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A Technology-Readiness Mapping Framework for Defect Detection in Quality 4.0: An MCDM-Based Study of Algerian Manufacturing

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Abstract

Selecting appropriate defect-detection technologies is a critical challenge in the transition toward Quality 4.0, particularly in developing industrial contexts. This study proposes an Inspection Technology-Readiness Mapping (ITRM) framework integrating Multi-Criteria Decision-Making (MCDM) to support structured and context-aware selection of inspection methods. Based on a survey of fifty Algerian manufacturing firms, companies are classified into three readiness levels: Foundational, Developing, and Advanced. The framework quantitatively links each level to compatible classes of defect-detection technologies while explicitly incorporating metrological reliability as a decision criterion. The proposed approach delivers a hybrid and actionable roadmap that connects global technological options with local industrial capabilities. Results highlight both emerging Industry 4.0 adoption and persistent challenges related to data, skills, and infrastructure, confirming the practical value of the ITRM for managers and policymakers.

Keywords: Quality control; Industry 4.0; Quality 4.0; Survey; Empirical study; Inspection System; Artificial Intelligence; Defect detection.

Introduction

In the current context of globalized manufacturing, where competition is intense and customer expectations continue to rise, product quality plays a strategic role in enhancing productivity, optimizing the use of resources, and strengthening customer confidence. Manufacturing companies are therefore under continuous pressure to integrate quality as a core component of their operational and strategic decision-making processes. As production systems expand in scale and complexity, the ability to ensure consistent quality has become a fundamental requirement for survival, growth, and technological advancement in the industrial sector. (Chen et al., 2021)

Recent advances in digital technologies have profoundly reshaped manufacturing systems, transforming how products are produced, monitored, and inspected. Modern production environments increasingly rely on real-time data acquisition, automated analysis, and intelligent decision-making to ensure stable and high-quality output. A wide spectrum of defect-detection approaches is currently available, extending from conventional vision-based and rule-driven inspection techniques to more advanced machine learning and deep learning solutions. At the same time, the emergence of Industry 4.0 and Quality 4.0 paradigms has accelerated the shift toward smart, connected, and adaptive quality control. (Schmitt et al., 2020) However, the selection and deployment of appropriate defect-detection methods remain strongly conditioned by multiple constraints. As a result, identifying technologies that can both meet stringent quality requirements and remain compatible with real industrial conditions has become a central challenge for contemporary manufacturing.

This study addresses a critical gap in the literature: while prior research (Govindan & Arampatzis, 2023; Haffar et al., 2019; Hendrik et al., 2021; Journal & November, 2024) has separately examined defect-detection methods and industrial readiness for digital transformation, few studies have linked the technical selection of defect-detection methods with the actual readiness of firms to adopt these methods, especially in developing countries. In Algeria, where manufacturing plays a strategic role in economic development, the integration of Industry 4.0 technologies into quality management is still limited, and the readiness of companies to implement such innovations is not well documented. To address this knowledge gap, the present study makes several important contributions to the field of quality management and industrial metrology. It introduces a Method-Readiness Framework that uniquely bridges the technical selection of defect-detection methods with the actual readiness levels of manufacturing firms. Furthermore, the framework delivers actionable insights for Algerian companies, offering a stepwise roadmap for adopting advanced defect-detection technologies according to their current capabilities. Moreover, this research establishes a foundation for a succeeding studies aimed at developing predictive, data-driven models, ensuring continuity in the research program and supporting the long-term implementation of Quality 4.0 practices in Algeria.

The remainder of this paper is organized as follows: Section 2 establishes the theoretical basis and analyses existing defect detection and prediction methods to extract relevant technical and practical selection criteria. Section 3 presents the empirical investigation of the industrial readiness assessment to evaluate the maturity of Algerian firms. Section 4, use MCDM approach to Match feasible methods to readiness levels (Inspection technology-readiness mapping).

1. Existing quality defect detection and prediction methods of industrial product

A. Methodological framework

The methodological approach for this section comprised a systematic, multi-stage literature study designed to identify and classify methods for detecting and predicting product quality defects. First, we established a clear research objective focused on categorizing defect-detection and prediction techniques relevant to industrial quality control. Next, we searched primary and secondary information repositories (academic databases, conference proceedings, and technical reports) using a variety of targeted query terms (for example, “defect detection”, “defect prediction”, “machine learning”, “deep learning”, “industrial vision”, and “quality control classification”)to ensure comprehensive coverage of the field. The initial search produced a large corpus of items; these were screened by title and abstract to remove clearly irrelevant records. Remaining documents were then evaluated against explicit inclusion/exclusion criteria: only works addressing classification, development, implementation, or empirical evaluation of quality-control methods were retained; inaccessible or off-topic publications were excluded. Finally, the selected literature was critically reviewed and synthesized to identify convergent findings, methodological trends, and gaps in metrological validation, thereby informing the taxonomy and recommendations presented in this study.

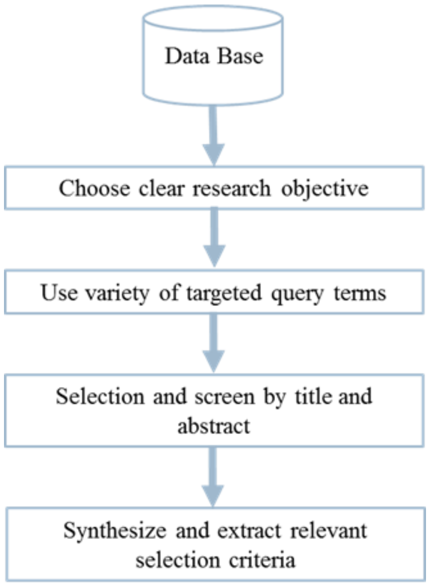

Figure 1: *research methodology*

B. Classification of defect detection and prediction methods for industrial product

Defect detection methods refers to techniques applying processes performing controls to identify and locate various problems and imperfections in order to ensure company’s integrity operations and optimize production. (Zsifkovits et al., 2020) Defect identification in manufacturing can be broadly classified into two complementary categories. The first is physical detection, which relies on direct measurement of the manufactured part using sensing or inspection instruments. The acquired measurement data are then evaluated against predefined quality criteria to determine the presence or absence of defects. The second category is virtual detection, commonly referred to as virtual metrology or predictive inspection. In this approach, product quality is inferred indirectly from process-related data acquired through sensors during manufacturing. These data streams are processed using statistical and data-driven algorithms to predict defect occurrence without performing direct measurements on the finished part. Virtual detection thus enables earlier, faster, and often non-destructive quality assessment, while shifting the focus from part-based inspection to process-based quality prediction. (Dashti et al., 2021)

Product quality prediction aims to anticipate the occurrence of defects by analyzing historical operational and process data rather than relying solely on post-production inspection. This approach exploits pattern recognition techniques and machine learning algorithms to model the relationships between process behavior and system reliability. In recent years, predictive analysis has attracted growing scientific interest as a means of enhancing product quality while significantly reducing the cost and duration of experimental testing, which represents a substantial portion of the overall development effort. (Rostami et al., 2015) Predictive quality assessment is therefore fundamentally rooted in manufacturing process data, where recurrent data patterns are extracted, validated, and quantitatively associated with measurable quality indicators. (Tercan & Meisen, 2022)

In table 1, we review the main classifications we obtained in our research:

Table 1: main defect detection classification

Reference	Classification	Presentation
(Venkatasubramanian et al., 2003)	1. Model-based methods: - Analytical methods; - Knowledge-based methods. 2. History-based methods: - Data-driven methods; - Knowledge-based methods	The categorization is according to the type of prior knowledge employed. 1. Rely on qualitative or quantitative physical representations of the process. 2. Extract diagnostic features from large volumes of process data without requiring first-principles models. Data-based approaches are particularly effective for complex systems, enabling cost-efficient defect detection through measurement data analysis across the product lifecycle.
(Sun et al., 2015)	1. Signal-based approaches; 2. model-based approaches ; 3. knowledge-based approaches ; 4. hybrid approaches.	1. Rely on parameterized measurement signals (e.g., vibration) for threshold-based fault detection. 2. Use dynamic system models and residual analysis for decision-making. 3. including neural networks that emulate expert reasoning from complex signals. 4. integrate multiple techniques to improve robustness and diagnostic reliability
(Bartova & Vachova, 2019)	1. The seven basic quality tools; 2. Complexes methods; 3. Statistical methods ; 4. Data mining techniques	1. Process Diagram, Checklist, Histogram, Pareto Chart, Correlation Analysis, Performance Chart, Ishikawa Diagram. 2. Quality improvement philosophies and management frameworks (TQM, Lean Six Sigma, Kaizen, DMAIC, FMEA, PDCA, Poka-Yoke, and Quality Circles) 3. Such as descriptive statistics, ANOVA, hypothesis testing, capability indices, reliability analysis, and control schemes. 4. applied to quality management, including association rules, clustering, decision trees, neural networks, and regression analysis for pattern recognition and predictive insights.

(Yang et al., 2020)	1. Traditional techniques ; 2. Advanced approaches : - Computer vision; - Deep learning (convolutional neural network, Autoencoder neural network, Deep residual neural network, Full convolution neural network, Recurrent neural network)	1. Include: magnetic particle testing, eddy current testing, and ultrasonic inspection. 2. Computer vision analyzes color, texture, and geometry for fast, accurate, and non-destructive surface quality inspection, while deep learning employs multi-layer neural networks to automate defect recognition and classification across diverse industrial applications.
(Chen et al., 2021)	1. Traditional machine vision approaches ; 2. deep learning-based approaches	1. Rely on feature extraction from texture, color, and shape, often combining multiple features to improve detection accuracy. 2. Include **supervised approaches** (e.g., classification, detection, and segmentation networks such as Siamese, Faster RCNN, and Mask RCNN), **unsupervised approaches** (e.g., autoencoders for pattern learning without labels), and **weakly supervised approaches**, which integrate both strategies to reduce labeling effort while maintaining high detection performance.
(Tercan & Meisen, 2022)	1. Machine learning methods; 2. Deep learning methods	- **Multilayer Perceptrons** for deep neural network-based output prediction, - **Support Vector Machines** for supervised classification and regression tasks, - **Random Forests**, which leverage ensembles of decision trees to improve predictive accuracy and reduce bias in data-driven modeling.

C. Analysis and discussion

A broad body of research demonstrates that defect detection and prediction in manufacturing encompass a wide spectrum of approaches, from conventional inspection techniques to advanced artificial intelligence-based solutions. These methods are generally applied in two principal contexts:

- Monitoring, locating, and tracking faults in industrial equipment and processes (such as electromechanical systems) to ensure reliable operation;
- Identifying defects in finished products, including internal structural imperfections and external surface anomalies such as dimensional errors or color inconsistencies.

Recent studies consistently show that machine vision and deep learning-based approaches offer superior detection accuracy and improved economic efficiency, particularly in high-throughput production environments. Nevertheless, their effectiveness remains strongly dependent on the availability of large, well-annotated datasets. While deep learning currently achieves the most promising experimental performance, it is primarily deployed during the manufacturing and processing stages rather than at early design phases.

The literature further highlights that no single defect detection method is universally optimal. Instead, method selection must be guided by a set of technical, economic, and operational criteria. These include:

- The physical nature and material properties of the product, which determine the feasibility of contact-based or remote inspection techniques;
- The type, size, and location of potential defects, which influence the suitability of methods such as ultrasonic testing, radiography, or visual inspection;
- The applicable quality standards, which often impose the use of non-destructive techniques.
- Economic considerations, technological availability, and the level of automation also play a decisive role,
- Environmental conditions such as temperature, vibration, and safety constraints.
- Human factors, including operator expertise and training requirements, further affect the practical deployment of certain techniques.
- The required sensitivity, reliability, and tolerance to false alarms must be carefully balanced against production speed, especially in high-rate manufacturing lines where real-time automated inspection is mandatory.

Effective quality control rarely relies on a single inspection approach. Instead, hybrid strategies that integrate multiple complementary techniques (such as combining real-time process monitoring with visual inspection) are often adopted to enhance detection robustness and overall system reliability.

The computational efficiency of machine learning and deep learning models is a critical requirement for real-time defect detection in smart manufacturing environments, where inspection decisions must be delivered within strict latency constraints. Performance improvements can be achieved through two complementary strategies: algorithm-level optimization and hardware-level acceleration. On the algorithmic side, real-time capability is enhanced by adopting lightweight model architectures, applying pruning and knowledge distillation, and reducing numerical precision through quantization or low-rank approximations. Further gains arise from optimized software implementations, including efficient computational kernels, graph-level compilation, batching policies, caching, and mixed-precision arithmetic, as well as from faster training and inference algorithms based on approximate optimization and search. From a system perspective, real-time execution is supported by deploying models on specialized platforms and by exploiting parallel and distributed computing across multi-core and multi-device architectures. High-bandwidth memory and low-latency interconnects further reduce data transfer bottlenecks. In industrial inspection systems, the most effective real-time performance is achieved through the co-design of algorithms and hardware, ensuring that defect detection models meet throughput, latency, and metrological reliability requirements simultaneously. (Liu et al., 2025)

2. Empirical investigation of the industrial readiness assessment (Algerian firms)

Based on the preceding sections, an increasingly connected and digitized world has emerged. Industry 4.0 offers new opportunities and has become particularly popular in developed countries. The combination of its new technologies (such as Internet of Things, Artificial intelligence, Cloud Computing, and computer vision) and emerging ML and DL approaches has contributed to improving product quality and strengthening the competitiveness of manufacturing companies in countries leveraging these innovations by offering new solutions for automated data analysis. Therefore, staying abreast of these technological innovations is imperative.

To assess the impact of technological advances on product quality in developing economies (with a focus on Algeria) and to identify how cutting-edge innovations can enhance competitiveness in domestic and international markets, a targeted investigation was conducted. Specifically, this section explores the integration of Industry 4.0 technologies into quality control processes within the Algerian manufacturing sector. Through a structured questionnaire, the study examines both current quality management practices in Algerian firms and the potential pathways through which Algeria, given its industrial capabilities, can address existing challenges and leverage Industry 4.0 tools to foster innovation and industrial modernization.

A. Methodological framework

The development and implementation of the survey instrument adhered to a structured methodological sequence, as outlined below:

- Objective Clarification: Establishing t he precise aims of the study to align all subsequent design choices.
- Sample Selection: Ensuring representativeness by targeting a diverse cross-section of Algerian manufacturing firms, varied by region, industrial sector, and company size.
- Question Design: Formulating clear, concise, and unambiguous items to maximize respondent comprehension and accuracy.
- Questionnaire Structuring: Organizing questions into logical thematic sections to improve flow and facilitate ease of completion.
- Instrument Pre-testing: Administering a preliminary version to a small pilot group to assess clarity, functionality, and timing, with adjustments made prior to full deployment.
- Distribution: Disseminating the finalized questionnaire via electronic and, where feasible, direct channels to reach the intended sample.
- Data Collection: Systematically compiling the completed responses for subsequent analysis.
- Data Analysis: Processing the collected data using statistical software (e.g., SPSS) to identify prevailing trends, extract meaningful insights, and draw evidence-based conclusions.

The survey was designed to fulfill the following research objectives:

- To systematically assess the prevailing quality management practices and performance levels within Algerian manufacturing enterprises.
- To identify and characterize the principal challenges and operational constraints impacting product quality in the national industrial landscape.

- To analyze managerial attitudes, perceptions, and behavioral dispositions towards quality enhancement initiatives and technological adoption.
- To evaluate the extent to which scientific research outputs and technological advancements are integrated into local industrial processes and their measurable benefits.
- To explore pathways for fostering an innovation-centric culture by promoting the strategic adoption of Industry 4.0 technologies within the industrial sector.
- To derive evidence-based recommendations aimed at addressing identified gaps and enhancing overall quality performance.

The questionnaire was disseminated to a purposively selected sample of industrial enterprises to ensure broad national representation across Algeria's geographic regions (North, South, East, and West). A target list of 200 companies was compiled, complete with relevant contact details, including telephone numbers, email addresses, and physical locations. The survey instrument was developed in a bilingual format (French and Arabic) using the Google Forms platform. Subsequently, a direct email campaign was initiated, distributing electronic invitations containing the bilingual questionnaire link to the identified contacts.

B. Analysis and discussion of the results

Fifty responses were collected from companies across diverse geographic locations (see Figure 2), comprising 41 submitted electronically and nine in hard-copy format. This yielded a final response rate of 25%. In the context of this study, a response rate exceeding 20% was deemed satisfactory for analysis. (Zulqarnain & Wasif, 2022)

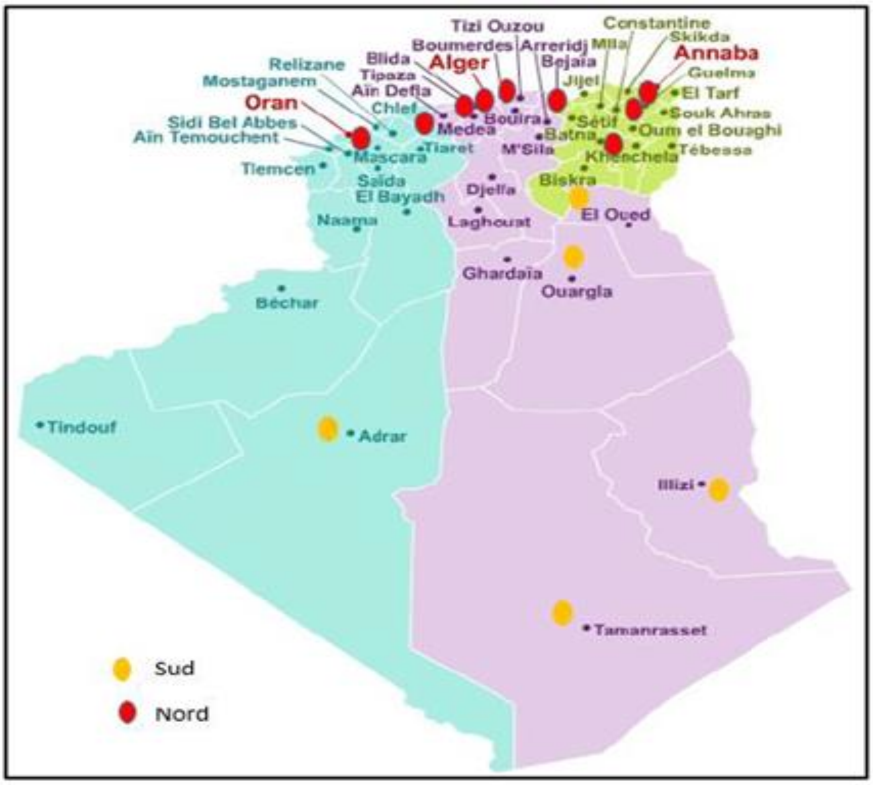

Figure 2: Geographic Distribution of Responding Companies

To facilitate systematic analysis, the survey responses were categorized into six thematic areas, as detailed below.

1) Company Profile

This section comprised four items designed to capture general firmographics. Respondents represented diverse industrial sectors, with participation rates descending as follows: hydrocarbons, construction, food processing, automated systems manufacturing, renewable energy, chemicals, and healthcare. Company outputs included both solid and liquid products. In terms of size distribution, 50% of responses originated from medium-sized enterprises, 44% from large corporations, and a minor share from small firms. Domestically owned entities constituted over three-quarters of the sample, while multinational enterprises (predominantly within the hydrocarbons sector) represented the remainder.

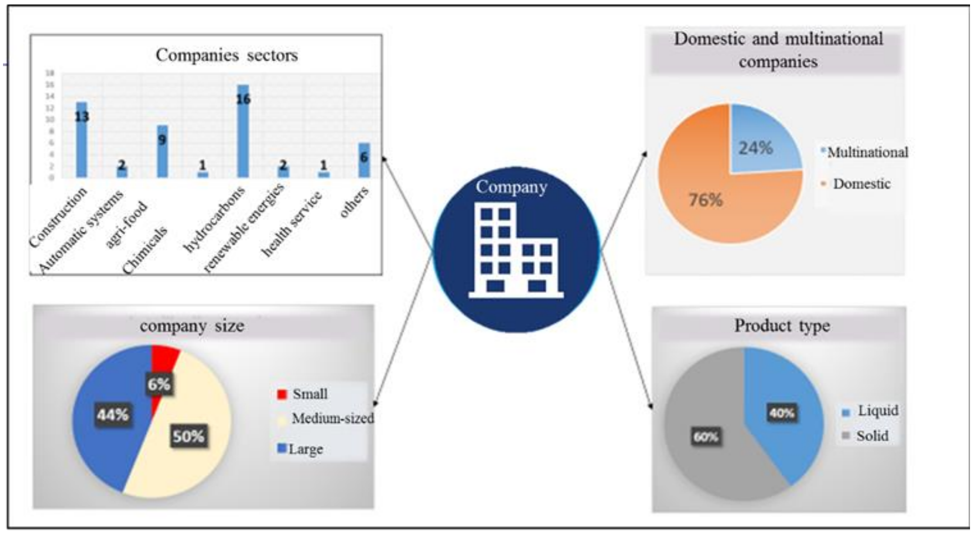

Figure 3: Results from the "company profile" section.

2) Customer Orientation and Feedback

Four questions assessed customer-centric practices concerning quality requirements and complaint management. To evaluate whether a product's quality meets acceptable standards, 60% of firms rely on holistic customer satisfaction metrics, emphasizing service and durability. In contrast, 34% prioritize specific attributes such as price, features, and functionality. A significant majority (68%) reported encountering stringent customer demands that directly impact quality specifications. To align products with these expectations, half of the companies employ active listening channels, including social media, surveys, and direct communications. Meanwhile, 30% depend strictly on predefined specifications, and a minority (10%) adopt an innovative, empathetic approach by anticipating unmet customer needs. (Figure 4)

Regarding formal complaint resolution, 52% have documented procedures, 22% lack any structured process, and approximately 34% utilize either automated or computerized systems for this purpose.

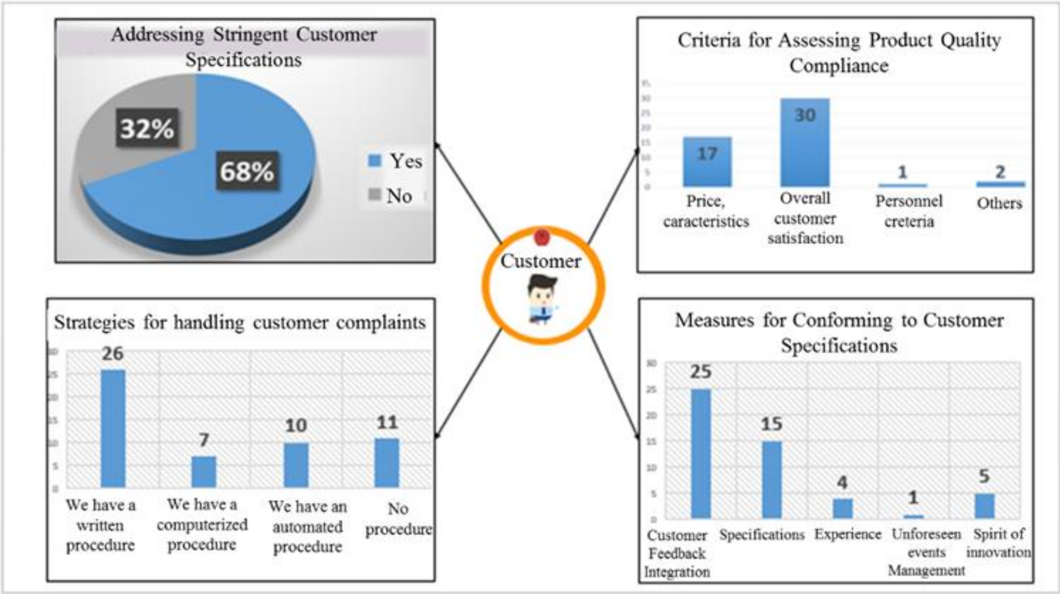

Figure 4: Results from" Customer Orientation and Feedback" section

3) Defect Identification and Correction

The data (illustrated in Figure 5) indicate a strong focus on preventive measures, with 94% of companies taking action to eliminate potential causes of non-conformities. Among these, half specifically aim to ensure production and delivery adherence to specifications, thereby reducing defects and minimizing returns. For corrective actions, 86% of procedures mandate a root-cause analysis following a non-conformity.

[2]Notably, 46% of firms do not conduct quality inspections at every production stage; only 10% limit inspections to finished goods. Inspection duration varies considerably by sector, with hydrocarbon industry inspections extending to several weeks. While 12% of companies inspect all output, the remainder employ sampling rates that differ across sectors (Figure 6). Defect identification remains predominantly manual, though a trend toward automation is emerging.

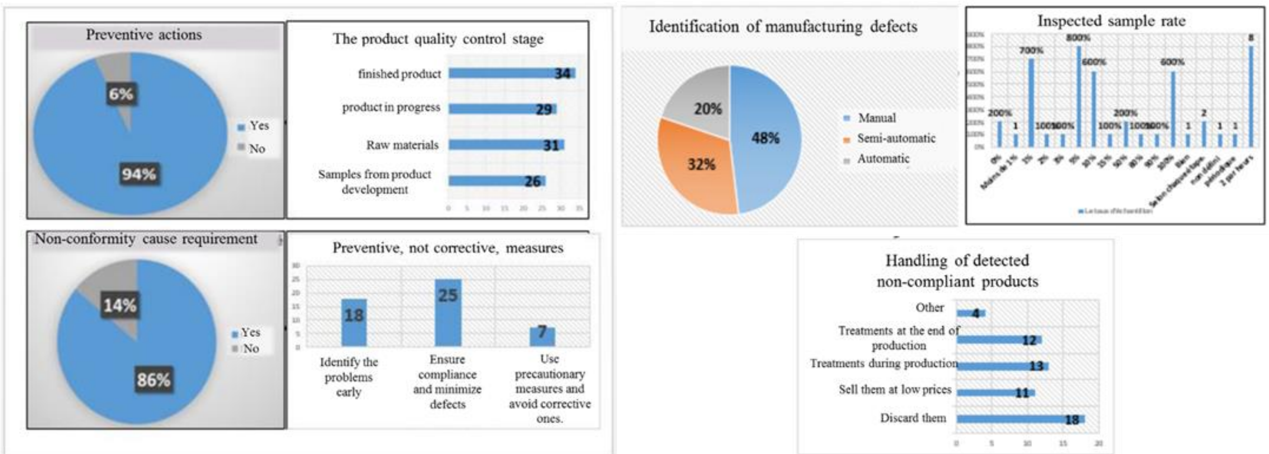

Figure 5: Results from "Defect Identification and Correction" section (a)

Non-conforming products are typically segregated and discarded; most companies either scrap these items or sell them at reduced prices rather than reworking them. According to survey results, human error was cited as the primary cause of defects (60%), followed by raw materials, measurement inaccuracies, procedural methods, and environmental factors (the latter being particularly influential in chemical production). Losses attributed to quality issues were estimated at 5-15%, with nearly all factories allocating dedicated resources to address them.

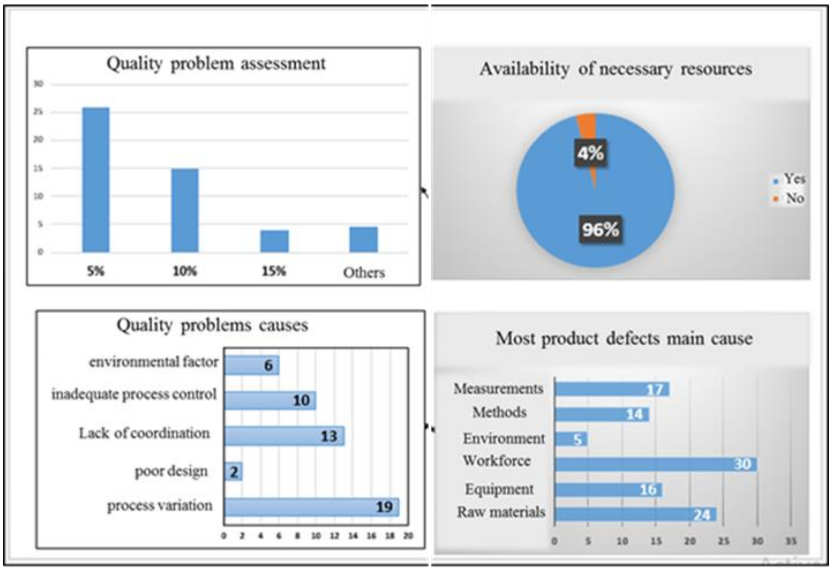

Figure 6: Results from "Defect Identification and Correction" section (b)

4) Quality Management Systems and Standards

Certification serves as the primary quality benchmark for 54% of companies (Figure 7). Relevant standards are documented and accessible in 52% of organizations; however, 78% lack a formal quality management system, and 88% do not utilize dedicated quality software. Additionally, quality personnel in 28% of firms receive no formal training.

Despite this, 84% of companies perform quality-critical processes under controlled conditions and 68% have implemented systems for continuous quality improvement. The seven classic quality tools (e.g., Pareto charts) are the most widely adopted improvement methods, with 70% of firms planning to integrate additional methodologies in the future. Half of the respondents reported only a moderate understanding of organizational quality objectives.

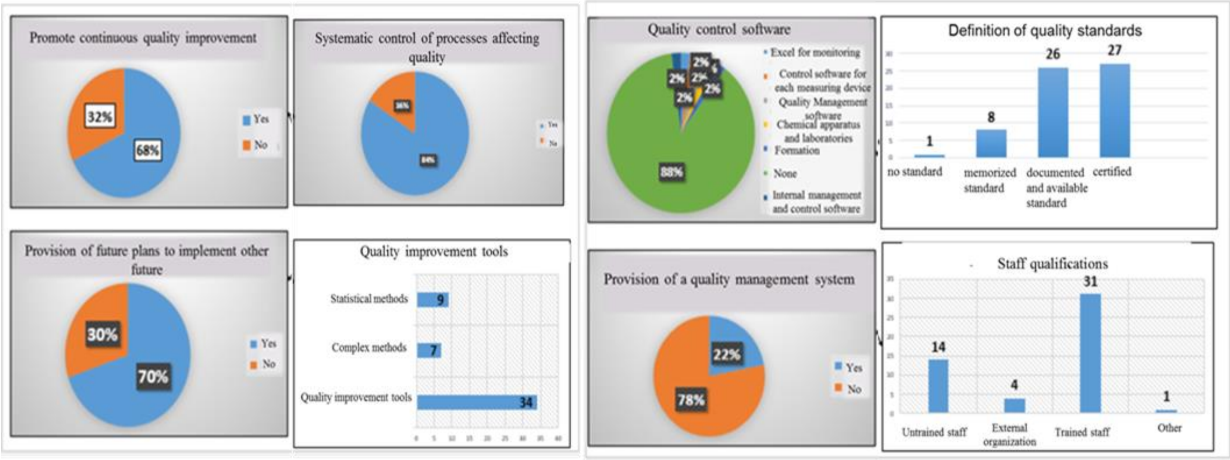

Figure 7: Results from "Quality Management Systems and Standards" section

5) Information Availability and Traceability

Data collection practices show that 74% of companies clearly record whether a product passes or fails inspection. Furthermore, 67% have established documented procedures to identify staff training needs (Figure 8). Data collection remains predominantly manual, with only 4% of firms employing automated systems. For traceability, most companies maintain records for non-conforming materials, as well as for the inspection and testing of incoming raw materials, work-in-process, and finished goods.

Firms utilizing modern, data-driven quality control methods consistently establish documented procedures to define required competencies and training for quality-related roles, with a strong focus on systematic data utilization and processing.

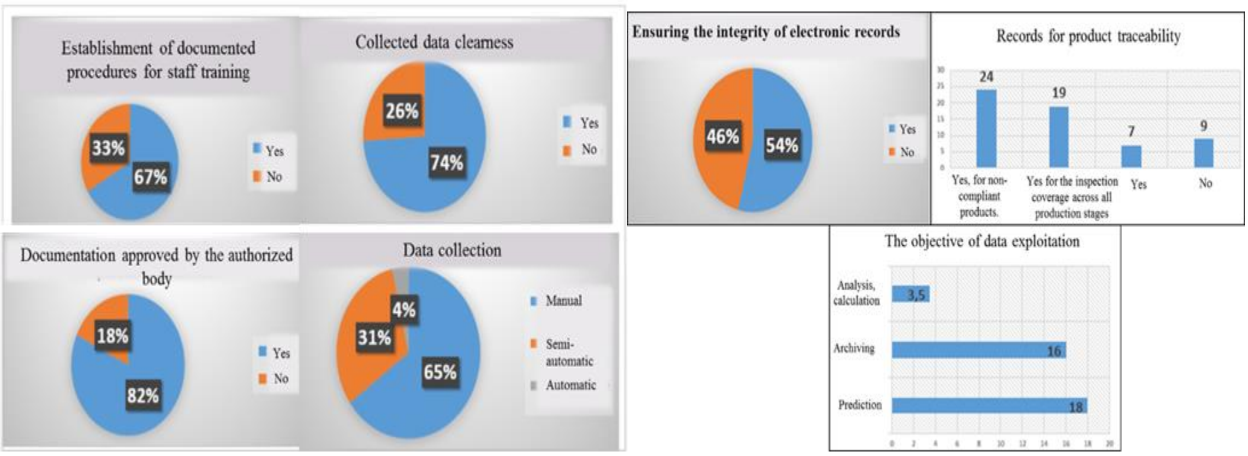

Figure 8: Results from “Information Availability and Traceability” section

6) Industry 4.0 and Quality (Quality 4.0)

Survey results indicate limited familiarity with Industry 4.0 within the Algerian industrial sector, with 60% of respondents unaware of the concept. Among those familiar with it, only 18% have a detailed strategy for future implementation (Figure 9). The most recognized and utilized technologies include the Internet of Things (IoT), computer vision, machine/deep learning techniques, and cloud computing. (Figure 9)

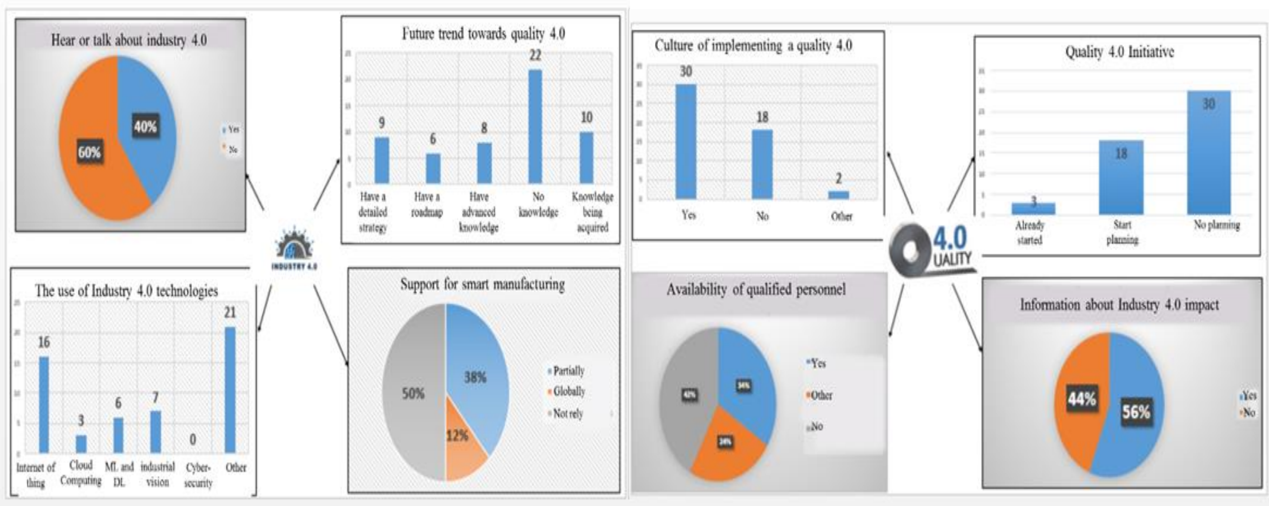

Figure 9: Results from "Industry 4.0 and Quality (Quality 4.0)" section (a)

A principal barrier to adoption is cultural resistance, with approximately 40% of companies skeptical of its benefits. Conversely, 42% have initiated planning and possess personnel capable of leading Quality 4.0 initiatives. Additional impediments, ranked in descending order, include:

- Legacy and obsolete technological systems.
- Fragmented data quality and integrity.
- Unclear digital strategy.
- Shortage of digital skills and specialized talent.

Primary motivations for pursuing Industry 4.0 adoption are market demands, competitive pressures, differentiation opportunities, and an innovative mindset. Respondents identified robotics and data analytics as the most strategically important technologies. In practice, 54% of companies currently employ data mining technologies (Figure 10).

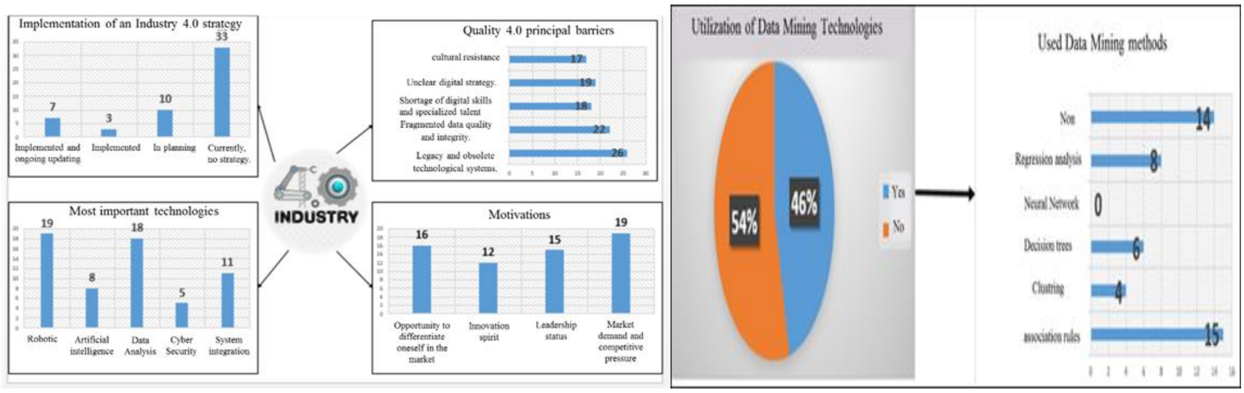

Figure 10: Results from "Industry 4.0 and Quality (Quality 4.0)" section (b)

To examine the relationships between key organizational variables, a series of chi-square tests of independence were conducted.

All analyses were performed using SPSS software, with the significance level set at $\alpha = 0.05$.

Test 1: Association between Smart Manufacturing Adoption and Firm Size

The null hypothesis (H_0) posited that smart manufacturing adoption is independent of firm size.

The alternative hypothesis (H_1) proposed a significant association between the two variables.

The computed test statistic ($\chi^2 = 7.4845$) was less than the critical value (χ^2_critical = 9.4) at the specified significance level. Consequently, H_0 cannot be rejected, indicating no statistically significant relationship between firm size and the adoption of smart manufacturing practices within the sample.

Test 2: Association between Data Collection Automation and Geographic Region

This test assessed whether the method of quality data collection (automated vs. manual) is independent of the company's geographic region.

H_0 stated independence, while H_1 predicted dependence.

The analysis yielded an observed statistic of $\chi^2 = 12.333$, which exceeds the critical value of χ^2_critical = 5.99. Therefore, H_0 is rejected, confirming a statistically significant association between region and the automation of data collection.

Test 3: Association between Quality Data Collection Method and Region

Consistent with Test 2, this analysis evaluated the broader relationship between the method of quality data collection and region. The hypotheses mirrored those of Test 2. The result (χ^2_observed = 12.333 > χ^2_critical = 5.99) leads to the rejection of H_0, reaffirming a significant dependence between geographic region and the chosen method for collecting quality data. This finding aligns with and substantiates the result from Test 2.

C. Proposed solutions

The survey provided critical insights into the prevailing quality assurance methodologies employed by manufacturing firms in Algeria. Building upon the analysis of these empirical findings and informed by international best practices, this study proposes some strategic solutions to address existing challenges and facilitate the integration of Industry 4.0 technologies within the Algerian industrial context, comprising the following key steps:

- **Cultivating Organizational Competence:** The foundational step involves designing and executing specialized capacity-building initiatives focused on Quality 4.0 concepts. Training must be customized to align with firm-specific and sectorial operational contexts, targeting the entire workforce to promote universal digital literacy and secure buy-in for sustained process enhancement.

- **Diagnostic Analysis of Quality Maturity:** A rigorous assessment of current quality systems is required to quantify existing capabilities and gaps. This evaluation should leverage methodological tools such as process audits, statistical analysis of operational data, and systematic solicitation of customer feedback to establish a reliable performance benchmark.
- **Formulation of Targeted Quality Metrics:** Strategic quality aims must be articulated as precise operational targets. These goals should conform to the SMART framework (ensuring they are Specific, Measurable, Achievable, Relevant, and Time-bound) to provide a clear directive for implementation and a basis for evaluation.
- **Technology Integration for Quality Enhancement:** Organizations must strategically select and implement Industry 4.0 enablers to augment quality assurance. Applicable technologies may encompass IoT networks for continuous equipment and product monitoring, AI-driven analytics for defect prediction, computer vision for automated inspection, and cyber-physical systems to streamline production and improve consistency.
- **Iterative Performance Management:** Upon deployment of Quality 4.0 projects, a closed-loop monitoring system must be established. This involves defining and tracking relevant Key Performance Indicators (KPIs) to measure efficacy against objectives and to guide data-driven, continuous optimization efforts.
- **Extended Quality Ecosystem Collaboration:** Achieving end-to-end quality necessitates proactive integration with supply chain partners. Collaborative quality agreements and shared data protocols with suppliers are vital to assure the conformity of incoming materials, thereby elevating final product standards and supply chain resilience.

3. Inspection Technology- Readiness Mapping: An MCDM framework for industrial Quality 4.0 implementation

While the proposed solutions defines the strategic pathway for advancing toward Quality 4.0, its effective deployment critically depends on the alignment between organizational readiness and the technical complexity of the selected quality assurance technologies. In practice, advanced tools such as AI-based defect detection, computer vision, and cyber-physical systems cannot be implemented uniformly across firms with heterogeneous levels of digital maturity, infrastructure, and human capital (particularly in contexts with heterogeneous capabilities like the Algerian manufacturing sector). This necessitates a structured mechanism that links the current readiness profile of each enterprise to the most technically and economically feasible defect detection and inspection methods. To address this requirement, we introduce the Inspection Technology-Readiness Mapping, which serves as an operational bridge between the strategic Quality 4.0 roadmap and the concrete selection of defect detection technologies adapted to the real capabilities of manufacturing firms.

Unlike technology-driven approaches that prioritize performance in isolation, the Inspection Technology-Readiness framework ensures that defect detection solutions are selected based on their technical effectiveness, metrological reliability, economic feasibility, and organizational compatibility. In this way, the framework provides manufacturers with a structured mechanism for systematically aligning potential defect detection tools with organization's operational readiness using Multi-Criteria Decision-Making (MCDM). The core objective is not only to progress toward Quality 4.0 theoretically, but also practically ensure controlled, scalable, and sustainable technology adoption.

A. Core Conceptual Structure

The Inspection Technology-Readiness is built upon the explicit coupling of two complementary dimensions:

1. Inspection Technology Dimension: the spectrum of defect detection and inspection strategies that can be deployed in manufacturing environments. It ranges from Manual and rule-based visual inspection, to Feature-based machine learning (ML), Pre-trained and custom deep learning (DL) models, and Cloud-connected, cyber-physical Quality 4.0 platforms. Each class of methods is associated with different requirements in terms of data availability, computational resources, metrological validation, automation level, and integration complexity.

2. Readiness Dimension: This dimension captures the organization's preparedness across multiple critical axes, including: Digital and sensing infrastructure, Data availability and quality, Workforce skills and training level, Management commitment, Financial and technological capacity, Metrological control and traceability. By explicitly coupling these two dimensions, the Inspection Technology-Readiness framework ensures that technological ambition is continuously bounded by organizational capacity, avoiding premature investments and reducing implementation risk.

B. Integrated MCDM Procedure

The integration of MCDM provides the rigorous mechanism to evaluate and rank each practical alternative against the weighted readiness and performance criteria. The process is operationalized through the following structured phases (figure 11):

Phase 1 Define the decision matrices: In this phase we establish the foundational elements for evaluation.

- Identify Candidate Inspection technologies (Alternatives): Define the set of potential quality assurance techniques T_i to be evaluated. For example: T_1: Manual visual inspection with digital logging; T_2: Rule-based image processing on local PCs; T_3: Inspection using Machine Learning models; T_4: A fully fine-tuned deep learning model with automated defect localization; T_5: A cloud-based vision inspection platform with real-time dashboards and strong capabilities.
- Define Readiness Criteria: Establish the dimensions R_j that quantify organizational preparedness. Each criterion is scored for the specific firm on a scale. For instance, R_1: Digital Infrastructure (network, servers, and sensors/cameras); R_2: Data Readiness (availability of labeled datasets, data governance); R_3: Workforce Skills (IT/AI competency of operators and maintenance staff); R_4: Management and Cultural Support (for change and innovation); R_5: Budgetary and Financial Flexibility.

- Define Performance Criteria: Determine the decision criteria C_k for evaluating the methods, assigning strategic weights w_k (where $\sum w_k = 1$). For instance, C_1: Defect Detection Performance (Accuracy, Recall); C_2: Implementation Cost; C_3: Time to Deploy; C_4: Operational Robustness; C_5: Scalability and Flexibility; C_6: Interpretability and Operational Acceptance.

Phase 2 Build the Inspection technology-Method matrix and evaluate performance: This phase quantifies the feasibility and expected benefit of each method.

- Assess readiness compatibility: For each technology T_i, define its minimum readiness requirement for each criterion R_j . A score of 1 indicates full readiness; lower scores indicate significant gaps. Technologies with score <0.5 can be filtered out as currently infeasible.
- Score Method Performance: Experts score each technology T_i on the performance criteria C_k. These scores are normalized to create a standardized performance vector.

Phase 3: MCDM synthesis for ranking and roadmapping

This phase synthesizes feasibility and benefit to prioritize actions.

- Compute composite selection index: An MCDM technique (e.g., TOPSIS, AHP, VIKOR) is applied to the performance scores, using the predefined weights w_k, to compute final selection index which balances theoretical benefit with practical feasibility.
- Rank Methods and Identify Gaps: The framework outputs are a prioritized list of immediately viable technologies (highest final score) and a gap analysis for high-potential but currently infeasible technologies, specifying which readiness criteria must be improved and by how much.

Phase 4: Staged implementation and iterative reassessment

The output translates into a dynamic action plan.

- Immediate deployment: The highest-ranked method becomes the Phase-1 implementation target.
- Roadmap development: The readiness gaps identified for more advanced methods define concrete readiness improvement projects (e.g., "Improve by establishing a data labeling

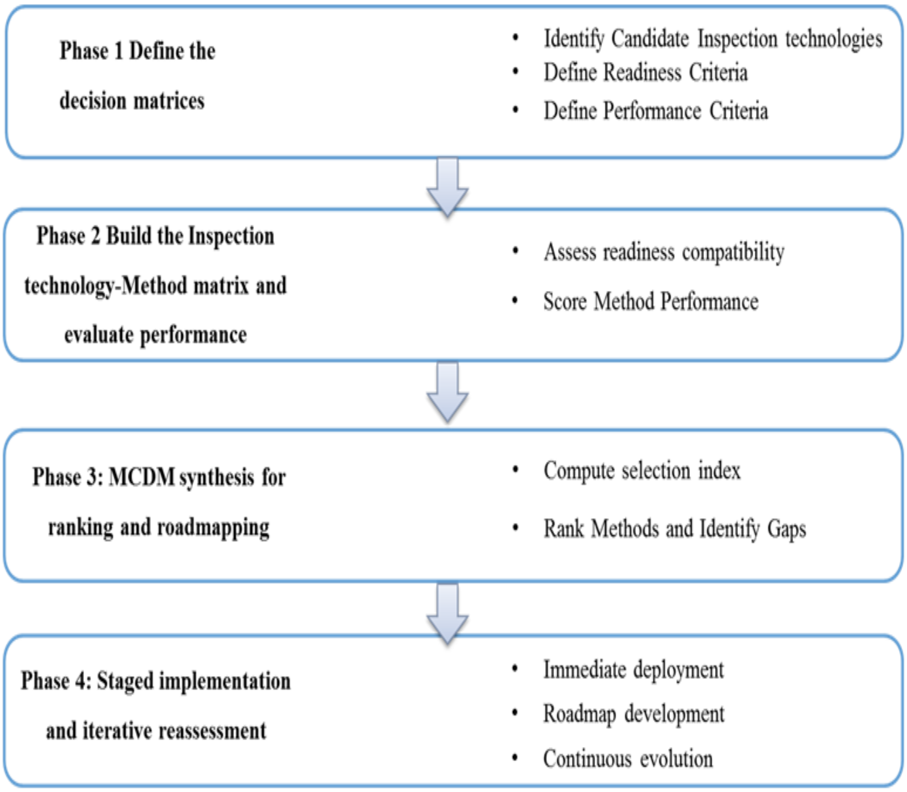

Figure 11: The process of Technology Inspection-Readiness Mapping

protocol and storage system").

- Continuous evolution: Periodically (e.g., every 6–12 months), the firm's readiness profile is reassessed. The Inspection Technology-Readiness Mapping evaluation is re-run, enabling a structured, evidence-based transition to more advanced technologies in subsequent phases.

Tableau 2 : translate the Inspection Technology-Readiness Framework into practice

Level	Typical Capabilities	Recommended Detection Methods	Data Requirements	Metrological Requirements	Strategic Objective
Foundational	Basic automation Limited digital infrastructure No annotated datasets	Manual inspection with digital checklists Rule-based machine vision (thresholding, morphological filters)	Low-volume images Structured defect labeling template	Camera calibration Repeatability checks Basic false-alarm monitoring	Stabilize inspection and initiate digital data acquisition
Developing	Moderate IT infrastructure Partial data structuring Trained technicians	Feature-based ML (SVM, RF, KNN) Hybrid vision-ML systems	Medium-scale labeled datasets Engineered features	Performance uncertainty estimation Sensor drift monitoring Cross-validation of classification accuracy	Transition from deterministic to data-driven inspection

Advanced	High data maturity Strong computing capacity AI expertise	Deep Learning (CNN, segmentation networks) Cyber-physical Quality 4.0 platforms	Large annotated datasets Continuous multi-source data streams	Uncertainty quantification in DL outputs Continuous calibration Traceability to national standards	Achieve autonomous, predictive, and adaptive quality control

Conclusion

Quality remains a fundamental pillar of industrial performance and competitiveness, whether in manufacturing or service-oriented activities. In the context of Industry 4.0, quality management is no longer limited to post-production inspection but evolves toward intelligent, data-driven, and predictive systems under the paradigm of Quality 4.0, with objectives such as cost reduction, improved reliability, and the pursuit of zero defects. However, the effective deployment of advanced defect-detection technologies remains strongly conditioned by product characteristics, inspection objectives, metrological requirements, and, above all, organizational readiness.

In this study, a theoretical synthesis of defect-detection techniques was systematically combined with empirical survey data collected from fifty Algerian manufacturing companies. Based on this dataset, firms were classified into three readiness levels (Foundational, Developing, and Advanced) reflecting their technological, organizational, data-related, and metrological capacities. To operationalize the transition toward Quality 4.0, the research developed an Inspection Technology-Readiness Mapping (ITRM) framework, which bridges method selection criteria with the actual industrial context. Supported by expert validation and structured multi-criteria evaluation, this framework explicitly connects the technical characteristics of defect-detection methods with the local readiness of Algerian firms, offering a concrete and rational basis for technology selection.

The survey results indicate that while several Algerian firms (particularly multinational subsidiaries) are progressing in the adoption of Industry 4.0 technologies such as robotics, IoT, data analytics, artificial intelligence, and cloud computing, significant structural challenges persist. These include legacy systems, insufficient availability of clean and structured data, data integrity limitations, skills gaps, and resistance to organizational change. Nevertheless, the growing awareness of Industry 4.0 benefits observed in the sample reflects an encouraging shift toward digital transformation in the Algerian industrial ecosystem.

In this context, the proposed ITRM framework serves as a decisive tool for industrial digitalization. It forces explicit, evidence-based trade-offs between ideal technological solutions and real operational constraints, enhances transparency and managerial buy-in through explainable decision mechanisms, and enables scalable and sustainable adoption via a stepwise transition from traditional inspection practices to advanced Quality 4.0 systems. By aligning each technological choice with actual organizational capability, the framework ensures that digital transformation remains strategic, economically viable, and operationally achievable.

This research can represent the first stage of a broader scientific program aimed at developing predictive, metrologically validated, and multi-objective quality-control models. Future work may focus on expanding the study population, performing sectorial and regional readiness analyses, conducting international benchmarking with both advanced and comparable economies, and quantitatively estimating the economic impacts of Quality 4.0 adoption in terms of productivity, efficiency, and competitiveness. Such extensions will further strengthen the role of the ITRM as a national decision-support reference for structured and trustworthy Quality 4.0 deployment.

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