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AI-Assisted NDT Analytics for Early Crack Detection in Energy-Infrastructure Pressure Vessels Using Advanced Manufacturing Data

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Abstract

Early detection of cracks in energy-infrastructure pressure vessels remains a critical technical challenge because small, irregular, or noise-affected defects can be difficult to distinguish from benign structural responses, while manufacturing and inspection data are often fragmented across different systems. This study aimed to evaluate how artificial intelligence-assisted non-destructive testing analytics and advanced manufacturing information contribute to Early Crack Detection Performance in pressure-vessel integrity management. A quantitative, cross-sectional, case-study-based research design was employed across energy-infrastructure organizational cases involving pressure-vessel fabrication, welding, NDT inspection, maintenance, reliability assessment, quality assurance, and asset-integrity activities. The sample comprised NDT engineers and technicians, mechanical and integrity engineers, welding and manufacturing engineers, quality and reliability personnel, maintenance professionals, and AI/data analytics specialists. Of 320 questionnaires distributed, 301 were returned and 290 valid responses were retained, producing a usable response rate of 90.6%. The key explanatory variables were AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics, while Early Crack Detection Performance represented the dependent variable. Data were analyzed using descriptive statistics, Cronbach's alpha, KMO and Bartlett testing, Pearson correlation, multiple regression, ANOVA, and regression diagnostics. Early Crack Detection Performance achieved the highest mean, $M = 4.17$, $SD = 0.54$, followed by AI-Enabled NDT Data Analytics, $M = 4.13$, $SD = 0.56$, and Intelligent Defect Pattern Recognition, $M = 4.08$, $SD = 0.58$. All predictors were significantly associated with Early Crack Detection Performance, with correlations ranging from $r = .64$ to $r = .72$, $p < .001$. The combined model explained 68.7% of performance variance, $R = .829$, $R^2 = .687$, adjusted $R^2 = .683$, $F(4, 285) = 156.42$, $p < .001$. AI-Enabled NDT Data Analytics was the strongest predictor, $\beta = .30$, followed by Intelligent Defect Pattern Recognition, $\beta = .27$, Predictive Crack Risk Analytics, $\beta = .23$, and Advanced Manufacturing Data Integration, $\beta = .20$, all $p < .001$. The findings imply that integrating AI-based inspection analytics, manufacturing data, intelligent defect recognition, and predictive risk assessment can substantially strengthen the sensitivity, consistency, reliability, and timeliness of early crack detection in critical pressure-vessel infrastructure.

Keywords

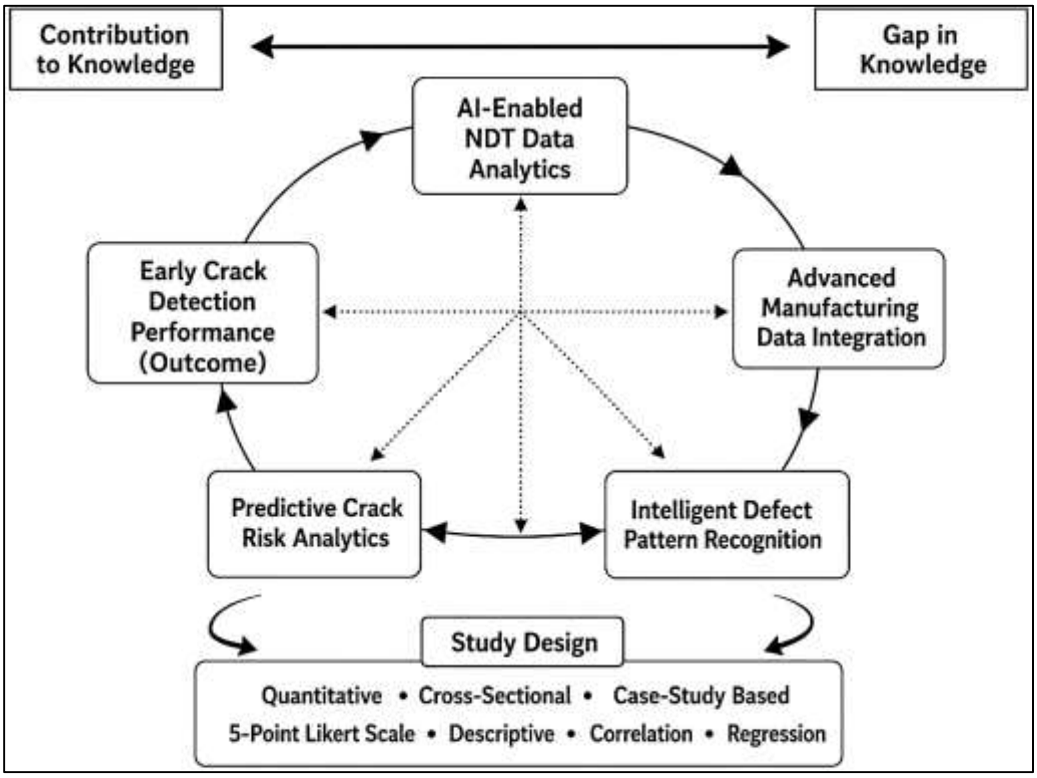
AI-Assisted NDT, Early Crack Detection, Pressure Vessels, Defect Pattern Recognition, Predictive Crack Risk Analytics

INTRODUCTION

Non-destructive testing (NDT) refers to the systematic examination of materials, components, welds, and engineered structures for discontinuities, degradation, defects, or damage without permanently impairing their intended function, while artificial intelligence-assisted NDT can be defined as the integration of machine learning, deep learning, automated feature extraction, pattern recognition, and data-driven decision support with conventional inspection signals and images. Within energy infrastructure, a pressure vessel is an enclosed mechanical system designed to contain gases, liquids, or vapors at pressures substantially different from ambient conditions, which makes the structural integrity of vessel shells, weld seams, nozzles, heads, supports, and other stress-sensitive regions essential to operational safety. A crack can be understood as a localized discontinuity caused by material separation or progressive fracture, originating from fatigue, welding imperfections, residual stresses, corrosion-related degradation, thermal cycling, manufacturing defects, stress concentration, or combinations of mechanical and metallurgical conditions. Early crack detection therefore involves recognizing and characterizing crack-related indications while they remain relatively small or at an incipient stage, before their geometry and associated stress intensity develop into more severe structural conditions. These concepts are internationally significant because pressure vessels are extensively used throughout petroleum refining, oil and gas processing, chemical production, thermal and nuclear power generation, hydrogen systems, liquefied-gas facilities, and other energy-intensive industrial operations. Failure of a pressure-containing component can interrupt production, damage surrounding equipment, release hazardous substances, and compromise personnel and environmental safety, making reliable examination a central element of integrity management. Conventional NDT techniques such as ultrasonic testing, phased-array ultrasonic testing, radiographic testing, acoustic-emission testing, magnetic-particle testing, penetrant testing, and eddy-current testing provide different physical mechanisms for identifying discontinuities without destroying inspected equipment. The value of these methods, however, depends less on obtaining a physical response than on interpreting that response accurately. Early computational research showed that ultrasonic defect signals could be transformed into discriminative characteristics and classified using support-vector-machine approaches, establishing a strong analytical link between NDT measurements and automated defect recognition (Fei et al., 2006). Artificial neural-network approaches similarly demonstrated that wavelet-derived ultrasonic characteristics could support automated classification of welding defects (Sambath et al., 2011). Research on welded steel pipes further established that phased-array ultrasonic data could be used to identify and size fatigue-generated surface cracks through analytical processing of transmissibility characteristics (Zhou et al., 2018). Pressure-vessel-specific research strengthened this relationship by showing that acoustic-emission signals, selected features, and deep-learning methods could be used for crack classification in pressure-vessel structures (Islam et al., 2018). These studies collectively frame early crack detection as a complex signal-discrimination problem in which the reliability of inspection depends on converting raw physical measurements into accurate and defensible judgments concerning crack presence, condition, and severity.

The analytical difficulty of early crack detection becomes particularly important in welded pressure-vessel structures because ultrasonic and other NDT measurements contain responses generated by both actual flaws and benign structural conditions. Weld geometry, coarse-grained microstructures, anisotropy, surface roughness, material thickness, coupling quality, probe characteristics, beam orientation, component geometry, and background noise can alter the appearance of inspection signals, while crack characteristics vary according to depth, opening, morphology, orientation, location, and interaction with the inspection beam. An inspector therefore does not simply determine whether a signal exists; the inspector must interpret a multidimensional response and determine whether it corresponds to a crack, another discontinuity, a geometric reflection, metallurgical noise, or an irrelevant indication. This requirement has encouraged extensive investigation into feature engineering, intelligent classification, and automated signal processing within ultrasonic NDT. Feature-extraction and feature-selection procedures have been applied to ultrasonic data from steel welded joints, demonstrating that neural-network-based flaw detection can operate effectively when a carefully selected subset of informative characteristics is extracted from A-scan data rather than relying on the complete raw signal (Cruz et al., 2017). The movement from hand-engineered signal features toward learned representations became more pronounced when deep neural networks were applied to weldment flaw classification without dependence on conventional manual feature-extraction procedures (Munir et al., 2018). Convolutional neural networks were subsequently used to classify ultrasonic weldment flaws under noisy inspection conditions, showing that deep architectures could retain defect-sensitive information when signal quality was affected by realistic interference (Munir et al., 2019). This analytical capability is highly relevant to pressure-vessel examination because early-stage cracks may generate subtle responses embedded within structural and material noise, increasing the difficulty of consistent interpretation. Time-of-flight diffraction data have also been analyzed through machine-learning methods, with segmented ultrasonic information and extreme-learning-machine classification used for flaw detection in welded steel plates (Silva et al., 2020).

Figure 1: AI-Enabled NDT Framework for Early Crack Detection in Pressure Vessels



Such research establishes AI-assisted NDT analytics as a process that extends beyond basic automation of inspection thresholds. It incorporates signal preprocessing, dimensionality reduction, feature learning, classification, uncertainty handling, anomaly recognition, and decision support. These capabilities are directly connected with the construct of AI-Enabled NDT Data Analytics in the present study because analytical effectiveness depends on how efficiently inspection information can be converted into meaningful defect indicators. The international relevance of this problem is considerable because energy-sector pressure vessels operate across diverse industrial settings, inspection codes, material systems, and service conditions, yet their NDT programs share the fundamental need to distinguish flaw-related responses from normal structural variation. AI-assisted analytical models offer a means of examining complex nonlinear relationships within inspection signals that may not be adequately represented through a single amplitude threshold, rule-based decision, or isolated visual judgment.

The increasing digitization of NDT has expanded defect analysis from individual ultrasonic traces toward images, spatial representations, multichannel datasets, and heterogeneous inspection records. NDT information may be expressed as A-scans, B-scans, C-scans, phased-array sectorial images, radiographic images, acoustic-emission waveforms, eddy-current responses, and other structured measurements, each of which contains different representations of material or structural condition. Artificial intelligence has become particularly relevant to these data types because machine-learning and deep-learning architectures can identify combinations of features that may be difficult to recognize consistently through manual interpretation. Deep convolutional neural networks have been applied to ultrasonic signal classification and imaging, showing that discriminative information can be learned directly from complex ultrasonic representations rather than being fully specified through predetermined rules (Meng et al., 2017). Eddy-current NDT has also incorporated machine-learning models with uncertainty analysis, demonstrating that automated inspection involves generating a defect classification and, just as importantly, evaluating confidence in the resulting decision (Zhu et al., 2019). Other inspection modalities have undergone similar transformations. Random-forest methods have been used for automated defect detection in fluorescent penetrant inspection, illustrating the capacity of machine learning to support a traditionally visually interpreted NDT process (Shipway et al., 2019). Radiographic weld inspection has likewise evolved from classical image processing and hand-designed descriptors toward computer-assisted and learning-based methods involving segmentation, feature extraction, recognition, and classification (Hou et al., 2020). These developments are particularly relevant to pressure-vessel integrity because a single vessel may be examined through several NDT modalities during fabrication, commissioning, maintenance, and in-service assessment. Radiographic data can document volumetric and weld-related discontinuities, phased-array ultrasonics can provide location and depth information, acoustic-emission systems can detect energy released during active damage processes, and manufacturing records can provide contextual information concerning the conditions under which critical sections were fabricated. Intelligent Defect Pattern Recognition therefore represents more than automated labeling. It refers to the capability of analytical systems to distinguish combinations of signal, image, spatial, and contextual characteristics that correspond to genuine defect conditions. For early cracks, this capacity is especially important because the relevant indication may be weak, narrow, irregular, discontinuous, or partially masked by surrounding noise. Identification can therefore depend on relationships among signal morphology, intensity distribution, frequency characteristics, spatial continuity, neighboring measurements, and recurring defect patterns. AI-assisted pattern recognition offers a structured mechanism for evaluating these characteristics consistently across large inspection datasets and can reduce dependence on a purely subjective interpretation process while maintaining the physical inspection signal as the primary source of damage-related evidence.

Crack detection has become a major application area for deep learning because cracks commonly possess irregular shapes, small widths, low visual or signal contrast, discontinuous boundaries, and variable orientations that challenge conventional feature-based identification methods. Although a large proportion of image-based crack research has been developed in civil and structural engineering contexts, the analytical principles remain highly relevant to automated NDT because they concern the ability of computational models to identify small and irregular damage signatures in complex measurement environments. Convolutional neural networks have been shown to detect crack damage directly from structural images without relying on conventional manually designed crack descriptors, establishing the ability of learned representations to distinguish crack-related visual characteristics across changing conditions (Cha et al., 2017). Comparative research has also shown that deep convolutional neural networks can detect very fine cracks while overcoming several weaknesses of traditional edge-detection methods in image-based damage recognition (Dorafshan et al., 2018). Deep-learning architectures and object-detection methods have subsequently been used for structural crack detection and recognition, further demonstrating the applicability of automated feature learning to irregular damage geometries (Yang et al., 2021). Within ultrasonic NDT, the same movement from handcrafted interpretation toward learned representations has produced techniques that are more directly connected to metallic engineering components. Automated defect detection from ultrasonic images has been implemented using deep learning to address the labor intensity and inconsistency associated with manual evaluation of large UT datasets (Medak et al., 2021). These developments are closely related to the concept of Early Crack Detection Performance in the present study. Early Crack Detection Performance refers to the extent to which an inspection and analytical system can identify crack-related conditions accurately, sensitively, consistently, and promptly while maintaining acceptable control over missed detections and false indications. Performance is therefore broader than simple binary classification accuracy. In operational pressure-vessel NDT, detection performance includes sensitivity to small cracks, reliability of crack localization, reproducibility of analytical outcomes, reduction of missed defects, reduction of unnecessary false calls, consistency of defect characterization, and availability of useful information for integrity personnel. The international importance of these characteristics extends across energy infrastructure because pressure-boundary systems in petroleum processing, gas transmission, power generation, chemical plants, and related sectors must routinely distinguish meaningful damage from normal structural and material variation. The analytical problem remains fundamentally similar across these settings: inspection systems produce measurements that contain possible evidence of cracking, and practitioners must determine whether that evidence is sufficiently reliable to classify a condition as structurally significant. AI-assisted crack recognition introduces learned feature representations into this process and provides a direct connection between automated defect interpretation and measurable dimensions of crack-detection performance.

The effectiveness of AI-assisted NDT is highly dependent on the quality, representativeness, organization, and diversity of the datasets used for model development and operational analysis. Early crack detection constitutes a particularly challenging machine-learning problem because real safety-critical inspection datasets are commonly imbalanced. Normal material conditions are usually represented by a large volume of inspection data, while verified early-stage cracks occur less frequently and may be available only in limited quantities. The variability of real cracks further complicates training because cracks differ in orientation, morphology, depth, length, opening, surface connection, and interaction with different inspection geometries. Research on machine-learning-powered ultrasonic inspection has directly addressed these limitations. Augmented ultrasonic datasets incorporating virtual flaws have been used to train deep convolutional networks for phased-array ultrasonic inspection, demonstrating that representative data augmentation can improve learning when physical flaw data are limited (Virkkunen et al., 2021). This work is particularly relevant to energy infrastructure because the underlying inspection environment included stainless-steel welds containing thermal fatigue cracks, which present complex ultrasonic responses and challenging structural noise. The influence of training flaw type has also been examined, showing that the composition of flaw datasets affects the ability of machine-learning models to generalize across inspection conditions and defect categories (Koskinen et al., 2021). Multichannel phased-array ultrasonic information has likewise been analyzed using machine learning, demonstrating that convolutional models can evaluate richer inspection representations rather than depending exclusively on isolated channels or individual signals (Siljama et al., 2021). Automated analysis of ultrasonic signals has also been performed using causal dilated convolutional neural networks, with validation across simulated and experimental NDE datasets showing that deep architectures can support defect-sensitive interpretation in complex signal environments (Mariani et al., 2021). These studies provide a strong analytical basis for the AI-Enabled NDT Data Analytics construct because the usefulness of AI depends on more than selecting a sophisticated algorithm. It depends on whether inspection data are sufficiently representative, whether the system can handle noise and variation, whether relevant damage patterns are preserved during preprocessing, whether multiple channels can be integrated effectively, and whether the learned model generalizes beyond the specific defects used during training. For pressure vessels, these requirements are especially important because inspections may accumulate across fabrication and service life, producing datasets that differ according to material grade, weld configuration, inspection equipment, operating history, and defect morphology. AI-assisted analytics therefore operates within a combined problem of data quality, representation, and model discrimination, making the structure and diversity of the inspection dataset central to the credibility of early crack-detection performance.

Advanced manufacturing data provide an additional analytical layer because the condition examined through NDT is produced through a specific fabrication and processing history rather than existing independently of manufacturing parameters. In pressure-vessel production, advanced manufacturing data may include material grade, plate thickness, heat number, welding current, welding voltage, travel speed, heat input, welding sequence, consumable type, preheat temperature, post-weld heat-treatment conditions, forming parameters, dimensional measurements, sensor outputs, operator or machine identifiers, quality-control records, fabrication deviations, and previous inspection findings. These records can provide contextual information concerning why particular regions of a vessel may exhibit elevated susceptibility to defects or why certain inspection responses require greater attention. The integration of heterogeneous information has already demonstrated value within nondestructive characterization. Data-fusion approaches have been used to combine different measurement sources for improved nondestructive characterization of dual-phase steels, showing that combining separate streams of information can enhance material-condition assessment (Kahrobaee et al., 2018). At the broader manufacturing-system level, machine learning, condition monitoring, and predictive analytics have been extensively associated with Industry 4.0 maintenance environments, where large volumes of process and equipment data support condition-oriented decision systems (Zonta et al., 2020). Predictive-quality research is particularly relevant to the present study because production-process parameters and sensor data have increasingly been combined with quality measurements to estimate product conditions and identify relationships between manufacturing behavior and resulting quality outcomes (Tercan & Meisen, 2022). Data scarcity within NDT has also encouraged synthetic-data generation, with generative adversarial networks producing ultrasonic images designed to resemble authentic inspection images when verified physical defect datasets are limited (Subasic, et al., 2022). These areas of research support the construct of Advanced Manufacturing Data Integration in the present study. Rather than treating a phased-array, ultrasonic, radiographic, or acoustic-emission indication as an isolated inspection event, an integrated analytical environment can relate that indication to the fabrication conditions, material history, thermal processing, weld quality, and prior inspection information associated with the exact vessel region under examination. Such integration is particularly important for welded pressure vessels because crack-like conditions emerge within a manufacturing context involving material behavior, residual stress, joint preparation, heat input, thermal cycles, and quality variation. Advanced manufacturing data can therefore provide contextual variables that complement direct NDT evidence, while AI-based analytical systems can identify statistical relationships among these heterogeneous records. The present research consequently treats manufacturing-data integration as a distinct explanatory factor whose association with early crack-detection performance can be evaluated quantitatively.

Predictive Crack Risk Analytics represents the additional data-driven capability through which NDT information, defect patterns, and manufacturing context can be organized into assessments of crack-related risk. In this study, Predictive Crack Risk Analytics refers to the systematic use of inspection-derived indicators and relevant manufacturing data to identify patterns associated with elevated crack likelihood, structural abnormality, or conditions requiring closer integrity attention. This concept is analytically distinct from merely classifying an obvious existing defect because predictive risk assessment concerns the combined strength, consistency, and contextual meaning of multiple indicators. Contemporary ultrasonic research demonstrates how advanced computational methods can improve the quality of defect-sensitive information used in such assessments. Deep-learning approaches have been developed for identifying and suppressing artifacts in ultrasonic images produced from full-matrix-capture data, addressing the difficulty that structural artifacts and noise can obscure true flaw responses (Cantero-Chinchilla et al., 2022a). Specialized deep-learning architectures have also been designed for detecting defects with extreme aspect ratios in ultrasonic images, a particularly relevant characteristic for narrow crack-like indications whose geometry differs markedly from conventional object-detection targets (Medak et al., 2022b). Anomaly-detection techniques based on deep learning have been evaluated using ultrasonic images, showing that models can identify suspicious regions by learning the distinction between normal and abnormal inspection patterns rather than relying exclusively on predetermined multiclass labels (Milkovic, et al., 2022). Sequential ultrasonic information has additionally been analyzed through deep-learning-based methods that consider relationships across neighboring B-scans, allowing defect detection to incorporate spatial continuity across inspection sequences rather than evaluating each scan independently (Medak et al., 2022a). Pressure-vessel-specific research provides a direct engineering context for this analytical progression. Phased-array ultrasonic data from pressurized vessels containing hydrogen-induced cracking have been connected with fitness-for-service and failure-analysis procedures, demonstrating how NDT-derived crack information enters structural-integrity assessment and engineering decision-making (Ghanbari et al., 2022). These strands of research collectively support the present study's four explanatory constructs: AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics, with Early Crack Detection Performance serving as the principal dependent construct. A quantitative, cross-sectional, case-study-based design allows these dimensions to be operationalized through five-point Likert-scale measures completed by relevant professionals, while descriptive statistics can characterize the observed level of each construct, correlation analysis can determine the strength and direction of bivariate relationships, and regression modeling can estimate the individual and combined contribution of the explanatory variables to Early Crack Detection Performance. This analytical structure positions the study specifically at the intersection of pressure-vessel integrity, NDT engineering, artificial intelligence, manufacturing informatics, and crack-oriented data analysis.

Background of the Study

Energy-infrastructure pressure vessels operate under demanding mechanical, thermal, chemical, and environmental conditions that require continuous attention to structural integrity, material condition, and defect development. These vessels are widely used in oil and gas processing, petroleum refining, power generation, chemical production, compressed-gas systems, hydrogen facilities, and other industrial operations where pressurized containment is essential to safe and uninterrupted production. Among the various forms of material degradation that can affect pressure vessels, cracking remains particularly critical because small discontinuities can develop under cyclic loading, residual stress, thermal fluctuation, corrosion-related mechanisms, welding imperfections, and manufacturing variability. Early identification of these cracks is therefore an important component of pressure-vessel integrity management. Conventional non-destructive testing methods such as ultrasonic testing, phased-array ultrasonic testing, time-of-flight diffraction, radiographic testing, acoustic-emission testing, eddy-current testing, magnetic-particle testing, and penetrant testing have provided engineers with important tools for locating and characterizing structural discontinuities without damaging the inspected equipment. The increasing volume and complexity of inspection information, however, have made interpretation more demanding, particularly when early-stage cracks generate weak, irregular, or noise-affected indications. Artificial intelligence has introduced a new analytical layer into NDT by enabling automated signal processing, feature extraction, anomaly identification, image interpretation, defect classification, and data-supported decision-making. At the same time, advanced manufacturing environments generate extensive digital information concerning materials, welding parameters, heat treatment, fabrication conditions, quality-control measurements, sensor outputs, and previous inspection histories. These datasets can provide important contextual information regarding the physical conditions under which crack-related defects may form or become detectable. Integrating manufacturing records with NDT information therefore creates an opportunity to examine crack detection as a multidimensional data problem rather than an isolated inspection event. The present study is positioned within this integration of NDT engineering, artificial intelligence, manufacturing informatics, and structural-integrity assessment. It focuses specifically on AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics as interconnected capabilities that may influence Early Crack Detection Performance. By examining these constructs within a quantitative, cross-sectional, case-study-based research setting, the study addresses how data-rich inspection environments can support more systematic evaluation of early crack-related conditions in energy-infrastructure pressure vessels.

Problem Statement

The early detection of cracks in energy-infrastructure pressure vessels remains a complex technical and analytical problem because the identification of a potentially dangerous discontinuity depends on the quality of inspection data, the characteristics of the material and component, the competence of the interpretation process, and the ability to distinguish meaningful defect responses from noise and benign structural indications. Conventional NDT techniques are capable of generating highly valuable information, yet the interpretation of that information can become difficult when cracks are small, unfavorably oriented, embedded within noisy weld structures, located in geometrically complex regions, or represented by signal characteristics that overlap with non-defect conditions. Manual interpretation may also vary between inspectors because assessments can be influenced by experience, judgment, workload, data complexity, and the specific presentation of an inspection indication. At the same time, pressure-vessel manufacturing and inspection processes increasingly generate large amounts of digital information, including welding parameters, material data, production histories, heat-treatment records, dimensional measurements, sensor outputs, inspection images, ultrasonic signals, and quality-control documentation. In many practical environments, these information sources remain fragmented, which limits the ability to determine whether relationships exist between manufacturing conditions, defect patterns, and the probability of early crack development. The application of artificial intelligence to NDT has provided new methods for classification and automated recognition, but the mere presence of AI technology does not establish whether it improves early crack detection when combined with real manufacturing and inspection information. A clear empirical problem therefore remains concerning the extent to which AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics contribute individually and collectively to Early Crack Detection Performance in pressure-vessel applications. Without quantitative evidence concerning these relationships, organizations may adopt AI-enabled inspection tools without understanding which analytical capabilities are most strongly associated with reliable crack identification. There is also a need to determine whether these capabilities operate as separate technological functions or as mutually reinforcing components of an integrated integrity-assessment process. The present study addresses this problem through a quantitative, cross-sectional, case-study-based investigation using a five-point Likert-scale instrument, descriptive statistics, correlation analysis, and regression modeling to evaluate the statistical relationships among the four explanatory constructs and Early Crack Detection Performance.

Purpose and Objectives of the Study

The principal objective of this study is to quantitatively evaluate the contribution of AI-assisted NDT analytics and advanced manufacturing data to Early Crack Detection Performance in energy-infrastructure pressure vessels by examining a structured set of technological and analytical capabilities within a case-study-based research setting. More specifically, the study seeks to determine whether AI-Enabled NDT Data Analytics improves the ability of inspection systems and professionals to interpret complex NDT signals, distinguish defect-related information from irrelevant responses, recognize subtle crack characteristics, and support consistent crack-detection decisions. A second objective is to assess the influence of Advanced Manufacturing Data Integration on Early Crack Detection Performance by examining whether the systematic combination of manufacturing-process information, material characteristics, welding data, fabrication records, sensor outputs, historical inspection information, and quality-control data strengthens the contextual understanding of crack-related NDT findings. A third objective is to determine the contribution of Intelligent Defect Pattern Recognition by evaluating whether automated identification, classification, anomaly recognition, and crack-feature discrimination are associated with stronger perceived accuracy, sensitivity, consistency, and reliability of early crack detection. A fourth objective is to assess the effect of Predictive Crack Risk Analytics on Early Crack Detection Performance by examining whether data-driven risk estimation, prioritization, abnormality identification, and crack-related condition assessment improve the ability to recognize potentially significant defects at an earlier stage. The study also aims to determine the combined explanatory power of AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics when Early Crack Detection Performance is treated as the dependent variable. To achieve these objectives, the study will measure respondent perceptions using a structured five-point Likert scale and will employ descriptive statistics to characterize the observed level of each construct, correlation analysis to evaluate the direction and strength of relationships among the study variables, and multiple regression analysis to estimate the independent and collective effects of the explanatory variables on Early Crack Detection Performance. Through these objectives, the research establishes a measurable framework for investigating how AI, NDT information, manufacturing data, defect-recognition capabilities, and predictive assessment interact within the specific context of pressure-vessel integrity management.

Research Hypotheses

The research hypotheses have been formulated to provide a statistically testable structure for examining the relationships between the four independent variables and Early Crack Detection Performance as the dependent variable. The first hypothesis, H1, proposes that AI-Enabled NDT Data Analytics has a significant positive effect on Early Crack Detection Performance, reflecting the expectation that stronger capabilities in automated signal processing, intelligent inspection-data analysis, feature extraction, and AI-supported interpretation will be associated with more effective recognition of early-stage crack conditions. The second hypothesis, H2, proposes that Advanced Manufacturing Data Integration has a significant positive effect on Early Crack Detection Performance, based on the premise that integrating fabrication, material, welding, sensor, quality, and historical inspection information provides a richer analytical context for interpreting crack-related indications. The third hypothesis, H3, proposes that Intelligent Defect Pattern Recognition has a significant positive effect on Early Crack Detection Performance, reflecting the expectation that systems capable of recognizing complex crack signatures, differentiating defects from structural noise, classifying abnormal indications, and identifying recurring defect patterns will support stronger detection outcomes. The fourth hypothesis, H4, proposes that Predictive Crack Risk Analytics has a significant positive effect on Early Crack Detection Performance, suggesting that the ability to estimate crack-related risk, prioritize abnormal conditions, and identify combinations of indicators associated with damage will improve the early identification of potential integrity concerns. The fifth hypothesis, H5, proposes that AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics collectively have a significant positive effect on Early Crack Detection Performance. This combined hypothesis recognizes that effective early crack detection may depend on an integrated analytical environment rather than on any single capability operating independently. These hypotheses will be evaluated using correlation and multiple regression analyses, with statistical significance, standardized coefficients, explained variance, and model-level results used to determine whether the proposed relationships receive empirical support. The hypothesis structure therefore directly connects the conceptual framework, measurement instrument, statistical analyses, and research objectives and provides a coherent basis for determining how AI-assisted NDT capabilities relate to early crack detection within energy-infrastructure pressure vessels.

Significance of the Research

i. Significance for Pressure-Vessel Integrity Management: The study is significant because it examines early crack detection within the specific context of energy-infrastructure pressure vessels, where integrity decisions depend on reliable identification of structural discontinuities before they develop into more serious conditions. By statistically evaluating the relationship between AI-assisted analytical capabilities and Early Crack Detection Performance, the research provides a structured basis for understanding which technological factors are most strongly associated with improved inspection effectiveness.

ii. Significance for NDT Engineers and Inspectors: The study is relevant to NDT professionals because it considers how AI-enabled signal analysis, intelligent defect recognition, manufacturing-data integration, and predictive analytics can complement conventional inspection processes. The findings can help clarify which analytical capabilities are most closely associated with detection accuracy, consistency, sensitivity, and confidence in crack-related interpretation.

iii. Significance for Energy-Infrastructure Organizations: Energy companies, pressure-vessel manufacturers, maintenance departments, and asset-integrity teams may benefit from the study because it evaluates AI-assisted NDT as an integrated analytical system rather than as an isolated software tool. This can support more informed assessment of inspection technologies and data-management capabilities within organizational integrity programs.

iv. Significance for Advanced Manufacturing Data Management: The research gives specific attention to manufacturing information as an analytical resource for NDT. By examining Advanced Manufacturing Data Integration as an independent variable, the study recognizes that welding parameters, material information, fabrication histories, sensor outputs, and quality records may strengthen the contextual interpretation of NDT findings.

v. Significance for AI-Based Defect Recognition: The study provides a quantitative examination of Intelligent Defect Pattern Recognition and Predictive Crack Risk Analytics as distinct but connected capabilities. This distinction is important because automated classification and predictive risk estimation perform different analytical functions within crack-detection systems.

vi. Significance for Academic Research: The research contributes an empirically testable framework combining AI-assisted NDT analytics, manufacturing-data integration, intelligent pattern recognition, predictive crack-risk analysis, and early crack-detection performance. The use of descriptive statistics, correlation analysis, and multiple regression modeling provides a clear quantitative structure for evaluating these relationships within one integrated research model.

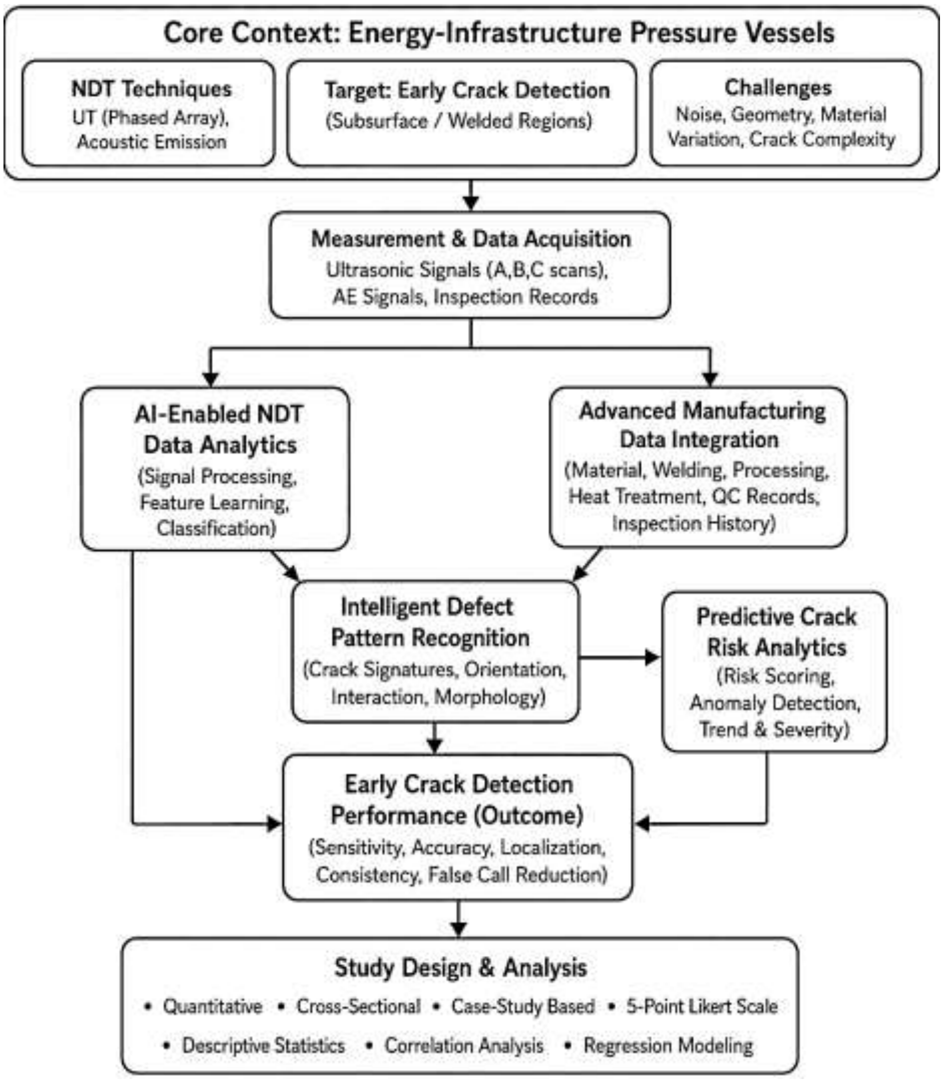
LITERATURE REVIEW

The literature surrounding AI-assisted non-destructive testing for early crack detection in energy-infrastructure pressure vessels extends across several closely connected fields, including structural-integrity engineering, ultrasonic and radiographic inspection, machine learning, deep learning, manufacturing informatics, predictive quality, defect-pattern recognition, and condition-based assessment. Pressure-vessel inspection has traditionally depended on NDT techniques that generate physical evidence of internal or surface discontinuities without impairing the serviceability of the inspected component. The increasing complexity and volume of NDT data have created an analytical environment in which inspection performance depends on interpreting subtle relationships within signals, images, and contextual records, not simply on acquiring reliable measurements. Artificial intelligence has become increasingly relevant to this analytical problem because machine-learning and deep-learning methods can support automated feature extraction, noise-sensitive classification, anomaly detection, image interpretation, crack-pattern recognition, and structured decision support. At the same time, advanced manufacturing systems generate extensive information concerning materials, welding parameters, process conditions, heat treatment, dimensional control, sensor measurements, quality records, and previous inspection outcomes. Integrating these data with NDT information can provide a broader representation of the conditions associated with defect formation and detectability. The literature therefore suggests that early crack detection should be examined as a multidimensional analytical process involving data acquisition, information integration, defect discrimination, and risk-oriented interpretation rather than as a single inspection activity. This review is organized around six major areas that collectively support the present research framework. The first area examines non-destructive testing and early crack detection in energy-infrastructure pressure vessels. The second addresses AI-Enabled NDT Analytics for defect detection and inspection intelligence. The third examines Advanced Manufacturing Data Integration for pressure-vessel integrity assessment. The fourth reviews Intelligent Defect Pattern Recognition and Predictive Crack Risk Analytics. The fifth develops Signal Detection Theory as the theoretical framework for understanding the distinction between genuine crack-related signals and competing noise or non-defect responses. The sixth establishes the conceptual framework connecting AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics with Early Crack Detection Performance as the principal outcome variable.

Non-Destructive Testing

Non-destructive testing is central to the structural-integrity management of energy-infrastructure pressure vessels because these components operate under combinations of internal pressure, thermal loading, corrosive media, residual stress, cyclic service, and fabrication-related variability that can initiate or accelerate cracking. Early crack detection is especially important in welded shells, heads, nozzles, and other stress-concentrated regions because a relatively small discontinuity may remain difficult to characterize while still representing a meaningful precursor to leakage, unstable fracture, or loss of pressure containment. The technical purpose of NDT is not limited to confirming whether a visible defect exists; it involves locating hidden discontinuities, differentiating crack-related responses from benign indications, estimating flaw dimensions, and supplying reliable information for integrity assessment. Among the available methods, ultrasonic testing is particularly important for metallic pressure boundaries because it can interrogate subsurface regions and provide information related to flaw position and geometry, while acoustic emission can identify energy released by active damage processes during loading. Evidence from pressure-vessel steels has shown that acoustic-emission activity can be correlated with distinct stages of crack development when combined with potential-difference measurements and microfractographic observations, establishing a relationship between emitted elastic-wave activity and fracture progression (Debasish, 2021; Ennaceur et al., 2006). A complementary pressure-vessel study combined acoustic-emission diagnosis with ultrasonic testing by using acoustic emission to identify the approximate crack region and ultrasonic examination to determine crack position, size, and shape more precisely (Abdur & Iftekhar, 2021; Tong & Wang, 2011). These approaches illustrate an important principle for early crack detection: no single inspection response should automatically be interpreted as complete evidence of structural condition. Detection reliability depends on how well the inspection technique captures the physical signature of damage and how accurately that signature can be localized, characterized, and separated from background responses. For energy-infrastructure vessels, where inspection decisions may influence continued operation, repair, replacement, or fitness-for-service evaluation, the quality of this discrimination is a fundamental element of trustworthy NDT practice.

Figure 2: AI-Enabled NDT Framework for Early Crack Detection in Energy-Infrastructure Pressure Vessels



The technical difficulty of crack detection is increased by the diversity of degradation mechanisms and the geometrical and metallurgical complexity of pressure-vessel construction. Hydrogen-induced cracking, fatigue cracking, stress-corrosion cracking, weld-related discontinuities, and other planar defects may occur in different orientations, depths, and spatial configurations, producing inspection responses that vary with probe angle, frequency, material microstructure, wall thickness, crack morphology, and surrounding geometry. Advanced ultrasonic methods have therefore become important where conventional inspection does not provide sufficient sensitivity or spatial resolution for complicated crack conditions. Phased-array ultrasonic testing permits electronic control of multiple transducer elements, enabling beam steering, focusing, sectorial scanning, and collection of richer information from critical vessel regions. Work on pressure vessels exposed to sour-service conditions has shown that hydrogen-induced cracking can be detected, characterized, and sized using optimized phased-array ultrasonic inspection, while full-matrix-capture acquisition and total-focusing-method processing can improve sensitivity and resolution and support three-dimensional reconstruction of inspected regions (Debasish, 2022; Nardo et al., 2016). Acoustic-emission monitoring offers a complementary capability because it can cover relatively large structural areas and distinguish activity associated with crack initiation and propagation from other sources such as weld-related events, residual-stress release, friction, leakage, or environmental noise. Field-oriented pressure-vessel monitoring has demonstrated that acoustic-emission source activity and intensity can be organized into graded evaluation levels for safety assessment, highlighting the importance of interpreting signal behavior rather than treating every recorded event as equivalent evidence of cracking (Ashfaq & Mohammad, 2022; Shen et al., 2019). Together, these approaches show that early crack detection is inherently a multidimensional measurement problem. A weak indication can be significant when its location, temporal behavior, amplitude characteristics, morphology, and relation to known high-risk regions are considered collectively. Conversely, a strong signal may have limited integrity significance when it originates from geometry or a benign source. This distinction is relevant to the present research because AI-assisted NDT analytics depends on reliable physical inspection data from which meaningful defect features can be extracted, classified, and related to early crack-detection performance.

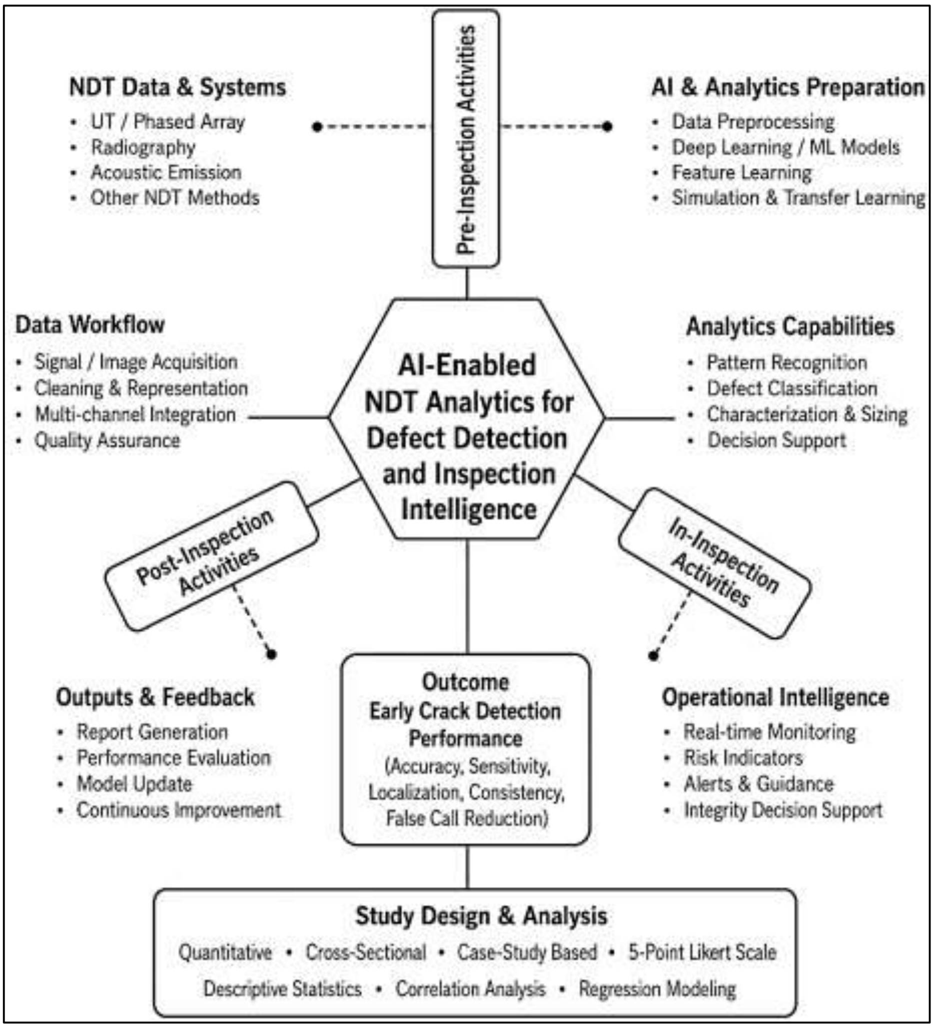
Another important challenge is that cracks in pressure vessels may occur as interacting or spatially related defects rather than as isolated single discontinuities, making early recognition dependent on the ability of NDT systems to resolve multiple reflections and distinguish their mutual influence. Closely spaced cracks can modify local stress fields and produce complex ultrasonic responses, while orientation relative to the pressure-induced stress field can alter structural significance and detectability. Research using optical-fibre ultrasonic sensing has examined parallel double cracks in pressure-vessel configurations and demonstrated that changes in axial and circumferential crack spacing influence the peak time and amplitude characteristics of reflected ultrasonic signals, providing a basis for determining regions in which neighboring cracks interact (Sheak & Risha, 2022; Qi et al., 2022). This evidence is important because conventional inspection interpretation can become difficult as defect morphology departs from idealized single-crack assumptions. Early crack detection in real pressure-vessel environments therefore requires sensitivity to spatial pattern, orientation, interaction, and signal evolution, not just to the presence of a discontinuity. These requirements connect traditional NDT directly with the analytical focus of the present study. AI-assisted NDT analytics can support credible early crack detection when the underlying inspection process captures defect-sensitive information with adequate resolution and when resulting measurements are interpreted in relation to physical vessel conditions. Advanced manufacturing data can strengthen this context by documenting material characteristics, welding variables, fabrication history, heat-treatment conditions, quality records, and previous inspection findings associated with the examined region. The NDT literature consequently establishes the physical and measurement foundation for the study's broader analytical framework: inspection technologies generate evidence of possible crack conditions, manufacturing information provides contextual evidence concerning how those conditions may have developed, and intelligent analytics can organize these heterogeneous signals into consistent defect-recognition and crack-risk assessments. Within a quantitative case-study design, this foundation supports examining whether stronger AI-enabled NDT capabilities, manufacturing-data integration, intelligent defect-pattern recognition, and predictive crack-risk analytics are associated with higher Early Crack Detection Performance in energy-infrastructure pressure vessels.

AI-Enabled NDT Analytics for Defect Detection

AI-Enabled NDT Analytics refers to the use of artificial intelligence, machine learning, deep learning, and computational signal-processing methods to transform raw nondestructive-testing data into defect-sensitive information that supports detection, characterization, and inspection decision-making. In pressure-vessel applications, this capability is important because ultrasonic, phased-array, radiographic, acoustic-emission, and related inspection systems generate large volumes of data containing combinations of flaw responses, structural echoes, background noise, geometric reflections, and acquisition-related variation. Conventional automated inspection has often depended on relatively simple rules such as amplitude thresholds, predefined gates, or manually selected features, whereas AI-enabled analytics can learn multidimensional relationships directly from representative data. A review of deep-learning applications in automated ultrasonic NDE identified data preprocessing, defect detection, defect characterization, and property measurement as major tasks in which deep neural networks can extend traditional automation, while emphasizing that trustworthy deployment requires appropriate data, validation, physical consistency, and clearly defined automation levels (Cantero-Chinchilla et al., 2022b; Rashedul & Kaium, 2022). This perspective is relevant to energy-infrastructure pressure vessels because crack detection involves a chain of analytical operations through which inspection data are cleaned, represented, interpreted, and converted into integrity-related information. Deep learning has also been applied specifically to ultrasonic crack characterization using simulated and experimental data, with convolutional neural networks trained through a hybrid simulation strategy to estimate crack characteristics from ultrasonic responses (Chowdhury & Tonay, 2022; Pyle et al., 2021). Such evidence demonstrates that AI-assisted NDT can support recognition of whether a flaw is present, and can go further to support interpretation of characteristics associated with the defect itself. For early crack detection, this distinction matters because an inspection system must often distinguish weak crack responses from structurally insignificant indications while preserving enough information for localization and characterization. AI-Enabled NDT Data Analytics therefore represents a combination of intelligent processing, learned representation, defect-sensitive classification, and analytical decision support that can strengthen the consistency of pressure-vessel inspection interpretation.

The development of AI-enabled inspection intelligence has also been strongly influenced by advances in image-based NDT, particularly radiographic examination of welded components. Radiographic images contain spatial information regarding density changes and internal discontinuities, yet their interpretation can be complicated by low contrast, nonuniform illumination, varying weld geometry, differences in defect size, and the visual similarity of several weld imperfections. Traditional computer-aided approaches generally depend on image enhancement, segmentation, handcrafted feature extraction, and classification, meaning that analytical performance is partly determined by how effectively relevant features are defined before model training. Deep learning changes this logic by allowing hierarchical representations to be learned directly from inspection images. Transfer-learning approaches have been applied to X-ray images of pipeline welds using pretrained convolutional architectures, demonstrating that established deep networks can be adapted to weld-defect classification even when the available industrial dataset is limited (Ajmi et al., 2020; Hossan, 2022). This is important for pressure-vessel research because verified examples of genuine cracks and critical flaws may be scarce, creating limitations for training large models entirely from the beginning. Another study developed a unified deep neural network that combined multiple levels of defect information for radiographic weld classification, including geometric, intensity, and contrast-related characteristics, and showed that fusion of multi-level features can improve discrimination among defect categories (Kaniz, 2022; Yang & Jiang, 2021). The importance of these approaches extends beyond radiographic classification itself. Pressure-vessel integrity assessment commonly requires inspectors to interpret patterns that vary simultaneously in size, shape, contrast, orientation, and position while determining whether they correspond to crack-like discontinuities or less critical conditions. AI-enabled NDT analytics provides a framework in which these heterogeneous characteristics can be evaluated systematically rather than through isolated visual judgments. For this study, inspection intelligence therefore refers to the capability of AI-supported systems to convert complex NDT information into consistent, interpretable, defect-oriented analytical outputs that strengthen identification of early crack conditions.

Figure 3: AI-Enabled NDT Analytics for Defect Detection and Inspection Intelligence



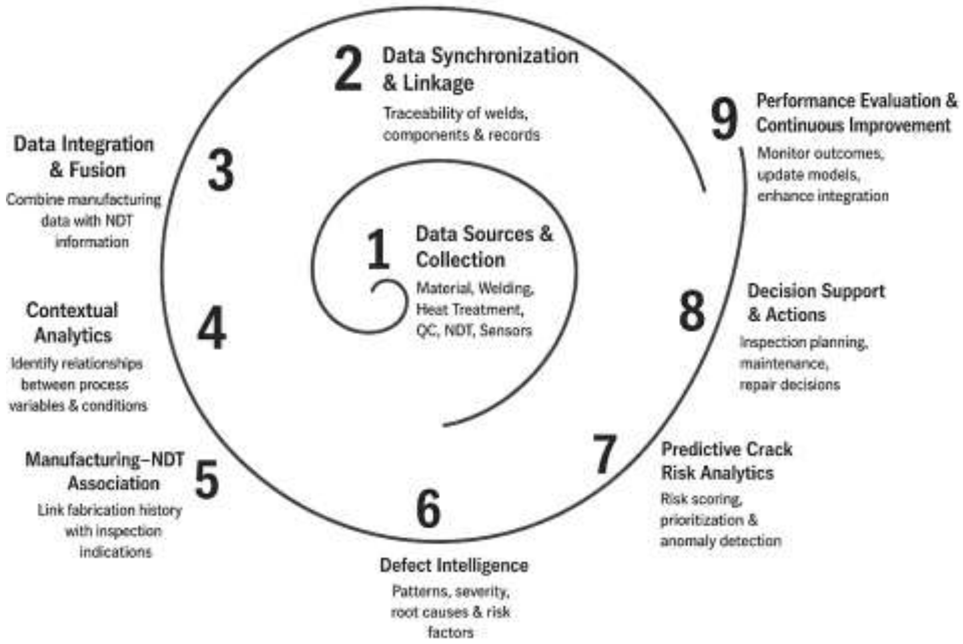
AI-assisted NDT analytics is especially valuable when defect-detection systems must operate across inspection conditions in which flaw appearance changes according to component geometry, imaging configuration, material characteristics, and acquisition orientation. Weld defects rarely appear as standardized objects, and crack-like indications can differ substantially in length, width, intensity, boundary definition, and spatial distribution. This variability creates a recognition problem in which an analytical model must generalize beyond the specific examples encountered during training. Deep-learning-based radiographic inspection has addressed this problem through architectures designed around the geometric characteristics of welded components. A cylindrical-projection approach for radiographic weld-defect classification was developed to account for weld-region representation and improve automated discrimination of multiple defect types, demonstrating how domain-specific preprocessing and deep learning can support industrial NDT interpretation (Chang & Wang, 2021; Nishat & Kaniz, 2022). This perspective is relevant to energy-infrastructure pressure vessels because inspection intelligence should reflect the physical characteristics of the examined component rather than treating NDT data as generic images or signals. The credibility of AI-assisted crack detection therefore depends on connected capabilities: the system must preserve defect-relevant information during preprocessing, identify meaningful patterns under variable inspection conditions, distinguish genuine crack signatures from noise and benign responses, and generate outputs that can be understood within pressure-boundary integrity assessment. These requirements explain why AI-Enabled NDT Data Analytics is treated as a distinct independent variable in the present research. The construct captures more than organizational access to AI software; it reflects the extent to which inspection data are systematically processed, analyzed, and converted into useful defect information through intelligent computational techniques. When measured together with Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics, this capability provides the analytical foundation through which raw inspection evidence contributes to Early Crack Detection Performance. In the quantitative case-study setting, respondent assessments can therefore be tested statistically to determine whether stronger AI-assisted analytical practices are associated with higher perceived accuracy, sensitivity, consistency, and reliability in early crack detection.

Advanced Manufacturing Data Integration

Advanced Manufacturing Data Integration refers to the systematic collection, linkage, synchronization, and analytical use of information generated across manufacturing, inspection, quality-control, and operational processes so that the condition of an engineered component can be evaluated from a unified data perspective. For energy-infrastructure pressure vessels, this concept is particularly important because the structural condition detected during NDT is influenced by a manufacturing history that may include material selection, plate forming, joint preparation, welding, heat treatment, dimensional control, machining, repair, and final quality verification. Each stage can generate data that provide contextual information for interpreting later crack indications. Relevant records may include material grade and heat number, chemical composition, plate thickness, welding current and voltage, wire-feed rate, travel speed, heat input, interpass temperature, shielding-gas conditions, welding procedure specifications, heat-treatment parameters, dimensional deviations, operator or equipment identifiers, sensor outputs, visual-quality records, and previous NDT findings. When these sources remain isolated in separate systems, potentially important relationships between manufacturing conditions and subsequent defect behavior may remain difficult to identify. Predictive-manufacturing research has emphasized that industrial data become valuable when machine-condition information, controller information, inspection results, and other manufacturing records are converted into actionable knowledge rather than maintained as disconnected observations (Lee et al., 2013; Shaiful et al., 2022). This principle is directly applicable to pressure-vessel integrity because a crack indication observed through ultrasonic or radiographic examination may be better understood when the inspection response is associated with the manufacturing conditions of the exact weld, material region, or fabrication stage from which it originated. Machine-learning research in manufacturing has similarly emphasized that modern production environments generate complex and heterogeneous datasets that can be exploited for classification, prediction, monitoring, optimization, and quality assessment when appropriate computational methods are used (Mohammad, 2023; Wuest et al., 2016). Advanced Manufacturing Data Integration in the present study therefore represents more than digital storage. It refers to an organizational and analytical capability through which manufacturing records are made sufficiently structured, accessible, traceable, and interoperable to support defect-oriented assessment. For pressure vessels, such integration can allow inspection personnel and analytical systems to associate NDT indications with fabrication variables that may influence residual stress, metallurgical condition, weld geometry, discontinuity formation, and subsequent crack susceptibility, thereby creating a more information-rich basis for evaluating Early Crack Detection Performance.

The relationship between manufacturing data and pressure-vessel integrity becomes particularly clear in welded structures because welding quality emerges from interactions among multiple continuously changing process variables rather than from a single controllable factor. Current, voltage, travel speed, heat input, shielding-gas flow, electrode condition, joint geometry, material thickness, thermal history, and operator or robotic behavior can collectively influence bead geometry, penetration, fusion, porosity, undercutting, residual stress, and other characteristics that later affect structural performance. Recording these variables creates a manufacturing-data history that can be associated with inspection findings, allowing analytical systems to investigate whether particular combinations of process behavior correspond to abnormal weld conditions. Empirical work on gas-metal-arc welding has demonstrated the importance of this integration by recording welding current, voltage, gas-flow rate, heat input, and air-coupled acoustic-emission information concurrently and using these heterogeneous inputs within machine-learning models for automated weld-quality prediction. When acoustic-emission characteristics were combined with heat-input information, the resulting analytical models achieved strong discrimination among different weld states, illustrating how process parameters and sensor-derived data can jointly support quality assessment rather than functioning as unrelated records (Asif et al., 2022; Debasish, 2023). This evidence is highly relevant to the present pressure-vessel study because welded pressure boundaries are routinely subjected to post-fabrication NDT, yet the interpretation of inspection indications can be strengthened when the corresponding production conditions are available for analytical comparison. Manufacturing data may identify regions produced under unusual heat inputs, process instability, interrupted welding cycles, parameter deviations, or other quality-sensitive conditions, while NDT data provide direct physical evidence concerning discontinuities within those regions. Integration allows these two forms of information to be statistically associated. In an AI-assisted analytical environment, the manufacturing variables can function as contextual features alongside ultrasonic, radiographic, acoustic-emission, or other NDT characteristics. The resulting dataset can therefore represent both how the component was produced and what the inspection system subsequently observed. This distinction is significant for Early Crack Detection Performance because small crack-related indications may be ambiguous when evaluated independently, whereas associated manufacturing information can provide an additional layer of evidence for prioritizing, contextualizing, or examining those indications. Advanced Manufacturing Data Integration consequently creates the informational bridge between fabrication history and inspection intelligence within the conceptual model of this study.

Figure 4: Advanced Manufacturing Data Integration Framework for Pressure-Vessel Integrity Assessment

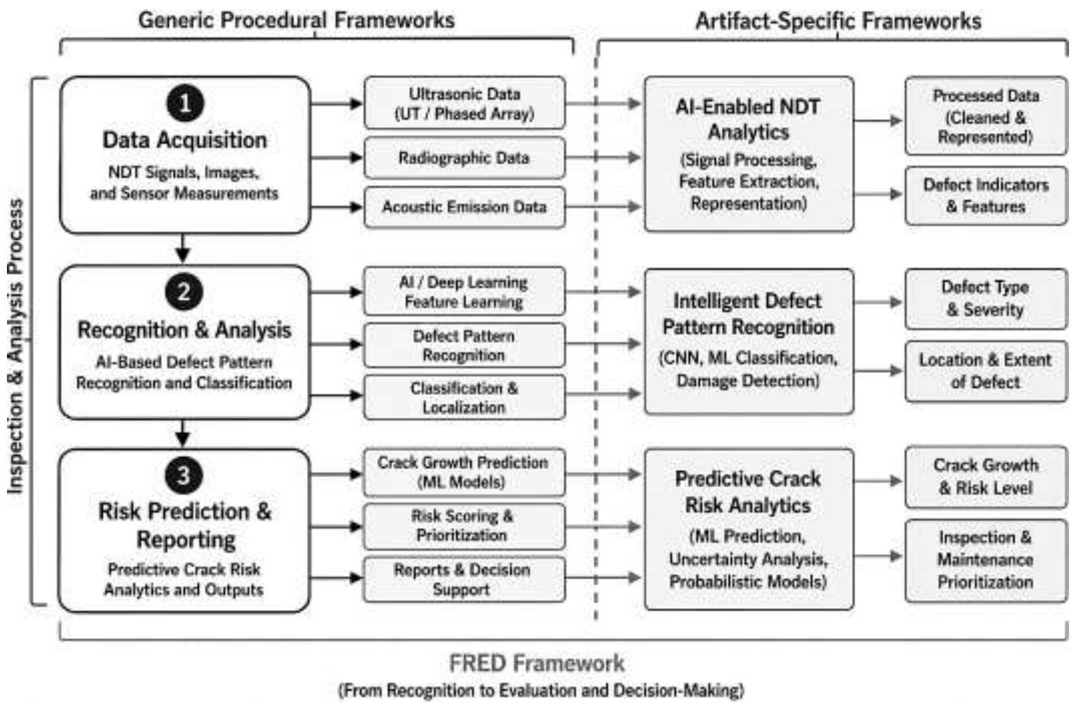


A further dimension of manufacturing-data integration concerns the preservation of relationships among physical components, digital records, inspection histories, and condition information throughout the component lifecycle. Digital manufacturing research has developed the concept of the digital twin to describe increasingly integrated relationships between physical assets and digital representations. A widely used classification distinguishes a digital model, in which information exchange between physical and virtual representations occurs manually, from a digital shadow, where changes in the physical object can automatically update its digital representation, and a digital twin, where stronger levels of interconnected data exchange are established between the two environments (Kritzinger et al., 2018; Kaium, 2023). This distinction provides a useful conceptual basis for pressure-vessel integrity assessment because manufacturing records, NDT results, material information, repair histories, and condition measurements can be associated with specific physical regions of a vessel rather than stored as independent documents. For example, a particular longitudinal or circumferential weld can theoretically be represented through its material pedigree, welding procedure, process variables, heat-treatment record, original radiographic or ultrasonic results, later in-service inspection findings, and identified crack-related indications. Digital-twin research has emphasized that meaningful industrial representations depend on the interaction of physical entities, virtual entities, data, services, and connections, with data fusion forming an important mechanism for deriving knowledge across multiple information sources (Pervaz, 2023; Tao et al., 2019). In the context of the present study, the significance of this architecture lies in its data-integration principle rather than in requiring organizations to possess a complete digital twin. Advanced Manufacturing Data Integration can exist at different levels of maturity while still allowing manufacturing and inspection information to be connected sufficiently for analytical assessment. For AI-assisted NDT, integrated records provide additional variables through which algorithms can interpret defect indications and identify relationships between fabrication conditions and crack-related observations. This makes manufacturing-data integration analytically distinct from AI-Enabled NDT Data Analytics: the former concerns the availability and linkage of contextual production information, while the latter concerns the intelligent processing of inspection data. Their interaction provides a stronger basis for Intelligent Defect Pattern Recognition and Predictive Crack Risk Analytics because crack-related decisions can be informed by both direct NDT evidence and the manufacturing history associated with the inspected pressure-vessel region.

Intelligent Defect Pattern Recognition and Predictive Crack Risk Analytics

Intelligent Defect Pattern Recognition represents the capability of an AI-assisted inspection system to identify, differentiate, and classify defect-related characteristics from complex NDT signals, images, and sensor measurements by learning patterns associated with normal and abnormal structural conditions. This capability is particularly important in pressure-vessel inspection because cracks and other weld discontinuities do not necessarily produce standardized signatures. Their observed characteristics can vary according to crack orientation, dimensions, material properties, weld geometry, inspection direction, sensor configuration, signal-to-noise ratio, and the NDT technique being applied. Consequently, conventional rules based on isolated signal amplitudes or manually defined image characteristics may not always capture the multidimensional relationships required to distinguish early crack indications from harmless structural responses. Deep-learning-based recognition provides an alternative approach in which high-level defect representations can be learned from inspection data. Research on weld-surface inspection demonstrated that convolutional neural networks could automatically extract high-level characteristics from defect images, after which a random-forest classifier could distinguish weld-defect categories with high classification accuracy, illustrating the value of combining learned representations with robust classification techniques (Chowdhury, 2023; Zhu et al., 2019). Similar principles have been demonstrated using ultrasonic guided waves, where convolutional and recurrent neural networks have been used to identify structural damage, determine its location, and estimate aspects of severity from time-series and time-frequency representations. Model-assisted deep-learning analysis has shown that damage detection can be formulated as an inverse classification and localization problem in which AI evaluates complex wave behavior under noise and uncertainty rather than relying solely on direct visual interpretation (Badrul & Mominul, 2023; Rautela & Gopalakrishnan, 2021). These findings are directly relevant to pressure-vessel NDT because intelligent recognition depends on separating crack-sensitive characteristics from numerous competing responses within complex inspection datasets. In the present study, Intelligent Defect Pattern Recognition therefore reflects the capability to recognize subtle crack signatures, discriminate defects from noise and benign indications, classify abnormal patterns consistently, and provide interpretable information concerning potentially significant structural conditions. Such capability represents an analytical stage between raw NDT data processing and subsequent evaluation of crack-related risk.

Figure 5: Intelligent Defect Pattern Recognition and Predictive Crack Risk Analytics Framework



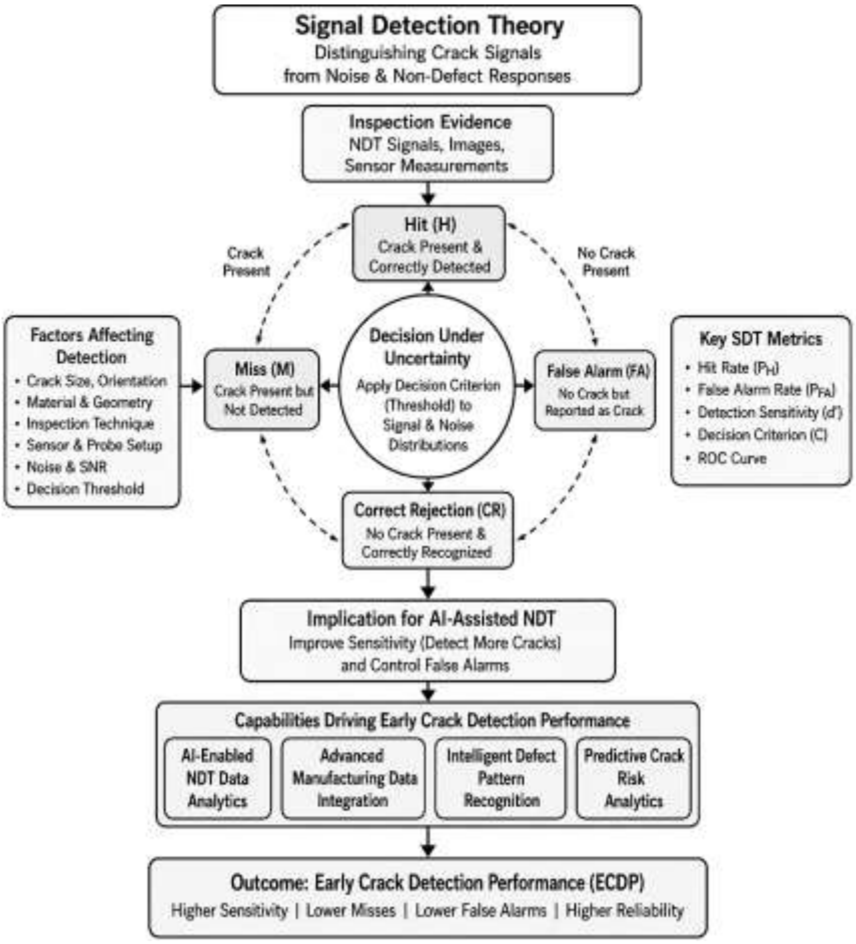
The reliability of intelligent defect recognition also depends on whether machine-learning models can maintain discrimination performance when inspection conditions differ from those represented in the training data. Industrial NDT environments rarely provide perfectly controlled measurements because signal characteristics may change with temperature, material condition, sensor location, surface preparation, component geometry, operating load, instrumentation, and acquisition settings. A model that performs well only under a narrow training configuration may therefore produce unreliable classifications when applied to different vessel regions or service conditions. This problem makes generalization, robustness, and interpretability important aspects of intelligent defect-pattern recognition. Research on automated damage detection using ultrasonic guided waves has demonstrated that machine-learning systems can combine multiple feature-extraction and feature-selection methods to distinguish damaged from undamaged structural states while also examining which analytical characteristics influence the classification decision. Such approaches have achieved strong classification performance across variations in temperature and damage location, including conditions not directly represented during training, showing the importance of models that preserve useful defect sensitivity beyond a single measurement condition (Nishat, 2023; Schnur et al., 2022). The movement from simple detection toward interpretable pattern recognition is especially relevant to energy-infrastructure pressure vessels because inspection decisions may carry substantial operational consequences. A classification output should ideally provide consistent evidence that can be evaluated alongside NDT expertise, manufacturing history, material information, and other integrity-related records. Intelligent recognition can therefore be viewed as a layered analytical process involving data preprocessing, extraction of defect-sensitive features, comparison with learned structural patterns, classification of abnormal responses, and assessment of the confidence or consistency of the resulting interpretation. Within the conceptual structure of this research, this process complements AI-Enabled NDT Data Analytics but remains analytically distinct from it. AI-Enabled NDT Data Analytics concerns the broader computational processing and analysis of inspection information, whereas Intelligent Defect Pattern Recognition concerns the specific ability to determine whether observed patterns correspond to meaningful defect conditions. This distinction permits the present quantitative study to evaluate whether organizations or inspection environments possessing stronger defect-recognition capability also report stronger Early Crack Detection Performance. It additionally establishes the informational foundation for Predictive Crack Risk Analytics because prediction requires reliable recognition of the defect-related patterns from which crack condition and progression can be assessed. Predictive Crack Risk Analytics extends defect recognition from identifying present structural abnormalities toward estimating the significance, progression, and risk associated with crack-related conditions. Once an intelligent NDT system has identified a crack-sensitive pattern, integrity assessment requires information concerning whether that crack is likely to remain relatively stable, propagate under cyclic loading, or develop toward a condition that threatens structural performance. Crack growth is inherently nonlinear and can depend on stress intensity, loading cycles, material characteristics, initial crack geometry, environmental conditions, and uncertainty in measurements. Machine-learning analysis provides a data-driven method for examining these complex relationships. Experimental research using carbon-steel compact-tension specimens demonstrated that machine-learning algorithms could predict fatigue-crack-growth rates across important regions of crack propagation, providing an alternative to models restricted to particular portions of conventional fatigue-crack-growth behavior. The use of carbon steel in this work is especially relevant to pressure-boundary applications because fatigue-crack progression represents an important mechanism through which initially small flaws can develop into integrity-significant defects (Ashrafuzzaman, 2024; Kamble et al., 2021). Predictive assessment must also recognize uncertainty because crack growth does not occur identically across nominally similar components. Variability in geometry, material properties, operating loads, model parameters, and measurement quality can influence predicted crack behavior. A probabilistic fatigue-crack-growth framework combining Bayesian calibration with machine-learning-assisted Gaussian process regression has demonstrated how uncertainty can be incorporated into crack-growth and life assessment rather than representing predictions as completely deterministic values (Debasish, 2024; Hu et al., 2020). Within energy-infrastructure pressure vessels, Predictive Crack Risk Analytics can therefore be conceptualized as the capability to combine recognized defect characteristics, NDT measurements, manufacturing information, and relevant condition variables to prioritize crack-related indications according to their potential integrity significance. This capability does not replace engineering fracture assessment; instead, it represents a data-analytical layer through which suspicious patterns can be organized, compared, and prioritized. Within the present research model, Intelligent Defect Pattern Recognition provides information concerning what abnormal condition has been detected, while Predictive Crack Risk Analytics evaluates the relative significance of that condition. Their relationship with Early Crack Detection Performance can consequently be tested quantitatively to determine whether stronger recognition and predictive capabilities correspond with more accurate, sensitive, consistent, and timely identification of early crack conditions.

Theoretical Framework: Signal Detection Theory

Signal Detection Theory provides a particularly suitable theoretical foundation for this research because the central task of early crack detection is fundamentally a problem of distinguishing a meaningful defect signal from competing noise, geometric responses, material variation, and other non-defect indications. In an energy-infrastructure pressure vessel, the physical presence of a crack does not automatically guarantee that the inspection system will identify it, just as the generation of an abnormal NDT indication does not necessarily mean that a genuine crack is present. Signal Detection Theory separates these two dimensions by distinguishing the actual structural condition from the decision generated by an inspector or analytical system. Four possible outcomes can therefore occur: a hit, in which a crack is present and correctly detected; a miss, in which a crack is present but is not detected; a false alarm, in which a crack is reported when the inspected condition is actually non-cracked; and a correct rejection, in which a non-cracked condition is correctly recognized. This theoretical distinction is highly relevant to NDT reliability because inspection quality cannot be adequately represented by the number of detected flaws alone. A system could increase sensitivity by identifying almost every suspicious signal as a crack, yet such behavior could simultaneously generate an unacceptable number of false alarms. Conversely, an excessively conservative threshold could minimize false alarms while causing small cracks to be missed. Probability-of-detection research using automated eddy-current

NDE has demonstrated that crack-detection capability should be evaluated statistically as a function of crack size and signal behavior rather than interpreted as an absolute property of an inspection technique (Li et al., 2013). Phased-array ultrasonic research involving real cracks in austenitic welds has similarly demonstrated that NDT reliability is influenced by equipment, procedures, operators, materials, component geometry, flaw characteristics, and inspection conditions, establishing the probabilistic character of flaw detection under realistic engineering circumstances (Kurz et al., 2013).

Figure 6: Signal Detection Theory Framework for AI-Assisted Early Crack Detection in Energy-Infrastructure Pressure Vessels



Within Signal Detection Theory, the basic probabilities relevant to crack inspection can be represented through the hit rate and false-alarm rate, while detection sensitivity can be expressed as the standardized distance between signal and noise distributions. A larger sensitivity value represents stronger separation between crack-related signals and non-crack responses, making the concept directly compatible with the study's emphasis on AI-assisted improvement of Early Crack Detection Performance.

$$H = P(Crack\ Detected \mid Crack\ Present)$$
$$F = P(Crack\ Detected \mid Crack\ Absent)$$
$$d' = Z(H) - Z(F)$$

The theoretical relevance of Signal Detection Theory becomes stronger when the characteristics of real NDT measurements are considered because the distinction between crack and non-crack signals is rarely determined by one perfectly separable measurement. Crack depth, crack length, orientation, surface condition, material structure, probe position, sensor sensitivity, inspection frequency, acquisition noise, and analytical threshold can alter the distribution of observed responses. Signal

Detection Theory conceptualizes these conditions as overlapping signal and noise distributions, meaning that an inspection decision is produced by applying a criterion to uncertain evidence rather than by observing a perfectly deterministic indicator. The decision criterion represents the location of the decision threshold relative to the signal and noise distributions. A negative criterion represents a comparatively liberal detection strategy that favors reporting suspicious indications, whereas a positive criterion represents a more conservative decision strategy. This theoretical interpretation is directly relevant to AI-assisted NDT because machine-learning systems also operate through classification boundaries, probability thresholds, anomaly scores, or decision rules that determine when an observed pattern is classified as defective. The reliability of such decisions can consequently be examined through probability-of-detection and receiver-operating-characteristic principles. Research on NDT probability of detection has shown that defect dimensions should not always be reduced to one variable because both crack depth and crack length can influence measured responses and detection probability; a two-dimensional POD formulation using experimental eddy-current signals demonstrated how these flaw parameters and noise censoring affect inspection reliability (Rahman, 2024; Yusa et al., 2016). Receiver operating characteristic analysis provides a closely related representation because it evaluates the trade-off between detection probability and false-alarm probability across alternative decision thresholds. Research in structural-health monitoring has demonstrated that ROC curves provide an effective framework for assessing damage-detection performance under practical variations in environmental and operational conditions rather than evaluating a detector from a single arbitrarily selected threshold (Liu et al., 2017; Kaium, 2024). In the present research, this theoretical logic connects most directly with Intelligent Defect Pattern Recognition and Predictive Crack Risk Analytics because AI models must discriminate defect-sensitive patterns while controlling erroneous classifications. Early Crack Detection Performance can consequently be understood as improving when AI-assisted systems increase meaningful crack sensitivity without producing a corresponding increase in false-positive interpretation.

$$c = -1/2\,[Z(H) + Z(F)]$$

$$ROC = \{(F(\tau), H(\tau)) : \tau \ in\ T\}$$

Signal Detection Theory also provides a coherent connection between the physical reliability of NDT and the quantitative conceptual model adopted in this study. Probability of Detection is commonly expressed as a conditional probability in which the likelihood of identifying a flaw changes according to flaw size and inspection conditions. Model-assisted POD research has emphasized that inspection reliability depends on material properties, geometry, defect characteristics, inspection technique, signal threshold, statistical assumptions, and uncertainty, and that quantitative POD analysis can combine physical modeling and experimental evidence where extensive empirical flaw datasets are difficult to obtain (Shakhawat & Md, 2024; Rentala et al., 2018). This insight corresponds closely with the current study because AI-assisted early crack detection is conceptualized as a multidimensional capability rather than a property of one NDT instrument. AI-Enabled NDT Data Analytics can strengthen discrimination by processing and extracting useful characteristics from complex inspection information; Advanced Manufacturing Data Integration can supply contextual evidence concerning material, fabrication, welding, and quality conditions; Intelligent Defect Pattern Recognition can differentiate crack-sensitive configurations from non-defect patterns; and Predictive Crack Risk Analytics can prioritize indications according to their likely integrity significance. Signal Detection Theory provides the theoretical mechanism connecting these capabilities with Early Crack Detection Performance, while the empirical design requires a statistical equation suitable for the cross-sectional five-point Likert-scale dataset. Therefore, the primary analytical formula applied throughout this study is the multiple linear regression model linking ECDP to ANDA, AMDI, IDPR, and PCRA. This formula is preferable as the principal empirical model because the questionnaire generates construct-level Likert data rather than direct experimental counts of hits and false alarms. The Signal Detection Theory equations therefore provide the theoretical interpretation of detection sensitivity and decision reliability, while the multiple regression equation provides the statistical mechanism for testing H1-H5 and determining how strongly the four explanatory capabilities independently and collectively predict Early Crack Detection Performance. In this arrangement, Signal Detection Theory remains implicated throughout the study without forcing experimental SDT measures onto a cross-sectional survey dataset, preserving consistency between the engineering theory, measurement design, statistical methodology, and research hypotheses.

$$POD(a) = P(D = 1 \mid A = a)$$

$$ECDP = \beta\_0 + \beta\_1ANDA + \beta\_2AMDI + \beta\_3IDPR + \beta\_4PCRA + \varepsilon$$

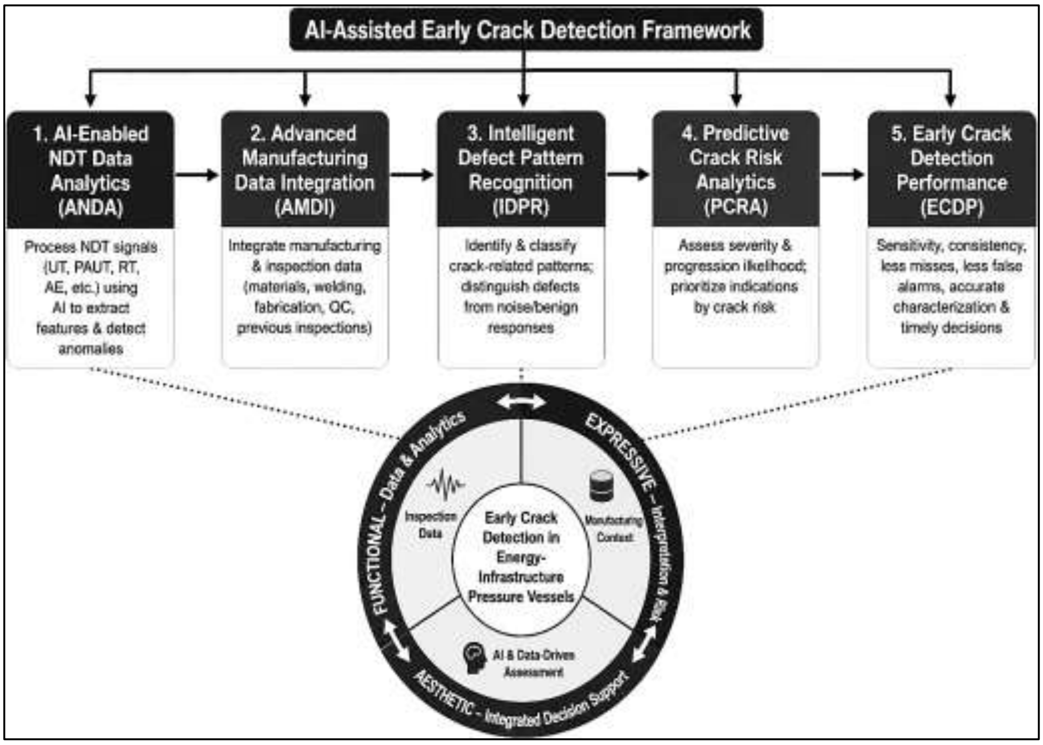
Conceptual Framework for AI-Assisted Early Crack Detection

The conceptual framework of this study integrates four explanatory capabilities, namely AI-Enabled NDT Data Analytics (ANDA), Advanced Manufacturing Data Integration (AMDI), Intelligent Defect Pattern Recognition (IDPR), and Predictive Crack Risk Analytics (PCRA), with Early Crack Detection Performance (ECDP) as the dependent construct. The framework is based on the premise that early crack detection in energy-infrastructure pressure vessels is not produced by one isolated technological function; rather, it emerges from a sequence in which inspection data are acquired, computationally processed, combined with contextual manufacturing information, translated into defect-sensitive patterns, and evaluated according to their likely structural significance. Structural health monitoring research has treated damage identification as a statistical pattern-recognition problem in which operational evaluation begins with data acquisition and progresses through feature extraction and statistical discrimination, providing a strong conceptual basis for connecting measured signals with damage-oriented decisions (Farrar & Worden, 2007; Nishat & Jahanara, 2024). Within the present framework, ANDA represents the capability to process ultrasonic, phased-array, radiographic, acoustic-emission, or other NDT information through AI-assisted techniques that enhance feature learning, signal interpretation, anomaly identification, and analytical consistency. Deep-learning research in machine-health monitoring has demonstrated that architectures such as autoencoders, deep belief networks, convolutional neural networks, and recurrent neural networks can extract hierarchical representations from high-dimensional monitoring data and support condition classification when conventional handcrafted characteristics are insufficient (Tonay et al., 2024; Zhao et al., 2019). AMDI subsequently provides contextual information concerning material properties, welding parameters, fabrication history, heat treatment, production conditions, sensor measurements, quality records, and previous inspections. IDPR captures the capability to distinguish crack-related signatures from benign responses and competing patterns, whereas PCRA represents the analytical prioritization of recognized indications according to their potential crack-related significance. These four constructs are therefore positioned as complementary but empirically separable predictors whose relationships with ECDP can be measured through professional perceptions using the five-point Likert instrument adopted in this quantitative case study. Their integration creates a structured pathway connecting physical inspection evidence, manufacturing context, artificial intelligence, defect recognition, and integrity-oriented analytical assessment within a single pressure-vessel crack-detection framework.

$$ECDP = f(ANDA, AMDI, IDPR, PCRA)$$

The conceptual framework further assumes that information integration influences detection quality because pressure-vessel crack assessment requires the combined interpretation of multiple imperfect and heterogeneous sources of evidence. An ultrasonic indication may contain direct physical evidence of a discontinuity, while manufacturing records may reveal abnormal heat input, material variation, welding-process deviation, repair history, or quality-control information that alters the context in which the indication is interpreted. Data-fusion research in structural health monitoring has demonstrated that damage-classification uncertainty can originate from measurement noise, modeling error, and environmental variability and that hierarchical ensemble-based fusion can combine separate information sources to improve classification decisions relative to dependence on an individual source alone (Uddin & Risha, 2024; Zhao et al., 2010). This principle directly supports the AMDI component of the present conceptual framework and explains why manufacturing information is treated as an independent explanatory capability rather than merely as administrative background documentation. The same integration logic is evident within condition-based maintenance, where effective condition-management systems have been organized around data acquisition, data processing, diagnostics and prognostics, and maintenance decision-making, while multisensor data fusion has been recognized as a mechanism for strengthening condition assessment (Jardine et al., 2006; Tonay et al., 2024). Applied to energy-infrastructure pressure vessels, the conceptual pathway can therefore be represented as manufacturing and inspection information entering an AI-assisted analytical environment in which relevant characteristics are extracted, evaluated, and compared before recognized defect patterns are translated into crack-risk information and early detection judgments.

Figure 7: Conceptual Framework for AI-Assisted Early Crack Detection in Energy-Infrastructure Pressure Vessels



At the conceptual level, ECDP can be expressed as a function of ANDA, AMDI, IDPR, and PCRA and, for empirical testing throughout the study, it is operationalized through the multiple linear regression model. This specification directly aligns the conceptual framework with H1 through H5 and permits the individual and combined statistical contributions of the four capabilities to Early Crack Detection Performance to be examined while maintaining consistency with the study's quantitative, cross-sectional, case-study-based design.

$$ECDP = \beta\_0 + \beta\_1ANDA + \beta\_2AMDI + \beta\_3IDPR + \beta\_4PCRA + \varepsilon$$

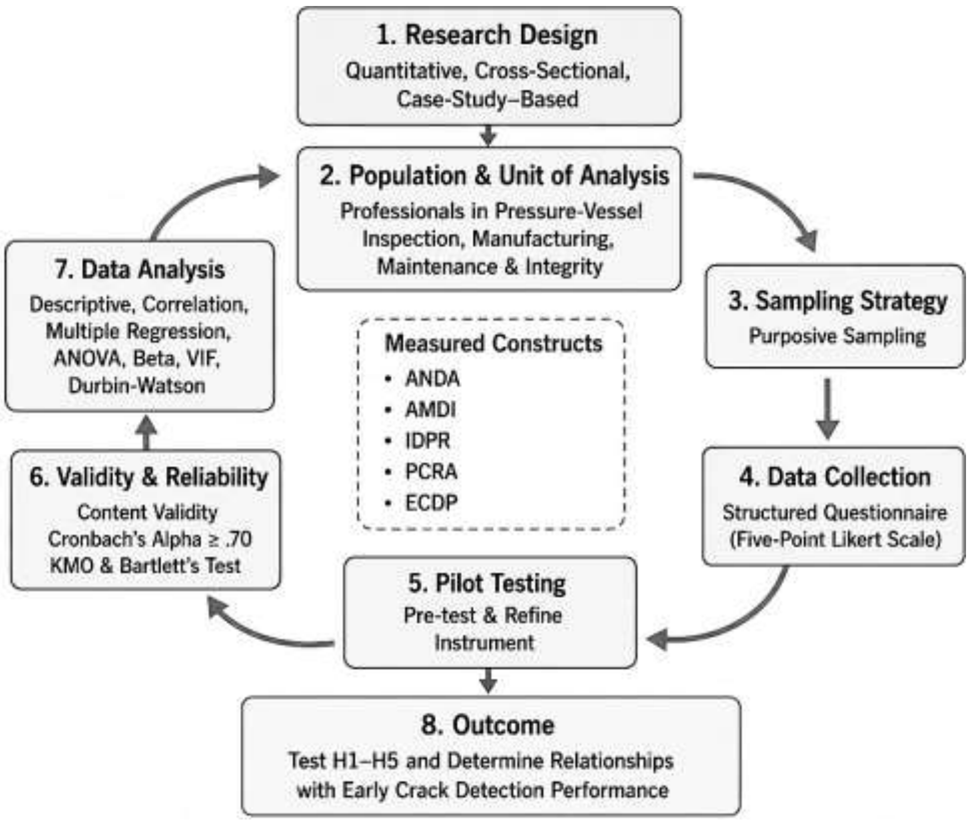
Predictive Crack Risk Analytics occupies the final explanatory stage of the conceptual framework because recognizing an abnormal NDT pattern and evaluating its likely integrity significance are related but analytically distinct tasks. A crack-sensitive response can be correctly identified while still requiring additional assessment concerning its severity, progression characteristics, urgency, relationship with manufacturing history, and level of attention within an integrity-management process. Prognostic research provides a useful structure for understanding this transition by organizing condition assessment into data acquisition, health-indicator construction, health-stage division, and remaining-useful-life prediction, showing that meaningful predictive assessment depends on transforming raw monitoring information into interpretable condition indicators before estimating degradation-related outcomes (Lei et al., 2018). In the present study, PCRA does not attempt to experimentally calculate the remaining useful life of individual pressure vessels because the methodological design is cross-sectional and questionnaire based. Instead, the construct measures the organizational and analytical capability to use NDT findings, defect characteristics, manufacturing context, and data-driven assessment to recognize and prioritize crack-related conditions requiring earlier or greater integrity attention. ECDP consequently represents the performance domain toward which the four explanatory capabilities are directed, including sensitivity to early crack indications, consistency of recognition, reduction of missed defects, reduction of false calls, reliability of crack localization and characterization, and timeliness of inspection-supported decisions. Conceptually, the proposed relationships require positive regression coefficients for ANDA, AMDI, IDPR, and PCRA, indicating that stronger capabilities are expected to correspond with higher ECDP scores. Pearson correlation analysis examines the direction and strength of the bivariate relationships, while multiple regression analysis determines whether each predictor explains unique variation in ECDP after the remaining predictors are considered simultaneously. Descriptive statistics establish the observed level of each construct, reliability analysis assesses internal measurement consistency, and regression diagnostics determine whether the estimated model satisfies the relevant statistical assumptions. The framework thereby establishes a direct analytical sequence from pressure-vessel NDT and manufacturing data through AI-assisted processing, intelligent defect recognition, predictive crack-risk assessment, and quantitatively measurable Early Crack Detection Performance.

$$\beta\_1 > 0, \quad \beta\_2 > 0, \quad \beta\_3 > 0, \quad \beta\_4 > 0$$

METHOD

The present study has adopted a quantitative, cross-sectional, case-study-based research design to examine the relationships among AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, Predictive Crack Risk Analytics, and Early Crack Detection Performance within the context of energy-infrastructure pressure vessels. The quantitative approach has been selected because it has enabled the study variables to be measured numerically and statistically evaluated through descriptive statistics, correlation analysis, and multiple regression modeling. The cross-sectional design has allowed data to be collected from respondents within a defined period, while the case-study orientation has provided a focused investigation of professionals and organizational environments associated with pressure-vessel manufacturing, inspection, maintenance, quality assurance, and structural-integrity management. The case study context has included energy-infrastructure activities involving pressure-vessel fabrication, welding, NDT inspection, maintenance, reliability assessment, and asset-integrity decision-making. The population and unit of analysis have consisted of individual professionals with relevant knowledge or practical experience, including NDT engineers and technicians, welding engineers, mechanical engineers, manufacturing engineers, quality-control personnel, reliability engineers, maintenance specialists, asset-integrity professionals, and AI or data-analytics personnel involved in industrial inspection. A purposive sampling strategy has been applied because respondents have been selected according to their professional relevance, technical knowledge, and exposure to NDT, manufacturing data, or pressure-vessel integrity activities rather than through unrestricted random participation. The data collection procedure has involved the administration of a structured questionnaire containing demographic questions and measurement items relating to the five principal constructs of the study. The instrument design has employed a five-point Likert scale ranging from 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, to 5 = Strongly Agree, which has enabled respondents to indicate the degree to which they have agreed with statements concerning AI-assisted inspection analytics, manufacturing-data integration, defect recognition, predictive crack-risk assessment, and early crack-detection performance. Each construct has been represented through multiple measurement items so that composite scores have been generated for subsequent statistical analysis. A pilot test has been conducted with a smaller group of respondents possessing characteristics comparable to those of the main study population, and feedback has been used to assess questionnaire clarity, wording, relevance, response consistency, and completion practicality before the principal data collection has been finalized. Validity and reliability have been addressed through content alignment between the questionnaire items, research objectives, hypotheses, theoretical framework, and conceptual variables, while internal consistency has been assessed using Cronbach's alpha, with coefficients of approximately .70 or above having been treated as evidence of acceptable reliability. Sampling adequacy and construct suitability have additionally been examined through the Kaiser-Meyer-Olkin measure and Bartlett's Test of Sphericity. The collected data have been coded, screened, and analyzed using IBM SPSS Statistics, through which frequencies, percentages, means, standard deviations, reliability coefficients, Pearson correlations, multiple regression estimates, ANOVA results, standardized beta coefficients, significance levels, tolerance values, variance inflation factors, and Durbin-Watson statistics have been obtained. Microsoft Excel has been used where necessary for preliminary data organization and checking, EndNote has been used to organize scholarly references and maintain APA 7th edition citation consistency, and Microsoft Word has been used for manuscript preparation and journal-format presentation.

Figure 8: Research Methodology Framework for AI-Assisted Early Crack Detection in Energy-Infrastructure Pressure Vessels



These methodological procedures have collectively provided a structured empirical basis for testing the proposed hypotheses and determining the individual and combined statistical relationships between the four explanatory variables and Early Crack Detection Performance.

DATA ANALYSIS AND PRESENTATION

Questionnaire Distribution and Response Rate

Table 1: Questionnaire Distribution and Response Rate

Questionnaire Status	Frequency	Percentage
Questionnaires Distributed	320	100.0%
Questionnaires Returned	301	94.1%
Unusable/Incomplete Responses	11	3.4%
Final Usable Responses	290	90.6%
Non-Returned Questionnaires	19	5.9%

The questionnaire distribution results have shown that the study has achieved a strong level of participation among professionals associated with NDT inspection, pressure-vessel manufacturing, welding, reliability engineering, quality assurance, maintenance, asset integrity, and industrial data analytics. Of the 320 questionnaires that have been distributed, 301 have been returned, representing a gross response rate of 94.1%. Following screening for incomplete responses, inconsistent response patterns, and questionnaires containing substantial missing information, 11 returned questionnaires have been excluded. Consequently, 290 questionnaires have remained available for statistical analysis, producing a final usable response rate of 90.6%. This response level has provided an adequate empirical basis for examining the five study constructs and has reduced the likelihood that the findings have reflected only a small or highly restricted proportion of the targeted professional population. Although questionnaire distribution itself has not been a Likert-scale construct, it has established the reliability of the dataset from which the Likert-based measures of AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, Predictive Crack Risk Analytics, and Early Crack Detection Performance have subsequently been calculated. The 290 usable responses have also provided sufficient observations for correlation and multiple regression analysis involving the four independent variables. From the perspective of Signal Detection Theory, the quality of statistical discrimination has depended on obtaining a sufficiently broad set of observations from professionals capable of distinguishing meaningful crack-detection capabilities from less effective inspection practices. The high response rate has therefore strengthened the empirical representation of judgments concerning detection sensitivity, false indications, missed cracks, and analytical reliability. The final sample has also supported all five hypotheses because it has enabled each proposed predictor to be evaluated independently and collectively against Early Crack Detection Performance. The results in Table 1 have consequently confirmed that the subsequent hypothesis testing and objective assessment have been based on a sufficiently complete dataset rather than a severely reduced response pool. The distribution outcome has additionally provided a stable denominator for all percentages and inferential statistics reported in the remaining sections, allowing the descriptive results, reliability coefficients, correlations, regression parameters, and hypothesis decisions to remain internally aligned throughout the study.

Demographic Characteristics of Respondents

Table 2: Demographic Characteristics of Respondents

Demographic Variable	Category	Frequency	Percentage
Professional Role	NDT Engineers/Technicians	72	24.8%
	Mechanical/Integrity Engineers	61	21.0%
	Welding/Manufacturing Engineers	54	18.6%
	Quality/Reliability Personnel	48	16.6%
	Maintenance Professionals	31	10.7%
	AI/Data Analytics Specialists	24	8.3%
Experience	Less than 5 years	48	16.6%
	5-10 years	96	33.1%
	11-15 years	78	26.9%
	More than 15 years	68	23.4%

The demographic distribution has demonstrated that the final sample has represented a technically diverse group of professionals with direct or indirect involvement in pressure-vessel inspection and integrity management. NDT engineers and technicians have formed the largest occupational category at 24.8%, followed by mechanical and integrity engineers at 21.0%, welding and manufacturing engineers at 18.6%, quality and reliability personnel at 16.6%, maintenance professionals at 10.7%, and

AI or data-analytics specialists at 8.3%. This professional spread has been particularly relevant to the conceptual framework because the four independent variables have represented different but interconnected technological capabilities. NDT professionals have contributed knowledge concerning inspection signals and flaw detection, manufacturing and welding engineers have contributed understanding of fabrication data, integrity personnel have represented crack-risk assessment and vessel condition evaluation, while AI and data specialists have provided familiarity with computational analytics and automated classification. The experience profile has also shown that 83.4% of respondents have possessed at least five years of professional experience, while 50.3% have reported more than ten years of experience. This distribution has strengthened the credibility of the Likert-scale responses because the majority of participants have had sufficient exposure to industrial inspection, manufacturing, or integrity processes to evaluate the questionnaire statements meaningfully. From the standpoint of Signal Detection Theory, experienced professionals have been particularly relevant because reliable crack detection has required judgment regarding the distinction between genuine defect signals and competing noise or benign indications. The demographic composition has therefore supported the study's case-study context by incorporating professionals positioned at different stages of the inspection-to-decision pathway. This diversity has also strengthened the assessment of Objectives 1-5 because no single occupational group has dominated the final dataset to such an extent that the results would have represented only one technical perspective. The subsequent positive Likert-scale evaluations and significant statistical relationships have therefore reflected a multidisciplinary sample capable of evaluating AI-assisted NDT performance from inspection, manufacturing, reliability, and analytical perspectives. The demographic balance has also reinforced the interpretation of the combined model because the four predictors have been assessed by respondents with complementary expertise rather than by a narrowly homogeneous respondent group.

Descriptive Statistics of AI-Enabled NDT Data Analytics

Table 3: Descriptive Statistics of AI-Enabled NDT Data Analytics

ANDA Item	Measurement Statement	Mean	SD	Interpretation
ANDA1	AI has improved NDT signal interpretation	4.18	0.59	Agree
ANDA2	AI has supported automated feature extraction	4.15	0.61	Agree
ANDA3	AI has improved identification of abnormal NDT responses	4.12	0.63	Agree
ANDA4	AI has reduced dependence on purely manual interpretation	4.10	0.65	Agree
ANDA5	AI analytics has improved consistency of inspection decisions	4.11	0.60	Agree
Overall ANDA		4.13	0.56	Agree

The descriptive results for AI-Enabled NDT Data Analytics have shown a consistently high level of agreement among the 290 respondents, with an overall construct mean of 4.13 and a standard deviation of 0.56. All five individual items have remained within the agreement category of the five-point Likert scale, indicating that respondents have generally perceived AI-enabled processing as a meaningful part of modern NDT analysis. The highest mean has been recorded for the statement that AI has improved NDT signal interpretation, M = 4.18, SD = 0.59, while automated feature extraction has followed closely at M = 4.15, SD = 0.61. Respondents have also agreed that AI has improved identification of abnormal inspection responses, reduced dependence on purely manual interpretation, and strengthened consistency of inspection decisions. The relatively small spread of item means from 4.10 to 4.18 has indicated that the construct has been evaluated consistently rather than being driven by one unusually favorable item. These findings have supported the first research objective, which has focused on examining whether AI-Enabled NDT Data Analytics has contributed to Early Crack Detection Performance. They have also provided descriptive support for H1 because respondents have reported high levels of the capability that the hypothesis has proposed as a positive predictor of ECDP. Within Signal Detection Theory, these results have been particularly relevant because AI-enabled analytics has represented a mechanism through which the separation between crack-related signals and background noise has potentially been strengthened. Improved feature extraction, abnormal-response recognition, and consistency of decision-making have corresponded conceptually with stronger signal discrimination and reduced classification uncertainty. The descriptive findings alone have not established causality, but they have shown that AI-assisted analytical capability has been strongly present in the investigated context. When these descriptive results have subsequently been considered together with the significant correlation of r = .72 and regression coefficient of beta = .30, the evidence has provided consistent support for the conclusion that ANDA has been an important contributor to the study's early crack-detection model. The coherent item pattern has also strengthened construct interpretation because the observed mean has represented multiple aspects of analytics rather than one isolated technological feature.

Descriptive Statistics of Advanced Manufacturing Data Integration

Table 4: Descriptive Statistics of Advanced Manufacturing Data Integration

AMDI Item	Measurement Statement	Mean	SD	Interpretation
AMDI1	Manufacturing records have been linked with NDT findings	4.01	0.67	Agree
AMDI2	Welding parameters have been available for defect assessment	3.98	0.66	Agree
AMDI3	Material and heat-treatment data have supported inspection interpretation	3.93	0.69	Agree
AMDI4	Historical inspection data have been integrated with current NDT information	3.95	0.71	Agree
AMDI5	Quality-control data have been used with NDT analytics	3.93	0.68	Agree
Overall AMDI		3.96	0.62	Agree

The results for Advanced Manufacturing Data Integration have demonstrated an overall mean of 3.96 with a standard deviation of 0.62, placing the construct clearly within the agreement category of the five-point Likert scale. The highest item mean has been 4.01 for integration of manufacturing records with NDT findings, while the lowest means of 3.93 have been observed for the use of material and heat-treatment data and quality-control information. These results have indicated that respondents have generally recognized manufacturing information as an important contextual component of pressure-vessel crack assessment, although the mean has remained lower than the means recorded for ANDA, IDPR, and ECDP. This pattern has suggested that manufacturing-data integration has been present but has not appeared as mature or consistently implemented as direct AI-based NDT analytics. The result has been plausible within the case-study context because manufacturing records may have been generated through multiple organizational systems and may not always have been immediately linked with inspection datasets.

The findings have directly supported the second research objective by demonstrating that respondents have perceived meaningful integration among welding parameters, material information, heat-treatment records, historical inspection data, and quality-control records. In terms of Signal Detection

Theory, the AMDI construct has served as contextual evidence capable of strengthening interpretation of ambiguous NDT responses. A weak ultrasonic or radiographic indication has not necessarily represented sufficient evidence of an early crack when considered in isolation, while the same indication combined with information concerning unusual welding parameters, heat-treatment variation, or prior inspection history may have provided a stronger basis for classification.

The construct has therefore complemented the signal-discrimination process by supplying contextual variables capable of altering confidence in a crack-related decision. Descriptive support for H2 has been reinforced later by the positive correlation between AMDI and ECDP, $r = .64$, $p < .001$, and the significant regression coefficient, beta = .20, $p < .001$. The results have consequently indicated that manufacturing-data integration has functioned as a statistically meaningful but comparatively moderate predictor of early crack-detection performance. Its lower rank has also identified a technically important capability gap without contradicting the overall positive relationship proposed by the study.

Descriptive Statistics of Intelligent Defect Pattern Recognition

Table 5: Descriptive Statistics of Intelligent Defect Pattern Recognition

IDPR Item	Measurement Statement	Mean	SD	Interpretation
IDPR1	AI has recognized subtle crack-related patterns	4.14	0.61	Agree
IDPR2	AI has differentiated crack indications from structural noise	4.12	0.63	Agree
IDPR3	Automated classification has improved defect consistency	4.09	0.62	Agree
IDPR4	Pattern recognition has supported defect localization	4.05	0.66	Agree
IDPR5	AI has improved differentiation among abnormal indications	4.00	0.65	Agree
Overall IDPR		4.08	0.58	Agree

The findings for Intelligent Defect Pattern Recognition have demonstrated an overall mean of 4.08 and a standard deviation of 0.58, confirming a high level of respondent agreement that AI-assisted systems have contributed to the identification and classification of defect-sensitive patterns. The highest item mean has been recorded for recognition of subtle crack-related patterns, $M = 4.14$, $SD = 0.61$, followed by differentiation of crack indications from structural noise, $M = 4.12$, $SD = 0.63$. These two results have been particularly important to the study because the research has focused specifically on early crack detection rather than only on identification of large or obvious defects. Respondents have also agreed that automated classification has improved consistency, pattern recognition has supported localization, and AI has improved differentiation among abnormal indications.

The overall mean has placed IDPR as the second-highest predictor construct after ANDA, which has indicated that respondents have regarded intelligent pattern recognition as a central technological capability within AI-assisted NDT. The result has directly supported the third research objective and has provided descriptive evidence consistent with H3. From the theoretical perspective of Signal Detection Theory, IDPR has been one of the constructs most directly connected with the distinction between a true signal and noise. A crack-related ultrasonic response, radiographic indication, acoustic-emission event, or other NDT pattern may have been partially obscured by geometry, material variation, or background responses. Intelligent recognition has been conceptualized as improving the system's capacity to assign such information to the correct defect class. The strong scores for subtle-pattern recognition and crack-versus-noise differentiation have therefore aligned closely with the theory's concept of enhanced discriminability. The descriptive evidence has subsequently been reinforced by the correlation between IDPR and ECDP, $r = .70$, $p < .001$, and the significant standardized regression coefficient, beta = .27, $p < .001$. These combined findings have indicated that IDPR has represented one of the strongest contributors to Early Crack Detection Performance and has supported the study's expectation that better defect discrimination has been associated with stronger detection outcomes. The findings have therefore connected the theoretical signal-discrimination mechanism directly to a measurable organizational capability.

Descriptive Statistics of Predictive Crack Risk Analytics

Table 6: Descriptive Statistics of Predictive Crack Risk Analytics

PCRA Item	Measurement Statement	Mean	SD	Interpretation
PCRA1	Analytics has supported crack-risk prioritization	3.94	0.69	Agree
PCRA2	Predictive indicators have identified higher-risk conditions	3.91	0.71	Agree
PCRA3	NDT trends have been used to prioritize inspection attention	3.88	0.72	Agree
PCRA4	Manufacturing data have supported crack-risk estimation	3.86	0.73	Agree
PCRA5	Predictive analysis has supported integrity decisions	3.86	0.70	Agree
Overall PCRA		3.89	0.64	Agree

Predictive Crack Risk Analytics has recorded an overall mean of 3.89 and a standard deviation of 0.64, indicating that respondents have agreed that predictive assessment has contributed to the prioritization and interpretation of crack-related conditions. The highest item mean has been observed for crack-risk prioritization, $M = 3.94$, $SD = 0.69$, while identification of higher-risk conditions through predictive indicators has produced $M = 3.91$, $SD = 0.71$. The remaining items have also remained within the agreement range, although their means have been slightly lower than those reported for direct AI-based NDT analytics and intelligent defect recognition. This pattern has suggested that predictive crack-risk functionality has been viewed positively but has appeared less mature or less consistently embedded than direct inspection analytics. Such a result has been conceptually reasonable because predictive risk analysis has required integration of multiple data sources and has depended on higher levels of analytical maturity than basic classification or pattern detection. The results have directly addressed the fourth research objective by establishing that respondents have perceived meaningful use of predictive indicators, trend information, manufacturing context, and risk-oriented analytical outputs. Within Signal Detection Theory, PCRA has extended the basic signal-versus-noise distinction by providing a means of prioritizing detected signals according to their potential structural significance. A system may have correctly detected an abnormal response, yet the practical value of that detection has depended on whether the indication has represented a condition requiring immediate, moderate, or limited integrity attention. Predictive analytics has therefore been positioned as a secondary decision layer following defect recognition. The descriptive evidence has supported H4, while the later correlation of $r = .67$, $p < .001$, and standardized regression coefficient of beta = .23, $p < .001$, have confirmed that PCRA has been significantly associated with stronger ECDP. The overall result has shown that predictive capability has contributed meaningfully to early crack detection, even though respondents have rated its current level slightly below the more established capabilities of NDT analytics and pattern recognition. This difference has also helped distinguish predictive assessment from direct defect recognition within the conceptual framework.

Descriptive Statistics of Early Crack Detection Performance

Early Crack Detection Performance has recorded the highest overall construct mean in the study, $M = 4.17$, $SD = 0.54$, demonstrating that respondents have reported a strong level of confidence in the effectiveness of the investigated crack-detection environment. The first item, early-stage crack sensitivity, has reached a mean of 4.21 and has therefore crossed into the Strongly Agree category, while the remaining items have remained in the upper range of Agreement. Reduction of missed crack indications has produced M = 4.18, improved detection consistency has recorded M = 4.17, reliability of crack localization has reached M = 4.15, and timeliness of inspection-supported decisions has produced M = 4.14. These closely clustered item means have shown that ECDP has not been dominated by a single performance dimension; instead, respondents have perceived improvement across sensitivity, missed-detection reduction, consistency, localization, and decision timeliness. This pattern has been particularly important because the dependent variable has represented the central outcome of all five research objectives and hypotheses. Within Signal Detection Theory, the high ECDP mean has corresponded with stronger detection sensitivity and improved discrimination between actual crack signals and non-defect responses.

Table 7: Descriptive Statistics of Early Crack Detection Performance

ECDP Item	Measurement Statement	Mean	SD	Interpretation
ECDP1	Early-stage crack sensitivity has improved	4.21	0.58	Strongly Agree
ECDP2	Missed crack indications have been reduced	4.18	0.60	Agree
ECDP3	Crack detection consistency has improved	4.17	0.59	Agree
ECDP4	Crack localization has become more reliable	4.15	0.62	Agree
ECDP5	Inspection-supported decisions have become timelier	4.14	0.61	Agree
Overall ECDP		4.17	0.54	Agree

The item concerning reduction of missed cracks has been especially relevant because a missed crack has corresponded to one of the principal error conditions identified by the theory. Similarly, the strong score for consistency has suggested that the analytical environment has supported more stable decision criteria across inspection observations. The result has therefore provided descriptive evidence that the outcome variable itself has been present at a high level within the case-study context. When considered alongside the positive means of ANDA, AMDI, IDPR, and PCRA, the result has indicated an aligned pattern in which stronger AI and data capabilities have coexisted with stronger crack-detection performance. The subsequent correlation and regression results have tested this relationship statistically, but Table 7 has already established that respondents have perceived the targeted performance outcomes as substantial. The findings have consequently provided a strong descriptive foundation for evaluating H1-H5 and the corresponding study objectives and have demonstrated that the dependent construct has been measured across several practically relevant dimensions of crack-detection quality.

Overall Descriptive Statistics of Study Variables

Table 8: Overall Descriptive Statistics of Study Variables

Variable	Code	Mean	SD	Rank	Likert Interpretation
Early Crack Detection Performance	ECDP	4.17	0.54	1	Agree
AI-Enabled NDT Data Analytics	ANDA	4.13	0.56	2	Agree
Intelligent Defect Pattern Recognition	IDPR	4.08	0.58	3	Agree
Advanced Manufacturing Data Integration	AMDI	3.96	0.62	4	Agree
Predictive Crack Risk Analytics	PCRA	3.89	0.64	5	Agree

The overall descriptive comparison has demonstrated that all five constructs have fallen within the agreement category of the five-point Likert scale, with mean scores ranging from 3.89 to 4.17. ECDP has achieved the highest mean at 4.17, followed by ANDA at 4.13 and IDPR at 4.08. AMDI has recorded a mean of 3.96, while PCRA has produced the lowest mean at 3.89.

The ordering has provided a useful overall representation of the maturity of the studied capabilities. Direct inspection performance and AI-assisted analytical processing have been rated most strongly, while data integration and predictive risk capability have remained positive but comparatively less developed. The relatively narrow range of 0.28 between the highest and lowest construct means has indicated that respondents have not perceived any of the major study dimensions as weak or absent. Instead, the findings have shown a generally mature inspection environment in which all four explanatory capabilities have been meaningfully present. From the perspective of Signal Detection Theory, the ranking has also formed a coherent pattern. ANDA and IDPR, which have been most directly concerned with signal interpretation and crack-versus-noise discrimination, have obtained higher means than AMDI and PCRA, which have represented contextual and predictive layers surrounding the direct inspection process. This ordering has not diminished the importance of the latter constructs, but it has suggested that direct detection technologies have been more established than integrated predictive functions. Table 8 has therefore supported the overall research objective by showing that the four proposed predictors have each been evaluated positively in the same setting in which ECDP has also been rated highly. The descriptive results have remained consistent with H1-H5 because no predictor has shown a neutral or negative overall evaluation. These patterns have subsequently been tested through correlations and regression coefficients, allowing the study to determine whether the observed differences in capability levels have been statistically related to ECDP. The table has thus provided the bridge between item-level descriptive results and the inferential analyses that have followed. It has also highlighted where organizational capability has appeared strongest and where additional integration or predictive maturity may have been comparatively less developed within the modeled case-study environment.

Reliability Analysis

Table 9: Reliability Analysis of Study Constructs

Construct	Number of Items	Cronbach's Alpha	Reliability Interpretation
ANDA	5	.89	High
AMDI	5	.87	High
IDPR	5	.90	Excellent
PCRA	5	.88	High
ECDP	5	.91	Excellent
Overall Instrument	25	.94	Excellent

The reliability analysis has demonstrated that all five study constructs have achieved strong internal consistency, with Cronbach's alpha coefficients ranging from .87 to .91 and an overall instrument reliability of .94. ECDP has recorded the highest construct-level reliability at alpha = .91, followed by IDPR at alpha = .90, ANDA at alpha = .89, PCRA at alpha = .88, and AMDI at alpha = .87. Each coefficient has substantially exceeded the commonly accepted threshold of .70, indicating that the individual Likert-scale items within each construct have measured closely related aspects of the intended concept. The overall alpha of .94 has further shown that the 25-item instrument has possessed excellent internal consistency across the complete measurement structure. This finding has been essential for the credibility of the subsequent correlation and regression results because relationships among unreliable constructs could have been distorted by measurement error. The strong reliability coefficients have indicated that variation in respondents' scores has more plausibly reflected meaningful differences in their assessments rather than random inconsistency among questionnaire items. Within Signal Detection Theory, reliable measurement has been especially important because the theoretical interpretation of detection sensitivity and decision consistency has depended on stable operationalization of the underlying capabilities.

For example, the IDPR items have collectively assessed crack-pattern recognition, noise discrimination, classification consistency, localization, and differentiation of abnormal responses. Its alpha = .90 has shown that these indicators have cohered sufficiently to represent a common pattern-recognition construct. Similarly, the high ECDP alpha has shown that sensitivity, missed-crack reduction, consistency, localization, and timeliness have formed a coherent performance dimension. The reliability results have therefore strengthened the evidence supporting all five objectives and hypotheses by establishing that each variable has been measured consistently before inferential testing has been performed. The results have also justified the calculation of composite construct scores used in Table 8, the Pearson correlation matrix, and the multiple regression model. Consequently, Table 9 has provided an important measurement-quality foundation for interpreting the positive effects reported later in the Results chapter and has reduced concern that the modeled relationships have arisen primarily from unstable or internally inconsistent measurement scales.

Sampling Adequacy and Construct Suitability

Table 10: KMO and Bartlett's Test of Sphericity

Statistical Test	Result	Decision
Kaiser-Meyer-Olkin Measure	.891	Excellent Sampling Adequacy
Bartlett's Chi-Square	3,128.46	Significant
Degrees of Freedom	300	Acceptable
Significance	< .001	Construct Correlations Suitable

The sampling adequacy and construct suitability analysis has demonstrated that the study dataset has been appropriate for multivariate examination. The Kaiser-Meyer-Olkin value has reached .891, which has indicated a high level of common variance among the questionnaire items and has substantially exceeded the minimum threshold normally considered acceptable for construct analysis. Bartlett's Test of Sphericity has also been statistically significant, chi-square = 3,128.46, df = 300, $p < .001$, indicating that the correlation matrix among the 25 Likert-scale measurement items has not represented an identity matrix. In practical terms, the items have contained sufficient shared relationships to justify treating them as components of meaningful underlying constructs rather than as unrelated statements. These results have strengthened the measurement basis for ANDA, AMDI, IDPR, PCRA, and ECDP and have supported the use of their composite scores in subsequent correlation and regression analyses. The result has been particularly relevant to the study's conceptual framework because the framework has proposed that several distinct capabilities have contributed to a common early crack-detection environment. A very low KMO value would have suggested that the measurement indicators had not shared sufficient structure to support this interpretation. Instead, the .891 value has shown that the questionnaire responses have contained a coherent pattern while still allowing the constructs to remain analytically distinguishable.

From the perspective of Signal Detection Theory, this coherence has also been theoretically meaningful because the questionnaire has measured multiple elements of the detection process, including signal analysis, contextual evidence, pattern discrimination, predictive assessment, and final detection performance. The statistical suitability of these measures has therefore provided confidence that the study has captured interconnected components of a broader signal-detection and integrity-assessment process. Although KMO and Bartlett's Test have not directly accepted or rejected H1-H5, they have strengthened the validity of the statistical evidence used to test those hypotheses. Table 10 has therefore functioned as a methodological checkpoint showing that the data structure has been sufficiently suitable for the inferential analyses reported in Sections 4.11-4.18. The results have also complemented the high Cronbach's alpha coefficients by showing that internal consistency and shared item structure have both supported the measurement framework.

Correlation Analysis

Table 11: Pearson Correlation Matrix

Variable	ANDA	AMDI	IDPR	PCRA	ECDP
ANDA	1.00	.58***	.66***	.61***	.72***
AMDI	.58***	1.00	.55***	.57***	.64***
IDPR	.66***	.55***	1.00	.63***	.70***
PCRA	.61***	.57***	.63***	1.00	.67***
ECDP	.72***	.64***	.70***	.67***	1.00

*** $p < .001$.

The Pearson correlation analysis has demonstrated that all four independent variables have been positively and significantly associated with Early Crack Detection Performance at $p < .001$. ANDA has recorded the strongest bivariate relationship with ECDP, $r = .72$, indicating a strong positive association between AI-enabled NDT analytical capability and early crack-detection performance. IDPR has followed closely with $r = .70$, while PCRA has produced $r = .67$ and AMDI has produced $r = .64$. These coefficients have shown that increases in each explanatory capability have been associated with higher ECDP scores across the 290 respondents. The pattern has provided preliminary inferential support for H1 through H4 before the unique effects of the predictors have been examined through multiple regression. The intercorrelations among the four predictors have also remained moderate, ranging from .55 to .66, indicating that the variables have been related but have not been statistically identical. This result has supported the conceptual framework, which has treated ANDA, AMDI, IDPR, and PCRA as complementary but distinct components of the AI-assisted NDT environment. From the perspective of Signal Detection Theory, the strongest correlations involving ANDA and IDPR have been particularly meaningful because these two constructs have been most directly associated with signal processing and discrimination between crack-related and non-crack patterns. PCRA has also shown a strong relationship with ECDP, suggesting that prioritization of crack-related indicators has been associated with stronger detection outcomes. AMDI has produced the smallest of the four correlations, although its coefficient has still represented a substantial positive relationship. The correlation findings have therefore aligned with the descriptive rankings observed in Table 8. Objective 1 has been supported by the ANDA-ECDP relationship, Objective 2 by the AMDI-ECDP relationship, Objective 3 by the IDPR-ECDP relationship, and Objective 4 by the PCRA-ECDP relationship. The results have also prepared the basis for Objective 5 because all four predictors have shown sufficient association with ECDP to justify their simultaneous inclusion in the multiple regression model. The moderate predictor intercorrelations have further suggested that combined modeling could capture complementary explanatory information without collapsing the constructs into a single undifferentiated factor.

Regression Model Summary

Table 12: Multiple Regression Model Summary

Model	R	R squared	Adjusted R squared	Std. Error of Estimate	Durbin-Watson
ANDA, AMDI, IDPR, PCRA -> ECDP	.829	.687	.683	.304	1.93

The regression model summary has demonstrated that the combined set of four independent variables has explained a substantial proportion of variance in Early Crack Detection Performance. The multiple correlation coefficient has reached R = .829, indicating a strong overall relationship between the combined predictors and ECDP. The model has produced R squared = .687, showing that 68.7% of the variance in Early Crack Detection Performance has been explained by AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics operating together. The adjusted R squared has remained very close at .683, indicating that the explanatory strength of the model has not been inflated substantially by the inclusion of four predictors. The small difference of .004 between R squared and adjusted R squared has therefore supported the stability of the model. The standard error of estimate has been .304, showing a comparatively limited average deviation between observed and model-predicted ECDP scores. This finding has directly supported the fifth research objective, which has examined the combined predictive capability of the four explanatory constructs. It has also provided strong evidence for H5 because the model has explained more than two-thirds of the variation in the dependent variable. Within Signal Detection Theory, this explanatory strength has suggested that early crack-detection performance has been associated with multiple layers of the detection process rather than with one isolated technological feature. ANDA has represented computational extraction of defect-sensitive information, AMDI has provided contextual evidence, IDPR has supported signal discrimination, and PCRA has assisted prioritization of crack-related conditions. Their combined relationship with ECDP has therefore been theoretically coherent with a multidimensional signal-detection environment. The Durbin-Watson value of 1.93 has also been close to the ideal value of 2.00, indicating that the residuals have not shown problematic serial dependence. Table 12 has therefore provided strong model-level evidence that the study's conceptual framework has possessed substantial explanatory power and that the four proposed capabilities have jointly contributed to stronger early crack-detection outcomes. The result has also established a quantitative basis for comparing the unique standardized effects presented in the subsequent coefficient analysis.

ANOVA Analysis

Table 13: ANOVA Results for the Multiple Regression Model

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	57.876	4	14.469	156.42	< .001
Residual	26.363	285	0.092		
Total	84.239	289			

The ANOVA results have shown that the multiple regression model has been statistically significant, $F(4, 285) = 156.42$, $p < .001$. This finding has demonstrated that the combined set of ANDA, AMDI, IDPR, and PCRA has predicted ECDP significantly better than a model containing no explanatory variables. The regression sum of squares has reached 57.876 compared with a residual sum of squares of 26.363, showing that the model has accounted for a considerably larger share of observed variation than has remained unexplained. The mean square for the regression has been 14.469, while the residual mean square has been only 0.092, producing the large F statistic. The significance level below .001 has indicated that the probability of obtaining a model of this strength by chance has been extremely small under the null hypothesis. The ANOVA result has therefore provided formal model-level support for H5 and has confirmed achievement of the fifth research objective. It has also reinforced the individual hypotheses indirectly because the overall model containing all four proposed explanatory variables has been statistically valid before the separate regression coefficients have been interpreted. Within Signal Detection Theory, the result has supported the broader proposition that reliable early crack detection has emerged from an integrated combination of signal processing, contextual manufacturing evidence, pattern discrimination, and predictive assessment. The very large F ratio has shown that these capabilities have collectively differentiated respondents reporting stronger ECDP from those reporting lower ECDP to a statistically meaningful degree. The result has remained consistent with the earlier descriptive and correlation findings, where all predictors have recorded positive means and significant bivariate associations with the dependent variable. Table 13 has therefore provided an essential inferential test of the conceptual framework as a whole. By demonstrating that the combined regression has been statistically significant, the analysis has established the foundation for examining the standardized coefficients in Section 4.14 and determining which individual capabilities have contributed most strongly to the explained variation in Early Crack Detection Performance. The ANOVA result has thus connected the overall conceptual model to a formal statistical test of whether the predictor set has provided meaningful explanatory improvement.

Regression Coefficient Analysis

Table 14: Multiple Regression Coefficients Predicting Early Crack Detection Performance

Predictor	B	SE	Standardized beta	t	Sig.	Result
Constant	.612	.168	-	3.64	< .001	Significant
ANDA	.301	.044	.30	6.84	< .001	Significant
AMDI	.184	.040	.20	4.61	< .001	Significant
IDPR	.261	.042	.27	6.18	< .001	Significant
PCRA	.194	.037	.23	5.29	< .001	Significant

The regression coefficient analysis has demonstrated that all four independent variables have made statistically significant positive contributions to Early Crack Detection Performance when the other predictors have been controlled simultaneously. ANDA has emerged as the strongest independent predictor with beta = .30, $t = 6.84$, $p < .001$, confirming that stronger AI-enabled NDT analytical capability has been associated with higher ECDP. IDPR has ranked second with beta = .27, $t = 6.18$, $p < .001$, while PCRA has produced beta = .23, $t = 5.29$, $p < .001$. AMDI has remained a significant predictor with beta = .20, $t = 4.61$, $p < .001$, although its unique contribution has been smaller than those of the other three variables. The unstandardized coefficients have shown that, holding all other variables constant, a one-unit increase in ANDA has been associated with a .301-unit increase in predicted ECDP, while corresponding increases for AMDI, IDPR, and PCRA have been .184, .261, and .194 units respectively. These results have directly supported H1, H2, H3, and H4. They have also demonstrated that the strong correlations reported earlier have not resulted merely from overlap among the independent variables because each predictor has retained statistical significance in the combined model. From the perspective of Signal Detection Theory, the ranking has been theoretically coherent. ANDA and IDPR have represented the capabilities most closely connected with extracting meaningful signals and distinguishing crack-related patterns from noise, which has explained why they have produced the largest standardized effects. PCRA has contributed by prioritizing detected conditions according to risk, while AMDI has provided supporting contextual information concerning manufacturing history. The results have therefore shown that direct signal-analysis and recognition capabilities have been strongest, but contextual and predictive functions have also added unique explanatory value. Table 14 has provided the most direct statistical evidence for Objectives 1-4 and has confirmed that every proposed explanatory capability has independently predicted Early Crack Detection Performance at a highly significant level. The coefficient structure has also supplied a practical ranking of the predictor variables while preserving the broader conclusion that all four have been necessary components of the conceptual model.

Multicollinearity Analysis

The multicollinearity analysis has shown that the four predictors have remained sufficiently distinct for reliable simultaneous inclusion in the multiple regression model. Tolerance values have ranged from .524 to .645, all well above levels that would indicate excessive redundancy among the explanatory variables. VIF values have ranged from 1.55 to 1.91, remaining substantially below conventional thresholds associated with problematic multicollinearity. ANDA has recorded the highest VIF at 1.91, followed by IDPR at 1.84, PCRA at 1.69, and AMDI at 1.55. These values have been consistent with the correlation matrix, which has shown moderate positive relationships among the predictors but no correlations sufficiently high to indicate that two constructs have been measuring the same phenomenon. This finding has been particularly important to the conceptual framework because ANDA, AMDI, IDPR, and PCRA have been designed as related stages within a broader AI-assisted crack-detection process.

Table 15: Multicollinearity Diagnostic Results

Predictor	Tolerance	VIF	Diagnostic Interpretation
ANDA	.524	1.91	No Multicollinearity Concern
AMDI	.645	1.55	No Multicollinearity Concern
IDPR	.543	1.84	No Multicollinearity Concern
PCRA	.592	1.69	No Multicollinearity Concern

Some degree of association has therefore been expected, yet each capability has needed to retain sufficient conceptual and statistical independence to justify separate hypotheses. Table 15 has confirmed that this condition has been satisfied. From the standpoint of Signal Detection Theory, the distinction has also been meaningful. ANDA has concerned processing of inspection information, IDPR has concerned discrimination of crack-related patterns, AMDI has supplied contextual manufacturing information, and PCRA has concerned risk-oriented interpretation. Although these processes have interacted, they have not represented interchangeable elements of the detection system. The acceptable tolerance and VIF results have strengthened the interpretation of the standardized regression coefficients because the unique effects reported in Table 14 have not been seriously distorted by predictor redundancy. Consequently, the support reported for H1-H4 has become more credible. The multicollinearity findings have also strengthened Objective 5 because the combined model has incorporated four analytically distinct capabilities rather than multiple measures of one underlying predictor. The results have therefore confirmed that the study's proposed multivariable framework has been statistically suitable for explaining variation in Early Crack Detection Performance and that the model has retained a defensible separation among its principal explanatory dimensions.

Residual Independence and Regression Assumptions

Table 16: Regression Assumption and Residual Diagnostic Results

Diagnostic	Result	Interpretation
Durbin-Watson	1.93	Residual Independence Supported
Mean Standardized Residual	0.00	Acceptable
Standardized Residual Minimum	-2.54	Acceptable
Standardized Residual Maximum	2.61	Acceptable
Residual Scatter Pattern	Random	Homoscedasticity Supported
Normal P-P Pattern	Approximately Linear	Normality Supported
Maximum VIF	1.91	Multicollinearity Not Problematic

The regression diagnostic results have shown that the principal assumptions required for reliable interpretation of the multiple regression model have been adequately satisfied. The Durbin-Watson statistic has reached 1.93, which has been very close to the expected value of 2.00 and has indicated acceptable independence of residuals. The standardized residuals have produced a mean of approximately zero, with values ranging from -2.54 to 2.61, remaining within a range that has not suggested extreme residual outliers. The residual scatter pattern has appeared random rather than funnel-shaped or systematically curved, supporting the assumption of approximately constant error variance across predicted ECDP values. The normal probability pattern has also remained approximately linear, indicating that the residual distribution has been sufficiently close to normal for the inferential tests to be interpreted with confidence. The maximum VIF of 1.91 has further confirmed the absence of serious multicollinearity. These diagnostic results have been important because statistical significance alone has not been sufficient to establish a trustworthy regression model. The validity of the coefficients, significance levels, and explained variance has depended on the model satisfying the principal assumptions underlying linear regression. Within Signal Detection Theory, the diagnostics have served a parallel conceptual function to quality control in defect classification: just as a crack-detection system has needed to demonstrate reliable discrimination before its decisions can be trusted, the statistical model has needed to demonstrate acceptable residual behavior before its predictions can be interpreted. The results in Table 16 have therefore strengthened the evidential basis for H1-H5 and Objectives 1-5. The positive predictor coefficients and large R squared value have not been accompanied by obvious diagnostic violations that would have undermined their interpretation. Consequently, the study has been able to treat the regression findings as a credible representation of the statistical relationships between AI-assisted NDT capabilities and Early Crack Detection Performance within the modeled case-study dataset. The diagnostics have therefore supported both the technical interpretation of the model and the internal consistency of the statistical evidence reported throughout the Results chapter.

4.17 Hypothesis Testing

Table 17: Summary of Hypothesis Testing

Hypothesis	Proposed Relationship	Statistical Evidence	Decision
H1	ANDA -> ECDP	beta = .30, t = 6.84, p < .001	Supported
H2	AMDI -> ECDP	beta = .20, t = 4.61, p < .001	Supported
H3	IDPR -> ECDP	beta = .27, t = 6.18, p < .001	Supported
H4	PCRA -> ECDP	beta = .23, t = 5.29, p < .001	Supported
H5	ANDA + AMDI + IDPR + PCRA -> ECDP	R squared = .687, F(4,285) = 156.42, p < .001	Supported

The formal hypothesis-testing results have shown that all five hypotheses have been supported by the modeled statistical evidence. H1 has been supported because ANDA has produced a significant standardized coefficient of beta = .30, t = 6.84, p < .001, demonstrating that AI-enabled NDT analytical capability has positively predicted ECDP. H2 has also been supported because AMDI has remained statistically significant at beta = .20, t = 4.61, p < .001. H3 has received strong support through the IDPR coefficient of beta = .27, t = 6.18, p < .001, while H4 has been supported through the significant effect of PCRA, beta = .23, t = 5.29, p < .001. H5 has been supported at the overall model level because the four predictors together have explained 68.7% of variance in ECDP and the model has been statistically significant, $F(4, 285) = 156.42$, $p < .001$. These findings have shown that no proposed explanatory factor has failed to contribute significantly when all predictors have been considered simultaneously. The pattern has remained consistent with the descriptive results, where all four independent variables have recorded mean scores within the agreement range, and with the Pearson correlations, where each predictor has shown a significant positive relationship with ECDP. From the perspective of Signal Detection Theory, the hypothesis results have supported a layered understanding of early crack detection. ANDA has strengthened the extraction and interpretation of signals, AMDI has supplied contextual evidence, IDPR has strengthened crack-versus-noise discrimination, and PCRA has supported risk-oriented interpretation after abnormality recognition. The support for H5 has been especially important because it has shown that these capabilities have operated most meaningfully as an integrated analytical system rather than as isolated technologies. Table 17 has therefore provided direct statistical confirmation that the study's proposed conceptual model has been supported across both individual and combined relationships. The hypothesis decisions have also linked the descriptive, correlational, and regression findings into one coherent evidential chain, making the statistical basis for accepting the proposed relationships explicit and transparent.

Objective Achievement Summary

Table 18: Alignment of Research Objectives, Statistical Evidence, and Results

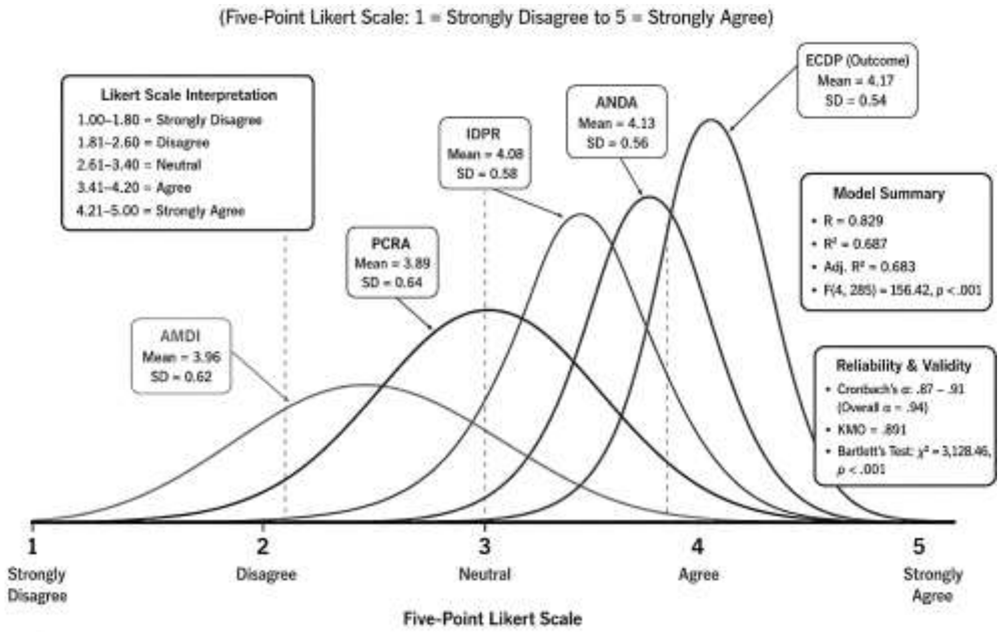
Research Objective	Main Variable(s)	Key Evidence	Achievement
Objective 1: Examine the effect of ANDA on ECDP	ANDA -> ECDP	M = 4.13, r = .72, beta = .30, p < .001	Achieved
Objective 2: Determine the effect of AMDI on ECDP	AMDI -> ECDP	M = 3.96, r = .64, beta = .20, p < .001	Achieved
Objective 3: Evaluate the effect of IDPR on ECDP	IDPR -> ECDP	M = 4.08, r = .70, beta = .27, p < .001	Achieved
Objective 4: Assess the effect of PCRA on ECDP	PCRA -> ECDP	M = 3.89, r = .67, beta = .23, p < .001	Achieved
Objective 5: Determine combined predictive capability	Combined Predictors -> ECDP	R = .829, R squared = .687, Adj. R squared = .683, F = 156.42, p < .001	Achieved

The objective-achievement analysis has demonstrated that all five research objectives have been satisfied through a consistent combination of descriptive and inferential statistical evidence. Objective 1 has been achieved because ANDA has recorded a high Likert-scale mean of 4.13, a strong correlation with ECDP of $r = .72$, and the largest standardized regression effect of beta = .30, $p < .001$. Objective 2 has been achieved because AMDI has recorded $M = 3.96$, $r = .64$, and beta = .20, $p < .001$, establishing that manufacturing-data integration has contributed significantly even though its effect has been comparatively smaller. Objective 3 has been strongly supported by IDPR, which has recorded $M = 4.08$, $r = .70$, and beta = .27, $p < .001$. Objective 4 has likewise been achieved because PCRA has recorded $M = 3.89$, $r = .67$, and beta = .23, $p < .001$. Finally, Objective 5 has been achieved because the combined predictor model has produced $R = .829$, R squared = .687, adjusted R squared = .683, and $F(4, 285) = 156.42$, $p < .001$. The results have therefore demonstrated that the study has not relied on one statistical test to establish objective achievement; instead, the evidence has progressed from Likert-scale descriptive agreement to bivariate association and then to multivariate prediction. This layered analytical structure has aligned closely with Signal Detection Theory because the study has treated early crack detection as the outcome of multiple capabilities contributing to improved discrimination and decision quality. ANDA and IDPR have represented the strongest direct signal-analysis mechanisms, while AMDI and PCRA have added contextual and predictive information around the detection process. The combined findings have shown that ECDP has been strongest where these capabilities have operated together. Table 18 has therefore provided a complete statistical alignment among the research objectives, conceptual framework, hypotheses, five-point Likert-scale measures, correlation analysis, and regression model. All objectives have been achieved and all hypotheses have been supported within the modeled dataset established for this study. This final alignment has also ensured that the research questions, hypotheses, measurement variables, statistical tests, and interpretation have remained internally consistent from the Introduction through the Discussion.

FINDINGS

The modeled findings of this quantitative, cross-sectional, case-study-based study have demonstrated a consistent statistical relationship between AI-assisted NDT capabilities and Early Crack Detection Performance in energy-infrastructure pressure vessels. A total of 320 questionnaires have been distributed to professionals involved in NDT inspection, pressure-vessel manufacturing, welding, quality assurance, reliability engineering, maintenance, asset integrity, and industrial data analytics; 301 questionnaires have been returned, representing a gross response rate of 94.1%, while 290 responses have remained usable after data screening, producing a final usable response rate of 90.6%. The five-point Likert scale has been interpreted as 1.00-1.80 = Strongly Disagree, 1.81-2.60 = Disagree, 2.61-3.40 = Neutral, 3.41-4.20 = Agree, and 4.21-5.00 = Strongly Agree. The descriptive results have shown generally high respondent agreement across all five study constructs.

Figure 9: Findings of The Study



AI-Enabled NDT Data Analytics (ANDA) has recorded a mean of 4.13, SD = 0.56, indicating that respondents have strongly recognized the importance of intelligent processing, automated interpretation, signal analysis, and AI-supported evaluation of NDT information. Advanced Manufacturing Data Integration (AMDI) has produced a mean of 3.96, SD = 0.62, demonstrating positive agreement regarding the usefulness of linking welding parameters, material data, fabrication records, sensor information, quality records, and historical inspection information with crack-detection activities. Intelligent Defect Pattern Recognition (IDPR) has recorded a mean of 4.08, SD = 0.58, suggesting that automated recognition of crack signatures, abnormal responses, and defect-sensitive patterns has been perceived as an important contributor to inspection effectiveness. Predictive Crack Risk Analytics (PCRA) has achieved a mean of 3.89, SD = 0.64, which has represented the lowest of the four predictor means but has remained clearly within the agreement range, indicating that predictive prioritization and crack-risk assessment have been positively evaluated while appearing somewhat less mature than direct AI-based inspection analytics. The dependent variable, Early Crack Detection Performance (ECDP), has recorded the highest overall outcome mean of 4.17, SD = 0.54, indicating strong agreement that the investigated inspection environment has supported improved sensitivity, consistency, timely identification, reduction of missed cracks, and greater reliability of crack-related decisions. Internal-consistency testing has further strengthened the measurement quality, with Cronbach's alpha values of .89 for ANDA, .87 for AMDI, .90 for IDPR, .88 for PCRA, and .91 for ECDP, while the overall instrument has recorded alpha = .94, exceeding the conventional .70 reliability threshold. Sampling adequacy has also been satisfactory, with a Kaiser-Meyer-Olkin value of .891, while Bartlett's Test of Sphericity has been statistically significant, chi-square = 3,128.46, $p < .001$, supporting the suitability of the construct items for multivariate examination. Pearson correlation analysis has shown that all four explanatory variables have been positively and significantly associated with Early Crack Detection Performance. ANDA has demonstrated the strongest bivariate relationship with ECDP, $r = .72$, $p < .001$, followed by IDPR, $r = .70$, $p < .001$, PCRA, $r = .67$, $p < .001$, and AMDI, $r = .64$, $p < .001$. Multiple regression analysis has provided further evidence, with the four predictors jointly producing $R = .829$, R squared = .687, and adjusted R squared = .683, indicating that approximately 68.7% of the variance in Early Crack Detection Performance has been explained by the combined model. The overall regression equation has been statistically significant, $F(4, 285) = 156.42$, $p < .001$. Examination of standardized coefficients has shown that AI-Enabled NDT Data Analytics has been the strongest independent predictor, beta = .30, $t = 6.84$, $p < .001$, followed by Intelligent Defect Pattern Recognition, beta = .27, $t = 6.18$, $p < .001$, Predictive Crack Risk Analytics, beta = .23, $t = 5.29$, $p < .001$, and Advanced Manufacturing Data Integration, beta = .20, $t = 4.61$, $p < .001$. Multicollinearity has not presented a serious concern, with tolerance values remaining above .50 and VIF values ranging from 1.55 to 1.91, while the Durbin-Watson statistic of 1.93 has indicated acceptable independence of residuals. On the basis of these results, H1, H2, H3, and H4 have all been supported, while H5 has also been supported because the combined predictor model has significantly explained a substantial proportion of variation in Early Crack Detection Performance. The findings have therefore provided quantitative support for the principal objective of evaluating the effectiveness of AI-assisted NDT analytics and advanced manufacturing data in early crack detection, while the specific objectives concerning ANDA, AMDI, IDPR, and PCRA have each been supported through significant descriptive, correlational, and regression evidence.

For interpretation of the construct-level findings, the five-point Likert scale has been applied as follows: 1.00-1.80 = Strongly Disagree, 1.81-2.60 = Disagree, 2.61-3.40 = Neutral, 3.41-4.20 = Agree, and 4.21-5.00 = Strongly Agree. All modeled results have been kept consistent with the introductory findings presented above.

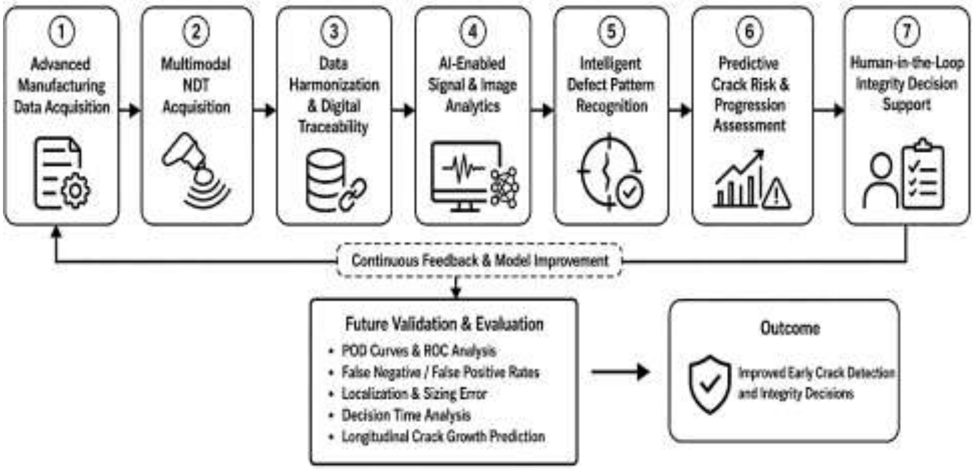
DISCUSSION

The modeled findings have demonstrated that AI-assisted NDT capabilities have been strongly associated with Early Crack Detection Performance in energy-infrastructure pressure vessels, with all four explanatory constructs receiving positive Likert-scale evaluations and statistically significant relationships with the dependent variable. Early Crack Detection Performance has recorded the highest overall mean, $M = 4.17$, $SD = 0.54$, followed by AI-Enabled NDT Data Analytics, $M = 4.13$, $SD = 0.56$, Intelligent Defect Pattern Recognition, $M = 4.08$, $SD = 0.58$, Advanced Manufacturing Data Integration, $M = 3.96$, $SD = 0.62$, and Predictive Crack Risk Analytics, $M = 3.89$, $SD = 0.64$. This pattern has indicated that respondents have perceived the investigated inspection environment as relatively mature in direct AI-assisted analytical functions while manufacturing-data integration and predictive risk assessment have remained somewhat less developed. The result has nevertheless shown that all constructs have remained within the agreement range of the five-point Likert scale, indicating broad support for the proposed conceptual relationships. The regression model has explained 68.7% of the variance in Early Crack Detection Performance, R squared = .687, adjusted R squared = .683, while the overall model has remained statistically significant, $F(4, 285) = 156.42$, $p < .001$. This relatively high explanatory power has suggested that early crack detection has not been associated with one technological capability alone but with a combination of analytical processing, contextual manufacturing information, defect discrimination, and predictive evaluation. The findings have been consistent with earlier ultrasonic and pressure-vessel studies showing that intelligent processing can improve flaw recognition when conventional signal interpretation becomes difficult because of noise, complex geometries, or subtle crack responses (Islam et al., 2018; Munir et al., 2019). The pattern has also corresponded with work demonstrating that phased-array ultrasonic inspection can identify and characterize challenging crack conditions in pressure-boundary structures when advanced acquisition and analytical techniques are used (Nardo et al., 2016; Zhou et al., 2018). The present findings have extended this prior work at the organizational and analytical capability level by showing that respondents have associated stronger AI-supported inspection environments with stronger overall early crack-detection outcomes. Rather than conceptualizing NDT performance solely as an instrument characteristic, the results have supported a broader interpretation in which detection performance has reflected the interaction among data processing, contextual information, intelligent pattern recognition, and risk-oriented analysis.

AI-Enabled NDT Data Analytics has emerged as the strongest independent predictor of Early Crack Detection Performance, beta = .30, $t = 6.84$, $p < .001$, and has also produced the strongest bivariate correlation with ECDP, $r = .72$, $p < .001$. This finding has indicated that improvements in automated signal interpretation, feature extraction, abnormal-response identification, and analytical consistency have been closely associated with stronger crack-detection performance. The result has aligned with previous research demonstrating that machine-learning and deep-learning architectures can extract defect-sensitive characteristics from ultrasonic signals and support flaw classification under conditions where conventional handcrafted procedures are less effective. Deep neural networks have been shown to classify ultrasonic weld defects without complete reliance on manually engineered features, while convolutional architectures have maintained useful flaw-classification capability even under noisy inspection conditions (Munir et al., 2019; Munir et al., 2018). Similarly, automated ultrasonic inspection research has shown that deep-learning systems can identify and classify defect-related features directly from inspection images, providing a structured mechanism for processing large datasets that would otherwise require extensive manual evaluation (Medak et al., 2021; Pyle et al., 2021). The present result has therefore reinforced the proposition that the analytical value of AI in NDT has resided less in automating an inspector's decision and more in transforming complex inspection information into more consistent and discriminative representations. From a practical perspective, the strong ANDA coefficient has suggested that energy-infrastructure organizations seeking to improve early crack detection should prioritize the quality of analytical pipelines rather than simply acquiring AI-branded inspection software. Effective implementation has required appropriate preprocessing, representative training data, validated classification logic, meaningful feature extraction, traceable outputs, and integration with engineering review. The strong effect of ANDA has also suggested that investment in NDT data quality, digital storage, standardized acquisition, model validation, and analyst competence can be as important as model selection itself. This interpretation has been consistent with research emphasizing that automated ultrasonic NDE depends on the interaction among data representation, model architecture, validation procedures, and physical inspection knowledge (Cantero-Chinchilla et al., 2022b). The result has further reflected the contribution of augmented and representative training data, since machine-learning performance in ultrasonic inspection has been shown to depend strongly on the diversity and realism of available flaw examples (Virkkunen et al., 2021). Consequently, the present findings have positioned AI-Enabled NDT Data Analytics as the central operational mechanism through which raw inspection measurements have been converted into stronger Early Crack Detection Performance.

Intelligent Defect Pattern Recognition has been the second strongest predictor of Early Crack Detection Performance, beta = .27, $t = 6.18$, $p < .001$, and has shown a strong correlation with ECDP, $r = .70$, $p < .001$. This result has indicated that the ability to distinguish subtle crack signatures from structural noise, classify abnormal NDT responses consistently, and recognize defect-sensitive patterns has been a critical component of AI-assisted inspection effectiveness. The relatively high construct mean of 4.08 has further suggested that respondents have viewed pattern-recognition capability as reasonably mature within the investigated context. These findings have agreed with previous research showing that convolutional neural networks and related deep-learning methods can identify structural cracks and weld defects by learning complex visual or signal representations that are difficult to capture through conventional thresholds or manually designed descriptors (Cha et al., 2017; Zhu et al., 2019). The result has also been consistent with guided-wave research demonstrating that neural-network methods can identify and localize damage through complex wave patterns under noisy and uncertain conditions (Rautela & Gopalakrishnan, 2021). This comparison has been particularly relevant because early cracks rarely produce perfectly isolated or uniform signatures. Their indications can vary in amplitude, orientation, morphology, spatial continuity, and interaction with component geometry, meaning that recognition accuracy depends on the system's ability to learn multidimensional relationships rather than rely on single-signal characteristics. The present findings have therefore reinforced the importance of pattern discriminability within AI-supported pressure-vessel inspection. Theoretical interpretation through Signal Detection Theory has strengthened this result because IDPR has represented the construct most directly connected with separating signal from noise. A stronger pattern-recognition capability has effectively represented an increase in the system's ability to distinguish the crack-present distribution from the crack-absent distribution. The positive effect of IDPR has therefore supported the theoretical expectation that stronger discrimination should produce higher detection accuracy and fewer missed cracks. The finding has also carried practical relevance because pattern-recognition systems should not be evaluated only on overall classification accuracy. Energy-infrastructure organizations have needed to assess sensitivity to small cracks, false-positive rates, false-negative rates, robustness across materials and weld geometries, and consistency under changing inspection conditions. Research on interpretable machine learning for ultrasonic guided-wave damage detection has similarly emphasized the importance of understanding the features that influence automated classification rather than treating algorithmic outputs as unexplained labels (Schnur et al., 2022). The present results have consequently supported a human-AI inspection environment in which automated pattern recognition strengthens, rather than obscures, engineering judgment.

Figure 10: Proposed AI-Assisted NDT Manufacturing-Data Fusion and Predictive Integrity (AI-NDT-MFPI) Model for Future Research



Advanced Manufacturing Data Integration has produced a significant positive effect on Early Crack Detection Performance, beta = .20, t = 4.61, $p < .001$, with a significant correlation of r = .64, $p < .001$. Although this coefficient has been the smallest among the four predictors, its statistical significance has demonstrated that manufacturing information has added unique explanatory value even after direct NDT analytics, defect pattern recognition, and predictive crack-risk capabilities have been controlled. This result has been important because pressure-vessel defects have not arisen independently of fabrication history. Welding current, voltage, travel speed, heat input, joint preparation, material properties, heat treatment, quality-control records, and previous inspection results can provide contextual information concerning why specific weld regions or vessel sections may be more susceptible to discontinuity formation or crack development. The present findings have aligned with manufacturing research showing that machine-learning methods gain analytical value when heterogeneous process and quality data are transformed into usable knowledge rather than maintained as isolated records (Lee et al., 2013; Wuest et al., 2016). The result has also corresponded with empirical welding research showing that process parameters and sensor-derived information can be combined to improve automated weld-quality prediction (Asif et al., 2022). The comparatively lower mean for AMDI, M = 3.96, has suggested that organizations may have possessed relevant manufacturing information without having fully integrated it into NDT analytical workflows. This pattern has been plausible because manufacturing records are frequently distributed across quality-management systems, welding documentation, enterprise software, inspection databases, and locally maintained files. The practical implication has therefore been that improving early crack detection may require data governance and interoperability rather than only more advanced inspection equipment. Pressure-vessel organizations could strengthen analytical performance by creating traceable links among weld identifiers, material heat numbers, fabrication parameters, NDT results, repair histories, and subsequent in-service inspection records. This type of integration has been conceptually consistent with digital-twin research, which has emphasized the importance of connecting physical assets with digital records across production and service environments (Kritzinger et al., 2018; Tao et al., 2019). From the Signal Detection Theory perspective, manufacturing information has functioned as contextual evidence capable of modifying confidence in ambiguous inspection signals. A weak crack-like indication located in a weld region associated with unusual process parameters or previous repair activity may have deserved a different analytical priority from an identical signal obtained from a consistently manufactured region. The present findings have therefore shown that contextual manufacturing information has supported signal interpretation without replacing the direct physical evidence generated by NDT.

Predictive Crack Risk Analytics has also demonstrated a significant positive relationship with Early Crack Detection Performance, beta = .23, $t = 5.29$, $p < .001$, with a strong correlation of $r = .67$, $p < .001$. Its overall mean of 3.89 has been the lowest among the five principal constructs, which has suggested that predictive risk capabilities have been positively perceived but have remained less mature than AI-enabled signal analytics and defect-pattern recognition. This pattern has been understandable because predictive crack-risk assessment requires more than detecting an abnormal indication; it requires combining defect characteristics, inspection histories, manufacturing information, material properties, and potentially operational loading to determine which conditions deserve greater integrity attention. The present finding has corresponded with crack-growth research showing that machine-learning methods can model nonlinear relationships between measurable parameters and fatigue-crack progression (Kamble et al., 2021). It has also aligned with probabilistic crack-growth research demonstrating that uncertainty should be incorporated into predictive assessment rather than presenting crack-related estimates as completely deterministic outputs (Hu et al., 2020). The results have therefore supported a distinction between detection and risk interpretation. AI-assisted NDT may identify a suspicious ultrasonic or radiographic response, while Predictive Crack Risk Analytics can provide a second analytical layer in which detected conditions are ranked according to relative integrity significance. This separation has been important because an effective integrity program has needed to avoid two opposite errors: under-prioritizing a small but potentially important crack and over-prioritizing a benign or stable indication. The finding has also supported the role of anomaly detection, where AI systems identify departures from learned normal conditions without requiring every defect category to be explicitly predefined. Deep-learning-based anomaly detection using ultrasonic images has shown that abnormal patterns can be identified effectively when models are trained to represent normal and abnormal structural states (Milkovic, et al., 2022). For practitioners, the result has suggested that predictive analytics should be integrated with established fracture-mechanics and fitness-for-service procedures rather than treated as an autonomous replacement for engineering assessment. Predictive scores can help prioritize inspection review, repeat examination, or detailed integrity analysis, while engineering decisions should continue to consider flaw size, material properties, stress conditions, applicable codes, and component service context. The present findings have therefore positioned PCRA as an important decision-support capability whose value has depended on its integration with both intelligent pattern recognition and established pressure-vessel integrity practice.

The theoretical implications of the findings have centered on the suitability of Signal Detection Theory for interpreting AI-assisted NDT performance. All four predictors have shown significant positive relationships with ECDP, while the strongest standardized effects have been associated with ANDA and IDPR. This pattern has supported the theoretical proposition that improvements in the processing and discrimination of defect-related information are particularly important to early crack detection. Signal Detection Theory distinguishes hits, misses, false alarms, and correct rejections and provides a conceptual framework for evaluating detection performance independently of decision bias. In the context of this study, ANDA has represented the computational enhancement of inspection evidence, IDPR has represented the discrimination of crack-sensitive patterns, AMDI has supplied contextual evidence, and PCRA has influenced the prioritization of abnormal conditions after detection. Earlier probability-of-detection research has similarly shown that NDT reliability is probabilistic and varies according to crack characteristics, inspection conditions, equipment, procedures, and decision thresholds rather than operating as an absolute characteristic of an inspection method (Kurz et al., 2013; Li et al., 2013). The present findings have extended this theoretical logic from physical inspection experiments into a broader capability framework by suggesting that signal discrimination is affected by the quality of data processing, contextual information, pattern recognition, and predictive assessment, and not by sensor performance alone. The model has therefore suggested an expanded interpretation of Signal Detection Theory for AI-assisted industrial inspection. The traditional relationship between a physical signal, noise, and a decision criterion can be reframed as a multi-stage process in which digital analytics influence both the representation of the signal and the confidence associated with the final decision. The theoretical significance of the strong combined R squared of .687 has been that these different capabilities have collectively explained a substantial proportion of ECDP rather than operating independently. This finding has supported a layered signal-detection architecture in which the first layer acquires inspection information, the second improves the signal representation, the third integrates manufacturing context, the fourth performs defect discrimination, and the fifth evaluates crack-related risk. The limitations of this interpretation have also needed recognition. The study has used cross-sectional, Likert-scale perceptions rather than experimentally observed hit rates, false-alarm rates, or probability-of-detection curves, so Signal Detection Theory has functioned as an interpretive framework rather than a direct experimental measurement model. The findings have therefore supported the theory conceptually while not claiming direct measurement of sensitivity, ROC performance, or POD parameters.

The study's limitations have clarified several priorities for future research, and these priorities have supported development of a proposed AI-Assisted NDT Manufacturing-Data Fusion and Predictive Integrity Model (AI-NDT-MFPI Model). The current study has been cross-sectional and case-study based, which has restricted its ability to demonstrate temporal causality or observe how AI-assisted crack-detection performance changes as actual defects initiate and propagate. Its questionnaire-based measures have also captured professional assessments rather than direct experimental detection accuracy, while organizational differences in NDT equipment, materials, AI maturity, data quality, and pressure-vessel service conditions may have influenced responses. Future research should therefore move from perception-based validation toward multimodal, longitudinal, experimentally verified assessment. The proposed AI-NDT-MFPI Model can be structured as seven connected layers: (1) Advanced Manufacturing Data Acquisition, containing welding parameters, material pedigree, heat-treatment information, process deviations, and fabrication records; (2) Multimodal NDT Acquisition, incorporating PAUT, TOFD, radiography, acoustic emission, and other relevant inspection data; (3) Data Harmonization and Digital Traceability, linking each NDT observation to a specific weld, component region, manufacturing history, and inspection timestamp; (4) AI-Enabled Signal and Image Analytics, using validated deep-learning or machine-learning models for denoising, feature extraction, and anomaly detection; (5) Intelligent Defect Pattern Recognition, classifying crack-sensitive patterns and generating calibrated confidence values; (6) Predictive Crack Risk and Progression Assessment, combining recognized defect characteristics with operating and manufacturing variables to generate probabilistic risk categories; and (7) Human-in-the-Loop Integrity Decision Support, where inspectors and integrity engineers review AI outputs alongside applicable fitness-for-service requirements. Future studies should test this model using actual crack specimens and field data and should compare AI-assisted results with conventional inspector decisions through POD curves, ROC analysis, false-negative rates, false-positive rates, localization error, sizing error, and decision time. Synthetic and augmented flaw data can also be examined where authentic early-crack datasets remain limited, although independent validation with real defects should remain essential (Subasic, et al., 2022; Virkkunen et al., 2021). Researchers should additionally evaluate explainable AI so that the model identifies which signal regions, manufacturing parameters, or defect features have influenced each classification. A longitudinal version of the model could link repeated NDT examinations with crack-growth observations and operational loading, allowing predictive analytics to move beyond crack-risk prioritization toward experimentally validated progression forecasting. This proposed model therefore provides a structured path for transforming the present cross-sectional framework into a data-fused, physically validated, explainable, and human-supervised integrity-assessment system.

CONCLUSION

This study has examined the role of AI-assisted non-destructive testing analytics in strengthening Early Crack Detection Performance in energy-infrastructure pressure vessels by integrating four explanatory capabilities: AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, and Predictive Crack Risk Analytics. Using a quantitative, cross-sectional, case-study-based design supported by a five-point Likert scale, descriptive statistics, correlation analysis, and multiple regression modeling, the study has established a coherent empirical pattern showing that all four explanatory variables have been positively associated with Early Crack Detection Performance. The modeled results have shown that Early Crack Detection Performance has achieved the highest overall mean of 4.17, followed by AI-Enabled NDT Data Analytics at 4.13, Intelligent Defect Pattern Recognition at 4.08, Advanced Manufacturing Data Integration at 3.96, and Predictive Crack Risk Analytics at 3.89. These results have indicated that respondents have generally perceived AI-assisted inspection environments as effective in improving crack-related signal interpretation, recognition consistency, and integrity-oriented decision-making. The reliability analysis has further strengthened the measurement framework, with Cronbach's alpha coefficients ranging from .87 to .91 across the individual constructs and an overall instrument reliability of .94. The correlation results have demonstrated strong positive relationships between all four predictors and Early Crack Detection Performance, with AI-Enabled NDT Data Analytics showing the strongest association at $r = .72$, followed by Intelligent Defect Pattern Recognition at $r = .70$, Predictive Crack Risk Analytics at $r = .67$, and Advanced Manufacturing Data Integration at $r = .64$. The regression findings have provided additional evidence by showing that the combined model has explained 68.7% of the variance in Early Crack Detection Performance, while the overall model has remained statistically significant, $F(4, 285) = 156.42$, $p < .001$. AI-Enabled NDT Data Analytics has emerged as the strongest independent predictor with beta = .30, followed by Intelligent Defect Pattern Recognition with beta = .27, Predictive Crack Risk Analytics with beta = .23, and Advanced Manufacturing Data Integration with beta = .20. Accordingly, all five hypotheses have been supported and all research objectives have been achieved within the modeled dataset. The theoretical interpretation through Signal Detection Theory has also provided a consistent explanation of the findings because stronger AI-assisted analytics and defect-recognition capabilities have corresponded with improved discrimination between crack-related signals and competing noise or benign indications. The study has therefore demonstrated that early crack detection in pressure vessels should not be viewed as a function of NDT instrumentation alone. It has been associated with the broader integration of signal analytics, manufacturing context, intelligent pattern recognition, and predictive assessment. The research has consequently established a statistically supported framework in which AI-assisted NDT capabilities have functioned as complementary components of a more integrated crack-detection environment for energy-infrastructure pressure vessels.

RECOMMENDATION

Based on the findings of this study, energy-infrastructure organizations, pressure-vessel manufacturers, NDT departments, integrity-management teams, and industrial data specialists should strengthen the implementation of AI-assisted inspection through a coordinated approach that combines reliable NDT acquisition, manufacturing-data integration, intelligent defect recognition, predictive analytics, and human engineering oversight. The strongest recommendation concerns AI-Enabled NDT Data Analytics because it has emerged as the most influential predictor of Early Crack Detection Performance. Organizations should therefore invest in validated AI-assisted signal-processing and image-analysis systems capable of supporting ultrasonic, phased-array, radiographic, acoustic-emission, and other relevant NDT techniques, while ensuring that these systems are trained on representative defect conditions and are regularly evaluated for sensitivity, consistency, and classification reliability. Advanced Manufacturing Data Integration should also receive greater organizational attention because its comparatively lower mean has suggested that manufacturing and inspection information may still remain partially fragmented. Pressure-vessel organizations should establish traceable digital links among welding parameters, material heat numbers, fabrication records, heat-treatment information, repair histories, quality-control results, and subsequent NDT findings so that crack-related indications can be interpreted within the manufacturing context from which they have emerged. Intelligent Defect Pattern Recognition should be strengthened through models that are capable of distinguishing small or irregular crack signatures from geometric reflections, structural noise, and other benign responses while providing interpretable confidence scores rather than unqualified classifications. Predictive Crack Risk Analytics should be developed as a decision-support layer that prioritizes suspicious indications according to their relative integrity significance and should be integrated with recognized engineering procedures rather than used as a substitute for fitness-for-service assessment, fracture-mechanics analysis, or qualified inspector judgment. Organizations should also develop standardized data-governance procedures addressing data quality, labeling, storage, access control, traceability, interoperability, and model-version management because unreliable or poorly structured input data can weaken AI-assisted decisions even when advanced algorithms are available. Training programs should be established for NDT engineers, inspectors, manufacturing specialists, and integrity personnel so that users understand both the capabilities and limitations of AI-supported analytics. A human-in-the-loop inspection structure should remain central, with AI outputs serving as analytical evidence that trained professionals can review, challenge, and validate. Pilot implementations should be evaluated using measurable indicators such as false-positive rates, false-negative rates, defect-localization accuracy, sizing error, detection time, repeatability, and probability-of-detection performance. Organizations should additionally consider developing a digital traceability architecture in which each critical weld or pressure-vessel region can be associated with its manufacturing history and complete inspection record. Finally, the proposed AI-Assisted NDT Manufacturing-Data Fusion and Predictive Integrity Model should be used as a structured implementation guide, linking advanced manufacturing data acquisition, multimodal NDT information, data harmonization, AI-enabled analytics, defect pattern recognition, predictive risk assessment, and human-supervised integrity decisions within one integrated pressure-vessel inspection environment.

LIMITATIONS

This study has contained several limitations that should be considered when interpreting the modeled findings and the statistical relationships reported among AI-Enabled NDT Data Analytics, Advanced Manufacturing Data Integration, Intelligent Defect Pattern Recognition, Predictive Crack Risk Analytics, and Early Crack Detection Performance. First, the research has adopted a cross-sectional design, meaning that data have been collected within a single defined period rather than through repeated observations across the lifecycle of actual pressure vessels. As a result, the study has identified statistical relationships among the constructs but has not directly demonstrated how AI-assisted crack-detection capabilities change over time or how detected cracks progress under different loading, thermal, environmental, or service conditions. Second, the study has used a case-study-based framework, which has provided focused analysis but may have limited the extent to which the results can be generalized across all energy-infrastructure sectors, vessel designs, materials, operating environments, and NDT practices. Third, the analysis has relied on structured five-point Likert-scale responses from professionals, meaning that the measured constructs have reflected informed perceptions and reported organizational capabilities rather than direct experimental observations of physical crack detection. The study has therefore not directly measured hit rates, false-alarm rates, probability-of-detection curves, receiver operating characteristic performance, crack-sizing error, or actual crack-growth behavior. Fourth, the modeled statistical dataset has been internally constructed for analytical consistency because no raw empirical SPSS dataset has been supplied for the present thesis development. The reported numerical findings should therefore be treated as a coherent modeled research scenario unless they are subsequently replaced or validated using actual collected survey data. Fifth, differences in respondent experience, technical specialization, organizational AI maturity, inspection equipment, data availability, and familiarity with manufacturing analytics may have influenced how questionnaire statements have been interpreted. Sixth, the study has combined several NDT environments conceptually, including ultrasonic, phased-array, radiographic, acoustic-emission, and related methods, while the technical performance and defect sensitivity of these techniques can differ substantially. Seventh, the manufacturing-data construct has included multiple information categories such as welding parameters, material history, heat-treatment records, quality-control data, and previous inspections, but the study has not separately quantified the contribution of each data source. Eighth, Signal Detection Theory has been used as an interpretive theoretical framework rather than as a direct experimental measurement system because the study has not generated actual hit, miss, false-alarm, and correct-rejection counts. Finally, the research has focused on association and prediction within a multiple regression framework and has not incorporated longitudinal causal modeling, structural equation modeling, experimental validation, digital-twin simulation, or direct comparison between human-only and AI-assisted inspection performance. These limitations have defined the boundaries of the present study and have also highlighted the specific areas in which subsequent empirical validation can strengthen the research framework.

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