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Review

From Detection to Prediction: The NDE 4.0 Transition

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Abstract

This review traces the four-generation evolution of non-destructive evaluation (NDE 1.0–4.0) and audits where the field genuinely stands today. The central finding is that statistically qualified probability of detection (POD), as defined in MIL-HDBK-1823A and related frameworks, is not interchangeable with machine-learning metrics such as accuracy or F1-score; the two answer different questions and rest on different statistical foundations. Reported AI performance on curated datasets does not, by itself, predict field reliability because domain shift, sensor variability, and class imbalance change the inspection signal once a model leaves the lab. Six recurring barriers limit industrial uptake: scarce open benchmark datasets, domain shift, weak interoperability, explainability constraints, cybersecurity exposure, and the lack of broadly accepted code provisions for AI-derived accept/reject decisions. The oil and gas sector is used as a case study because it combines high inspection volume, severe operating environments, mature risk-based inspection practice, and strong regulatory conservatism. NDE 4.0 is technically credible; its wider acceptance in safety-critical industries will be earned through representative field validation, auditable model governance, standardised data structures, and qualification pathways—not through stronger laboratory accuracy claims.

Keywords: NDE 4.0; non-destructive evaluation; artificial intelligence; probability of detection; digital twin; structural health monitoring; phased array ultrasound; Industry 4.0; AI limitations; NDE maturity

1. Introduction

Nuclear pressure vessels, aircraft fuselages, wind-turbine blades, subsea pipelines—these assets share a common requirement: reliable flaw detection before failure produces severe safety, environmental, or economic consequences. Non-destructive evaluation (NDE)—used interchangeably here with NDT and NDI—is the discipline of inspection methods that allow a component to return to service after evaluation. In many cases the inspection is in situ (for example, ultrasonic testing on aircraft skin or pipelines in operation); in others, the part must be removed (for example, X-ray computed tomography of an aerospace casting in a shielded vault) and then reinstalled. The defining feature is that the inspection itself does not destroy or consume the part being evaluated. Its roots lie in early industrial radiography, but the field is far from static. Ageing infrastructure, tightening regulation, and the explosion in affordable computing have each pushed NDE into territory that would have been speculative twenty years ago [1–3]. A key argument of this review, introduced here at the outset, is that statistically qualified probability of

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detection (POD) and common AI performance metrics such as accuracy, precision, recall, and F1-score are not interchangeable: POD asks whether a defined inspection system can reliably detect flaws of a given size under controlled and representative conditions, whereas AI metrics typically describe performance on a labelled dataset. This distinction shapes the generational analysis and the critical evaluation of AI-enabled NDE that follow [4].

The four-generation framework—NDE 1.0 through NDE 4.0—borrows the industrial-revolution language popularised around Industry 4.0 and is useful when it is treated as a technology-readiness map rather than a strict historical boundary. Each generation reflects a change in inspection hardware, data handling, and decision responsibility. However, the framework should not obscure the persistent gap between research demonstration and field-qualified practice. In AI-enabled NDE, high classification scores reported on curated datasets often do not transfer directly to production inspection data, where material variability, weld geometry, surface condition, coupling, sensor calibration, environmental noise, and class imbalance can change the signal distribution. This mismatch between laboratory and field inspection conditions remains one of the primary barriers to industrial deployment of AI-enabled NDE systems. A parallel question often asked by reviewers is how human inspectors themselves compare between qualification and field environments. Round-robin POD studies are typically run on carefully prepared specimens with controlled access, calibration, and procedure discipline, so a degree of performance reduction in routine field work is expected for humans as well as for AI. There is published evidence of this human lab-versus-field gap (for example in welded-joint round robins and in-service eddy-current inspections), but it has not been systematically benchmarked across modalities in the way that is now urgently needed for AI. This is itself a research gap worth closing, because any honest comparison between AI and human inspection should hold both to similar real-world conditions [5–8].

Commercial forecasts consistently indicate growth in NDE/NDT services and instrumentation, driven by ageing infrastructure, energy assets, aerospace quality requirements, additive manufacturing, and digital inspection workflows. Because market estimates differ substantially by geography, method, and whether inspection services are counted with equipment sales, this review does not rely on a single market-size value as technical evidence. The more important point is qualitative but well supported by industry practice: the organisations that most need advanced inspection—operators of ageing, high-consequence assets—are also the organisations that require the strongest validation before changing acceptance practice. Conservative adoption culture and tight regulatory oversight are therefore not simply inertia; they are rational responses to asymmetric risk.

Figure 1 captures the six core reasons NDE is specified across virtually every safety-critical industry. The common thread is that inspection must not compromise the thing being inspected. Beyond that, the value proposition spans safety assurance during operation, lifecycle cost reduction by avoiding premature retirement and destructive proof testing, documented quality evidence from fabrication through in-service maintenance, compliance with codes such as ASME and DNVGL-ST-F101, a credible foundation for condition-based rather than calendar-based maintenance, and—critically in any industry where a failure makes the news—defensible documentation. These are not abstract benefits. In a refinery turnaround or a pipeline integrity programme, each one translates directly to decisions about whether equipment runs, gets repaired, or gets replaced.

This paper works through each generation in turn—capabilities and limitations together, not one without the other—then provides a quantitative cross-generational comparison of POD and automation metrics, a focused analysis of AI failure modes, an oil and gas sector case study, and a forward-looking technology roadmap.

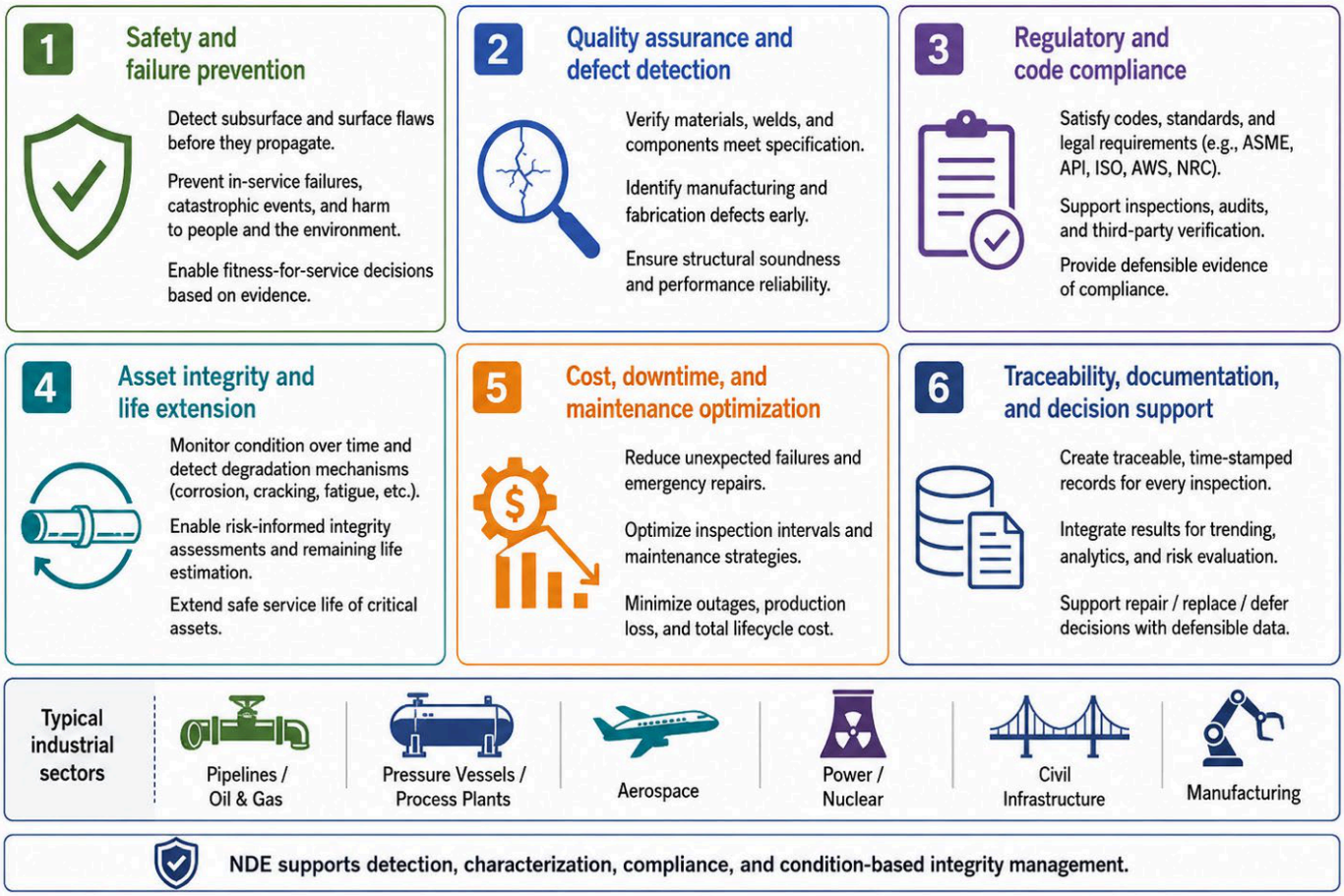


Figure 1. Six principal drivers for NDT deployment across safety-critical industries.

The contribution of this review is a field-oriented synthesis that separates demonstrated capability from qualified deploy ability. It combines a generational NDE framework, an AI-readiness critique, a standards-and-validation discussion, and an oil-and-gas case study to identify where NDE 4.0 is mature enough for operational support and where additional qualification evidence is still required.

Unlike many prior reviews that focus primarily on individual NDE technologies or AI algorithms, this review evaluates the transition from NDE 1.0 to NDE 4.0 through the combined perspectives of reliability qualification, probability of detection (POD), deployment maturity, regulatory acceptance, and operational integration. Particular emphasis is placed on the distinction between laboratory AI performance and field-qualified inspection reliability, an area that remains insufficiently addressed in much of the current NDE 4.0 literature. The review further uses the oil and gas sector as a longitudinal case study to examine how advanced NDE technologies transition from research demonstration to operational adoption in safety-critical environments.

Review Scope and Methodology

This work is a structured critical (narrative) review rather than a PRISMA-type systematic review or quantitative meta-analysis. This format was chosen deliberately. The manuscript spans four NDE generations across roughly a century of practice, and the underlying evidence combines peer-reviewed research, consensus codes and standards, and authoritative industry and technical reports that differ widely in methodology, terminology, and reporting detail. A strict systematic-review protocol, designed for homogeneous clinical-type evidence, would not meaningfully synthesise sources of such different character; in particular, it could not validly pool the AI performance figures discussed in

Sections 6 and 8, because those figures are reported on non-comparable datasets, defect taxonomies, and metrics. A critical narrative synthesis is therefore the appropriate instrument for a cross-generational maturity assessment, and the review is structured around the generational framework, an AI-readiness critique, a standards-and-validation discussion, and a single-sector case study.

The evidence base was assembled from three source classes: (i) peer-reviewed journal and conference literature on NDE methods, AI-enabled inspection, and inspection reliability and probability of detection; (ii) consensus codes, standards, and qualification frameworks, including ASME, API, DNV, ISO/EN, MIL-HDBK-1823A, and ENIQ; and (iii) authoritative industry, regulatory, and standards-body technical reports. Sources were selected for direct relevance to the four-generation framework, for currency, and for traceability to a primary origin, with priority given to material that distinguishes laboratory demonstration from field-qualified performance. Where quantitative values are reported, they are treated as indicative and method-dependent rather than as pooled or validated metrics, consistent with the distinction between AI classification accuracy and statistically qualified POD set out in Box 1. The oil and gas sector is then used as a longitudinal case study (Section 10) to test how the generational framework and its associated challenges play out within a single safety-critical industry that has an unusually long and well-documented inspection record. Search terms combined NDE/NDT/NDI descriptors with generation-specific and technology-specific terms, including: probability of detection, model-assisted POD, AI-enabled inspection, machine learning, digital twin, structural health monitoring, phased array ultrasonic testing, full matrix capture, total focusing method, guided waves, robotic inspection, oil and gas integrity management, and inspection data interoperability. Sources were excluded when they were promotional, lacked traceable technical detail, did not relate directly to NDE reliability or deployment maturity, or could not support the distinction between laboratory demonstration and field-qualified practice.

Box 1. POD versus AI accuracy—what they measure and why they are not interchangeable.

What it measures. POD (MIL-HDBK-1823A): Probability of detecting a flaw as a function of flaw size, under a defined and controlled inspection system. Accuracy is the fraction of correctly classified samples; F1 is the harmonic mean of precision and recall—computed on a test dataset.

Statistical basis. POD (MIL-HDBK-1823A): Log-normal (signal-response) or hit/miss model with explicit confidence bounds; reported as a90/95. AI Accuracy/F1-Score: Classification threshold on a labelled dataset; no inherent flaw-size dependence and no built-in confidence interval.

Measurement conditions. POD (MIL-HDBK-1823A): Qualified specimen sets with documented flaw populations, calibration, and inspector or system competence. AI Accuracy/F1-Score: Curated benchmark or laboratory dataset; conditions typically less representative of field acquisition.

Regulatory standing. POD (MIL-HDBK-1823A): Accepted by ASME, API, DNV, ENIQ and other code bodies as a reliability-qualification metric. AI Accuracy/F1-Score: Not accepted as a primary qualification metric in major NDE code at present.

Appropriate use. POD (MIL-HDBK-1823A): Demonstrating that an inspection system meets a reliability target for the intended accept/reject decision. AI Accuracy/F1-Score: Internal model development, comparison between architectures, training-set diagnostics.

2. The NDE Generational Framework

The four-generation framework used here follows the Industry 4.0 roadmap in structure but is grounded in what NDE practice actually looked like at each stage—what the technician carried, what the software could do, and what the code permitted. Figure 2 shows the capability staircase, while Figure 3 maps the key defining attributes of each era. Table 1 summarises the defining characteristics of the four NDE generations, including paradigm, technology basis, decision model, and human role across NDE 1.0–4.0.

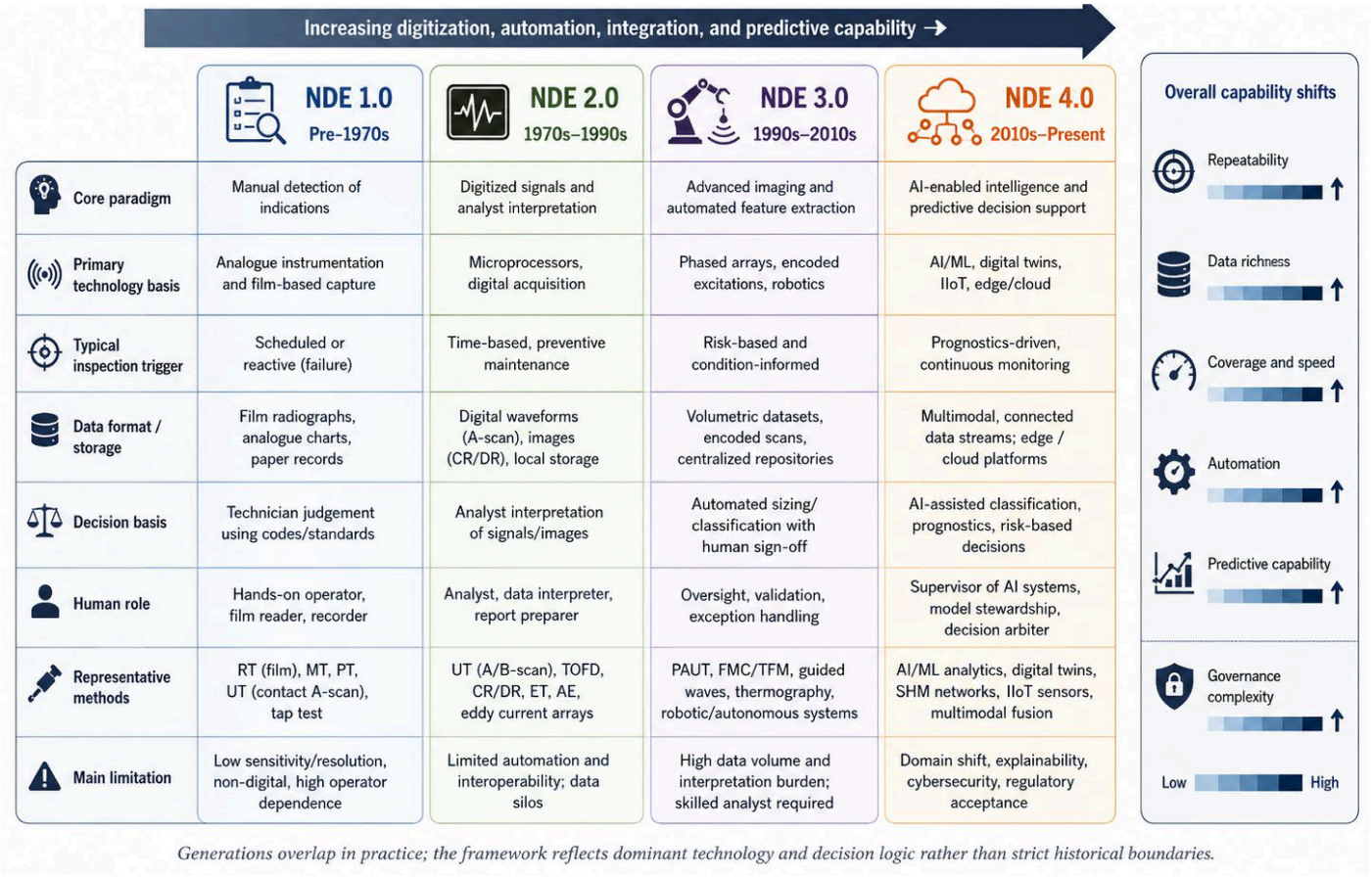


Figure 2. Evolution of NDE capability from manual analogue inspection to intelligent, AI-assisted, and connected inspection systems across NDE 1.0–4.0.

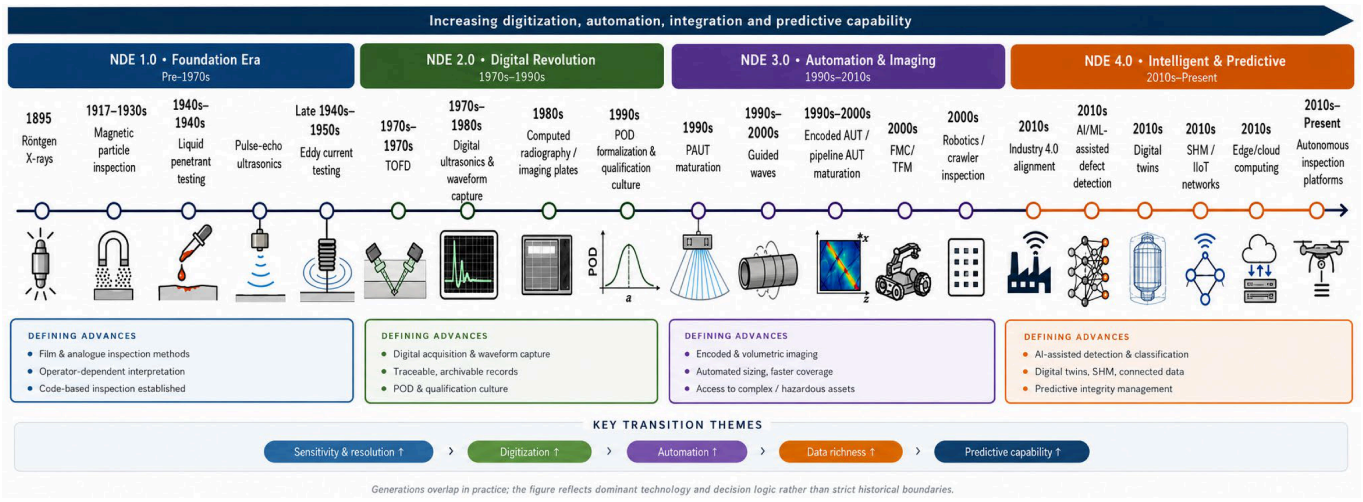


Figure 3. Historical development timeline of NDE technologies from early industrial radiography to AI-enabled NDE 4.0 systems.

Figure 2 highlights the transition from manual analogue inspection toward connected and predictive inspection ecosystems, while Figure 3 summarises the major technological milestones that enabled this transformation across successive NDE generations.

It is worth stating clearly that these generations overlap in practice. A power plant may run manual visual surveys on routine pipework while operating a digital-twin-enabled SHM network on its pressure-boundary components. The taxonomy describes the domi-

nant technology and decision-making model of each era, not a clean historical sequence where one era ends before the next begins.

Table 1. Defining characteristics of NDE generational eras: paradigm, technology basis, decision model, and human role across NDE 1.0–4.0.

Attribute	NDE 1.0 (Pre–1970s)	NDE 2.0 (1970s–1990s)	NDE 3.0 (1990s–2010s)	NDE 4.0 (2010s–Present)
Core Paradigm	Detection and documentation	Digitization and archival analysis	Automated imaging and quantitative evaluation	Predictive analytics and system integration
Primary Technology Driver	RT, MT, PT, manual UT	Microprocessors, ADC systems, TOFD, CR/DR (computed/digital radiography)	PAUT, FMC/TFM, guided waves, robotics	AI/ML, digital twins, IIoT, edge computing
Inspection Trigger	Scheduled shutdown or failure	Scheduled interval	Risk-informed interval	Continuous/ condition-based
Data Format	Paper film, analogue A-scan	Digital waveform, stored datasets	Volumetric imaging (B/C/S-scan), encoded AUT	Cloud-scale multimodal streams (Volumetric imaging)
Decision Basis	Technician judgement	Analyst interpretation of stored data	Automated sizing with human sign-off	AI-assisted classification with digital twin–enabled prognostics
Human Role	Primary detector and judge	Analyst and archivist	Supervisor of automated systems	Validation, oversight, and regulatory governance
Key Limitation	High operator dependency; limited repeatability	Proprietary formats; limited interoperability	High skill requirement for advanced data interpretation	Regulatory acceptance gaps; domain shift; limited explainability

3. NDE 1.0—The Foundation Era (Pre-1970s)

3.1. Historical Context

Röntgen's X-ray discovery in 1895 was a medical tool before it was an industrial one. It took improved high-voltage X-ray tube technology after 1913 to make radiographic inspection of metal welds practical, and the technique did not enter formal codification until ASME first permitted fusion-welded pressure-vessel construction in 1931; with radiographic examination of those welds following World War II, everything accelerated—the U.S. Navy's shipbuilding programme alone drove significant expansion of industrial radiography. Alongside this, William Hoke's magnetic particle inspection method, developed around 1922, gave inspectors a fast, portable surface-crack tool that required little specialist equipment. Liquid penetrant testing arrived in the 1940s, relying on capillary action to draw developer into surface-breaking discontinuities in non-magnetic materials. Ultrasonic testing built on Sokolov's pre-war research and Firestone's pulse-echo work, while eddy current testing—grounded in Faraday's induction principles—was industrialised through the 1950s for heat-exchanger tubing and aircraft skin inspection [9,10].

3.2. Defining Characteristics

NDE 1.0 was entirely manual. The instrument display was an A-scan oscilloscope or a piece of developed film, and the quality of the result depended on the technician's

experience and judgement. POD varied substantially between operators—something the field would only begin to quantify formally in the following generation. Records were paper, decisions were immediate and local, and there was only a limited mechanism for systematic post-acquisition analysis or quality trending [11].

3.3. Industrial Impact

Despite its limitations, NDE 1.0 established the conceptual and procedural foundations the discipline still rests on: wave–matter interaction physics, standard reference blocks, and the recognition that inspector human factors are a primary driver of reliability. Radiographic film archives, wherever they survived, gave operators the first longitudinal inspection record of an asset—the earliest form of what we now call fitness-for-service evidence [12,13].

4. NDE 2.0—The Digital Revolution (1970s–1990s)

4.1. Enabling Technologies

When microprocessors became affordable in the 1970s, NDE instrumentation started moving off the oscilloscope and onto the screen. By the mid-1980s, analogue-to-digital converters capable of capturing megahertz-range ultrasonic signals were commercially available, and computerised waveform storage changed the inspection workflow fundamentally. TOFD, developed at Harwell in the 1970s, used diffracted tip signals rather than reflected amplitude to size through-wall cracks—a significant step forward in accuracy. Digital and computed radiography replaced film with flat-panel detectors and phosphor plates, enabling quantitative greyscale analysis and storage. Eddy current array probes expanded spatial coverage on aircraft skin lap-joints, and industrial CT—adapted from medical imaging—opened volumetric characterisation of casting and composite defects. Software platforms such as TOMOVIEW, UTWIN and IMAGETEC introduced something conceptually important: the separation of data acquisition from analysis. A Level II or III analyst could now review a stored A-scan dataset away from the instrument and independently of the scan. Inspection data management became a discipline in its own right, though proprietary file formats kept creating interoperability headaches that have never been fully resolved [14–17].

4.2. Probability of Detection Advances

MIL-HDBK-1823A provides widely used guidance for assessing the reliability of an NDE system in terms of probability of detection as a function of flaw size, including the planning, analysis, and reporting of POD studies. It is important to treat this as a reliability-assessment framework, not as a generic accuracy score. A common form of the POD model expresses detection probability as a statistical response function of flaw size:

$$\mathrm{POD}(a) = \Phi\left[(\ln(a) - \mu)/\sigma\right]$$

The resulting curve describes how detection probability changes with flaw size under specified inspection conditions. The a90/95 value—the flaw size associated with 90% POD at 95% confidence—is useful precisely because it combines a detection target with statistical confidence. Machine-learning metrics such as accuracy, precision, recall, or F1-score may support comparative model development, but they do not independently establish flaw-size-conditioned reliability or satisfy conventional POD qualification requirements. For AI-enabled NDE, the relevant question is therefore not only whether the model performs well on a test set but whether the complete inspection system—sensor, procedure, data pipeline, model, operator oversight, and decision rule—can satisfy a reliability argument comparable to established POD qualification practice [17,18].

Classical POD studies also assume that the inspection procedure, personnel competence, calibration, specimen set, and environmental conditions are defined and controlled. AI-enabled inspection complicates this assumption because the detection function can be sensitive to the representativeness of training data and to distribution shifts after deployment. Mapping AI-derived outputs onto a defensible POD or model-assisted POD framework remains an active qualification challenge and should be presented as such, rather than as a solved regulatory problem.

An AI accuracy figure can only be read as a POD-equivalent claim if the full inspection system—sensor, procedure, data pipeline, model, oversight, and decision rule—has been evaluated against a flaw-size-conditioned reliability target on representative specimens. Where that has not been done, the two values should not appear side-by-side in the same comparative column.

5. NDE 3.0—Automation, Imaging and Quantification (1990s–2010s)

Scope note: the following subsections give a working-level overview of each major NDE 3.0 technology family rather than an exhaustive technical treatment. The aim is to convey the practical capabilities, limitations, and adoption drivers that matter when comparing NDE 3.0 to NDE 2.0 and NDE 4.0. Readers seeking detailed performance specifications, procedure parameters, or comparative qualification data are referred to the standards and primary literature cited in each subsection.

5.1. Phased Array Ultrasonic Testing (PAUT)

Of all the NDE 3.0 advances, PAUT had the broadest effect on industrial weld inspection. Electronic steering and focusing of a multi-element array allow full volumetric coverage at scan speeds that manual UT cannot approach, generating real-time sectorial and linear scan images without mechanical beam repositioning. Qualification under industrial standards moved PAUT from a specialist research technique into standard pipeline and pressure-vessel inspection practice [19,20].

5.2. Full Matrix Capture and Total Focusing Method

FMC/TFM represents a genuine conceptual step beyond the conventional phased array. Rather than acquiring pre-focused beams in real time, FMC records the full inter-element response matrix and defers all beam reconstruction to post-processing. TFM then synthetically focuses on every pixel in the reconstruction domain, which can improve resolution compared with fixed-focus approaches, depending on aperture, bandwidth, and reconstruction assumptions. This reconstruction flexibility is also the foundation for adaptive TFM and SAFT-based sizing algorithms that push crack characterisation accuracy further [21,22].

5.3. Guided Wave Testing and Long-Range Inspection

Guided wave testing exploits the fact that certain wave modes—particularly the torsional T(0,1) and longitudinal L(0,2) modes—propagate tens of metres along pipes and plates with acceptable attenuation. For buried pipelines, road crossings, and insulated pipework where point-by-point access is not practical, a single ring of transducers can screen the full pipe wall volume in both directions from one location. This is not a sizing technique, but as a screening and prioritisation tool it changed the economics of CUI inspection substantially [23–25].

5.4. Thermographic and Optical Methods

Active thermography—pulsed, lock-in, and vibrothermographic variants—found its primary application in composite aerospace structures, where subsurface delaminations,

disbonds, and impact damage produce detectable thermal contrast. The technique is non-contact, covers large areas quickly, and produces interpretable colour-map images. Digital image correlation and structured-light scanning added full-field strain mapping and geometric characterisation to the NDE 3.0 toolkit, capabilities that conventional pointwise ultrasonics cannot provide [26,27].

5.5. Robotic Delivery Platforms

Mechanising the delivery of NDE sensors was as important as developing better sensors. Crawler-based AUT systems for pipeline girth-weld inspection reached scanning speeds above traditional MUT speed with encoder-referenced positional accuracy, removing operator scan variability from the equation. ROVs extended similar consistency to subsea structures, and magnetic adhesion or suction-cup climbing robots addressed elevated and otherwise inaccessible assets. Automation in NDE 3.0 was about repeatability and coverage rate, not intelligence—the sensor still produced data that a human analyst interpreted [28,29].

6. NDE 4.0—Intelligent, Connected and Predictive NDE (2010s–Present)

For clarity, this section is organised into three thematic areas: (i) AI methodologies, (ii) deployment challenges, and (iii) regulatory and validation barriers.

6.1. The Industry 4.0 Alignment

Industry 4.0—introduced at Hannover Messe in 2011—describes the integration of cyber-physical systems, IoT connectivity, cloud computing, and cognitive automation into industrial operations. NDE 4.0 maps directly onto this: sensors feed networked data streams, storage and processing shift to the cloud, AI drives analysis, and inspection findings are absorbed into digital twin platforms rather than filed as standalone reports. Figure 4 shows how these nine technology pillars interact around the NDE 4.0 core [30,31].

Figure 4 presents a more structured view of the NDE 4.0 workflow than a simple list of technologies. It shows that NDE 4.0 is not defined by AI alone, but by the integration of sensing, data acquisition, analytics, digital infrastructure, and decision-making. The figure also emphasises that successful deployment depends on governance elements such as qualification, code compliance, auditability, cybersecurity, and expert oversight, which remain essential for adoption in safety-critical industries.

6.2. Artificial Intelligence and Machine Learning in NDE

In an NDE 4.0 workflow, AI may support preprocessing, feature extraction, indication classification, segmentation, anomaly detection, reporting, or prioritisation for human review. Three families of methods are especially visible in the literature: convolutional and transformer-based models for image-like data, physics-informed or hybrid physics-ML models for wave and heat-transfer problems, and generative or simulation-assisted methods for data augmentation. Reported performance must be interpreted cautiously. Results obtained on benchmark or laboratory datasets are best treated as evidence of algorithmic potential, not proof of field reliability across different materials, geometries, instruments, procedures, and operators [32–35].

6.2.1. Convolutional Neural Networks for Defect Detection

CNN-based architectures have demonstrated promising performance across selected radiographic, ultrasonic, thermographic, and visual-inspection datasets; however, reported performance remains highly dependent on dataset composition, acquisition conditions, preprocessing methodology, and defect taxonomy. However, cross-study comparison remains weak when authors use different datasets, defect taxonomies, preprocessing, train-test splits, and success metrics. CNN performance should therefore be treated as

application-specific and dataset-dependent, not as a general replacement for qualified analyst judgement [35–38].

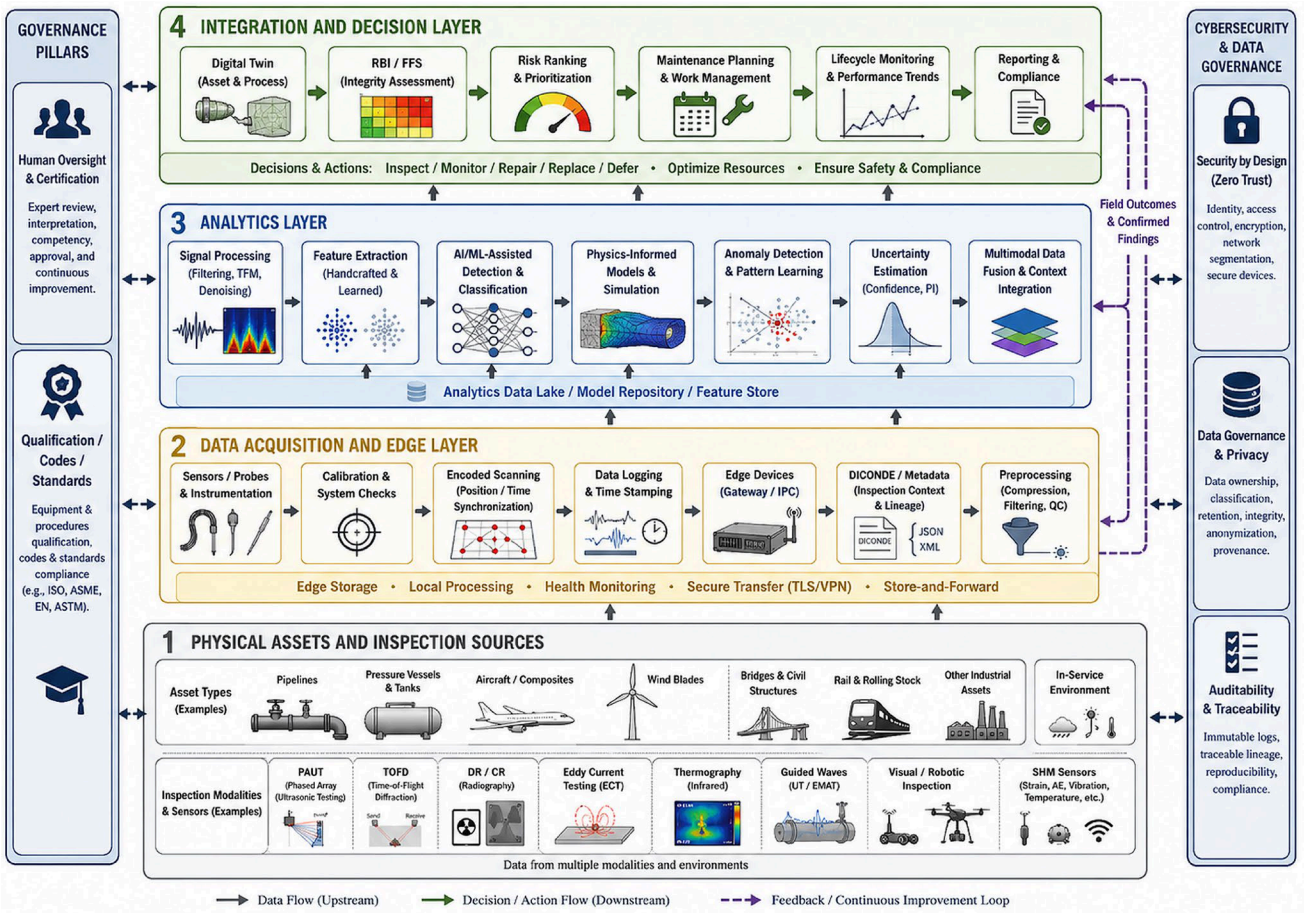


Figure 4. Integrated NDE 4.0 data-to-decision architecture for intelligent inspection and integrity management. This figure illustrates a layered NDE 4.0 ecosystem linking physical assets and inspection sources to data acquisition, edge processing, analytics, and decision support. It highlights how multimodal inspection data are captured, processed, analysed, and integrated into digital twin, risk-based inspection (RBI), and fitness-for-service (FFS) frameworks, while also showing the importance of human oversight, standards, cybersecurity, data governance, and continuous feedback from field outcomes.

6.2.2. Physics-Informed Neural Networks (PINNs)

Pure data-driven models have a specific weakness that matters a great deal in regulated inspection: when asked why they accepted or rejected an indication, they cannot answer in terms a code-body will accept. They also become unreliable at the edges of their training distribution, which is precisely where novel defect morphologies tend to appear. PINNs address this by embedding governing wave and heat equations directly into the loss function, so the model cannot produce outputs that violate known physics even when extrapolating. Active PINN applications in NDE include ultrasonic wavefield prediction, guided-wave wall-thickness profiling, and thermal diffusivity characterisation through pulsed thermography [39–41].

6.2.3. Generative Models and Data Augmentation

GANs and VAEs attack the labelled-data shortage directly by generating synthetic NDE signals and images that represent realistic defect populations. Conditional GANs trained on FE simulation data can produce physically plausible phased-array B-scan images across a range of defect geometries, giving downstream detection networks training mate-

rial that would otherwise require years of destructive specimen manufacture to assemble. A major limitation of simulation-driven augmentation is the potential mismatch between idealised synthetic signals and real inspection variability, including geometric complexity, noise, coupling variation, and defect morphology. Validation of synthetic training data therefore deserves explicit attention. Real laboratory data cannot be removed from the loop; synthetic data is best treated as augmentation rather than as a replacement for measured signals. Physics-based simulations have their own limitations—idealised geometry, simplified material models, omitted noise sources, and approximated transducer behaviour—that constrain how well they represent field-acquired signals. A defensible workflow therefore validates generative-model outputs against held-out experimental data drawn from the intended deployment conditions, monitors downstream task performance (not just visual plausibility), and re-evaluates whenever the inspection hardware, procedure, or material population changes. Treating synthetic data as a development convenience rather than as qualification evidence is the prudent default [42–44].

6.3. Digital Twins in NDE

A digital twin is a live virtual model of a physical asset that continuously absorbs design data, material properties, operational loading history, and inspection findings to project remaining life and flag maintenance priorities. A useful refinement is the digital thread, which is the connected record of design intent, manufacturing data, inspection history, operating data, and maintenance actions that flows alongside the asset throughout its life. NDE 4.0 depends on this thread because inspection findings are most actionable when they are placed into the context of design tolerances, prior repair history, fatigue spectra, corrosion exposure, and previous indication trending. The digital twin is then the live decision surface; the digital thread is the traceable evidence underneath it. Without traceable lifecycle data, the predictive capability of a digital twin becomes significantly constrained. Treating the two together is what allows inspection evidence to drive condition-based and risk-informed maintenance rather than only periodic reporting.

Figure 5 provides an illustrative comparison of how NDE capability and inspection-support maturity have evolved in aviation, nuclear, oil and gas, and civil infrastructure. The composite index reflects four enabling dimensions: inspection capability, code/regulatory maturity, data traceability and archiving, and monitoring/integration level. The figure is intended as a conceptual synthesis rather than a direct measurement of safety or accident rate.

Qualitative comparison of NDE maturity and inspection-support development across four industry sectors (1970–2025). Sector trajectories are placed on a four-level qualitative scale (foundational, developing, mature, advanced) synthesised from four equally weighted dimensions: inspection capability, code/regulatory maturity, data traceability and archiving, and monitoring/integration level. Band positions are indicative and reflect documented sector adoption histories—not measured values, accident rates, or failure-rate statistics. Trajectories are consistent with the inspection-reliability, in-service-inspection, and risk-based-inspection literature for the respective sectors.

Digital-twin implementations in airframes, turbines, wind assets, and civil infrastructure show that the concept is feasible, but they also demonstrate that a useful twin is not simply a software dashboard. It requires validated models, sensor governance, configuration control, data-quality rules, uncertainty treatment, and maintenance integration. For NDE, the key value of a digital twin is the ability to place inspection findings into an asset-specific degradation and risk context, not merely to store inspection files in a connected platform [45–49].

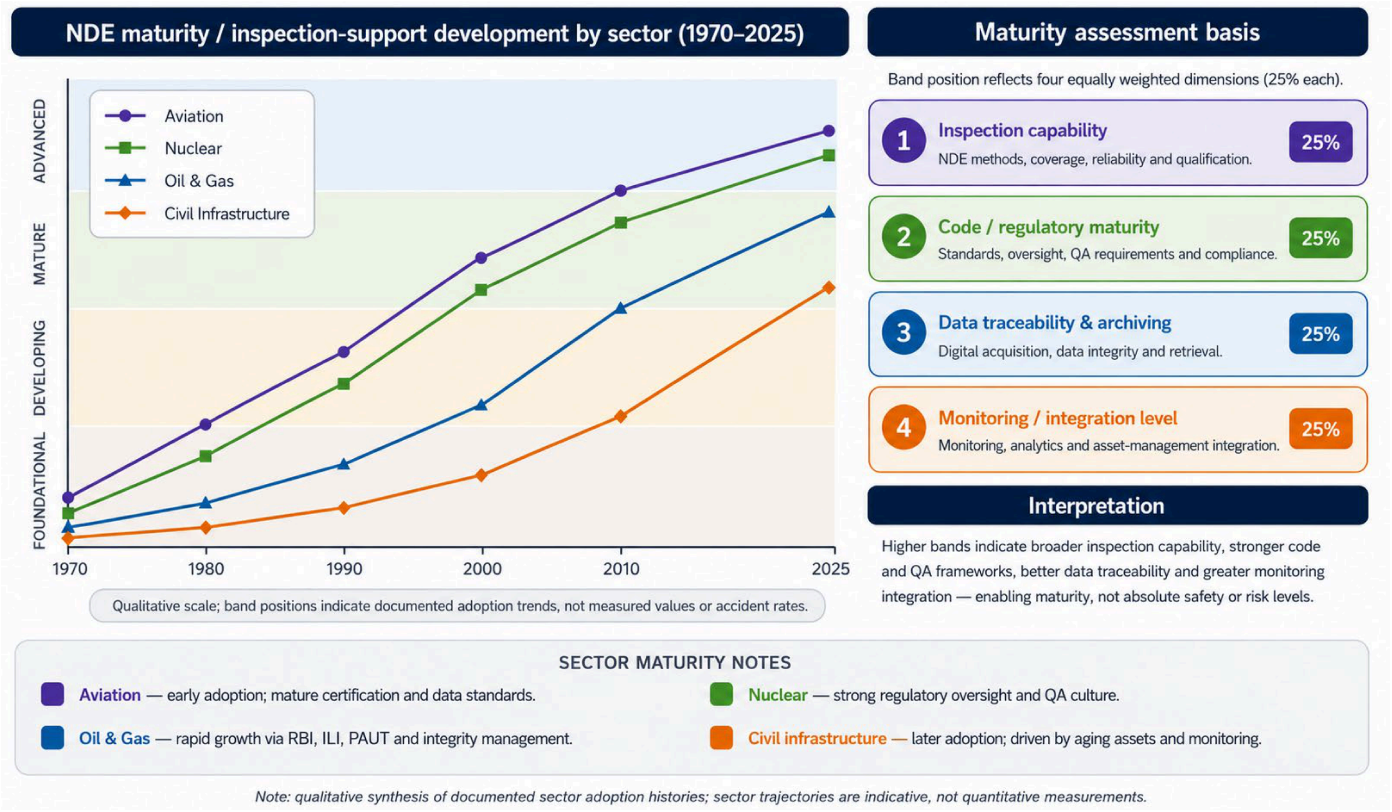


Figure 5. Conceptual illustration of NDE-enabled safety and inspection-maturity progression across major industry sectors (1970–2025).

6.4. Structural Health Monitoring (SHM) as Continuous NDE

SHM replaces the periodic, access-dependent inspection campaign with continuous embedded monitoring. PWAS, FBG optical sensors, AE arrays, and electrochemical corrosion sensors transmit diagnostic data over wireless mesh networks to centralised analysis platforms. The FAA's SHM-based Damage Tolerance roadmap for composite airframes represents the most emerging guidance for treating SHM as a primary inspection method—and the level of validation evidence it requires gives a realistic sense of what other industries will eventually face [50,51].

6.5. Autonomous and Semi-Autonomous Inspection Systems

Autonomous inspection platforms now combine SLAM, multi-beam sonar, LIDAR, and onboard NDE sensors to reach environments where a human cannot—GPS-denied nuclear vaults, confined-space tank interiors, live high-voltage substations, and subsea jacket structures. UAVs carrying ground-penetrating radar and PAUT probes have been demonstrated on bridge decks and aircraft fuselages. What these platforms have not yet solved is the gap between navigation autonomy and inspection decision autonomy: the robot reaches the location reliably, but the NDE data it collects still typically goes to a human analyst [52,53].

6.6. Edge and Cloud Computing for NDE Data

Data volume is no longer a theoretical concern. Encoded PAUT, FMC/TFM, radiographic imaging, ILI, and SHM networks can generate data at scales that exceed traditional report-based workflows. Edge computing can reduce bandwidth demand and support near-real-time screening, while cloud platforms support fleet-level analytics and long-term data retention. These benefits introduce governance questions that are not solved by com-

pute capacity alone: ownership of inspection data, model version control, cybersecurity, auditability, retention period, and liability for AI-assisted recommendations [54–56].

7. Cross-Generational Comparative Analysis

Table 2 summarises cross-generational maturity using conservative, application-dependent descriptors rather than unsupported universal performance values. Where numerical values appear, they should be treated as indicative examples that require method-specific qualification, not as general NDE performance guarantees.

Table 2. Comparative maturity of NDE generations across inspection-performance parameters. Quantitative entries are intentionally avoided or qualified where no single standardised dataset supports direct comparison across generations.

Parameter	NDE 1.0	NDE 2.0	NDE 3.0	NDE 4.0
Inspection reliability/POD evidence	Procedure- and operator-dependent; reliability must be demonstrated for each method and flaw class	Improved traceability and repeatability where digital records and qualified procedures are used	Higher repeatability for encoded/automated procedures when qualified for the target application	Potentially improved screening and consistency, but AI outputs require system-level validation before being treated as POD
Detectable flaw/sizing capability	Application-specific; limited by access, contrast, surface condition, and manual interpretation	Improved waveform and image storage support post-analysis and trending	Enhanced imaging and sizing for qualified PAUT, TOFD, TFM, CT, and guided-wave applications	Application-specific; AI may assist segmentation or classification but does not remove physics-based detectability limits
Inspection speed	Low; manual and access-dependent	Low to medium; digital acquisition improves record handling	Medium to high; encoded scanning and robotics reduce scan variability	Potentially high for screening, triage, and fleet analytics; constrained by validation and data governance
Automation level	None to very low	Partial digital acquisition and storage	High acquisition automation; human interpretation remains central	AI-assisted interpretation and connected workflows; autonomous acceptance remains limited
Operator dependence	Very high	High, with improved reviewability	Medium; reduced scanning variability but skilled analysis required	Lower for repetitive screening tasks, but qualified human oversight remains essential
Data volume per campaign	Low; paper, film, or analogue records	Moderate; stored waveforms and digital images	High; encoded scans, volumetric images, and robotic inspection files	Very high; multimodal streams, ILI, SHM, and digital-twin records

Table 2. *Cont.*

Parameter	NDE 1.0	NDE 2.0	NDE 3.0	NDE 4.0
Real-time decision capability	Generally no	Limited	Partial for automated acquisition and encoded imaging	Possible for monitoring and prioritisation; acceptance decisions need qualification
Predictive capability	None	Limited trending where records exist	Risk-informed trending in selected applications	Digital-twin and RBI/FFS integration possible where models and data are validated
Defect characterisation	Location and approximate size in favourable cases	Improved sizing and archiving	3D morphology in selected modalities and geometries	AI-assisted classification/segmentation possible; uncertainty must be reported
Regulatory maturity	Mature for established methods	Mature for many digital implementations	Mature for mainstream PAUT/TOFD and selected automated methods; newer methods require qualification	Emerging; AI-specific acceptance criteria are still limited and application-dependent
Cost profile	Low equipment cost but high labour and outage dependence	Moderate equipment and data-management cost	Higher equipment/training cost; potential savings through repeatability and reduced access time	Higher integration and governance cost; lifecycle value depends on avoided downtime, reduced false calls, and validated risk reduction

Note: POD, defect resolution, and sizing capability are strongly dependent on material, geometry, flaw morphology, access, procedure, equipment, calibration, operator competence, and qualification protocol. AI classification metrics should not be interpreted as POD-equivalent reliability evidence unless the complete inspection system has been validated under representative qualification conditions.

Figure 6 should therefore be interpreted as a conceptual maturity comparison rather than a quantitative benchmark, since actual inspection capability depends strongly on material, geometry, inspection method, and qualification procedure.

The apparent improvement from manual analogue inspection to automated and AI-assisted workflows should therefore be interpreted as a maturity trend, not as a universal numerical trajectory. Earlier NDE generations gained acceptance through decades of procedure qualification, personnel certification, and code incorporation. NDE 4.0 must pass through the same evidentiary filter. At present, AI is most defensible as decision support, triage, prioritisation, and analyst-assistance unless the full inspection system has been separately qualified for the intended acceptance decision [35,57,58].

Figure 7 outlines a comprehensive five-phase implementation roadmap for NDE 4.0, focusing on a risk-based approach to integration and continuous improvement. The roadmap starts with a detailed assessment and planning phase, progressing through foundation building, pilot validation, integration, and optimisation. Key activities, deliverables, and success metrics are included for each phase, with an emphasis on stakeholder engagement, digital foundation, and ongoing refinement of NDE processes to meet evolving industry needs. This structured approach ensures that NDE 4.0 deployments are effective, sustainable, and aligned with industry best practices.

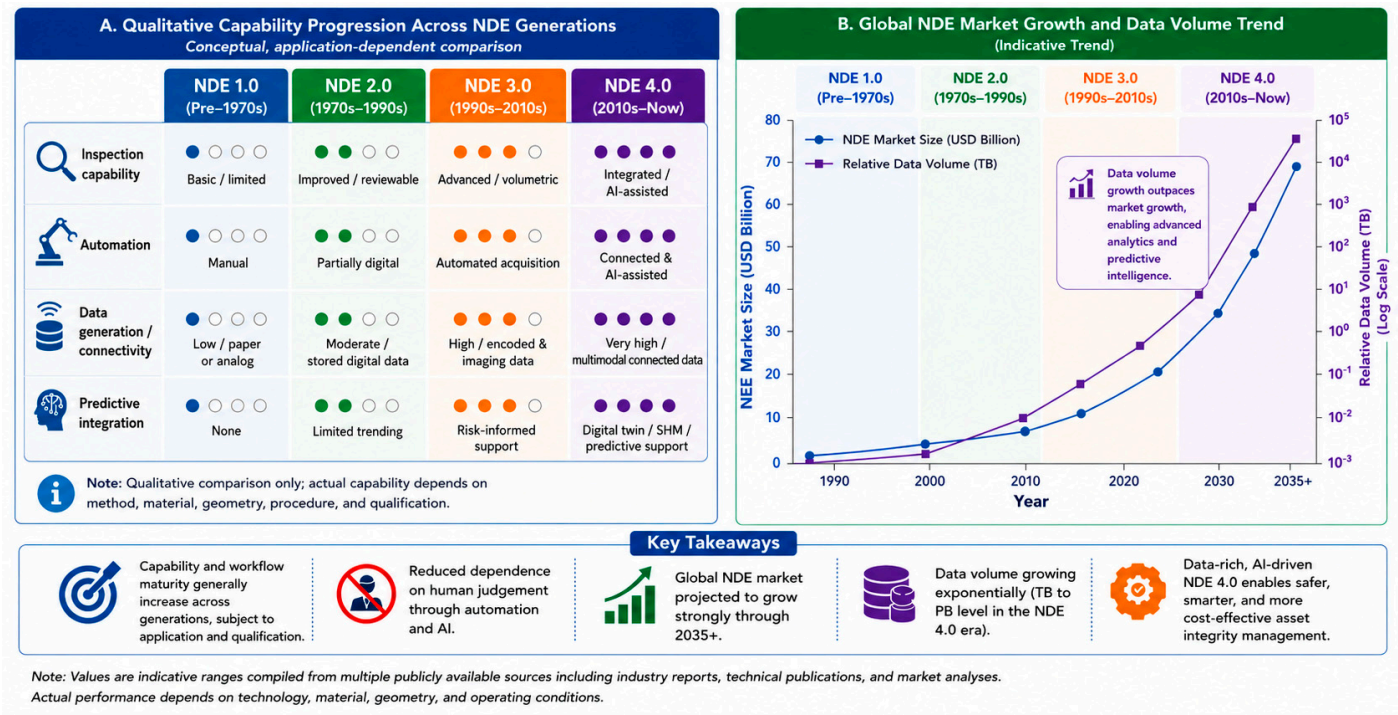


Figure 6. Conceptual comparison of inspection capability growth, automation, data generation, and predictive integration across NDE generations.

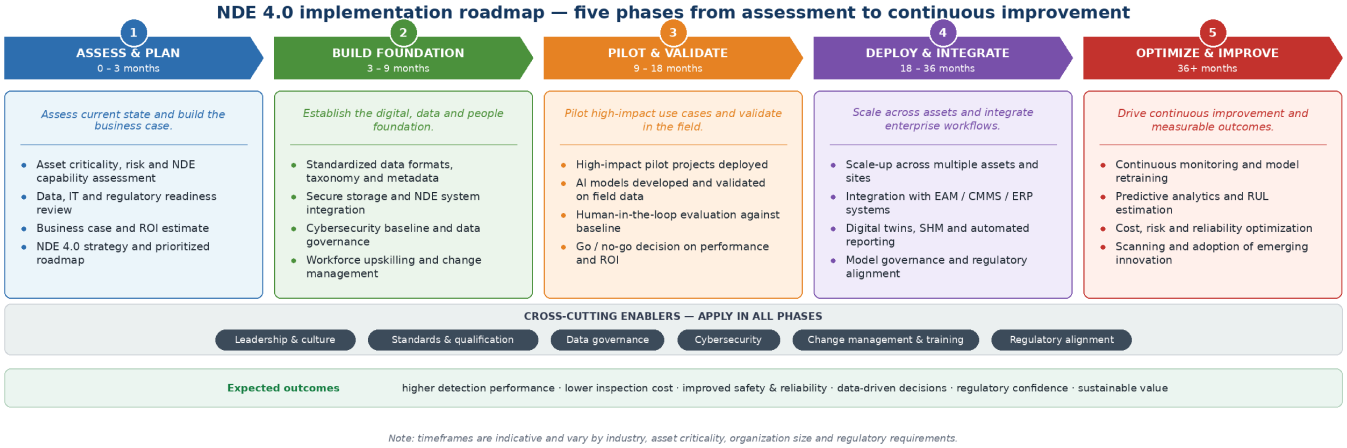


Figure 7. Implementation roadmap for NDE 4.0 in industry: A five-phase risk-based pathway from assessment to continuous improvement.

Each generation also widened the required skill profile. NDE 4.0 demands working knowledge of machine learning, data engineering, and digital-twin architecture—areas not yet covered comprehensively in current certification standards. Closing that gap through targeted upskilling is as strategically important as any algorithmic improvement. The following section examines the principal barriers constraining wider NDE 4.0 deployment and maps each against the most promising response strategies [57–59].

8. Current Challenges

Scope note: the following discussion focuses primarily on metallic structural inspection in industries commonly governed by ASME, API, DNV, ISO/EN, ENIQ-style qualification logic, and owner/operator procedures. Composite-dominant applications, civil infrastructure, nuclear-specific qualification, and non-Western regulatory systems are referenced only where they illuminate broader NDE 4.0 barriers.

The transition toward NDE 4.0 introduces several technical, operational, and regulatory challenges. Table 3 maps the principal challenges and the most promising responses. For clarity, this section is organised as a set of key challenges paired with their most promising response pathways, consolidating the technical, data-related, and regulatory barriers that recur across NDE 4.0 deployment [58–60].

Table 3. Key challenges facing NDE 4.0 implementation and associated emerging solutions.

Key Challenges	Impact	Emerging Solutions in AI-Enabled NDE Systems
Data Quality and Volume	Massive datasets from SHM and automated scanning overwhelm traditional pipelines	Cloud high-performance computing (HPC), edge AI, federated learning
Standardisation	Weak comparability across instruments, vendors, datasets, and studies	DICONDE/ASTM E2339-style data structures, shared benchmark datasets, qualification protocols
Physics-Informed AI	Pure data-driven models lack physical interpretability	PINN, hybrid physics-ML models
Digital Twin Fidelity	High-fidelity simulation is computationally costly	Surrogate modelling, reduced order model (ROM) approaches
Cyber-Security	Connected inspection data and SHM systems increase exposure to manipulation, data loss, and audit failure	Secure edge devices, access control, encryption, audit logs, model/version control, data provenance
Skill Gap	Workforce lacks combined NDE + data science expertise	Cross-disciplinary training programmes
Regulatory Acceptance	Limited use of AI as a primary accept/reject authority in high-consequence inspection	Explainable AI, locked-model validation, human-in-the-loop governance, POD/MAPOD-style qualification
Harsh Environments	Extreme temperature, pressure, radiation degrade sensors	Radiation-hardened electronics, wireless power

8.1. Data Standardisation and Interoperability

The absence of universally adopted, vendor-neutral data structures remains a practical obstacle to AI development and cross-platform validation. DICONDE, formalised through ASTM E2339, was created to support interoperability by harmonising NDE imaging data with DICOM-style concepts, but implementation remains uneven across modalities, vendors, and owner systems. NDE 4.0 requires not only stored images or waveforms, but also standardised metadata for procedure, probe, calibration, coordinate system, material, geometry, indication type, analyst decision, and ground-truth status [59,61].

8.2. Explainability and Regulatory Trust in AI

Safety-critical industries require traceable, auditable decisions. Explainability tools such as Grad-CAM, LIME, and SHAP can help analysts understand which regions or features influenced a model, but they do not automatically create a code-compliant acceptance pathway. For this reason, the more realistic near-term role for AI is assisted interpretation: prioritising indications, reducing analyst workload, supporting consistency checks, and flagging anomalous data for review by qualified personnel. Moving beyond that role will require formal qualification procedures that define training data controls, performance limits, failure modes, uncertainty, human oversight, and revalidation triggers [62,63].

8.3. Physics-Informed Model Development

Model-assisted POD (MAPOD) can extend reliability assessment by using validated simulations to supplement experimental data where full physical specimen programmes are impractical. Its credibility depends on how well the model represents the inspection physics, flaw morphology, material variability, noise, coupling, and geometry found in the target application. For AI-enabled NDE, MAPOD and physics-informed modelling are promising because they can reduce dependence on purely empirical datasets, but neither removes the need for representative field validation. The word "validated" carries weight here. Numerical models intended to feed MAPOD or to generate training data require their own validation campaigns—comparison against experimental signals across representative material grades, wall thicknesses, probe configurations, surface conditions, and defect morphologies. Without that campaign, simulation-derived POD curves should not be treated as production-ready, and AI models trained primarily on simulation outputs should not be qualified solely against simulation-based reference data [64,65].

8.4. Cybersecurity and Data Integrity

Connecting SHM networks to plant control systems introduces attack surfaces that previous NDE generations simply did not have. Compromised inspection or monitoring data could adversely affect integrity assessments, maintenance prioritisation, and operational decision-making. Blockchain-based data provenance, secure hardware attestation, and federated learning have all been proposed as countermeasures, but deployment at industrial scale is still limited. The cybersecurity posture of most operating NDE 4.0 installations lags well behind the threat landscape [66,67].

8.5. Workforce Transition

The skill set NDE 4.0 requires—machine learning, data engineering, systems integration alongside traditional NDE physics and signal processing—was not what any existing certification scheme was built around. BINDT, ASNT, and EFNDT are revising their competency frameworks, but curriculum development moves more slowly than technology adoption. The workforce gap is not a training inconvenience; it is a real deployment constraint that limits how quickly even technically mature NDE 4.0 capabilities can be put into field operation [68,69].

8.6. Limitations and Failure Modes of NDE 4.0 Technologies

This subsection is intentionally retained as a consolidating synthesis rather than as an additional, separate challenge. It draws together the failure modes that recur across Sections 8.1–8.5—limited interoperability, weak explainability, immature physics-informed validation, cybersecurity exposure, and the workforce gap—and examines a common cross-cutting mechanism behind many of them: domain shift between training and field conditions, together with the domain-adaptation responses now being investigated to narrow it. In this sense, Section 8 should be read as a set of key challenges paired with their response pathways, with the present subsection providing the closure of that discussion.

A model trained on one inspection population—for example, carbon-steel weld B-scans acquired with a specific probe, procedure, and instrument—should not be assumed to generalise to titanium components, composite laminates, additively manufactured nickel alloys, or different weld processes without validation. This is the practical meaning of domain shift in NDE. Labelled defect data are also scarce because ground truth often requires destructive sectioning, controlled manufacturing of representative flaws, or long-term service follow-up. These realities limit the speed at which AI can move from research prototype to qualified industrial tool. Several technical responses to domain shift are now

active research areas in NDE. Unsupervised domain adaptation aligns feature distributions between a labelled source domain (for example, lab data) and an unlabelled target domain (field data) without requiring matched ground truth in the target. Adversarial domain-adversarial neural networks, correlation alignment, and maximum mean discrepancy losses have all been demonstrated on ultrasonic and radiographic data. Style transfer methods translate source-domain images to match target-domain statistics, which can mitigate appearance shifts caused by different probes, instruments, or surface conditions. Physics-constrained augmentation uses simulation-derived priors to enrich training data while keeping outputs physically plausible. Studies (provide a particularly clear critical treatment of CNN overfitting and generalisation limits in automated ultrasonic NDE; their analysis underlines why domain adaptation alone does not eliminate the need for representative field validation. These techniques have not yet become broadly standardised in regulated NDE acceptance procedures, but they are the most plausible near-term routes to narrowing the lab-versus-field gap [36,70–72].

9. Future Prospects

Several emerging technology areas are expected to influence the future development of intelligent inspection systems, although their maturity levels remain highly application-dependent. Figure 8 should therefore be interpreted as a roadmap of opportunity rather than a prediction of uniform industrial adoption.

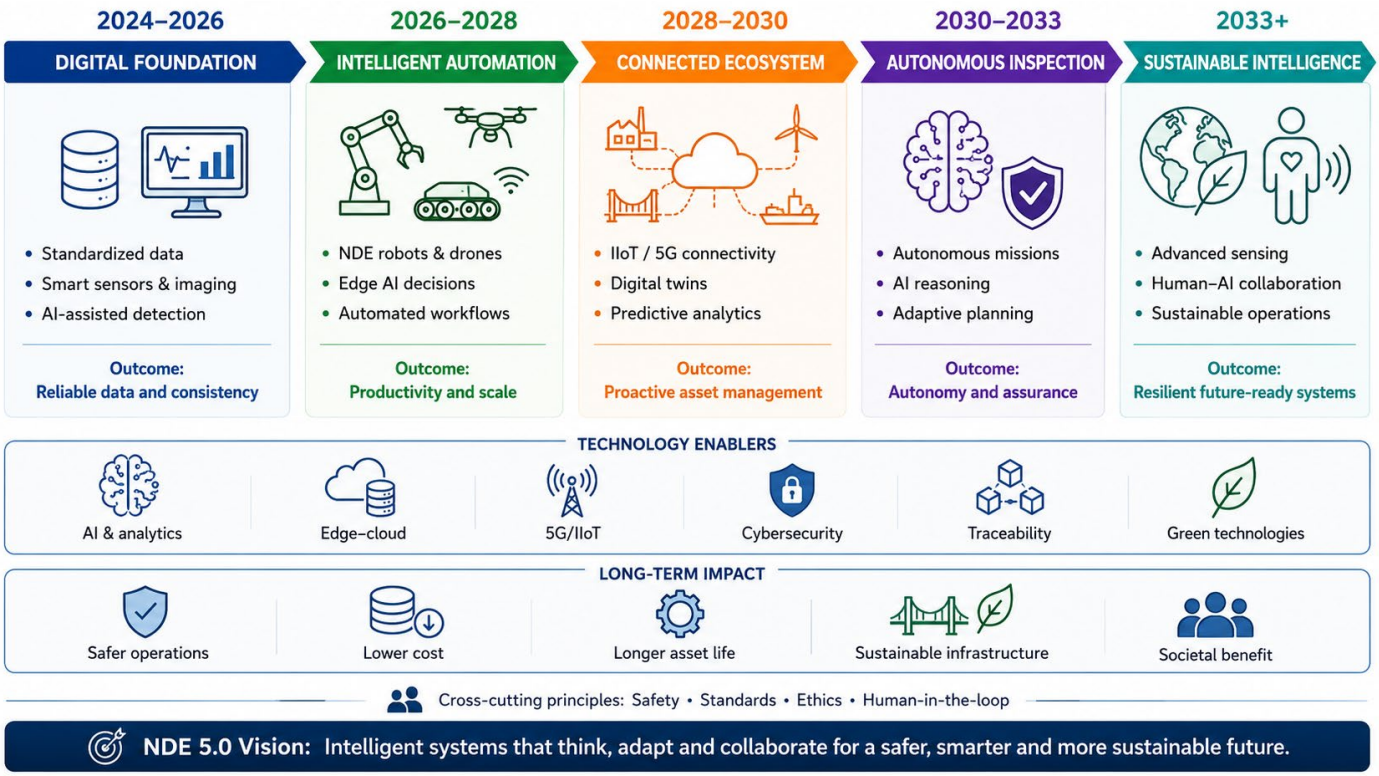


Figure 8. Emerging technology roadmap for future NDE systems, showing major innovation clusters and indicative technology-readiness progression toward 2040.

Figure 8 illustrates that future NDE evolution will likely depend on the convergence of AI, robotics, quantum sensing, and multi-modal sensor fusion technologies rather than a single dominant pathway.

The horizontal axis presents in Figure 8 indicative deployment time horizons, used here as a qualitative proxy for technology-readiness progression; discrete technology-readiness-level (TRL) values are intentionally not assigned because the readiness of each

cluster is strongly application-dependent and no single TRL figure would hold across the modalities, environments, and defect targets represented.

9.1. Quantum Sensing and Imaging

Quantum sensing, including nitrogen-vacancy-centre diamond magnetometry and atom-interferometric gravimetry, offers sensitivity advantages for selected magnetic-field and subsurface-mapping problems. Most structural NDE applications remain at an early adoption stage and claims of near-term routine industrial use should be avoided unless they are tied to a specific demonstrated modality, environment, and defect target [73,74].

9.2. Autonomous Robotic Inspection Swarms

Single inspection robots are now commercial. The next step is coordinated swarms—multiple miniaturised autonomous agents mapping and inspecting large structures simultaneously. On an offshore platform, a long-span bridge, or a nuclear decommissioning facility, swarm inspection could compress a multi-week campaign into hours. The technical challenges are non-trivial: inter-agent coordination, data fusion across overlapping scan zones, and safe operation in confined or cluttered environments. But the potential inspection economics are compelling enough that active development programmes exist [75–77].

9.3. Multi-Modal Sensor Fusion

Every NDE modality has blind zones and false-call mechanisms. Multi-modal fusion can improve reliability when the combined measurements are complementary and when registration, calibration, and uncertainty propagation are handled rigorously. Transformer and attention-based architectures are promising for heterogeneous data streams, but their value must be demonstrated against baselines and validated on inspection conditions that represent intended deployment [78,79].

9.4. 4D NDE and In Situ Process Monitoring

4D NDE—time-resolved volumetric imaging—can reveal the evolution of cracks, corrosion, fatigue damage, and additive-manufacturing defects rather than only their final state. Synchrotron and advanced laboratory XCT systems are important research platforms, but routine industrial deployment remains limited by access, scan time, component size, radiation safety, reconstruction speed, and cost [80,81].

9.5. Integration with Additive Manufacturing Quality Assurance

AM scatters defect populations through complex volumetric geometries that conventional post-build NDE struggles to interrogate fully. The NDE 4.0 response is to move inspection into the build process itself: AE monitoring, melt-pool optical emission sensing, and in situ X-ray imaging during layer deposition. The leading edge is closed-loop process control, where in situ NDE signals feed back directly into build parameter adjustments to suppress defect formation in real time. This integration of inspection and manufacturing is conceptually different from anything in NDE 1.0 through 3.0 [82–84].

10. Case Study: NDE Evolution in the Oil and Gas Industry

Before tracing the sector chronology, it is useful to map each NDE generation in oil and gas directly onto the challenges identified in Section 8, so that this case study functions as a test of those challenges rather than only as a technology history (Figure 9). NDE 1.0 was limited primarily by operator dependence and the absence of traceable records—the very issues that later motivated formal reliability assessment and data standardisation. NDE 2.0 introduced digital records, TOFD, and the first POD and qualification culture, but left the

interoperability problem of Section 8.1 unresolved through proprietary in-line inspection and instrument data formats. NDE 3.0 delivered encoded PAUT/AUT, guided-wave screening, and robotic delivery, raising repeatability and coverage but also the data-volume and skilled-interpretation burdens discussed in Sections 8.5 and 8.6. NDE 4.0 in oil and gas is now constrained less by sensing capability than by the institutional and evidentiary barriers of Section 8: domain shift is visible in the variation in AI-assisted in-line inspection false-call and sizing performance across different pipelines, vintages, and product streams; explainability and regulatory acceptance (Section 8.2) confine AI to an advisory role in excavation and fitness-for-service decisions; and cybersecurity exposure (Section 8.4) grows as monitoring data is connected to integrity-management systems. The subsections below follow the sector chronology with these mappings in mind.

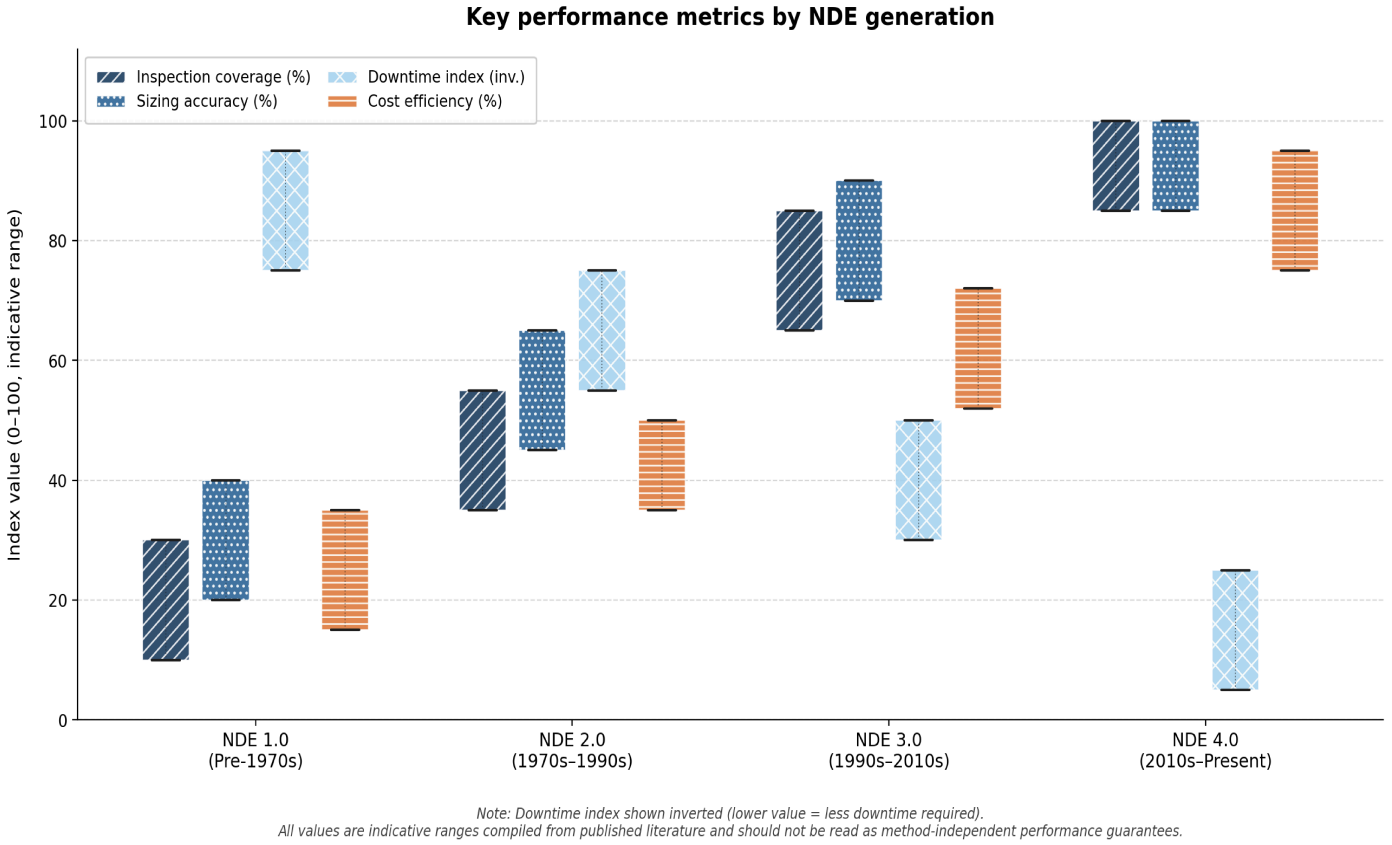


Figure 9. Key performance metrics for NDE evolution in the oil and gas sector. Note: indicative inspection coverage, sizing accuracy, required downtime, and relative cost efficiency are shown by generation. The downtime index is inverted so that a higher plotted value represents lower required downtime. All values are indicative ranges from the cited literature and should not be read as method-independent performance guarantees.

The oil and gas sector is a strong test case for NDE generational progression because pipelines, pressure vessels, storage tanks, risers, and subsea systems operate under interacting corrosion, fatigue, pressure, temperature, and environmental loads. Major incidents such as Piper Alpha, Buncefield, and Deepwater Horizon reinforced the need for robust integrity management, but this review avoids implying that any single event can be attributed only to NDE practice. The broader lesson is that inspection evidence, risk-based prioritisation, and fitness-for-service assessment have become central to safe operation. The oil and gas sector provides a particularly relevant case study for NDE generational analysis because it combines long asset lifecycles, high inspection volumes, harsh operating environments, mature integrity-management frameworks, and strong regulatory over-

sight. The sector also spans a wide range of inspection challenges, including long-distance pipeline monitoring, subsea inspection, corrosion management, hazardous-area operation, and fitness-for-service assessment. These characteristics make oil and gas one of the most representative environments for evaluating the practical deployment maturity of NDE 4.0 technologies. There are three reasons: first, the sector spans all four NDE generations across an unusually long and documented operating timeline (roughly 70 years). Second, it carries the widest range of inspection challenges encountered anywhere—long-distance in-line inspection, subsea access, corrosion-dominated degradation, high-pressure piping, hazardous-area constraints, and regulatory change driven by named incidents. Third, longitudinal data on inspection programmes, regulatory response, and integrity outcomes are more accessible in the public domain than for comparable industries. The brief cross-sector picture is similar in direction but not in pace. Aerospace and nuclear adopted formal POD qualification frameworks (MIL-HDBK-1823A and ENIQ respectively) earlier than oil and gas, and both maintain stricter procedural conservatism around AI use. Civil infrastructure has moved fastest on UAV-based visual and image-based AI inspection but lags the regulated industries on formal qualification frameworks. A full multi-sector comparative analysis is beyond the scope of this review; the points relevant to NDE 4.0 are that conservatism is not unique to oil and gas, and that AI uptake in any high-consequence sector is being set by similar evidentiary requirements rather than by algorithmic capability alone [1,6,13,85].

10.1. NDE 1.0 in Oil and Gas (Pre-1970s)

Post-war oil-and-gas inspection relied heavily on radiographic film, manual MPI/LPT, visual examination, thickness gauging, and pit assessment. The approach was largely periodic and access-dependent. In many applications, equipment was inspected during scheduled outages or when degradation was suspected, and decision quality depended strongly on inspector competence, procedure discipline, surface access, and record quality [86–88].

10.2. NDE 2.0 in Oil and Gas (1970s–1990s): Digital Inspection and the Birth of Smart Pigging

The expansion of long-distance pipelines, offshore production, and integrity regulation increased demand for in-service inspection during the 1970s–1990s. In-line inspection tools using magnetic flux leakage and ultrasonic technologies became central to pipeline integrity management because they could screen long segments without full excavation. Digital UT and TOFD also improved record retention and flaw-sizing capability for pressure-boundary welds. Specific detection thresholds and sizing accuracy should be stated only for a defined ILI tool, wall thickness, defect morphology, velocity, and validation dataset [88–90].

10.3. NDE 3.0 in Oil and Gas (1990s–2010s): Phased Array, Guided Waves, and Robotic Deployment

Refs. [91–94] show that three capabilities defined NDE 3.0 in oil and gas: encoded PAUT/AUT for pipeline and pressure-boundary welds, guided-wave screening for access-limited corrosion threats such as CUI and road crossings, and robotic or remotely operated delivery for subsea and hazardous environments. These methods improved repeatability and coverage, but they did not remove the need for procedure qualification, calibration, skilled data interpretation, and confirmatory inspection where screening tools identified suspect areas.

10.4. NDE 4.0 in Oil and Gas (2010s–Present): AI, Digital Twins, and Autonomous Inspection

Refs. [88,95] show that NDE 4.0 is gradually shifting oil-and-gas integrity management from periodic, access-driven campaigns toward data-assisted and risk-informed decision cycles. High-resolution ILI permanently installed sensors, UAV/ROV/AUV inspection,

cloud-based data management, and AI-assisted anomaly classification can reduce analyst burden and improve prioritisation. However, AI-derived excavation calls, repair decisions, or fitness-for-service inputs still require validation against conventional analysis, field verification, destructive evidence where available, and owner/operator acceptance criteria.

Refs. [96–98] show that oil and gas also have matured risk-based inspection and fitness-for-service practice through frameworks such as API RP 580/581 and API 579-1/ASME FFS-1. These frameworks are compatible with NDE 4.0 because they already link inspection evidence to probability of failure, consequence, remaining life, and repair planning. The practical route for AI is therefore likely to be incremental: first as analyst assistance and anomaly prioritisation, then as a validated input to RBI/FFS workflows, and only later—where evidence supports it—as part of a qualified acceptance decision. Summary of NDE techniques and their O&G applications across four generations are shown in Table 4.

Table 4. Summary of NDE techniques and their O&G applications across four generations.

Generation	Key NDE Techniques	O&G Applications	Key Advances/Limitations
NDE 1.0 (Pre-1970s)	Radiographic film, manual MPI/LPT, visual inspection, pit gauging	Pressure vessel weld QA, storage tank floor inspection, process pipework	High operator dependence; no in-service capability; reactive approach
NDE 2.0 (1970s–90s)	Smart pig MFL/UT ILI, digital UT thickness mapping, TOFD, EC tubing inspection	Long-distance pipeline surveying, offshore riser welds, heat exchanger tubing	First quantitative coverage of long pipelines; data archiving; POD frameworks
NDE 3.0 (1990s–2010s)	PAUT AUT girth welds, guided wave CUI screening, ROV-mounted probes, XCT	Pipeline construction QA, CUI detection, subsea structure inspection	Automated volumetric imaging; guided wave CUI breakthrough; subsea robotics
NDE 4.0 (2010s–Now)	AI-assisted ILI analysis, digital twins (RBI/FFS), autonomous UAV/AUV, AE networks	Fleet-wide integrity management, anomaly prioritisation, targeted monitoring, risk-informed maintenance planning	Data-assisted and predictive workflows; AI supports classification and prioritisation but requires validation for acceptance decisions

11. Conclusions

NDE 4.0 represents the convergence of AI, connected sensors, robotics, cloud/edge computing, and digital twins. Its value is not simply faster defect detection; its more important contribution is the possibility of linking inspection evidence to asset-specific degradation, risk, and maintenance decisions. This review shows that the transition is technically credible but unevenly qualified. Conventional NDE methods earned industrial acceptance through decades of codification, personnel certification, and reliability demonstration. AI-enabled NDE must meet a comparable burden of evidence.

Four conclusions follow. First, NDE generations overlap in practice; manual, digital, automated, and AI-assisted methods will coexist for the foreseeable future. Second, AI performance metrics should not be presented as POD unless the full inspection system has been evaluated through an appropriate reliability framework. Third, the limiting barriers for NDE 4.0 are now as much institutional and evidentiary as computational: benchmark data, domain-shift control, explainability, cybersecurity, interoperability, and regulatory qualification. Fourth, high-consequence sectors such as oil and gas will adopt AI-enabled NDE only where field evidence, auditability, and liability allocation are clear. The pathway to wider adoption is therefore not stronger claims, but better validation: representative datasets, transparent model documentation, controlled comparison with

qualified methods, uncertainty reporting, and standards that define when AI may support or influence acceptance decisions.

Future progress in NDE 4.0 will likely depend less on incremental improvements in standalone AI accuracy and more on the development of standardised qualification frameworks, representative benchmark datasets, uncertainty-aware models, interoperable data architectures, and transparent validation procedures acceptable to regulators and owner-operators. From a practical standpoint, industrial users should prioritise deploying AI-enabled NDE first in well-bounded, lower-risk applications where representative validation datasets exist and human expert oversight is retained. Model version control, auditable decision logs, defined revalidation triggers, and cybersecurity controls should be in place before extending AI to acceptance-critical decisions. Workforce development—combining NDE physics with data science competence—is as strategically important as any algorithmic advancement.

A final implication runs through every generation examined here and becomes more important, not less, in NDE 4.0. No inspection method—film or digital radiography, conventional or phased-array ultrasonics, TFM/FMC, or AI-assisted analysis—achieves a 100% probability of detection; detection remains a statistical curve, and field realities such as restricted access, coupling variation, scanning speed, and operator fatigue push real-world POD below the values demonstrated under laboratory qualification. Artificial intelligence, machine learning, digital twins, and connected sensing improve consistency, throughput, and data richness, but they do not convert that probability into a guarantee. No organisation is therefore truly "covered" simply because it performs 100% inspection, however advanced the toolset. The more defensible posture is to treat NDE not as a pass/fail gate but as a continuous-improvement instrument: inspection records are process data, and trending defect type, location, and rate against defined investigation limits converts each finding into an early warning of upstream process drift. Used this way, the greatest contribution of NDE 4.0 may be less about catching the next defect and more about feeding inspection intelligence back into production so that fewer defects are created in the first place—precisely where the residual risk left by imperfect POD is most effectively reduced. This reframing complements rather than replaces the validation and qualification priorities set out above: dependable field performance is earned both by qualifying the inspection system and by using its output to improve the process that produces the flaws.

This review primarily focuses on metallic structural inspection applications commonly encountered in the oil and gas, aerospace, manufacturing, and infrastructure sectors. Composite-specific qualification, nuclear-sector licencing requirements, and highly specialised modality-specific implementations are discussed only where directly relevant to the broader NDE 4.0 transition.

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Abbreviations

The following abbreviations are used in this manuscript:

AE	Acoustic Emission
AI	Artificial Intelligence
AUT	Automated Ultrasonic Testing
AUV	Autonomous Underwater Vehicle
cGAN	Conditional Generative Adversarial Network
CNN	Convolutional Neural Network
CUI	Corrosion Under Insulation
DVI	Direct Visual Inspection
ECT/ECA	Eddy Current Testing/Eddy Current Array
FFS	Fitness-for-Service
FMC	Full Matrix Capture
GAN	Generative Adversarial Network
GWT	Guided Wave Testing
HPC	High-Performance Computing
IIoT	Industrial Internet of Things
ILI	In-Line Inspection (intelligent pig)
LIDAR	Light Detection and Ranging
LPT	Liquid Penetrant Testing
MAPOD	Model-Assisted Probability of Detection
MFL	Magnetic Flux Leakage
MPI	Magnetic Particle Inspection
NDE/NDT/NDI	Non-Destructive Evaluation/Testing/Inspection
PAUT	Phased Array Ultrasonic Testing
PINN	Physics-Informed Neural Network
POD	Probability of Detection
RBI	Risk-Based Inspection
ROM	Reduced Order Model
ROV	Remotely Operated Vehicle
RUL	Remaining Useful Life
SHM	Structural Health Monitoring
SLAM	Simultaneous Localization and Mapping
TFM	Total Focusing Method
TOFD	Time-of-Flight Diffraction
UAV	Unmanned Aerial Vehicle (drone)
UT	Ultrasonic Testing
VAE	Variational Autoencoder
XCT	X-ray Computed Tomography

References

1. Dasgupta, A.; Sarkar, D.; Podder, S. *Recent Trends in non Destructive Testing and Evaluation in Civil Engineering*; Iterative International Publishers Selfypage Developers Pvt Ltd.: Chikkamagaluru, India, 2024. [CrossRef]
2. Bond, L.J. Through the Looking Glass: The Future for NDE? *AIP Conf. Proc.* **2014**, *1581*, 21. [CrossRef]
3. Smith, J.A.; Ramos, H.G. TC-01: Nondestructive Evaluation and Industrial Inspection (NDE & amp; II). *IEEE Instrum. Meas. Mag.* **2023**, *26*, 3. [CrossRef]
4. Vrana, J.; Meyendorf, N.; Ida, N.; Singh, R. *Introduction to NDE 4.0*; Springer: Berlin/Heidelberg, Germany, 2022. [CrossRef] [PubMed]
5. Tiwari, S.; Balasubramaniam, K.; Ananthanarayanan, R. NDE4.0 in Action—Driving Operational Efficiencies Through Unified Digital Platforms. *e-J. Nondestruct. Test.* **2025**, *30*, 1435–4934. [CrossRef]
6. Sunil, P.; Chandu, P.; Vivek, D. A review: Non-destructive testing (ndt) techniques, applications and future prospects. *J. Sci. Technol.* **2024**, *9*, 9–15. [CrossRef]
7. Chen, B. Exploring the Future of Ai in Industrial Automation Development. *IET Conf. Proc.* **2024**, *24*, 282. [CrossRef]
8. Venkatraman, B.; Raj, B. Nondestructive Testing. *Overv. Tech. Appl. Qual. Eval.* **2019**, *1*, 1–55. [CrossRef]
9. Moussa, J.R.; Harmon, D.; Rane, S. Industrial Radiography: Trends, Market Drivers, and Alternatives to Gamma-based Devices. *Health Phys.* **2025**, *129*, 174. [CrossRef] [PubMed]
10. Schall, W.E. Techniques of Non-destructive Testing. *Br. J. Radiol.* **1961**, *34*, 639. [CrossRef]
11. Brown, J. There's More to NDT Reliability than POD—And Statistics Plays a Role. In Proceedings of the ASNT Research Symposium 2023, Columbus, OH, USA, 1 January 2023. [CrossRef]
12. Crane, R.L.; Dillingham, G. Nondestructive Inspection. In *Mechanical Engineers' Handbook*; John Wiley & Sons: Hoboken, NJ, USA, 2015. [CrossRef]
13. Li, W.; Kundu, T. *Nondestructive Evaluation (NDE) of Materials and Structures from Production to Retirement*; CRC Press: Boca Raton, FL, USA, 2018. [CrossRef]
14. Bossi, R.H.; Georgeson, G.E. The application of X-ray computed tomography to materials development. *JOM* **1991**, *43*, 8–15. [CrossRef]
15. Lysenko, I.; Kuts, Y.; Uchanin, V.; Mirchev, Y.; Levchenko, O. Evaluation of Eddy Current Array Performance in Detecting Aircraft Component Defects. *Trans. Aerosp. Res.* **2024**, *2024*, 1–9. [CrossRef]
16. *ASTM E2373/E2373M-19(2024)*; Practice for Use of the Ultrasonic Time of Flight Diffraction (TOFD) Technique. ASTM: West Conshohocken, PA, USA, 2024. [CrossRef]
17. Lei, X.; Wirdelius, H.; Rosell, A. Simulation-Based Investigation of a Probability of Detection (POD) Model Using Phased Array Ultrasonic Testing (PAUT) Technique. *J. Nondestruct. Eval.* **2022**, *41*, 40. [CrossRef]
18. Guo, Y.; Yang, K. Composite Non-Destructive Evaluation System for Probability of Detection Assessment. *Int. J. Qual. Eng. Technol.* **2011**, *2*, 29. [CrossRef]
19. Uzun, H.; Gustiani, D. Review of Phased Array Ultrasonic Testing of Weld Joints. *J. Mar. Eng. Technol.* **2024**, *4*, 77–92. [CrossRef]
20. Haworth, W. The Evolution of Weld Inspection: Unlocking the Potential of Phased Array Ultrasonic Testing. *Mater. Eval.* **2024**, *82*, 32–37. [CrossRef]
21. Dolmatov, D.O.; Zhvyrblya, V.Y. Optimal Design of Sparse Matrix Phased Array Using Simulated Annealing for Volumetric Ultrasonic Imaging with Total Focusing Method. *Sensors* **2024**, *24*, 1856. [CrossRef] [PubMed]
22. Ingram, M.; Gachagan, A.; Nordon, A.; Mulholland, A.J.; Hegarty, M. Calibration of Ultrasonic Hardware for Enhanced Total Focusing Method Imaging. *Insight—Non-Destr. Test. Cond. Monit.* **2020**, *62*, 408–415. [CrossRef]
23. Tavossi, H.M. Nondestructive Inspection of In-Service Pipelines by Guided Ultrasonic Waves. *J. Acoust. Soc. Am.* **2006**, *119*, 3336. [CrossRef]
24. Raghu, D.; Figueroa, H.; Whittington, L.; Haupt, J. Experience with Torsional Guided Wave Ultrasonic Technique for the Inspection of Offshore Pipeline Installations. In Proceedings of the CORROSION 2004, New Orleans, LA, USA, 27 March–1 April 2004. [CrossRef]
25. Lee, P.-H.; Yang, S.-K. *Defect Inspection of Complex Structure in Pipes by Guided Waves*; Springer: Dordrecht, The Netherlands, 2010. [CrossRef]
26. Ibarra-Castanedo, C.; Grinzato, E.; Marinetti, S.; Bison, P.; Avdelidis, N.; Grenier, M.; Piau, J.-M.; Bendada, A.; Maldague, X. Quantitative Assessment of Aerospace Materials by Active Thermography Techniques. In Proceedings of the 9th International Conference on Quantitative InfraRed Thermography, Kraków, Poland, 2–5 July 2008. [CrossRef] [PubMed]
27. Avdelidis, N.P.; Ibarra-Castanedo, C.; Marioli-Riga, Z.P.; Bendada, A.; Maldague, X.P.V. A Study of Active Thermography Approaches for the Non-Destructive Testing and Evaluation of Aerospace Structures. *Proc. SPIE* **2008**, *6939*, 693918. [CrossRef]
28. Carpenter, C. Robotic Technology Enables Automated Nondestructive Weld Inspection in Subsea Zone. *J. Pet. Technol.* **2024**, *76*, 109–111. [CrossRef]

29. AL Rashed, M.; Kimball, M.; Vega, L.; Vera, D.; Soler, J.; Correa, M.; Garcia, A.; Virk, G.S.; Sattar, T.P. Climbing Robots for NDT Applications. Clawar 2017. In *Human-Centric Robotics*; Word Scientific: Singapore, 2017. [CrossRef]
30. Engelbrecht, A.; Saleh, V.; Rahman, M. *Industry 4.0—Perspectives and Applications*; IntechOpen: London, UK, 2023. [CrossRef] [PubMed]
31. Rani, S.; Bhambri, P. *Industry 4.0*; CRC Press: Boca Raton, FL, USA, 2024. [CrossRef]
32. Safhi, A.E.M.; Keserle, G.C.; Blanchard, S.C. AI-Driven Non-Destructive Testing Insights. *Encyclopedia* **2024**, *4*, 1760–1769. [CrossRef]
33. Chen, C.H. *Applications of Artificial Intelligence in Nondestructive Evaluation*; Springer Nature: Dordrecht, The Netherlands, 1994. [CrossRef]
34. Schulenburg, L. Artificial Intelligence in Digital Radiography. *e-J. Nondestruct. Test.* **2025**, *30*, 31297. [CrossRef] [PubMed]
35. *Applied Artificial Intelligence for Industrial Nondestructive Evaluation NDE4.0*; Multidisciplinary Digital Publishing Institute: Basel, Switzerland, 2025. [CrossRef]
36. Cantero-Chinchilla, S.; Wilcox, P.D.; Croxford, A.J. Deep learning in automated ultrasonic NDE–developments, axioms and opportunities. *NDT E Int.* **2022**, *131*, 102703. [CrossRef]
37. Salehi, A.W.; Khan, S.; Gupta, G.; Alabduallah, B.I.; Almjally, A.; Alsolai, H.; Siddiqui, T.; Mellit, A. A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope. *Sustainability* **2023**, *15*, 5930. [CrossRef]
38. Alzubaidi, L.; Duan, Y.; Al-Dujaili, A.; Ibraheem, I.K.; Ahmed, H.A.; Santamaría, J.; Fadhel, M.A.; Al-Shamma, O.; Zhang, J. Deepening into the Suitability of Using Pre-Trained Models of ImageNet against a Lightweight Convolutional Neural Network in Medical Imaging: An Experimental Study. *PeerJ Comput. Sci.* **2021**, *7*, e715. [CrossRef] [PubMed]
39. Mohamed Salem, M.Y. Physics-Informed Machine Learning: Bridging Data-Driven Models and Physical Laws. *Authorea* **2025**, *preprints*. [CrossRef]
40. Li, Z. A Review of Physics-Informed Neural Networks. *Appl. Comput. Eng.* **2025**, *133*, 165. [CrossRef]
41. Thawon, I.; Vo, D.; Bui, T.Q.; Rattanamongkhonkun, K.; Chamroon, C.; Tippayawong, N.; Mona, Y.; Wanison, R.; Suttakul, P. Physics-Informed Neural Networks: Current Progress and Challenges in Computational Solid and Structural Mechanics. *Comput. Model. Eng. Sci.* **2026**, *138*, 2. [CrossRef]
42. Mohseni, E.; Mcknight, S.; Loukas, C.; Pierce, S.G.; O'Hare, T.; Mackinnon, C.; Macleod, C. GANs and Alternative Methods of Synthetic Noise Generation for Domain Adaption of Defect Classification of Non-Destructive Ultrasonic Testing. *arXiv* **2023**, arXiv:2306.01469. [CrossRef]
43. Gosswami, B.M.; Chanda, R.K.; Wittenberg, T. Synthetic X-Ray Image Generation for Non-Destructive Testing Using Generative Adversarial Networks. *e-J. Nondestruct. Test.* **2024**, *29*, 29930. [CrossRef]
44. Posilović, L.; Medak, D.; Subašić, M.; Budimir, M.; Lončarić, S. Generative adversarial network with object detector discriminator for enhanced defect detection on ultrasonic B-scans. *Neurocomputing* **2021**, *459*, 361–369. [CrossRef]
45. Ospina-Bohórquez, A.; López-Rebollo, J.; Muñoz-Sánchez, P.; González-Aguilera, D. A Digital Twin for Monitoring the Construction of a Wind Farm. *Infrastructures* **2023**, *8*, 10. [CrossRef]
46. Daraki, M.-S.; Mina, B.; Almasoudi, M.; Charalambidi, B.; Mančić, M.; Junlin, H.; Baniotopoulos, C. Applications and Challenges of Digital Twins of Floating Wind Turbines. *SimTerm Proc.* **2024**, 53–60. [CrossRef]
47. Govindasamy, A. Building Digital Twins. *Zenodo* **2022**, *ahead of print*. [CrossRef]
48. Thomas, L.; Kernicky, T.; Whelan, M.; Park, Y.; Cox, R. *Application of a Structural Digital Twin on a Laboratory Model for Performance Monitoring of Aging and Degradation*; Pakzad, S., Ed.; Springer Nature Switzerland: Cham, Switzerland, 2023; Volume 2, pp. 11–18. [CrossRef]
49. Smarsly, K.; Peralta, P.; Dragos, K.; Ahmad, M.E.; Al-Zuriqat, T.; Geck, C.C.; Al-Nasser, H. A Multivocal Literature Review of Digital Twins, Architectures, and Elements in Civil Engineering. *e-J. Nondestruct. Test.* **2024**, *29*, e29579. [CrossRef] [PubMed]
50. Sundaram, R.; Kamath, G.M.; Gupta, N. Structural Health Monitoring of Composite Structures—Issues and Challenges. *Int. J. Veh. Struct. Syst.* **2012**, *4*, 83–94. [CrossRef]
51. Giurgiutiu, V.; Soutis, C. Enhanced Composites Integrity Through Structural Health Monitoring. *Appl. Compos. Mater.* **2012**, *19*, 813–829. [CrossRef]
52. Soto, J.R. Design of a Robotic Inspection Platform for Structural Health Monitoring. Ph.D. Dissertation, Florida International University, Miami, FL, USA, 2020. [CrossRef]
53. Thompson, F.; Hansen, P.N.; Galeazzi, R.; Palma, M.; Brock, A.L.; Mariani, P. Autonomous Inspection and Data Fusion for Maritime Critical Infrastructures. In Proceedings of the 27th International Conference on Information Fusion (FUSION 2024), Venice, Italy, 7–11 July 2024; pp. 1–8. [CrossRef]
54. Mahida, A. Impact of Edge Computing on Cloud Infrastructure- A Review Paper. *Int. J. Sci. Res.* **2019**, *8*, 1840–1844. [CrossRef]
55. Belcastro, L.; Marozzo, F.; Orsino, A.; Talia, D.; Trunfio, P. Using the Compute Continuum for Data Analysis: Edge-Cloud Integration for Urban Mobility. In Proceedings of the 31st Euromicro International Conference on Parallel, Distributed and Network-Based Processing (PDP 2023), Naples, Italy, 1–3 March 2023; pp. 338–345. [CrossRef]

56. Lin, J.-M. *Research and Application of Cloud Non-Destructive Testing and Evaluation*; Leibniz-Institut für Ost- und Südosteuropaforschung: Re-gensburg, Germany, 2015. [CrossRef]
57. Pérez, E.; Ardıç, C.E.; Çakıroğlu, O.; Jacob, K.; Kodera, S.; Pompa, L.; Rachid, M.; Wang, H.; Zhou, Y.; Zimmer, C.; et al. Integrating AI in NDE: Techniques, trends, and further directions. *NDT E Int.* **2025**, *156*, 103442. [CrossRef]
58. Osman, A.; Duan, Y.; Kaftandjian, V. Applied Artificial Intelligence in NDE. In *Handbook of Nondestructive Evaluation 4.0*; Meyendorf, N., Ida, N., Singh, R., Vrana, J., Eds.; Springer: Cham, Switzerland, 2021; pp. 1215–1243. [CrossRef]
59. Chakraborty, D.; McGovern, M.E. NDE 4.0: Smart NDE. In Proceedings of the 2019 IEEE International Conference on Prognostics and Health Management (ICPHM), San Francisco, CA, USA, 17–20 June 2019; pp. 1–6. [CrossRef]
60. Siddig, M. Scientometric Analysis of the Dynamics of Artificial Intelligence Applications in NonDestructive Testing and Structural Integrity Monitoring. *e-J. Nondestruct. Test.* **2023**, *29*, e28899. [CrossRef] [PubMed]
61. Sampson, B. Unleashing The Power of 4.0. *Aerosp. Test. Int.* **2024**, *2024*, 80–84. [CrossRef]
62. Batishchev, D.; Saad, M. The Black Box Problem: AI Decision-Making in Critical Infrastructure and Its Implications. Available online: https://www.preprints.org/manuscript/202511.2276 (accessed on 28 November 2025). [CrossRef]
63. Andres, A.; Martinez-Seras, A.; Laña, I.; Del Ser, J. On the black-box explainability of object detection models for safe and trustworthy industrial applications. *Results Eng.* **2024**, *24*, 103498. [CrossRef]
64. Xu, P.; Jones, R.; Sarris, G.; Huthwaite, P. Efficient Generation of Realistic Guided Wave Signals for Reliability Estimation. *Struct. Health Monit.* **2025**, *25*, 1353–1367. [CrossRef]
65. Calmon, P.; Mesnil, O.; Miorelli, R.; Artusi, X.; Chapuis, B.; D'Almeida, O. Model Assisted Probability of Detection for Guided Wave Imaging Structural Health Monitoring. In Proceedings of the 12th International Workshop on Structural Health Monitoring 2019, Stanford, CA, USA, 10–12 September 2019. [CrossRef] [PubMed]
66. Abdel-Basset, M.; Moustafa, N.; Hawash, H. Privacy-Preserved Cyberattack Detection in Industrial Edge of Things (IEoT): A Blockchain-Orchestrated Federated Learning Approach. *IEEE Trans. Ind. Inf.* **2022**, *18*, 7920–7931. [CrossRef]
67. Ulybyshev, D.; Yilmaz, I.; Northern, B.; Kholodilo, V.; Rogers, M. Trustworthy Data Analysis and Sensor Data Protection in Cyber-Physical Systems. *ACM Trans. Cyber-Phys. Syst.* **2021**, *5*, 13–28. [CrossRef]
68. Protasov, A. The Professional Training Features For Non Destructive Testing Graduate Students. In Proceedings of the 2020 ASEE Virtual Annual Conference, Virtual Online, 22–26 June 2020; p. 14.1245.1. [CrossRef]
69. Singh, R.; Fernandez, R.S.; Vrana, J. Principles for Successful Deployment of NDE 4.0. *J. Non-Destruct. Test. Eval. (JNDE)* **2022**, *19*, 28–34. Available online: https://jnde.isnt.in/index.php/JNDE/article/view/21 (accessed on 28 November 2025).
70. Sun, H.; Ramuhalli, P.; Jacob, R.E. Machine Learning for Ultrasonic Nondestructive Examination of Welding Defects: A Systematic Review. *Ultrasonics* **2023**, *127*, 106854. [CrossRef] [PubMed]
71. Pyle, R.J.; Bevan, R.L.T.; Hughes, R.R.; Rachev, R.K.; Ali, A.A.S.; Wilcox, P.D. Deep Learning for Ultrasonic Crack Characterization in NDE. *IEEE Trans. Ultrason. Ferroelectr. Freq. Control* **2020**, *68*, 1854–1865. [CrossRef] [PubMed]
72. Ye, J.; Toyama, N. Benchmarking Deep Learning Models for Automatic Ultrasonic Imaging Inspection. *IEEE Access* **2021**, *9*, 36986–36998. [CrossRef]
73. Traina, P.; Degiovanni, I.P.; Gramegna, M.; Vidal, X.; Gil, G. Quantum (Sensing) Leap: Pushing the Technology Readiness of Nitrogen-Vacancy Sensors in Europe Forward. *Photoniques* **2025**, *131*, 28–33. [CrossRef]
74. Vindolet, B.; Bourcin, G.; Nguyen, H.N.; Hingant, T. Diamond Quantum Sensors for Non-Destructive Testing. In *Proceedings of the 62nd Annual British Conference on Non-Destructive Testing (NDT 2025)*; The British Institute of Non-Destructive Testing: Northampton, UK, 2025; Volume 2025, pp. 1–10. [CrossRef]
75. Jahanshahi, M.R.; Shen, W.-M.; Mondal, T.G.; Abdelbarr, M.; Masri, S.F.; Qidwai, U.A. Reconfigurable Swarm Robots for Structural Health Monitoring: A Brief Review. *Int. J. Intell. Robot. Appl.* **2017**, *1*, 287–301. [CrossRef]
76. Wong, E.; Litt, J. Autonomous Multi-Agent Robotics for Inspection and Repair of Propulsion Systems. In Proceedings of the 40th AIAA/ASME/SAE/ASEE Joint Propulsion Conference, Fort Lauderdale, FL, USA, 11–14 June 2004. [CrossRef]
77. Correll, N.; Martinoli, A. *Collective Inspection of Regular Structures Using a Swarm of Miniature Robots*; Springer: Berlin/Heidelberg, Germany, 2006. [CrossRef]
78. Wilcox, P.D.; Croxford, A.J.; Budyn, N.; Bevan, R.L.T.; Zhang, J.; Kashubin, A.; Cawley, P. Fusion of Multi-View Ultrasonic Data for Increased Detection Performance in Non-Destructive Evaluation. *Proc. R. Soc. A* **2020**, *476*, 20200086. [CrossRef] [PubMed]
79. Sun, K.; Udpa, S.; Udpa, L.; Xue, T.; Lord, W. Registration Issues in the Fusion of Eddy Current and Ultrasound NDE Data Using Q-Transforms. In *Review of Progress in Quantitative Nondestructive Evaluation*; Springer Nature: New York, NY, USA, 1996; pp. 813–820. [CrossRef]
80. Baig, S.; Jam, A.; Beretta, S.; Shao, B.; Shamsaei, N. Non-Destructive Detection of Critical Defects in Additive Manufacturing. *Sci. Rep.* **2025**, *15*, 6740. [CrossRef] [PubMed]
81. Obaton, A.-F.; Van Den Bossche, A.; Burnet, O.; Butsch, B.; Zouggarh, I.; Florent, S.; Johnson, W. *Novel or Improved NDE Inspection Capabilities for Additively Manufactured Parts*; ASTM International: West Conshohocken, PA, USA, 2022. [CrossRef] [PubMed]

82. Zimermann, R.; Mohseni, E.; Foster, E.A.; Vasilev, M.; Loukas, C.; Vithanage, R.K.W.; Macleod, C.N.; Lines, D.; Javadi, Y.; Espirindio E Silva, M.P.; et al. In-Process Non-Destructive Evaluation of Metal Additive Manufactured Components at Build Using Ultrasound and Eddy-Current Approaches. *J. Manuf. Process.* **2023**, *107*, 549–563. [CrossRef]
83. Hossain, M.S.; Taheri, H. In Situ Process Monitoring for Additive Manufacturing Through Acoustic Techniques. *J. Mater. Eng. Perform.* **2020**, *29*, 6249–6261. [CrossRef]
84. Slotwinski, J.A. Additive Manufacturing: Overview and NDE Challenges. *AIP Conf. Proc.* **2014**, *1581*, 1173–1180. [CrossRef]
85. Sherwood, P.W. Non-Destructive Techniques in Refinery Inspection. *Corros. Technol.* **1957**, *4*, 148–152. [CrossRef]
86. Kishawy, H.A.; Gabbar, H.A. Review of Pipeline Integrity Management Practices. *Int. J. Press. Vessel. Pip.* **2010**, *87*, 373–380. [CrossRef]
87. Yagi, K. Acquisition of Long-Term Creep Data and Knowledge for New Applications. *Int. J. Press. Vessel. Pip.* **2008**, *85*, 22–29. [CrossRef]
88. Pandey, M.D. Probabilistic Models for Condition Assessment of Oil and Gas Pipelines. *NDT E Int.* **1998**, *31*, 349–358. [CrossRef]
89. Akrasi, I.L.; Hamaqi, M.S.; Hathloul, T.I.; Almakinzi, A.F.; Naim, A.A. Field Experience on Why Pipeline In-Line Inspections (ILI) Fail. In *NACE Corrosion*; NACE: Houston, TX, USA, 2021. [CrossRef]
90. Uzelac, N.I. In-Line Inspection (ILI) ("Intelligent Pigging"). In *Pipeline Engineering Handbook*; Wiley: Hoboken, NJ, USA, 2025; pp. 462–495. [CrossRef]
91. Moles, M.; Dube', N.; Ginzel, E. Pipeline Girth Weld Inspections Using Ultrasonic Phased Arrays. In Proceedings of the ASME Pressure Vessels and Piping Conference (PVP2003), Cleveland, OH, USA, 20–24 July 2003; pp. 19–27. [CrossRef]
92. Rodriguez, A.C. The Phased Array Single Shot: Real-Time, Multidirectional Tubular Inspection for Enhanced OCTG Integrity. In Proceedings of the SPE Middle East Oil & Gas Show and Conference, Manama, Bahrain, 17–19 March 2026. [CrossRef]
93. De Vries, R. Technology Update: New 3D Ultrasonic System Tests Pipeline Integrity. *J. Pet. Technol.* **2014**, *66*, 34–38. [CrossRef]
94. Belanger, A.; Greene, K.; Goller, C. Data Fusion of Non-Destructive Evaluation and Inline Inspection for Higher Accuracy Integrity Evaluation. In *Corrosion 2014*; NACE International: Houston, TX, USA, 2014; p. 4139. [CrossRef]
95. Lutfallah, M.H.; Felemban, T.O.; Alrashidi, A.F.; Alsubhi, Y.S.; Fandem, Q.A.; Batiste, R.S. Advancement in Asset Integrity Management through Digitalized Eddy Current Testing Technology for Corrosion Cracking Inspections. In Proceedings of the AMPP Annual Conference + Expo 2023, Denver, CO, USA, 19 March 2023; p. 19049. [CrossRef]
96. Ali, A.; Sabry, H. Implementing a Successful Risk Based Inspection Program. In Proceedings of the Abu Dhabi International Petroleum Exhibition & Conference, Abu Dhabi, United Arab Emirates, 11–14 November 2019. [CrossRef]
97. Aditiyawarman, T.; Kaban, A.P.S.; Soedarsono, J.W. A Recent Review of Risk-Based Inspection Development to Support Service Excellence in the Oil and Gas Industry: An Artificial Intelligence Perspective. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.* **2022**, *9*, 010801. [CrossRef]
98. Santos, A.D.; Al Hajri, A.A. Risk Based Inspection—A Valuable Approach. In Proceedings of the SPE International Oil and Gas Conference and Exhibition in China, Beijing, China, 13–15 October 2000. [CrossRef]

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