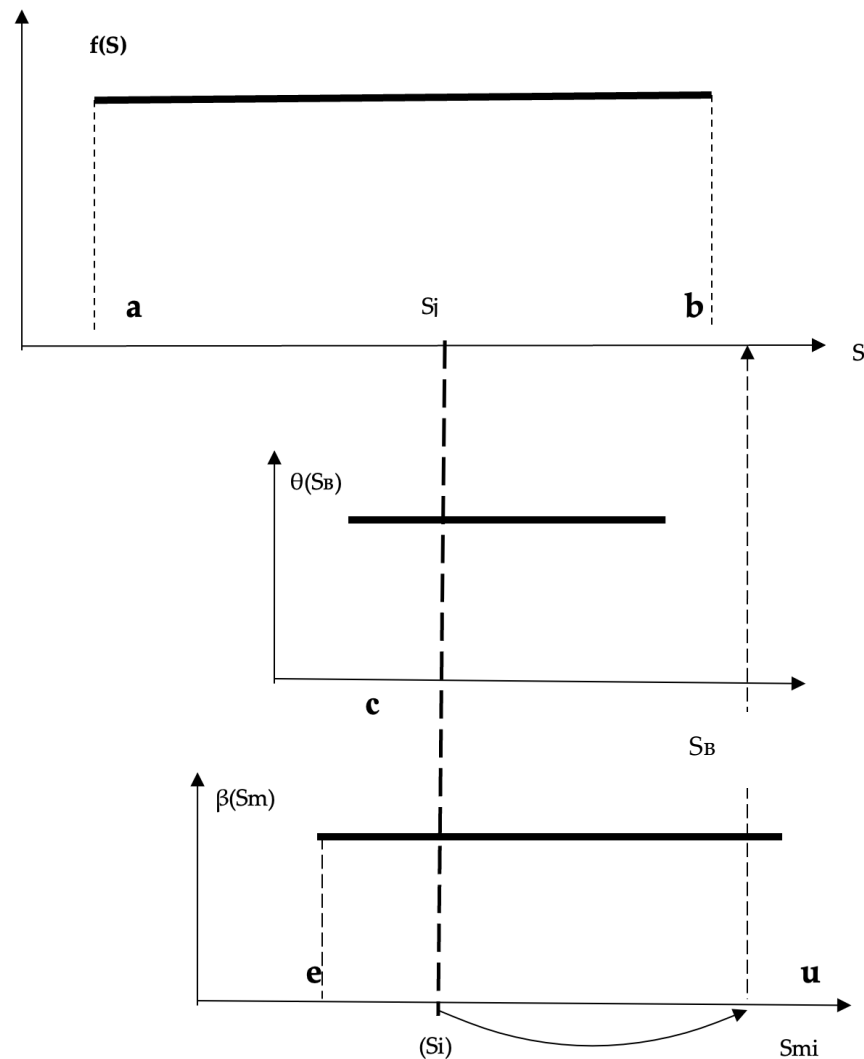


Figure 9. Graphical interpretation of control error formation under uncertainty for the controlled parameter S , decision boundary S_B , measurement/interpretation error Δ , and measured value S_m .

3.6. Results of the FE Analysis: Contact Pressures and Equivalent Stresses

The FE analysis (Section 2.4) showed that contact loads on the UHMWPE insert are predominantly localized in the medial and lateral primary-contact zones with the femoral component. The maximum contact pressure on the articulating surface reached 85.449 MPa, forming distinct peak regions (Figure 10a). The maximum von Mises equivalent stress within the UHMWPE volume reached 43.686 MPa (Figure 10b). The spatial configuration of the pressure and stress fields is consistent with the applied axial load $F = 1150$ N at 0° flexion and with the boundary conditions specified in Figures 4 and 5.

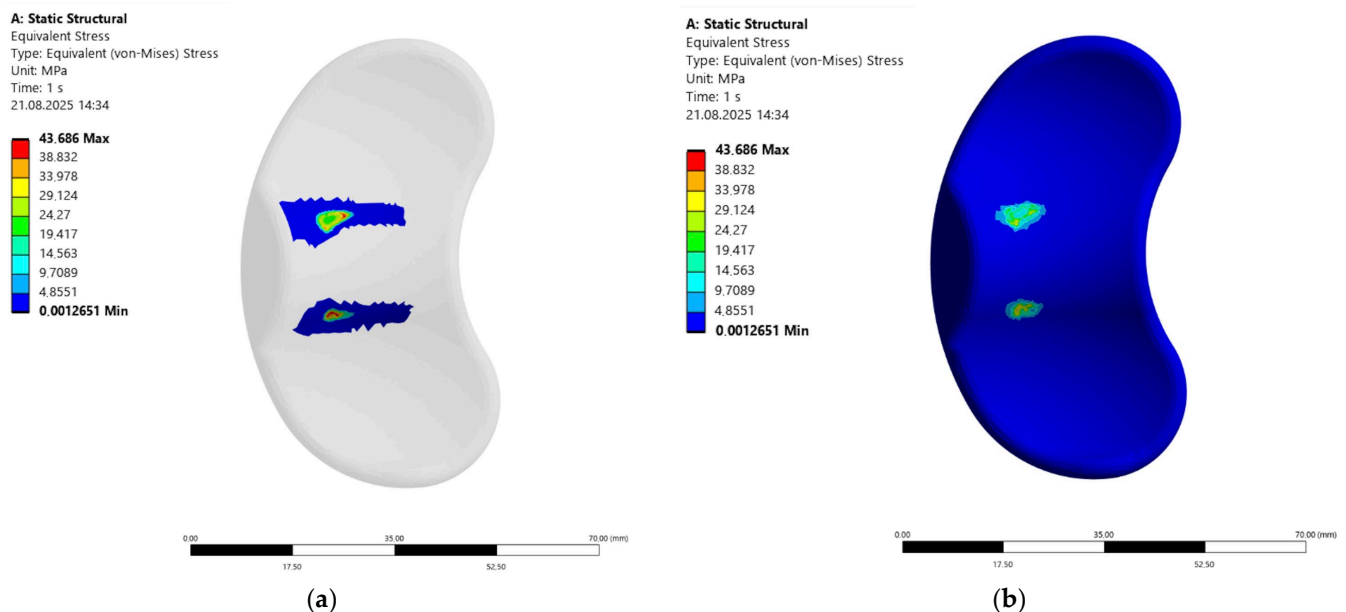


Figure 10. FE analysis results for the tibial assembly under $F = 1150$ N at 0° flexion: (a) contact pressure distribution on the UHMWPE insert; (b) von Mises equivalent stress distribution within the UHMWPE insert.

From a tribo-mechanical wear perspective, both indicators are relevant: peak contact pressure relates to local energy intensity in micro-cycles of sliding and rolling, while elevated equivalent stress in UHMWPE indicates increased risk of localized deformation and microdamage under repeated gait loading. The obtained extrema and the shape of the iso-fields motivate the need for parametric optimization of component positioning and contact-surface geometry to reduce peak stresses and, consequently, potential wear intensity.

4. Discussion

This study proposes an integrated pathway for strengthening the reliability of knee MRI by combining (i) an operational diagnostic control-risk model under uncertainty and (ii) a quantitative assessment of organizational digital maturity. The central contribution is the two-vector framework: a horizontal vector that formalizes misclassification risks relative to an acceptance boundary, and a vertical vector that captures departmental capability to execute, monitor, and improve diagnostic workflows under digital transformation. By quantifying both dimensions and explicitly coupling them (digital maturity $\rightarrow$ uncertainty magnitude $\rightarrow$ risk), the framework clarifies where uncertainty accumulates and which organizational levers can reduce diagnostic error risk most efficiently.

4.1. Interpretation of the Horizontal Vector Results: What Drives Risk in MRI Decision Control

The results demonstrate that the estimated producer's and consumer's risks increase monotonically with the uncertainty ratio σ_μ/σ_S , consistent with decision-control theory: as measurement/interpretation variability becomes comparable to intrinsic variability of the controlled parameter, misclassification becomes more likely. The computer experiment further shows that the position of the acceptance boundary SB strongly shapes error probabilities: moving from $SB = S_{sr} + \sigma_S$ to $SB = S_{sr} + 2\sigma_S$ reduces the consumer-facing error probability across the tested range, while $SB = S_{sr} + 3\sigma_S$ drives $\hat{N}_{cr}$ toward zero under the modeled assumptions (Figure 9). This behavior is consistent with the probabilistic structure of the risk expressions (Equations (8) and (9)) and provides a quantitative basis for understanding how tighter acceptance criteria, when clinically justified, can suppress undetected-defect risk.

A practical implication is that risk reduction cannot be achieved solely by improving one isolated step (e.g., a marginal gain in slice quality or a single post-processing operation). Instead, the risk curves imply that reducing diagnostic error probability requires controlling (i) the magnitude of the measurement/interpretation uncertainty Δ (training, protocol stability, QA), and (ii) the operational definition and stability of the acceptance boundary SB (clear thresholds, documented criteria, consistent application). In other words, reliability emerges from governance of the full chain rather than from local “accuracy” improvements alone.

4.2. Interpretation of the Vertical Vector and the Coupling: Why Digital Maturity Matters Quantitatively

Digital maturity is frequently discussed qualitatively, but the present work treats it as a measurable capability that influences diagnostic reliability through explicit coupling. The 2024 maturity value $K_{\text{sum}} = 0.67$ corresponds to a “Good” maturity category and indicates that the department operates with substantive—but not maximal—readiness across technical, informational, metrological, staffing, modeling, and software capabilities. The key added value is that maturity is not only reported but used as a parameterization mechanism for uncertainty bounds in the horizontal risk model (Equations (13) and (14)). This coupling makes the framework operational: improvements in maturity agents (e.g., protocol versioning, calibration traceability, systematic training) reduce the effective uncertainty magnitude and therefore shift operating points toward lower $\hat{N}_{pr}$ and $\hat{N}_{cr}$.

This finding is coherent with broader evidence that digital maturity shapes workflow reliability by affecting data completeness, traceability, and protocol adherence [24–26]. Mature electronic health record integration and governance are associated with consistent information exchange and auditability, which are prerequisites for dependable imaging pipelines [25,26]. Similarly, IoT and e-health infrastructure can enlarge the stream of contextual data and QA telemetry that supports systematic monitoring and correction of deviations when appropriately governed [27,28]. In the present framework, these influences are reflected through reduced uncertainty bounds and improved stability of operational thresholds.

4.3. Why a Bounded (Uniform) Uncertainty Baseline Is Defensible—And How It Should Evolve

A key methodological choice in the present study is the use of a bounded uniform distribution as a baseline representation of uncertainty when only plausible bounds can be justified. In early phases of digital transformation or when structured historical QA datasets are not yet sufficiently dense, assuming a Gaussian error model may impose unjustified symmetry and tail behavior. A bounded baseline can, therefore, be an appropriate conservative starting point: it explicitly encodes limited knowledge (“the error lies within known limits”) rather than asserting a distributional shape unsupported by data.

At the same time, this is an assumption that must be tested and refined as data accumulates. The framework is designed to support that evolution: as QA logs and outcomes-linked datasets expand (i.e., “Big Data systems” understood as continuously updated clinical and operational datasets), the uncertainty model can be calibrated toward empirically supported distributions. This is especially relevant in MRI contexts where error behavior may be heteroskedastic (varying with anatomy, motion, and sequence), bounded by protocol constraints, or multimodal due to reader-dependent effects. Accordingly, future deployments should include routine distributional diagnostics, and sensitivity checks to quantify how strongly $\hat{N}_{pr}$ and $\hat{N}_{cr}$ depend on the selected uncertainty family.

4.4. Why a Weighted Fuzzy Aggregation Model Was Chosen Instead of a Rule-Based Fuzzy Inference System

A further methodological choice concerns the digital maturity model. A rule-based fuzzy inference system (FIS) can be powerful when a stable and validated rule base exists (e.g., “IF software interoperability is low AND staffing competency is low THEN risk is high”). However, in multi-factor organizational contexts where institutions differ in workflow design and where rule bases are difficult to standardize across sites, a transparent weighted aggregation approach provides stronger portability and auditability. The weighted model used here (Equations (4) and (5)) is fully specified by (i) membership functions and (ii) weights; both can be elicited, documented, and updated systematically.

This choice also supports reproducibility under limited evidence: the model can be recalibrated by updating weights and membership parameters as more institutional data becomes available, without requiring a complete redesign of an inference rule base. Nonetheless, the approach has limitations: it assumes largely compensatory trade-offs between agents (high performance in one agent can partially offset weakness in another), which may not always hold. A hybrid design is, therefore, a reasonable future direction—using weighted aggregation for global maturity scoring, and a rule-based FIS for targeted high-risk patterns once sufficient evidence exists to validate rules.

4.5. Clinical Relevance of Linking MRI Reliability to FE Contact Mechanics

One concern raised by the reviewers is whether coupling MRI diagnostic reliability to FE wear analysis is clinically meaningful rather than conceptual. The intent of the FE module in this manuscript is not to claim that MRI uncertainty directly determines implant wear in a deterministic manner, but to demonstrate a pragmatic pathway by which upstream reliability can be translated into downstream consequence-aware reasoning.

The FE results quantify contact pressure and UHMWPE stress under standardized loading and boundary conditions. The predicted maxima—85.449 MPa peak contact pressure and 43.686 MPa von Mises stress in UHMWPE under $F = 1150$ N at 0° flexion (Figure 10)—identify where mechanical demands concentrate and, therefore, where wear or damage risk is expected to be most sensitive to alignment, geometry, and loading assumptions. In practice, diagnostic reliability affects downstream decisions by influencing:

1. Whether the imaging evidence supports high-confidence characterization of pathology and alignment-relevant anatomy;
2. Whether repeat imaging or second reading is indicated for ambiguous cases;
3. Whether planning should incorporate conservative assumptions for geometry/positioning when imaging uncertainty is high.

Thus, the linkage provides a consequence-based motivation for improving reliability: reducing diagnostic uncertainty is not only an abstract quality objective but supports more stable downstream decision pathways.

4.6. Practical Recommendations to Reduce MRI Diagnostic Error Risk

The framework yields actionable recommendations that map directly to the maturity agents and the risk mechanisms:

1. Stabilize and version MRI acquisition protocols (Y6, Y1): implement protocol templates with version control and enforce sequence completeness checks to reduce protocol-induced variability in Δ .
2. Strengthen metrological assurance (Y4): document calibration routines, acceptance criteria, and uncertainty bounds for key acquisition settings; ensure traceability of scanner maintenance and QA results.

3. Improve data completeness and auditability (Y2): standardize metadata capture (patient motion notes, coil selection, protocol IDs) and maintain QA logs linking protocol versions to outcomes and error events.
4. Targeted training and double-reading for high-uncertainty cases (Y5): define triggers based on risk indicators (e.g., cases near the decision boundary SB , low SNR, motion artefacts) that prompt second reading or repeat scanning.
5. Use normalization and ROI profiling as transparent aids—not replacements—for clinical judgment: row/column normalization and pixel-intensity profiling (Figures 7 and 8) should be treated as interpretive support tools; their parameters should be standardized to avoid operator-dependent variability.

These recommendations directly address the reviewer concern that “practical recommendations” were stated as an objective but not operationalized. Here, each recommendation is tied to a specific maturity agent and an uncertainty mechanism that feeds into $\hat{N}_{pr}$ and $\hat{N}_{cr}$.

4.7. Limitations and Future Work

Several limitations should be noted. First, expert elicitation is inherently subjective; although agreement was substantial, weights and membership functions may vary across institutions. Second, the bounded uncertainty baseline (uniform distribution) is appropriate under limited data but should be replaced by empirically estimated distributions as QA datasets expand. Third, the current validation is computational and illustrative; multicenter validation is required to establish generalizability across scanner vendors, clinical protocols, and patient populations. Fourth, the FE module demonstrates biomechanical consequence metrics under a standardized loading case; broader loading scenarios and patient-specific geometries are needed for direct clinical prediction.

Future work should, therefore, (i) deploy the framework across multiple sites and vendors, (ii) link uncertainty and risk estimates to clinical outcomes and revision events to close the learning loop, (iii) implement sensitivity analyses that quantify the impact of membership-function and weight variation on K_{sum} , $\hat{N}_{pr}$, and $\hat{N}_{cr}$, and (iv) incorporate explainable AI tools that identify local drivers of uncertainty at the case level while preserving auditability and safety in clinical use.

5. Conclusions

This study introduced an integrated two-vector framework to improve the reliability of knee MRI diagnostics by coupling a diagnostic control-risk model (horizontal operational vector) with a quantitative digital maturity assessment of the radiology service (vertical organizational vector). The vertical vector aggregates six capability agents—technical infrastructure, information and analytical support, mathematical/model support, metrological assurance, human resources, and software support—into a composite maturity score K_{sum} . The horizontal vector quantifies producer’s and consumer’s risks as misclassification probabilities relative to a standard boundary SB under uncertainty in measurement and interpretation.

The results show that diagnostic risk increases systematically as measurement/interpretation variability approaches intrinsic variability of the controlled parameter, and that the positioning of the decision boundary SB strongly modulates consumer-facing risk (Figure 9). The maturity assessment for 2024 yielded $K_{sum} = 0.67$ (“Good”), and the coupling principle demonstrates how maturity improvements can be translated into reduced uncertainty bounds and, therefore, lower estimated risks. The FE analysis further provides an illustrative consequence layer, reporting a peak contact pressure of 85.449 MPa and UHMWPE von Mises stress of 43.686 MPa under $F = 1150$ N at 0° flexion (Figure

10), motivating why upstream reliability improvements matter for downstream decision pathways.

Overall, integrating digital maturity monitoring with interpretable risk modeling provides a scalable and reproducible basis for risk-informed quality assurance in MRI diagnostics. The approach yields concrete targets for protocol governance, metrological traceability, workforce training, and software reliability, and it is readily extensible to multicenter validation and data-driven refinement as institutional QA datasets mature.

Author Contributions: Conceptualization, A.T. and S.K.; methodology, A.T., N.B., and S.K.; software, A.T., B.A., and Z.A.; validation, B.A. and Z.A.; formal analysis, B.A. and N.B.; investigation, A.T., S.K., B.A., and Z.A.; resources, S.K. and N.B.; data curation, Z.A. and N.B.; writing—original draft preparation, A.T., B.A., N.B., and M.S.; writing—review and editing, N.B. and M.S.; visualization, B.A.; supervision, B.A., N.B., and M.S.; project administration, B.A., N.B., and M.S.; funding acquisition, B.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research is funded by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. BR24992786 “Development of technology for manufacturing samples of domestic medical instruments and medical products”).

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MRI	Magnetic Resonance Imaging
CT	Computed Tomography
US	Ultrasound
HACCP	Hazard Analysis and Critical Control Point
ISO	International Organization for Standardization
EHR	Electronic Health Record
IoT	Internet of Things
AI	Artificial Intelligence
DL	Deep Learning
CNN	Convolutional Neural Network
PNO	Producer/Consumer Risk (in %)
Big Data	Large-Scale Data Collection and Processing
V	Vertical Management Vector
L	Horizontal Control Vector
ISO 31000	ISO Standard for Risk Management
T2 Map	Quantitative T2 Relaxation Mapping
3D MRI	Three-Dimensional Magnetic Resonance Imaging
RF	Radiofrequency

Appendix A



(a)



(b)



(c)



(d)

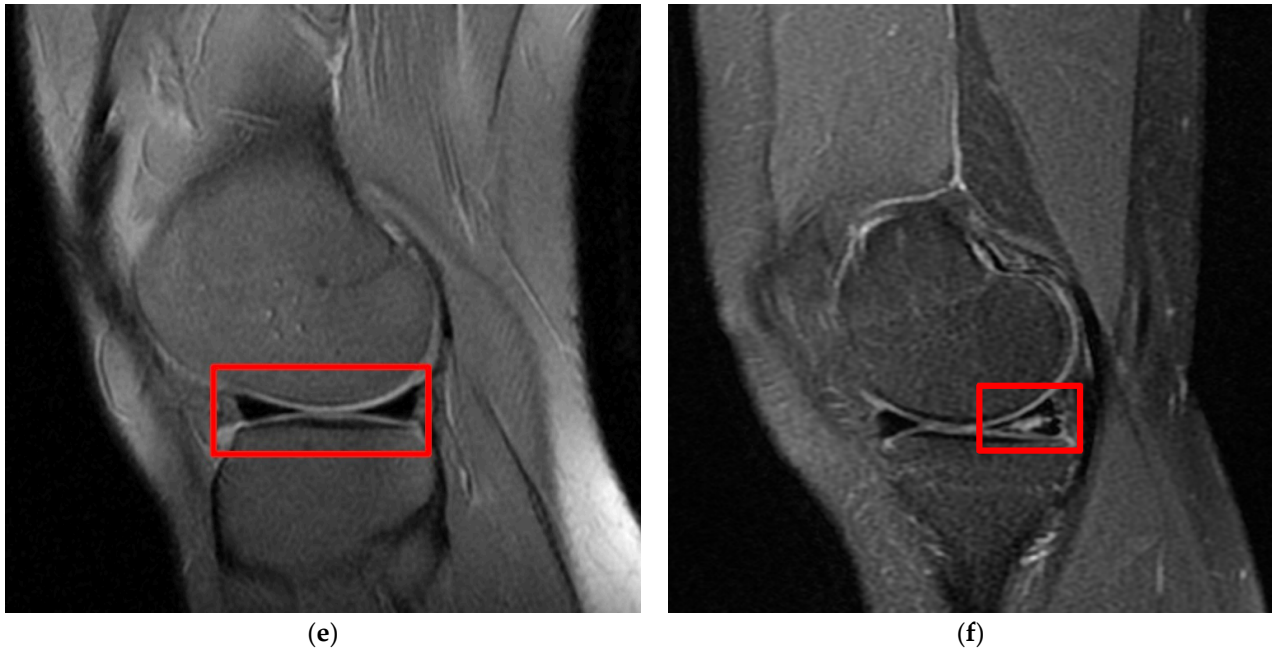


Figure A1. MRI images of the knee joint in the sagittal projection. Images (a), (c), and (e) show intact menisci (normal structure); images (b), (d), and (f) demonstrate pathological changes consistent with meniscus damage (tears or degeneration). The red boxes indicate the region of interest (meniscal area) used for visual comparison.



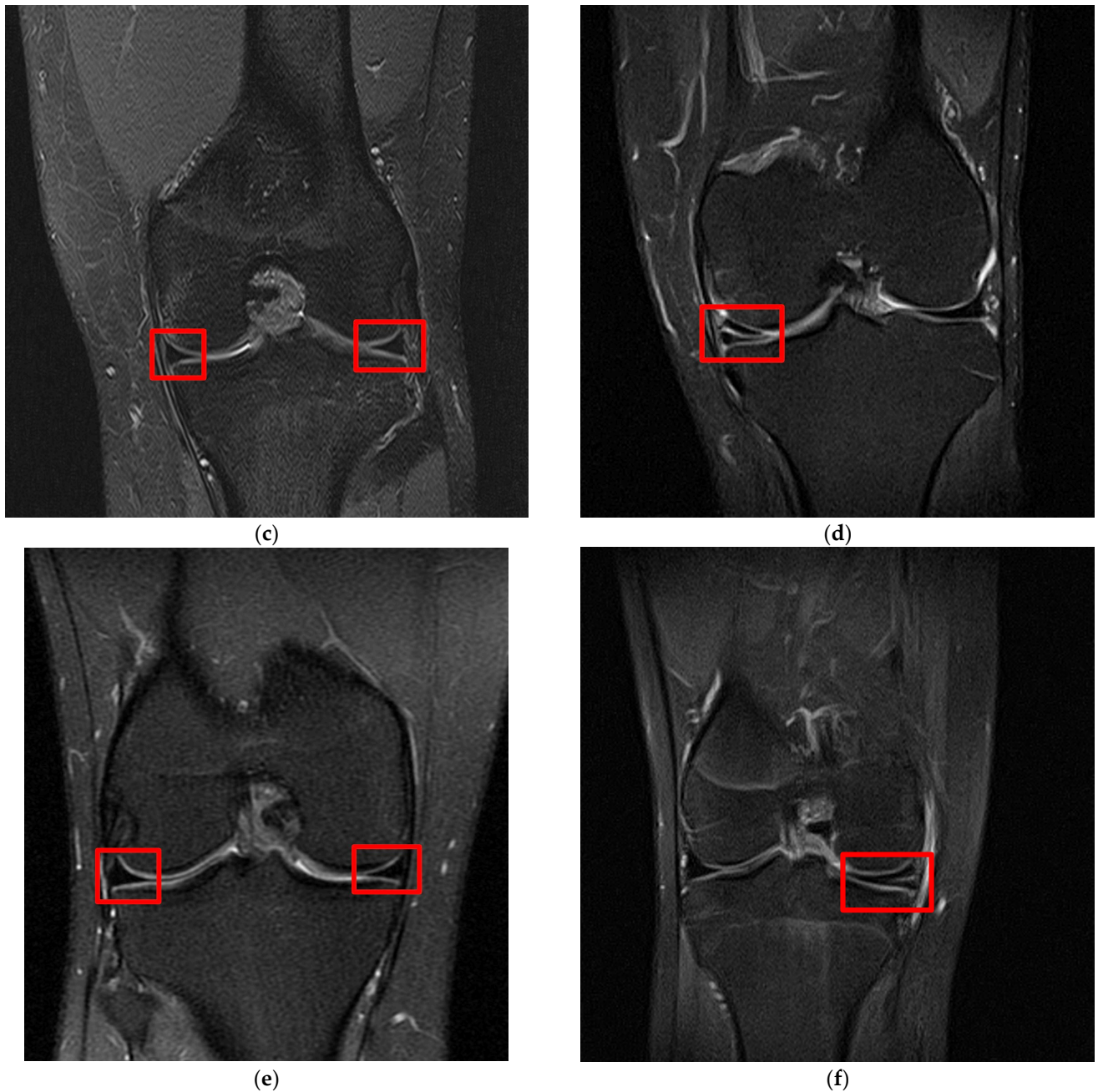


Figure A2. MRI images of the knee joint in the coronal projection. Images (a), (c), and (e) show intact menisci (normal structure); images (b), (d), and (f) demonstrate pathological changes consistent with meniscus damage (tears or degeneration). The red boxes indicate the region of interest (meniscal area) used for visual comparison.

References

1. Donelli, M.; Espa, G.; Feraco, P. A Semi-Unsupervised Segmentation Methodology Based on Texture Recognition for Radiomics: A Preliminary Study on Brain Tumours. *Electronics* **2022**, *11*, 1573. <https://doi.org/10.3390/electronics11101573>.
2. Siouras, A.; Moustakidis, S.; Giannakidis, A.; Chalatsis, G.; Liampas, I.; Vlychou, M.; Hantes, M.; Tasoulis, S.; Tsaopoulos, D. Knee Injury Detection Using Deep Learning on MRI Studies: A Systematic Review. *Diagnostics* **2022**, *12*, 537. <https://doi.org/10.3390/diagnostics12020537>.
3. Ma, Y.; Qin, Y.; Liang, C.; Li, X.; Li, M.; Wang, R.; Yu, J.; Xu, X.; Lv, S.; Luo, H.; et al. Visual Cascaded-Progressive Convolutional Neural Network (C-PCNN) for Diagnosis of Meniscus Injury. *Diagnostics* **2023**, *13*, 2049. <https://doi.org/10.3390/diagnostics13122049>.

4. Martel-Pelletier, J.; Paiement, P.; Pelletier, J.-P. Magnetic Resonance Imaging Assessments for Knee Segmentation and Their Use in Combination with Machine/Deep Learning as Predictors of Early Osteoarthritis Diagnosis and Prognosis. *Ther. Adv. Musculoskelet. Dis.* **2023**, *15*, 1759720X231165560. <https://doi.org/10.1177/1759720x231165560>.
5. Şuşan, M.; Cristea, A.M.; Drăghici, G.A.; Nica, D.V.; Florescu, S.; Damian, C.G. Patterns of Meniscal Injuries in Adults Aged 35 and Older: A Retrospective Analysis of Surgical Cases. *Medicina* **2025**, *61*, 643. <https://doi.org/10.3390/medicina61040643>.
6. Kuczyński, N.; Boś, J.; Białoskórska, K.; Aleksandrowicz, Z.; Turoń, B.; Zabrzyńska, M.; Bonowicz, K.; Gagat, M. The Meniscus: Basic Science and Therapeutic Approaches. *J. Clin. Med.* **2025**, *14*, 2020. <https://doi.org/10.3390/jcm14062020>.
7. Popper, H.R.; Fliegel, B.E.; Elliott, D.M.; Su, A.W. Surgical Management of Traumatic Meniscus Injuries. *Pathophysiology* **2023**, *30*, 618–629. <https://doi.org/10.3390/pathophysiology30040044>.
8. Vaz, C.E.S.; De Camargo, O.P.; De Santana, P.J.; Valezi, A.C. Accuracy of magnetic resonance in identifying traumatic intra-articular knee lesions. *Clinics* **2005**, *60*, 445–450. <https://doi.org/10.1590/s1807-59322005000600003>.
9. Braun, H.J.; Dragoo, J.L.; Hargreaves, B.A.; Levenston, M.E.; Gold, G.E. Application of Advanced Magnetic Resonance Imaging Techniques in Evaluation of the Lower Extremity. *Radiol. Clin. N. Am.* **2013**, *51*, 529–545. <https://doi.org/10.1016/j.rcl.2012.12.001>.
10. Nikiforaki, K.; Marias, K. MRI Methods to Visualize and Quantify Adipose Tissue in Health and Disease. *Biomedicines* **2023**, *11*, 3179. <https://doi.org/10.3390/biomedicines11123179>.
11. Wang, B.; Lian, Y.; Xiong, X.; Zhou, H.; Liu, Z. Progressive Feature Reconstruction and Fusion to Accelerate MRI Imaging: Exploring Insights across Low, Mid, and High-Order Dimensions. *Electronics* **2023**, *12*, 4742. <https://doi.org/10.3390/electronics12234742>.
12. Hadjidemetriou, S.; Malich, A.; Rossknecht, L.D.; Ferrarini, L.; Papageorgiou, I.E. Restoration for Intensity Nonuniformities with Discontinuities in Whole-Body MRI. *Signals* **2023**, *4*, 725–745. <https://doi.org/10.3390/signals4040040>.
13. Mašková, B.; Rožánek, M.; Gajdoš, O.; Karnoub, E.; Kamenský, V.; Donin, G. Assessment of the Diagnostic Efficacy of Low-Field Magnetic Resonance Imaging: A Systematic Review. *Diagnostics* **2024**, *14*, 1564. <https://doi.org/10.3390/diagnostics14141564>.
14. Giovannetti, G.; Frijia, F.; Santarelli, M.F.; Positano, V. Low-Field Magnetic Resonance Imaging: A Full-Wave Simulation of Radiofrequency Birdcage Coils for Musculoskeletal Limb Imaging. *Diagnostics* **2025**, *15*, 713. <https://doi.org/10.3390/diagnostics15060713>.
15. Bryan, F.L. Hazard Analysis Critical Control Point (HACCP) Systems for Retail Food and Restaurant Operations. *J. Food Prot.* **1990**, *53*, 978–983. <https://doi.org/10.4315/0362-028x-53.11.978>.
16. Høj, N.P.; Kroon, I.B.; Nielsen, J.S.; Schubert, M. System Risk Modelling and Decision-Making—Reflections and Common Pitfalls. *Struct. Saf.* **2024**, *113*, 102469. <https://doi.org/10.1016/j.strusafe.2024.102469>.
17. Zhao, Y.; Yang, Q.; Qian, S.; Dong, J.; Cai, S.; Chen, Z.; Cai, C. Improving the Sensitivity of Task-Based Multi-Echo Functional Magnetic Resonance Imaging via T2* Mapping Using Synthetic Data-Driven Deep Learning. *Brain Sci.* **2024**, *14*, 828. <https://doi.org/10.3390/brainsci14080828>.
18. Peuna, A.; Thevenot, J.; Saarakkala, S.; Nieminen, M.T.; Lammintausta, E. Machine Learning Classification on Texture Analyzed T2 Maps of Osteoarthritic Cartilage: Oulu Knee Osteoarthritis Study. *Osteoarthr. Cartil.* **2021**, *29*, 859–869. <https://doi.org/10.1016/j.joca.2021.02.561>.
19. Edjossan-Sossou, A.M.; Galvez, D.; Deck, O.; Heib, M.A.; Verdel, T.; Dupont, L.; Chery, O.; Camargo, M.; Morel, L. Sustainable Risk Management Strategy Selection Using a Fuzzy Multi-Criteria Decision Approach. *Int. J. Disaster Risk Reduct.* **2020**, *45*, 101474. <https://doi.org/10.1016/j.ijdrr.2020.101474>.
20. Glette-Iversen, I.; Flage, R.; Aven, T. Extending and Improving Current Frameworks for Risk Management and Decision-Making: A New Approach for Incorporating Dynamic Aspects of Risk and Uncertainty. *Saf. Sci.* **2023**, *168*, 106317. <https://doi.org/10.1016/j.ssci.2023.106317>.
21. Karunathilake, H.; Bakhtavar, E.; Chhipi-Shrestha, G.; Mian, H.R.; Hewage, K.; Sadiq, R. Decision Making for Risk Management: A Multi-Criteria Perspective. In *Methods in Chemical Process Safety*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 239–287.
22. Mokhov, V.; Aliukov, S.; Alabugin, A.; Osintsev, K. A Review of Mathematical Models of Macroeconomics, Microeconomics, and Government Regulation of the Economy. *Mathematics* **2023**, *11*, 3246. <https://doi.org/10.3390/math11143246>.
23. Willink, R. On Revision of the Guide to the Expression of Uncertainty in Measurement: Proofs of Fundamental Errors in Bayesian Approaches. *Meas. Sens.* **2022**, *24*, 100416. <https://doi.org/10.1016/j.measen.2022.100416>.
24. Geissler, A.; Hollenbach, J.; Haring, M.; Amelung, V.E.; Thun, S.; Haering, A. A Nationwide Digital Maturity Assessment of Hospitals—Results from the German Digital Radar. *Health Policy Technol.* **2024**, *13*, 100904. <https://doi.org/10.1016/j.hlpt.2024.100904>.

25. Hansen, S.; Baroody, A.J. Beyond the Boundaries of Care: Electronic Health Records and the Changing Practices of Healthcare. *Inf. Organ.* **2023**, *33*, 100477. <https://doi.org/10.1016/j.infoandorg.2023.100477>.
26. Alzghaibi, H.; Hutchings, H.A. The Impact of Leadership and Management on the Implementation of Electronic Health Record Systems in the Primary Healthcare Centers. *Healthcare* **2024**, *12*, 2013. <https://doi.org/10.3390/healthcare12202013>.
27. Abdulmalek, S.; Nasir, A.; Jabbar, W.A.; Almuahay, M.A.M.; Bairagi, A.K.; Khan, M.A.-M.; Kee, S.-H. IoT-Based Healthcare-Monitoring System towards Improving Quality of Life: A Review. *Healthcare* **2022**, *10*, 1993. <https://doi.org/10.3390/healthcare10101993>.
28. Da Fonseca, M.H.; Kovalski, F.; Picinin, C.T.; Pedroso, B.; Rubbo, P. E-Health Practices and Technologies: A Systematic Review from 2014 to 2019. *Healthcare* **2021**, *9*, 1192. <https://doi.org/10.3390/healthcare9091192>.
29. ISO 31000:2018; Risk Management—Guidelines. International Organization for Standardization: Geneva, Switzerland, 2018.
30. ISO 31000:2009; Risk Management—Principles and Guidelines. International Organization for Standardization: Geneva, Switzerland, 2009.
31. ISO 5807:1985; Information Processing—Documentation Symbols and Conventions for Data, Program and System Flowcharts, Program Network Charts and System Resources Charts. International Organization for Standardization: Geneva, Switzerland, 1985.
32. Khan, F.I.; Amyotte, P.R.; Amin, M.T. Advanced Methods of Risk Assessment and Management: An Overview. In *Methods in Chemical Process Safety*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 1–34.
33. Aven, T. Risk Assessment and Risk Management: Review of Recent Advances on Their Foundation. *Eur. J. Oper. Res.* **2015**, *253*, 1–13. <https://doi.org/10.1016/j.ejor.2015.12.023>.
34. Wrona, Z.; Ganzha, M.; Paprzycki, M.; Pawłowski, W.; Ferrando, A.; Cabri, G.; Bădică, C. Comparison of Multi-Agent Platform Usability for Industrial-Grade Applications. *Appl. Sci.* **2024**, *14*, 10124. <https://doi.org/10.3390/app142210124>.
35. Toma, S.-V.; Chiriță, M.; Șarpe, D. Risk and Uncertainty. *Procedia Econ. Financ.* **2012**, *3*, 975–980. [https://doi.org/10.1016/s2212-5671\(12\)00260-2](https://doi.org/10.1016/s2212-5671(12)00260-2).
36. Saatchi, R. Fuzzy Logic Concepts, Developments and Implementation. *Information* **2024**, *15*, 656. <https://doi.org/10.3390/info15100656>.
37. Zhang, Y.; Dong, Z. Medical Imaging and Image Processing. *Technologies* **2023**, *11*, 54. <https://doi.org/10.3390/technologies11020054>.
38. Mahmood, Z. Digital Image Processing: Advanced Technologies and Applications. *Appl. Sci.* **2024**, *14*, 6051. <https://doi.org/10.3390/app14146051>.
39. Li, J.; Jiang, P.; An, Q.; Wang, G.-G.; Kong, H.-F. Medical Image Identification Methods: A Review. *Comput. Biol. Med.* **2023**, *169*, 107777. <https://doi.org/10.1016/j.combiomed.2023.107777>.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.