Contents lists available at IdNNS

Journal of Intelligent Systems for Community Development

Volume 1 ; Issue 3

journal homepage: https://journal.idnns.org/index.php/jiscode

Mobile-Based Non-Conformance Report (NCR) Information System Using the Fuzzy Logic Algorithm

Ahmad Fathurrozi[a], Dwipa Handayani[a,*] and Muhammad Aprizal Wijatmiko[a]

[a]*Informatics Study Program, Faculty of Computer Science, Universitas Bhayangkara Jakarta Raya, Jalan Raya Perjuangan, Bekasi Utara, 17142, Indonesia*

ARTICLE INFO

Keywords:
Fuzzy Logic
Non-Conformance Report
Defective Products
RAD Method
Decision Support System

ABSTRACT

Human subjectivity in determining defective product disposition and the administrative latency of paper-based Non-Conformance Reports (NCR) hinder ISO 9001:2015 quality compliance in manufacturing. This study aims to develop a mobile-based NCR information system integrated with the Mamdani Fuzzy Logic algorithm as a decision support system for product disposition (repair, rework, scrap) at PT Ohgishi Indonesia. The software was built using the Rapid Application Development (RAD) methodology with an MVC architecture, a Flutter/Dart frontend, a Java Spring Boot backend, and Firebase Realtime Database. The novelty lies in the real-time automation of evaluating three quality parameters (Severity, Cost, Availability) through 27 expert IF-THEN rules. Black-box testing covered functional scenarios from role-based login and NCR creation to PDF report export. Testing results demonstrate that the system architecture executes all functions and fuzzy computations without functional errors. In conclusion, this system successfully mitigates quality decision subjectivity and accelerates reporting bureaucracy end-to-end.

1. Introduction

The Industry 4.0 era requires global manufacturers to adopt the *Zero Defect* and *Smart Manufacturing* philosophies through digital quality management systems (Powell et al., 2022; Ullah et al., 2025). In accordance with ISO 9001:2015 Clause 8.7, companies must maintain a comprehensive traceability system to control nonconforming products (Brkljač et al., 2022; Medić et al., 2024). The universal instrument used for this purpose is the *Non-Conformance Report* (NCR) (Brkljač et al., 2022). However, at PT Ohgishi Indonesia, NCR reporting still depends on manual paper documents. This dependence causes severe administrative latency because documents must be physically passed between divisions, leading to queue build-up, a risk of losing audit files, and delays in management's response to quality-trend anomalies in real time (Clancy et al., 2026; Powell et al., 2023).

The most crucial problem is not merely the physical bureaucratic bottleneck, but the high degree of human subjectivity in determining the disposition of defective products (*repair*, *rework*, or *scrap*). Inspectors' on-site judgments are strongly influenced by individual experience and fatigue, which leads to inconsistent decisions for the same type of defect. This systematic failure increases the *Cost of Poor Quality* (COPQ) (Lario et al., 2025; Muffato et al., 2024; Walston et al., 2025). Companies bear financial losses from wasted labor hours when products that should simply have been repaired are reworked, or from excessive material loss caused by erroneous scrap decisions (Ullah et al., 2025).

Conventional administrative digitalization (CRUD) has proven insufficient because it only accelerates data distribution without addressing the root cause, namely human assessment bias. The system requires integration with a Decision Support System capable of standardizing disposition verdicts (Elahi et al., 2023; Muffato et al., 2024). Binary Boolean logic is inadequate for mapping the reality of material damage, which lies in in-between states. Therefore, the Mamdani *Fuzzy Logic* method was chosen as the computational solution because of its superior capability to process ambiguous linguistic variables into a consistent mathematical formulation (Cardiel-Ortega and Baeza-Serrato, 2024; Díaz, 2025).

The novelty of this research lies in the strategy of integrating the Mamdani Fuzzy Logic decision model into a real-time mobile reporting ecosystem based on an MVC architecture. The system separates the interface layer (Flutter/Dart frontend), the server logic (Java Spring Boot backend), and data storage (Firebase). Unlike previous studies, most of which remain confined to mathematical model simulations, this platform is designed to be production-ready

*Corresponding author
afrijalwijatmiko@gmail.com (A. Fathurrozi);
dwipa.handayani@dsn.ubharajaya.ac.id (D. Handayani)
ORCID(s):

in order to eliminate bureaucratic latency and instantly remove inspector subjectivity bias, thereby maintaining ISO 9001:2015 quality compliance (Clancy et al., 2026; Elahi et al., 2023; Nurcahyo and Habiburrahman, 2021).

2. Research Method

This study applies the Rapid Application Development (RAD) methodology to build a mobile-based *Non-Conformance Report* (NCR) information system. RAD was chosen for its adaptive and iterative characteristics and its ability to shorten the software development life cycle within an efficient time frame. The system engineering stages were adapted into five structured phases.

2.1. Communication Phase

The initial phase focused on field observation and functional requirements analysis at PT Ohgishi Indonesia. Role identification was intended to serve three main actors: the Quality Control (QC) Inspector, who initiates defect reports on the shop floor; Quality Assurance (QA), who assesses the parameters; and the Quality Manager, who holds the highest authority for signing the disposition. This role-based access restriction is applied strictly to preserve the validity of non-conformance data.

2.2. Planning Phase

Based on the requirements analysis, the software architecture was planned using an integrated approach that separates the user interface layer (front-end) from the business logic (back-end). On the front-end side, Flutter/Dart is used to serve four user roles on mobile devices: the QC Inspector (inputting damage data and photographic evidence), QA (reviewing decisions), the Production Team (executing repairs), and the Manager (reviewing history and applying digital signatures). On the back-end side, the system is built with Java Spring Boot as the data orchestrator toward Firebase Storage (for photo and signature files) and Firebase Realtime Database (for instant synchronization of transaction data, status, and approvals).

The back-end also acts as the link between the damage parameters and the Fuzzy Logic module, which performs fuzzification, inference based on 27 expert rules, and defuzzification to return a disposition suggestion (Repair, Rework, Scrap) to the database. In addition, the back-end automates the generation of legal documents in the form of print-ready PDF reports. The overall blueprint of the interaction architecture and data flow of this integrated system is shown in Fig. 1.

2.3. Modeling Phase

The modeling phase focuses on designing the user interface (UI/UX) of the mobile application and modeling the data logic flow. The visual interface design is structured to serve the Inspector's need to enter material descriptions, as well as the Manager/QA dashboard for evaluating the quality parameters of defective products. The computation flow is designed so that the crisp input values entered through the interface are sent to the backend, evaluated automatically by the Fuzzy Inference System (FIS) module, and the results are stored in Firebase to trigger real-time notifications while updating the user's visual display. The entire interaction flow, from the input of quality parameters to the generation of a corrective-action recommendation on the interface, is illustrated by the flowchart in Fig. 2.

2.4. Construction Phase

The architectural design was translated into functional program code. The main focus of this phase is embedding the Mamdani Fuzzy Logic algorithm into the backend analytics module. The fuzzy model processes three main corporate input parameters: *Severity* (*Minor, Moderate, Major*), *Cost* (*Low, Medium, High*), and *Availability* (*Low, Medium, High*), which are mapped to triangular and trapezoidal membership functions. The inference engine evaluates a total of 27 expert rules (IF-THEN rules), whose output is then converted back through a defuzzification method to produce a crisp product-disposition decision: Repair, Rework, or Scrap. The fuzzy rule-processing logic on the backend is implemented as shown in Fig. 3.

2.5. Deployment Phase

The integrated mobile NCR application was deployed in a limited user-testing environment within the company's internal network. In this phase, the system underwent comprehensive functional testing using the *Black-Box Testing* method to validate workflow status transitions, role authentication, the accuracy of the fuzzy mathematical computation, and the automatic PDF report printing feature required for ISO 9001:2015 audits.

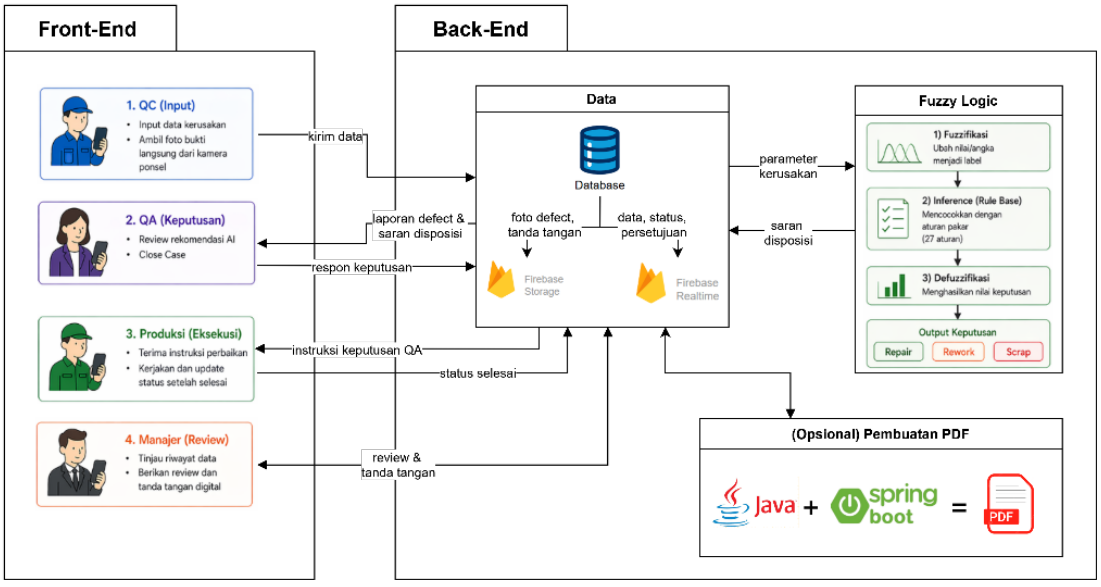


Figure 1: Architecture of the NCR information system. Source: research results (2026).

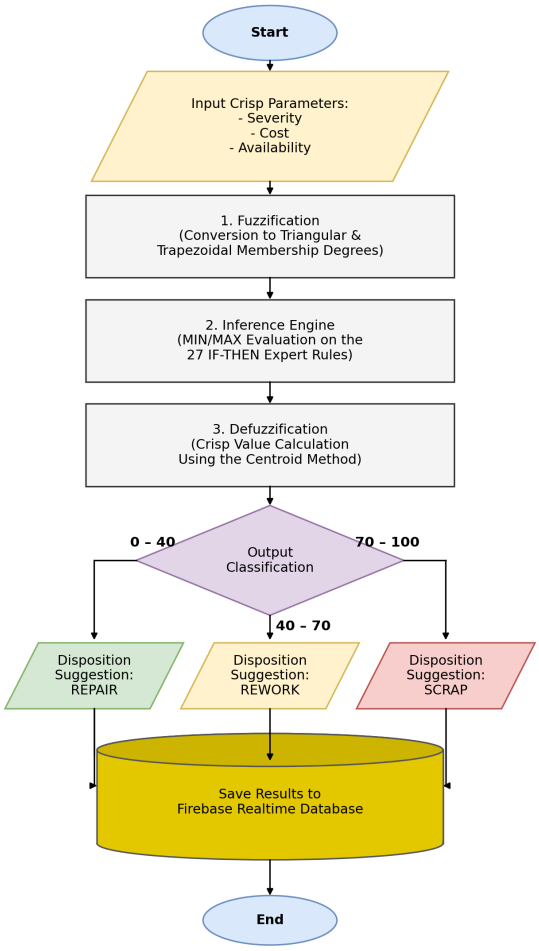


Figure 2: Flowchart of the fuzzy logic process. Source: research results (2026).

```
INPUT: Severity_Value, Cost_Value, Availability_Value
OUTPUT: Crisp_Value, Disposition_Recommendation
BEGIN
  BACKEND receives numeric quality-parameter values (scale 0–100)
    from the user interface.
  SYSTEM performs Fuzzification:
    Maps the values to membership functions (Triangular &
      Trapezoidal).
    Produces the input membership degrees (Severity, Cost,
      Availability).
  BACKEND executes the Inference Engine:
    Evaluates the 27 expert rules (IF-THEN rules) using the MIN
      operator.
    Aggregates all active rule outputs using the MAX operator.
  SYSTEM performs Defuzzification:
    Computes the crisp value (Crisp_Value) using the Centroid method.
  IF Crisp_Value lies in the range of highest membership THEN
    System classifies the result into a disposition: Repair, Rework,
      or Scrap.
    RETURN Disposition_Recommendation and Crisp_Value to the data
      repository.
  ELSE
    RETURN Calculation_Error
  ENDIF
END
```

Figure 3: Pseudocode of the fuzzy rule implementation on the backend. Source: research results (2026).

3. Results and Discussion

This section describes the implementation of the user interface of the *Non-Conformance Report* (NCR) information system based on the design produced in the modeling phase, the decision behavior of the Mamdani *Fuzzy Logic* algorithm embedded in the system, and the results of its functional testing.

3.1. User Interface Implementation

The user interface (UI) was developed with the *Flutter* framework and the *Dart* programming language to produce a responsive and interactive multiplatform mobile application. Based on the architectural design, the implementation focuses on three main flows, namely parameter data input, recommendation review, and document approval output.

(a) Implementation of nonconformance data input. Based on the architectural design, the implementation focuses on integrating the defective-product handling flow from the production floor (*shop floor*) up to the managerial level, whose functions are detailed in Fig. 4. Fig. 4(a), the Quality Control (QC) inspection module, serves as the place where product defect data are entered using three interactive sliders (Severity, Cost, Availability) and a camera button for uploading physical-evidence photos directly to Firebase Storage. Fig. 4(b), the Quality Assurance (QA) review dashboard, displays the detailed product failure history, complete with the Fuzzy Logic computation result in the form of a confidence-score percentage and a decision recommendation, as well as a radio button for manually overriding the system's decision. Fig. 4(c), the Production Workflow and Manager Review dashboard, serves as the task control center with a toggle button for changing the work status on the assembly line, and also allows the Quality Manager to apply a digital signature and download the NCR report in PDF format for ISO 9001:2015 audit purposes.

3.2. Fuzzy Logic Decision Behavior

The algorithmic intelligence of the Mamdani *Fuzzy* inference system runs asynchronously behind the scenes (the *backend service layer*) to orchestrate the conversion of uncertain material conditions into absolute, accountable decisions. The process begins by evaluating the numeric input values (*crisp input*), which are then converted using the parameters of the triangular and trapezoidal membership functions configured in the system.

Next, the inference engine processes the interactions among condition combinations using the *Minimum* (MIN) logical operator for implication and the *Maximum* (MAX) rule for aggregation. To extract the final deciding point from the domain of the resulting fuzzy set, the system performs a continuous numerical integral calculation using the *Centroid* defuzzification method:

$$z^* = \frac{\sum_{i=1}^{n} x_i \, \mu(x_i)}{\sum_{i=1}^{n} \mu(x_i)} \tag{1}$$

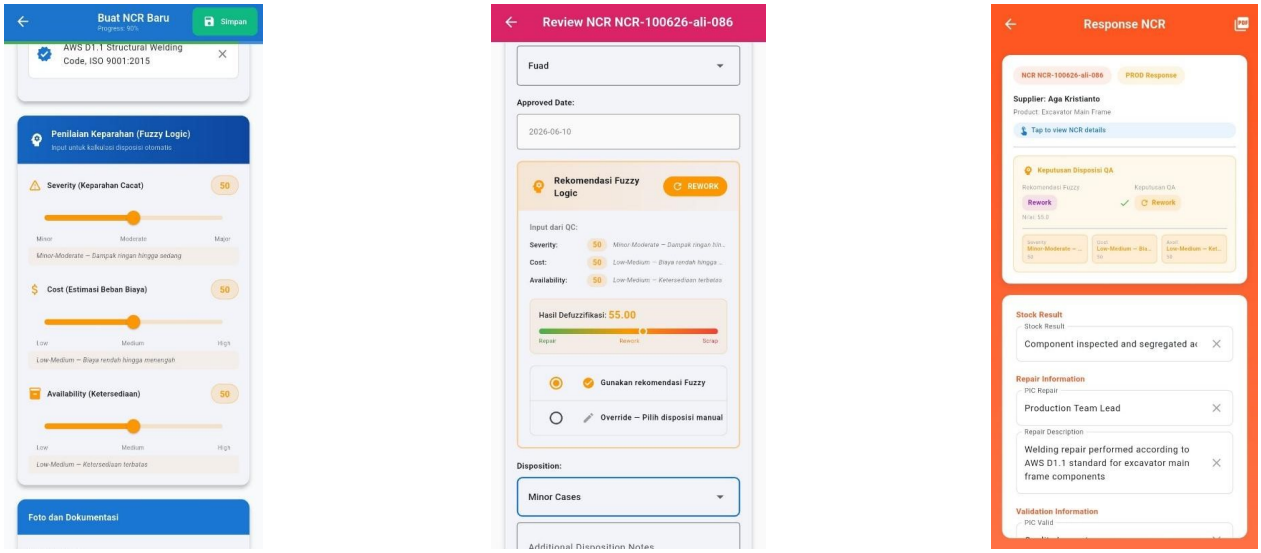
where z^* is the crisp value resulting from the final defuzzification, x_i is the domain sample value of the output variable, $\mu(x_i)$ is the aggregate membership degree resulting from the rule evaluation (maximum *firing strength*), and n is the number of domain sample points of the output variable.

The calculation above yields a crisp value in the quantitative range of 0 to 100. The system's output classification behavior dictates that if the value falls in the 0–40 range, the system recommends the *Repair* category for structurally and aesthetically minor damage with minimal cost intervention. Conversely, if the parameters show a medium-level anomaly in the 40–70 range, the system rules for *Rework* as a reconstructive instruction to restore the component's function to its original blueprint.

The most extreme decision is triggered when the calculation is pushed toward the 70–100 range, in which case the algorithm categorically determines *Scrap*, discarding the material because the repair burden is too large (*high cost*) and its functional integrity has exceeded the manufacturing safety limit. The entire distribution of recommended actions resulting from the combination of the 27 expert rules is summarized in an operational decision matrix (Table 1).

3.3. Testing Results

To validate the functional reliability of the *Non-Conformance Report* (NCR) information system architecture, software testing was carried out using the *Black-Box Testing* method. The test scenarios were designed rigorously to evaluate the entire life cycle of defective-product handling on the mobile platform (Android), with Firebase Realtime Database as the main repository. Both positive and negative test scenarios were executed to ensure that the system responds correctly to user instructions and rejects illegal operations that do not conform to the specification. Based on the evaluation of a total of 17 field test scenarios, the system's functional



(a) (b) (c)

Figure 4: Fuzzy Logic input sliders (a), Fuzzy Logic disposition result (b), and disposition decision result (c). Source: research results (2026).

Table 1
Summary matrix of the 27 fuzzy inference rules. Source: research results (2026).

		Availability		
Severity	Cost	Low	Medium	High
Minor	Low	Repair	Repair	Repair
	Medium	Rework	Repair	Repair
	High	Rework	Rework	Rework
Moderate	Low	Rework	Rework	Repair
	Medium	Rework	Rework	Rework
	High	Scrap	Scrap	Rework
Major	Low	Scrap	Rework	Rework
	Medium	Scrap	Scrap	Rework
	High	Scrap	Scrap	Scrap

implementation was divided into three main flow clusters, as follows.

3.3.1. User authentication feature testing

Testing of the authentication module aims to ensure that the system can validate login credentials and direct users correctly according to the access-right limits of their respective roles.

Based on Table 2, testing of the authentication feature shows that the system is able to verify user credentials accurately. The system intelligently distinguishes login sessions by role (*role-based login*) to secure the company's operational menu functionality. Access attempts that do not meet the requirements are automatically rejected with informative error messages.

3.3.2. NCR creation and Fuzzy Logic computation feature testing

Based on Table 3, testing of the operational module proves that server-side input data validation works very well. The Spring Boot backend module successfully eliminates the ambiguity of manual assessment by executing the fuzzy computation formula stably, and by storing the parameter history in the database in a structured manner.

Table 2
Test results of the authentication (login) feature.

No	Feature	Test case	Expectation	Result
1	Login	Valid QC credentials + correct password	Login succeeds, an authentication token is returned, and the user is redirected to the QC dashboard.	Passed
2	Login	Valid QA credentials + correct password	Login succeeds, an authentication token is returned, and the user is redirected to the QA dashboard.	Passed
3	Login	Username not registered in the database	Rejected because the user is not found; the message "Phone number is not registered" appears.	Passed
4	Login	Valid credentials + wrong password	Rejected because the credentials are invalid; the message "Wrong password" appears.	Passed
5	Login	Username field left empty	Rejected by the system because a required parameter must be filled (form validation).	Passed
6	Register	Password shorter than 6 characters	Rejected because the minimum password length is 6 characters (validation).	Passed

Source: research results (2026).

Table 3
Test results of the NCR creation feature and the fuzzy calculation.

No	Feature	Test case	Expectation	Result
1	Create NCR	All required fields filled + photo evidence uploaded	The report is saved in the database with draft status and the photo URL is stored in the repository.	Passed
2	Create NCR	Several required fields left empty	Rejected by the system; the empty fields are highlighted in red.	Passed
3	Fuzzy Logic	Input parameters: Severity = 10, Cost = 10, Availability = 90	Calculation succeeds, producing a low crisp value with the disposition **Repair**.	Passed
4	Fuzzy Logic	Input parameters: Severity = 85, Cost = 80, Availability = 20	Calculation succeeds, producing a high crisp value with the disposition **Scrap**.	Passed
5	Fuzzy Logic	Input parameters: Severity = 50, Cost = 50, Availability = 50	Calculation succeeds, producing a medium crisp value with the disposition **Rework**.	Passed
6	Fuzzy Logic	Boundary value input: Severity = 0	The system does not crash; the output remains valid and precise.	Passed

Source: research results (2026).

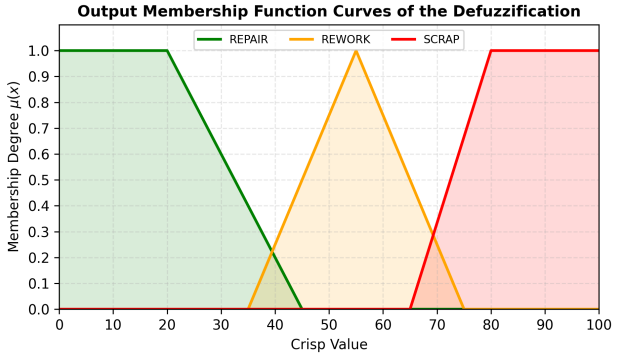


Figure 5: Output membership function curves of the defuzzification. Source: research results (2026).

4. Conclusions

This research successfully developed a digital *Non-Conformance Report* (NCR) information system based on Flutter and Firebase, integrated with a decision support system for the control of nonconforming products. The software architecture proved reliable in eliminating the bureaucratic dependence on paper-based document circulation, accelerating real-time cross-department collaboration, and improving the reliability of audit traceability in accordance with the ISO 9001:2015 standard. The integration of the Mamdani *Fuzzy Logic* algorithm, which processes the *Severity*, *Cost*, and *Availability* parameters through 27 expert rules, proved effective in mitigating subjectivity and cognitive bias in determining the *Repair*, *Rework*, or *Scrap* disposition. The functional testing results using the *Black-Box Testing* method showed a perfect (100%) success rate across all critical modules, covering access-right authentication validation, the accuracy of fuzzy decision calculation, operational workflow transitions, and the automated generation of PDF report files. As a prospect for future research, the system can be further optimized by strengthening data-security encryption at the *Application Programming Interface* (API) layer, and by fully integrating the platform into the company's *Enterprise Resource Planning* (ERP) ecosystem to broaden the scope of quality-management automation.

Acknowledgments

The authors would like to express their sincere gratitude to the Faculty of Computer Science and the Informatics Study Program of Universitas Bhayangkara Jakarta Raya for the guidance, academic facilities, and support provided during the preparation of this research. Deep appreciation and thanks are also extended to the management and all Quality Control and Quality Assurance staff of PT Ohgishi Indonesia for the operational permission, the provision of field data, and the outstanding collaboration throughout the implementation of this NCR information system.

References

Brkljač, N., Munić, N., Mićović, A., Kovačević, A.M., Rakonjac, P., 2022. Structure and frequency of product nonconformities in the context of customer. 17(1), 291–300.

Cardiel-Ortega, J.J., Baeza-Serrato, R., 2024. Probabilistic fuzzy system for evaluation and classification in failure mode and effect analysis.

Clancy, R., O'Sullivan, D., Bruton, K., 2026. Data-driven quality improvement approach to reducing waste in manufacturing. The TQM Journal 35, 51–72. doi:10.1108/TQM-02-2021-0061.

Díaz, G.M., 2025. Quality management in chemical processes through fuzzy analysis: A fuzzy c-means and predictive models approach.

Elahi, M., Afolaranmi, S.O., Martinez Lastra, J.L., Perez Garcia, J.A., 2023. A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. Discover Artificial Intelligence doi:10.1007/s44163-023-00089-x.

Lario, J., Mateos, J., Psarommatis, F., 2025. Towards zero defect and zero waste manufacturing by implementing non-destructive inspection technologies. 1–18.

Medić, S., Mihalić, T., Guštin, A., Groš, J., 2024. Contribution of new standard ISO 9001:2015 to the quality. Interdisciplinary Description of Complex Systems 22, 612–615. doi:10.7906/indecs.22.5.6.

Muffato, A., Alaíze, R., Orsoletta, D., Nunes, E., Costa, L., Sousa, S., 2024. Quality costs and industry 4.0: inspection strategy modelling and reviewing. The International Journal of Advanced Manufacturing Technology doi:10.1007/s00170-024-13184-9.

Nurcahyo, R., Habiburrahman, M., 2021. Relationship between ISO 9001:2015 and operational and business performance of manufacturing industries in a developing country (indonesia). Heliyon 7.

Powell, D., Eleftheriadis, R., Myklebust, O., 2023. Digitally enhanced quality management for zero defect manufacturing. 104, 1351–1354.

Powell, D., Magnanini, M.C., Colledani, M., Myklebust, O., 2022. Advancing zero defect manufacturing: A state-of-the-art perspective and future research directions. Computers in Industry 136, 103596. doi:10.1016/j.compind.2021.103596.

Ullah, A., Younas, M., Saharudin, M.S., 2025. Transforming manufacturing quality management with cognitive twins: A data-driven, predictive approach to real-time optimization of quality. 1–29.

Walston, J.D., Badar, M.A., Kluse, C.J., 2025. A review analysis of cost of quality, cost of poor quality, and hidden quality cost. Journal of Technology Studies 50, 1–13. doi:10.21061/jts.435.