

Eliminating Reference Mixing in Automotive Manufacturing: A DMAIC and Machine Vision Integration Approach

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Abstract—Purpose: Reference mixing in series windshield manufacturing creates severe downstream risks. This study investigates the operational causes of mixing in an automotive glass plant and implements an engineering solution to eliminate customer escapes. **Design/methodology/approach:** A DMAIC framework is utilized. The Define and Measure phases quantified baseline escape rates and attribute inspection subjectivity via Fleiss' Kappa. The Analyze phase integrated empirical findings into PFMEA and 5-Why analysis. The Improve phase deployed an automated quality gate coupling a Cognex In-Sight vision camera, Siemens PLC, and an ABB sorting robot. The Control phase validated system reliability across a six-month production run. **Findings:** Defect mixing originated from absent line-clearance standards, cognitive fatigue, and high reference similarity. Over a six-month monitoring period (700,000 windshields), the automated gate intercepted 5 confirmed reference mix-ups and 30 marking defects with zero customer escapes. Net Cost of Poor Quality (COPQ) avoidance reached €218,540 annually. Process Sigma performance improved toward the internal 6.0σ quality target. **Practical implications:** Relying solely on manual inspection and procedural clearance remains vulnerable to human error in high-mix assembly lines. Embedding an automated, sensor-based Poka-Yoke gate ensures reliable defect containment. **Originality/value:** This case demonstrates the physical and digital coupling of Lean Six Sigma with edge-based machine vision for automated part identity verification and robotic segregation in safety-critical glass production.

Keywords—Quality management; DMAIC; PFMEA; lean six sigma; machine vision; automotive manufacturing; Poka-Yoke

I. INTRODUCTION

In automotive series production, reference mixing represents a latent process non-conformity that appears superficial initially but generates severe downstream operational and financial consequences. When two visually similar components belonging to different product references are routed to the same assembly line simultaneously, the risk of processing or shipping non-conforming parts increases significantly. Unlike isolated physical defects, a mixed reference is challenging to catch once it has bypassed the production stage [1], [2], [3], [4].

When a customer files a complaint, it reveals a gap between what the company intended to deliver and what the customer received. The consequences reach beyond a simple product replacement. Inside the plant, quality complaints trigger rework, scrap, and material replacement costs. Outside the plant, they generate expenses related to complaint handling, warranty

claims, compensation, and legal proceedings. When complaint volumes rise, operational performance indicators deteriorate across the board—rejected products, cancelled orders, and reduced profitability follow [5].

The cost of fixing a defect grows dramatically the later it is caught. Correcting a quality failure at the customer stage can cost up to one hundred times more than addressing the same issue during the design or production phase [5]. Beyond the financial dimension, customer complaints signal a breakdown in trust. When a product fails in use, customers lose confidence in the manufacturer. If the company does not respond quickly and fairly, customers may not return [6].

A structured complaint management system helps personnel respond constructively rather than defensively, signaling that quality is prioritized. Investing in quality and responding promptly build durable customer relationships and prevent recurring defects [7], [8].

The manufacture of automotive windscreens involves cutting, curving, lamination with a PVB interlayer [9], [10], and autoclaving [10].

Each automotive windshield bears a permanent regulatory marking, screen-printed in the upper corner of the glazing, which constitutes a standardized traceability system governed by international regulations (Fig. 1).

This marking comprises nine distinct elements: 1) the vehicle manufacturer logo (OEM), identifying the vehicle brand for which the glazing was designed; 2) the glass manufacturer name, corresponding to the glazing producer; 3) the glass type symbol, where a double vertical line (||) denotes a laminated structure incorporating a polyvinyl butyral (PVB) interlayer; 4) the ECE homologation circle, containing the letter E followed by a country code (e.g., E1 for Germany, E2 for France), certifying compliance with United Nations Regulation No. 43 (ECE R43) on safety glazing materials; 5) the American Standard (AS) classification and light transmittance code (M), where AS1 designates windscreen position; 6) the Department of Transportation (DOT) approval number, mandatory for the United States market; 7) the ECE R43 type-approval number (43R-XXXXXX), unique to each glazing model; 8) the China Compulsory Certificate (CCC) mark accompanied by its reference number, required for the Chinese market; and 9) the date of manufacture, encoded as a dot matrix in which filled dots (●) indicate the month and open dots (○) encode the year of production. This marking represents a primary source

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Fig. 1. Regulatory marking elements on an automotive windscreen.

of quality control and traceability information throughout the product lifecycle.

In the facility under study, reference mixing events occurred at a rate of 47 incidents in the most recent baseline year (about 3.9 incidents per month), resulting in €225,600 in annual financial losses. The previous quality control mechanism relied entirely on manual visual inspection—a process vulnerable to fatigue, cognitive overload, and perceptual limitations when distinguishing between near-identical references [11]. This study presents the application of the DMAIC framework to this problem and the deployment of an automated vision-based sorting system.

To systematically address this issue, this study is guided by three research questions:

- RQ1: What are the underlying root causes contributing to reference mixing in high-mix windshield manufacturing?
- RQ2: How can traditional Lean Six Sigma methodologies (DMAIC) be combined with automated machine vision technologies to prevent these defects?
- RQ3: What is the operational and financial impact of transitioning from manual inspection to an automated Poka-Yoke sorting system?

The remainder of this study is structured as follows: Section II provides a literature review on quality control frameworks, glass inspection methods, and Industry 4.0 solutions. Section III details the industrial context and the selected research methodology. Section IV presents the application of the DMAIC framework. Section V discusses practical findings, system limitations, and economic implications. Finally, Section VI concludes the study.

II. LITERATURE REVIEW

A. Quality Control Frameworks in Automotive Manufacturing

Automotive manufacturing operates under rigorous quality requirements, with zero-defect objectives driving a layered architecture of quality control tools that combine proactive risk analysis, statistical process monitoring, and physical inspection at each production stage [12], [13]. Statistical Process Control (SPC), implemented through control charts and process capability indices (C_p , C_{pk}), constitutes the backbone of process-level quality management: by separating common-cause from special-cause variation, SPC enables corrective action before non-conforming parts are produced at scale, and its outputs are formally required within the Production Part Approval Process (PPAP) [14], [15]. The validity of these measurements depends on measurement system adequacy, verified through Gauge Repeatability and Reproducibility (R&R) studies within Measurement System Analysis (MSA), ensuring that observed variation reflects genuine process behaviour [16]. Upstream, Failure Mode and Effects Analysis (PFMEA) provides a structured framework for anticipating failure modes before they generate defects, prioritising risks through the Risk Priority Number (RPN), and directing inspection resources to critical process steps [17], [18]. These instruments are complemented by classical quality control tools—check sheets, histograms, Pareto charts, cause-and-effect diagrams, scatter plots, flow charts, and control charts—which enable teams to collect defect data, isolate root causes, and track corrective action effectiveness [17]. Structured problem-solving frameworks, including 8D, Six Sigma, and DMAIC, address non-conformity resolution and variability reduction, while Value Stream Mapping is applied to eliminate waste [19], [18], [20]. Cost of Quality modelling further reinforces this layer by quantifying the economic impact of inspection activities [21].

B. Inspection Techniques Specific to Automotive Glass and Windshields

Manual and off-line inspection methods are widely recognized as inadequate for meeting the throughput, consistency, and coverage requirements of modern automotive lines, particularly for tasks that demand sustained visual discrimination across high production volumes [22], [23]. Human inspectors become a bottleneck when full inspection of each produced unit is required: defect judgment is subjective, inter-operator variability reduces reliability, and performance degrades over a shift as fatigue accumulates, increasing the likelihood that subtle anomalies escape detection [22], [24]. Sample-based and off-line inspection introduce structural coverage gaps: because they assess only a fraction of units, non-systematic mismatches may go undetected until downstream assembly stages, generating costly rework or field returns [25], [26]. In windshield manufacturing, the challenge of distinguishing between references that differ only in subtle printed features—such as a logo, a ceramic frit pattern, or an antenna trace configuration—makes manual inspection unreliable: operators working at production line speed cannot consistently identify fine visual differences across a full shift, especially when parts arrive from mixed-reference batches or lack physical separation [27], [28].

For reference verification and logo inspection, Optical Character Recognition (OCR) and structural template matching

algorithms are preferred. These methods compare printed character strings and logo geometries against pre-defined master templates to verify part identity at production line speeds [27].

The literature on automotive and industrial glass inspection is extensive, yet it rarely addresses logo reading or reference verification. Several studies focus on defect detection under challenging optical conditions: Ding and Yang [29] applied an enhanced YOLOv5 architecture combined with data augmentation to detect surface defects on mobile phone flat glass under total reflection lighting conditions, while Chen et al. [30] proposed a modified YOLOv5 with multi-scale feature fusion and a dual lightweight strategy tailored to automotive glass defect detection. Lee et al. [31] investigated deep learning vision systems for detecting glass products and identifying defects within a smart factory environment, and Sari and Ulaş [32] improved defect detection performance on glass surfaces through color space conversion (HSV, CIE-Lab Luv) and adaptive histogram equalization combined with YOLOv3.

Ho et al. [33] developed an automatic optical detection system integrating deep learning and photoelastic reflection lighting for defect detection on TFT-LCD glass substrates after cutting. El Mazgualdi et al. [34] applied deep learning architectures to surface defect detection on glass panels. Adán and Adán [35] conducted a review of computer vision technologies for glass waste sorting and recycling, highlighting persistent challenges posed by reflections, transparency, and distinguishing glass from other materials, while Yamaura et al. [36] proposed a technique combining light-scattering imaging and machine learning to estimate flaw depths in glass substrates.

C. DMAIC Framework

The DMAIC (Define, Measure, Analyze, Improve, Control) framework was developed by Motorola as a structured, data-driven methodology within Lean Six Sigma to reduce process variation, eliminate critical defects, stabilize performance, and enhance operational efficiency [44], [43], [40], [41].

The methodology is structured into five sequential phases:

- **Define Phase:** Clarifies key process elements—including inputs, outputs, suppliers, customers, and stakeholders—while explicitly defining the quality standards expected by the customer. A Supplier, Input, Process, Output, Customer (SIPOC) diagram maps the end-to-end flow of activities [40], [42], complemented by the 5W1H method.
- **Measure Phase:** Establishes the key metrics required to understand baseline process performance and quantify the quality problem, involving data collection, calculation of Defects Per Million Opportunities (DPMO), and determination of the corresponding process Sigma level.
- **Analyze Phase:** Isolates the underlying root causes behind observed defects using diagnostic tools such as root cause analysis, Pareto charts, cause-and-effect (Ishikawa) diagrams, and PFMEA.
- **Improve Phase:** Designs, tests, and implements targeted corrective actions to eliminate or mitigate the identified root causes.

- **Control Phase:** Standardizes operational gains through Standard Operating Procedures (SOPs), statistical control tracking, and regular audits to sustain improvements over the long term.

D. Research Gap and Positioning of the Present Work

A structured search conducted across Scopus, Web of Science, and IEEE Xplore using the keywords ("windshield" OR "automotive glass") AND ("reference identification" OR "part sorting" OR "logo inspection") AND ("machine vision" OR "Poka-Yoke") revealed that existing published works focus almost exclusively on physical glass defect detection (such as scratches, air bubbles, and cracks) [37], [38]. No identified prior study documents an industrial system designed specifically to identify and classify windshield references based on regulatory screen-printed logos and homologation codes, integrated with a PLC and an industrial robot for automated in-line sorting. Classical quality management methods (SPC, PFMEA, manual sampling) operate at the batch level and do not guarantee part-level identity verification at line cadence.

The present work directly addresses this gap by validating an automated system where a machine vision camera acquires an image of the regulatory logo, a vision engine identifies the reference, and a PLC-controlled robot executes real-time sorting. This study links Lean Six Sigma (DMAIC) with edge-based vision processing to provide automated, Poka-Yoke defect containment.

III. CONTEXT AND METHODOLOGY

The study is based on an automotive supplier producing laminated windshields for original equipment manufacturers (OEMs), including Mercedes-Benz, Volkswagen Group, Stellantis, and Renault. Glazing components directly affect passenger safety, driver visibility, and structural vehicle performance.

The target facility experienced recurring windshield reference-mixing problems. Complaints concerned mixed references within pallets delivered to customer assembly plants. The defect manifested during final sorting and verification, where operators separated multiple visually identical references that differed only in screen-printed homologation and serial markings. Because the defect recurred across shifts, the problem was treated as a systemic process failure rather than an isolated human error, justifying a structured DMAIC intervention.

The DMAIC methodology provided the data-driven framework for problem definition, baseline measurement, root-cause isolation, technical improvement, and long-term control. The operational sequence adapted for this project is summarized in Fig. 2.

In the Define phase, the SIPOC process was constructed to map the end-to-end flow, followed by the 5W1H heuristic. Process flowcharts and reference diversity distributions were analyzed to locate high-risk transition zones.

In the Measure phase, quantitative performance was evaluated using the Parts Per Million (PPM) metric based on total production volume. Because reference correctness is evaluated on a discrete binary basis (the unit either matches the scheduled reference or does not), there is exactly one defect opportunity per windshield ($OPO = 1$). Under this definition, the Defect

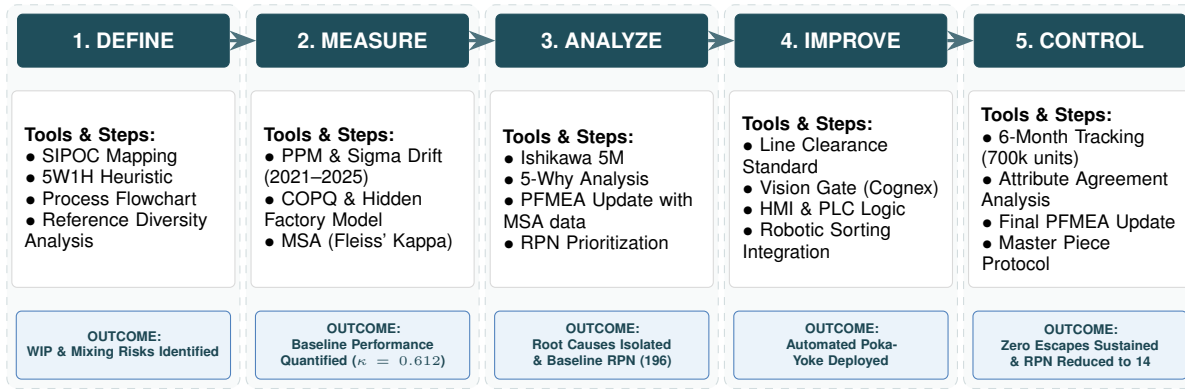


Fig. 2. Methodological framework mapping DMAIC phases to industrial quality tools and specific outcomes.

Per Million Opportunities (DPMO) is mathematically equivalent to PPM:

$$\text{DPMO} = \left(\frac{\text{Number of Defects}}{\text{Total Units} \times \text{OPO}} \right) \times 10^6 = \text{PPM} \quad (1)$$

Process Sigma levels are determined using the standard Six Sigma convention incorporating the standard 1.5σ long-term shift, calculated as $\text{Sigma} = \Phi^{-1}(1 - \text{DPMO}/10^6) + 1.5$, corresponding to the standard conversion values reported in Table I [39]. The target level of 6.0σ (3.4 PPM) represents an internal organizational benchmark adopted to satisfy stringent customer zero-defect expectations, rather than a universal regulatory mandate.

TABLE I. SIGMA CONVERSION TABLE INCORPORATING STANDARD 1.5σ SHIFT

Sigma (σ)	Defects per Million (DPMO)	Equivalent Yield (%)
6.0	3.4	99.9997%
5.0	233.0	99.977%
4.0	6,210.0	99.379%
3.0	66,807.0	93.32%
2.5	158,655.0	84.1%
2.0	308,538.0	69.1%
1.5	500,000.0	50.0%
1.0	691,462.0	30.9%
0.5	841,345.0	15.9%
0.0	933,193.0	6.7%

In the Analyze phase, Process Failure Mode and Effects Analysis (PFMEA) was applied. The Risk Priority Number (RPN) is calculated as:

$$\text{RPN} = \text{Severity (S)} \times \text{Occurrence (O)} \times \text{Detection (D)} \quad (2)$$

with each parameter evaluated on a 1 to 10 scale per the AIAG PFMEA manual. The critical reference-mixing failure mode was rated at Severity $S = 7$, Occurrence $O = 4$, and Detection $D = 7$, yielding a baseline RPN of 196. The risk evaluation thresholds adopted by the plant are summarized in Table II.

TABLE II. RPN CLASSIFICATION THRESHOLDS APPLIED IN THIS STUDY

RPN Range	Risk Classification	Required Action
$\text{RPN} \leq 100$	Low	Routine monitoring
$100 < \text{RPN} \leq 150$	Moderate	Monitoring with scheduled engineering review
$\text{RPN} > 150$	Critical	Immediate corrective engineering action
$\text{RPN} = 1000$	Maximum (theoretical)	Unacceptable process condition

During the Improve phase, procedural line-clearance standards and an automated machine vision sorting gate were implemented. Finally, in the Control phase, the system was tracked over a six-month production run of 700,000 units to validate long-term capability and stability.

IV. DMAIC FRAMEWORK IMPLEMENTATION

A. Define Phase

The SIPOC diagram presented in Fig. 3 defines the process boundaries, detailing how raw float glass, ceramic inks, and PVB interlayers are transformed into finished automotive windshields.

The 5W1H method was applied to define the defect condition (Table III).

TABLE III. 5W1H PROBLEM DEFINITION

What?	Reference mixing: Two distinct references packed in one shipping rack
Who?	Discovered by OEM customer at vehicle assembly entry line
Where?	Plant intermediate buffer between autoclave and final inspection
When?	During unloading, inspection feeding, and reference changeovers
How many?	Baseline rate of 47 incidents per year (mean: 3.9 cases/month)
Why?	Functional mismatches (rain sensor, acoustic, HUD, or heating divergence)

A mapping of the integrated production line was performed to locate the highest-risk process interface (Fig. 4).

The intermediate buffer between the autoclave exit and the final inspection cell was identified as the critical failure location.

Suppliers	Inputs	Process	Outputs	Customers
Preprocessing			Laminated Windshield (Finished Product)	Vehicle Assembly Line (OEM)
Float Glass Manufacturer PFG, ARBOS Super Cut	Float Glass Sheets	Glass Cutting		
	Grinding Wheels Water Water	Edge Grinding & Seaming		
Fenzi, Johnson Matthey Pemco	Ceramic Frit Ink	Washing Screen Printing (Frit Border / Obscuration Band)		
Bending				
Jowix Triomet Seva STARPOL	Bending Molds	Bending (Furnace Forming – Pair Bending) & Annealing		
Assembling				
Eastman, Kuraray, Sekisui	PVB Interlayer Film	PVB Lay-up Pre-Press (De-airing) Autoclaving (Intermediate stock)		
Control				
		Final Quality Inspection (Optical Distortion, Light Transmission, Dimension, Edge defect) Packaging		

Fig. 3. SIPOC diagram of windshield manufacturing process flow.

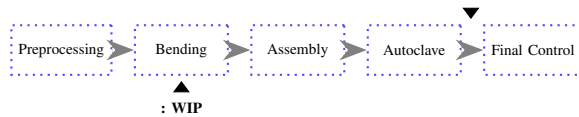


Fig. 4. Production line process mapping and Work-In-Process (WIP) storage points.

Production models encompass multiple visually identical variants (Fig. 5). For example, models M6 and M8 comprise seven references each with identical outer contours, frit bands, and logos, differing solely in small homologation text and internal sensor brackets.

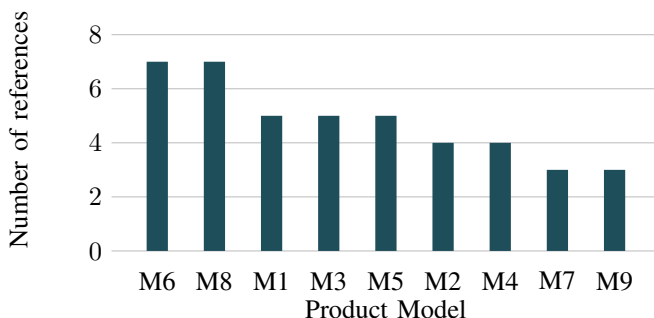


Fig. 5. Distribution of distinct references produced per vehicle model.

B. Measure Phase

1) *Longitudinal process performance (PPM analysis):*
Historical production data from 2021 to 2025 was analyzed using the Parts Per Million (PPM) indicator [Eq. (3)]:

$$PPM = \left(\frac{\sum \text{Detected Mixing Incidents}}{\sum \text{Total Production Volume}} \right) \times 10^6 \quad (3)$$

The hidden factory volume represents non-productive containment activities [45], [46]:

$$HF = D \times L \quad (4)$$

where, D is the number of recorded mixing incidents and L represents the quarantine lot size. In the host facility, intermediate glass storage utilizes standard staging racks containing 40 windshields, processed in batches of 20 racks per autoclave run ($L = 40 \times 20 = 800$ units), as documented in plant logistics procedures.

The Sorting Ratio is expressed as:

$$\text{Sorting Ratio (\%)} = \left(\frac{\text{Units Sorted}}{\text{Annual Production Total}} \right) \times 100 \quad (5)$$

Cost of Poor Quality (COPQ) incorporates fixed incident costs (customer freight returns, administrative penalties, and

quality engineering containment at €2,000 per incident) and variable sorting costs (€3.50 per manually inspected unit) [47].

A sensitivity evaluation on the assumed lot size indicates that if quarantined batches vary between 400 and 1,200 units, the 2025 sorted volume ranges from 18,800 to 56,400 units, with corresponding baseline COPQ ranging between €141,000 and €310,200, confirming the substantial economic drag of containment.

2) *Longitudinal drift analysis and predictive modeling:* From Table IV and Fig. 6, production volume expanded by 60% over the five-year period, while the customer escape rate increased by 144.8% (12.00 to 29.38 PPM). An ordinary least squares linear regression was fitted to the annual PPM values:

$$\text{PPM} = 4.80x + 5.20 \quad (6)$$

where, $x = \text{Year} - 2020$ ($x = 1, \dots, 5$), plotted in Fig. 7. Regression statistics yield a slope $\beta_1 = 4.80$ (standard error $\text{SE} = 0.69$, $t = 6.93$, $p = 0.006$), an intercept $\beta_0 = 5.20$ ($\text{SE} = 2.30$, $t = 2.26$, $p = 0.109$), $F(1, 3) = 48.06$, and $R^2 = 0.941$.

Because this regression is based on five annual macro observations ($n = 5$), it is interpreted here as a descriptive summary of historical plant degradation rather than a structural causal model. Nevertheless, the trajectory demonstrated that manual inspection performance was progressively deteriorating as volume and reference complexity grew.

3) *Statistical capability and target requirements:* Fig. 8 illustrates capability trends. External Sigma declined from 5.72σ to 5.52σ , while Internal Sigma dropped from 3.84σ to 3.49σ . To meet OEM contractual expectations, an internal quality target of 6.0σ (3.4 PPM) was set for reference identity compliance.

C. Measurement System Analysis (MSA) — Attribute Study

To evaluate manual inspection repeatability, an attribute agreement study was conducted with three qualified inspectors independently assessing a randomized set of $N = 150$ production samples (Table V).

Fleiss' Kappa (κ) was computed to assess agreement beyond chance [48]:

$$\kappa = \frac{\bar{P} - P_e}{1 - P_e} \quad (7)$$

For sample i , pairwise agreement is:

$$P_i = \frac{1}{n(n-1)} \sum_{j=1}^k (n_{ij}^2 - n_{ij}) \quad (8)$$

with $n = 3$ raters and $k = 2$ categories (OK vs. Mix-up). Table VI summarizes intermediate agreement scores.

Across all 150 parts, 111 samples yielded unanimous agreement ($P_i = 1.000$) and 39 samples yielded partial disagreement ($P_i = 0.333$), resulting in mean observed agreement:

$$\bar{P} = \frac{111 \times 1.000 + 39 \times 0.333}{150} = 0.8267 \quad (9)$$

Marginal rating proportions across all 450 observations were $p_{\text{OK}} = 298/450 = 0.662$ and $p_{\text{Mix}} = 152/450 = 0.338$. The expected chance agreement is:

$$P_e = (0.662)^2 + (0.338)^2 = 0.4382 + 0.1142 = 0.5525 \quad (10)$$

yielding a baseline Fleiss' Kappa:

$$\kappa = \frac{0.8267 - 0.5525}{1 - 0.5525} = 0.612 \quad (11)$$

Parameters are summarized in Table VII, and interpretation scales in Table VIII.

While $\kappa = 0.612$ is categorized as substantial on the Landis–Koch scale, automotive safety quality requires $\kappa \geq 0.80$ to be considered acceptable [48]. Manual inspection thus introduced unacceptable measurement variability.

D. Analyze Phase

A 5M Ishikawa root cause analysis (Fig. 9) and 5-Why investigation were conducted across Method, Man, and Machine dimensions.

The 5-Why analysis confirmed the sequence:

- Why are windshields rejected by OEM customers? Wrong reference delivered in rack.
- Why was the wrong reference in the rack? Non-conforming windshields were loaded from the buffer.
- Why were different references mixed in the buffer? The buffer station lacked physical clearance during changeovers.
- Why did inspection fail to catch the error? Operators verified glass physical integrity but missed small homologation text.
- Why was text inspection missed? No automated Poka-Yoke logo-reading system existed.

Representative examples of near-identical references leading to human error are illustrated in Fig. 10.

1) *PFMEA justification and mapping:* The baseline PFMEA ratings were calibrated against the Measure phase empirical findings (Table IX).

The resulting baseline PFMEA is presented in Table X.

The failure effect “*Specific windshield function disabled*” (e.g., ADAS camera bracket misalignment or acoustic layer absence) received $S = 7$, $O = 3$, $D = 7$, yielding $\text{RPN} = 147$. Although classified in the Moderate band ($100 < \text{RPN} \leq 150$) due to a lower historical frequency ($O = 3$), its high severity ($S = 7$) warrants direct mitigation. The automated machine vision system deployed in the Improve phase verifies complete homologation code strings, thereby safeguarding this failure mode simultaneously and reducing its detection score to $D = 1$.

E. Improve Phase

Corrective actions addressed the Method, Man, and Machine root causes (Table XI).

TABLE IV. LONGITUDINAL ANALYSIS OF PROCESS CAPABILITY, HIDDEN FACTORY, AND COPQ (2021–2025)

Year	Annual Volume (V)	External PPM (Escapes)	External Sigma (σ)	Sorting Volume (HF)	Internal PPM (Sorting)	Internal Sigma (σ)	Sorting Ratio (%)	Baseline COPQ Loss (EUR)
2021	1,000,000	12.00	5.72	9,600	9,600	3.84	0.96%	€57,600
2022	1,100,000	13.64	5.68	12,000	10,909	3.79	1.09%	€72,000
2023	1,400,000	17.14	5.63	19,200	13,714	3.71	1.37%	€115,200
2024	1,500,000	26.67	5.53	32,000	21,333	3.53	2.13%	€192,000
2025	1,600,000	29.38	5.52	37,600	23,500	3.49	2.35%	€225,600

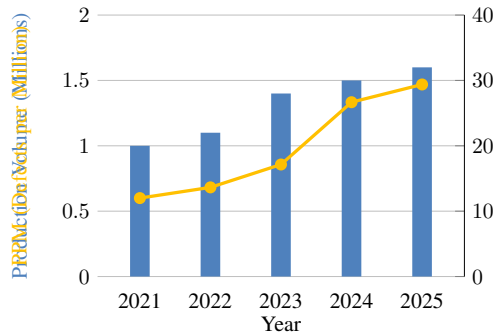


Fig. 6. Evolution of production volume vs PPM defect rate (2021–2025).

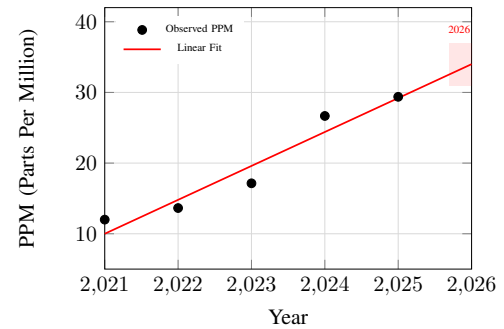


Fig. 7. PPM historical fit and descriptive projection ($R^2 = 0.94$).

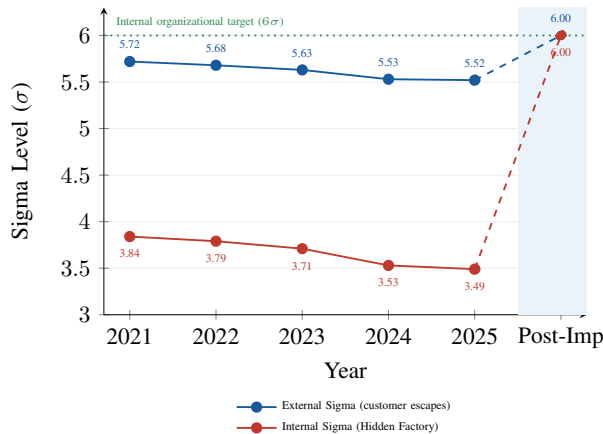


Fig. 8. Evolution of external and internal process capability (2021–2025) and convergence post-implementation.

TABLE V. ATTRIBUTE CONCORDANCE STUDY EXTRACT (FIRST 10 SAMPLES)

Sample	Standard Reference	Inspector 1	Inspector 2	Inspector 3	Concordance
1	Conforming (OK)	OK	OK	OK	Complete
2	Mix-up (NOK)	OK (error)	Mix-up	Mix-up	Disagree
3	Conforming (OK)	OK	OK	OK	Complete
4	Mix-up (NOK)	Mix-up	OK (error)	Mix-up	Disagree
5	Conforming (OK)	OK	Mix-up (error)	OK	Disagree
6	Conforming (OK)	OK	OK	OK	Complete
7	Conforming (OK)	OK	OK	OK	Complete
8	Mix-up (NOK)	Mix-up	Mix-up	Mix-up	Complete
9	Conforming (OK)	OK	Mix-up (error)	OK	Disagree
10	Conforming (OK)	OK	OK	OK	Complete

1) *Technical architecture and optical configuration:* The automated quality gate integrates three hardware components (Fig. 11):

TABLE VI. PER-SAMPLE AGREEMENT CALCULATIONS FOR EXTRACT SAMPLES

Sample	"OK" (n_{i1})	"Mix-up" (n_{i2})	Agreement (P_i)
1	3	0	$(3^2 + 0^2 - 3)/(3 \times 2) = 1.000$
2	1	2	$(1^2 + 2^2 - 3)/6 = 0.333$
3	3	0	1.000
4	1	2	0.333
5	2	1	0.333
6	3	0	1.000
7	3	0	1.000
8	0	3	1.000
9	2	1	0.333
10	3	0	1.000

TABLE VII. SUMMARY OF FLEISS' KAPPA PARAMETERS ($N = 150$, $n = 3$, $k = 2$)

Parameter	Symbol	Value
Number of samples	N	150
Number of inspectors	n	3
Number of rating categories	k	2
Mean observed agreement	$\bar{P}$	0.8267
Expected chance agreement	P_e	0.5525
Fleiss' Kappa	κ	0.612

TABLE VIII. LANDIS AND KOCH INTERPRETATION SCALE FOR CONCORDANCE [48]

κ Range	Strength of Agreement	Implication
< 0.00	Poor	Less than chance agreement
$0.00 - 0.20$	Slight	Minimal consistency
$0.21 - 0.40$	Fair	Some consistency
$0.41 - 0.60$	Moderate	Moderate consistency
0.61 – 0.80	Substantial	Baseline study result ($\kappa = 0.612$)
$0.81 - 1.00$	Almost Perfect	Near-complete agreement

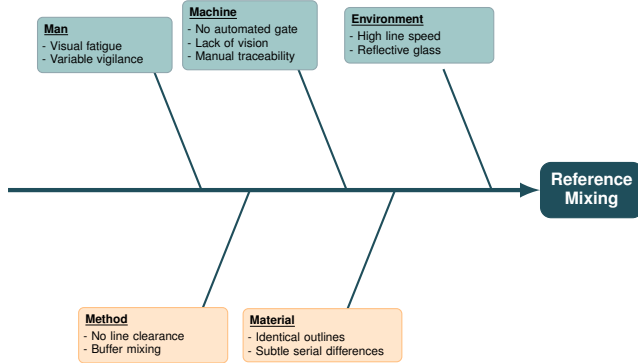


Fig. 9. Ishikawa diagram identifying root causes for reference mixing.

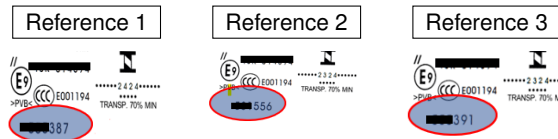


Fig. 10. Visual similarity among windshield references differing only in micro-printed regulatory codes.

TABLE IX. CALIBRATION OF PFMEA RATINGS AGAINST EMPIRICAL MEASURE-PHASE DATA

PFMEA Parameter	Empirical Input	Scale Mapping Justification
Severity ($S = 7$)	Cost and Customer Impact	Rating 7 denotes customer disruption (assembly line stoppage and functional mismatch) with €225,600 baseline losses.
Occurrence ($O = 4$)	Longitudinal Defect Rate	Under AIAG PFMEA criteria, $O = 4$ corresponds to an occurrence frequency of approximately 1 in 2,000 to 1 in 1,000 parts (~1,000 PPM batch risk during changeover shifts). With 47 escapes/year against active production runs, the baseline falls within rating 4.
Detection ($D = 7$)	Attribute Agreement Study	Rating 7 denotes low manual detection probability, corroborated by Fleiss' $\kappa = 0.612$.

- **Vision Sensor:** Cognex In-Sight 7802M monochrome camera (1600×1200 resolution, 1.3 MP) equipped with a 16 mm focal length lens. The working distance is set to 350 ± 15 mm, providing a field of view of 180×135 mm centered on the regulatory marking. Diffuse red LED ring lighting (630 nm) was selected to eliminate specular reflections from curved glass surfaces.
- **Software Configuration:** Programmed via Cognex In-Sight Explorer. Preprocessing applies localized contrast equalization. Pattern matching (Cognex PatMax) verifies logo presence and orientation with an acceptance threshold of 85%. Optical Character Recognition (Cognex OCRMax) segments and validates the homologation strings (ECE R43, DOT numbers) against master strings, with character confidence thresholds set at 80%.
- **Control and Execution:** A Siemens S7-1200 PLC interfaces with the camera over PROFINET. Image acquisition and classification require 400 ms within a total cell cycle time of 4.0 seconds. Downstream sorting is executed by an ABB IRB 6700 industrial robot.

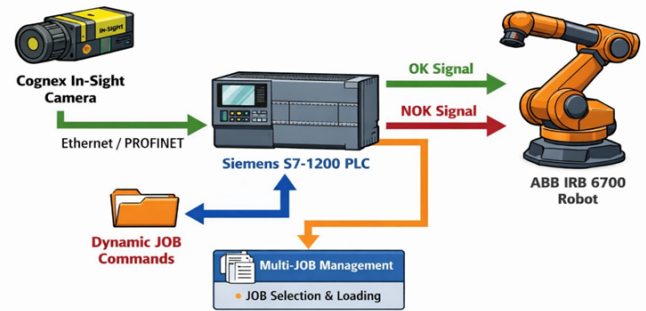


Fig. 11. System architecture integrating Cognex vision camera, Siemens S7-1200 PLC, and ABB sorting robot.

The physical layout on the shop floor is shown in Fig. 12.

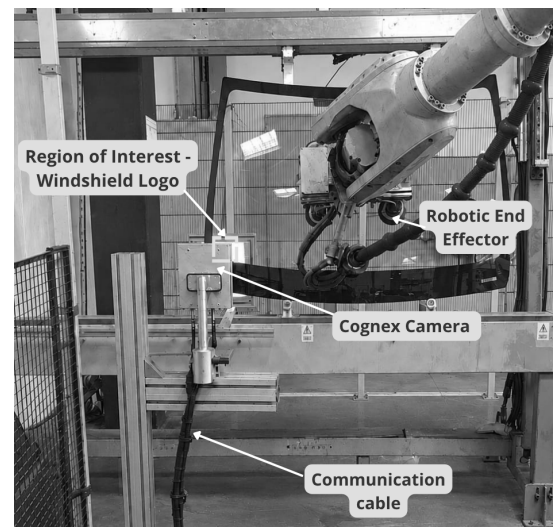


Fig. 12. Robotic presentation of windshield to the Cognex vision camera quality gate.

The operational sequence follows seven discrete steps:

- Reference program selection on HMI;
- Part loading;
- Robotic retrieval;
- Edge washing and drying;
- Manual visual check for surface scratches;
- Automated vision logo and reference inspection;
- Robotic sorting: conforming parts are released to packaging, while non-conforming parts are transferred to a quarantine rack (Fig. 13).

F. Control Phase

1) *Validation protocols and statistical sample justification:* A two-stage validation protocol was executed:

- Stage 1 (Pilot Challenge Test): A 30-day pilot test in January 2026 processed approximately 50,000 units

TABLE X. PFMEA EVALUATION FOR REFERENCE MIXING FAILURE MODES

Failure mode	Potential effect	S	Crit.	Potential cause	O	Current prevention	Current detection	D	RPN
Mixing reference	Customer assembly stoppage	7	F	Human fatigue / Visual similarity of logos / Lack of line clearance	4	None	100% manual visual inspection	7	196
	Vehicle mismatch	7	F		4	None		7	196
	Specific windshield function disabled	7	F		3	None		7	147

TABLE XI. ROOT CAUSES AND CORRESPONDING CORRECTIVE IMPLEMENTATIONS

Category	Root Cause Identified	Implemented Corrective Action
Method	Lack of changeover line clearance procedure.	Enforced line-clearance SOP: physical buffer purging prior to starting new production references.
Man	Insufficient risk awareness of visual similarity.	Operator training on micro-printed homologation differences and changeover discipline.
Machine	Absence of automated reference verification gate.	Deployment of a Cognex In-Sight machine vision cell with robotic rejection.

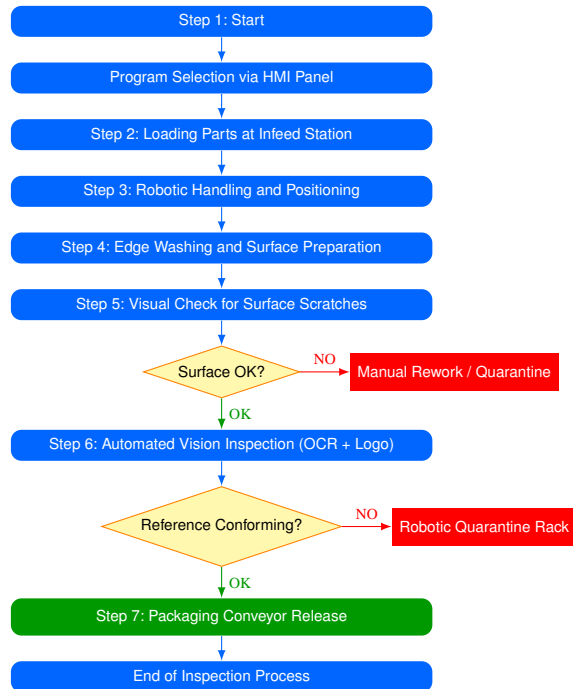


Fig. 13. Decision and sorting logic executed by the automated inspection cell.

across production shifts. A challenge set of 120 known non-conforming windshields (featuring mismatched homologation prints, alternative OEM logos, shifted stamps, and degraded ceramic ink) was systematically introduced across shifts. All 120 challenge units were successfully detected and rejected (100% sensitivity).

- Stage 2 (Audit Partition): A randomized audit set of $N_{val} = 300$ parts (including 50 seeded non-conforming units with subtle reference divergences) was evaluated. The resulting confusion matrix yielded:
 - True Negatives (TN): 246 conforming parts

accepted.

- True Positives (TP): 50 non-conforming parts rejected.
- False Positives (FP): 4 conforming parts rejected (overkill = 1.6%).
- False Negatives (FN): 0 non-conforming escapes (Type II error = 0.0%).

Based on this matrix, the performance metrics are:

$$\text{Accuracy} = \frac{TP + TN}{N_{val}} = \frac{50 + 246}{300} = 98.7\% \quad (12)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} = \frac{50}{50 + 0} = 100.0\% \quad (13)$$

$$\text{Specificity} = \frac{TN}{TN + FP} = \frac{246}{246 + 4} = 98.40\% \quad (14)$$

The attribute agreement statistic for this validation set yields $\kappa = 0.954$ (observed agreement $P_o = 0.9867$, chance agreement $P_e = 0.7133$), while extended Gage R&R multi-run trials confirmed overall attribute reliability at 0.98.

From a statistical standpoint, observing zero escapes in a sample of $N_{val} = 300$ yields a 95% one-sided Wilson confidence bound for the escape rate of $[0, 0.0099]$ (upper bound $\leq 0.99\%$). This validation sample confirms zero Type II error under test conditions. However, verifying compliance at extreme quality targets (6σ / 3.4 PPM) cannot be proven by a 300-unit sample alone. Operational proof was therefore established through the subsequent six-month longitudinal monitoring of 700,000 units.

2) *Longitudinal monitoring and process isolation:* Over six consecutive months, the automated cell inspected the full line throughput of 700,000 windshields. During this period, zero customer escapes were recorded. The vision system triggered 345 total alarms:

- True Positives (35 units): Exactly 5 units were confirmed reference mix-ups, and 30 units exhibited severe ceramic print defects or illegible homologation characters.
- False Positives / Overkill (310 units): Conforming units flagged due to surface reflections or low ink contrast (overkill rate = 0.044%).

This outcome allows the effects of procedural controls to be isolated from the machine vision gate. While line-clearance standards and training reduced upstream mix-up frequency, 5 actual mix-ups still occurred during changeovers. Without the

automated vision gate, these 5 units would have escaped to customers. The automated gate thus served as the necessary containment barrier.

3) *Updated key performance indicators and RPN*: Table XII provides a comparison between the baseline and the control phase.

TABLE XII. COMPARATIVE ANALYSIS OF BASELINE VERSUS AUTOMATED CONTROL STATE

Performance Metric	Manual Baseline (2025)	Control Phase (Vision)	Improvement
RPN ($S \times O \times D$)	196 ($7 \times 4 \times 7$)	14 ($7 \times 2 \times 1$)	−92.9%
Customer Escapes	47 cases/year	0 cases (in 6-month run)	−100.0%
Attribute Measurement Reliability	$\kappa = 0.612$ (Human)	$\kappa = 0.954$ (Validation set)	+55.9%
Classification Accuracy	~ 75.0% (estimated)	98.7% (Sens: 100%, Spec: 98.4%)	+23.7%
Baseline COPQ Incurred	€225,600 / year	€0 / year (escapes eliminated)	−100.0%
Inspection Cycle Time	5.0 s	4.0 s	−20.0%

The RPN decreased from 196 to 14 (Fig. 14). Severity remained at $S = 7$. Occurrence was reduced to $O = 2$ due to line-clearance SOPs, and Detection was updated to $D = 1$ based on 100% in-line robotic gatekeeping.

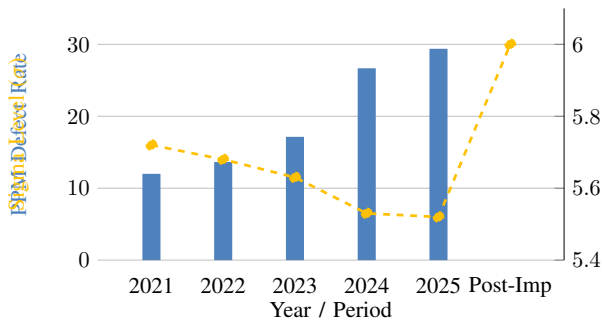


Fig. 14. Annual PPM and Sigma capability trends through post-implementation.

The human-machine interface (HMI) logs every inspection event, displays live counts, and manages alarm states (Fig. 15). Process sustainability is reinforced through a daily Master Piece ("Red Piece") protocol: at shift handover, a known non-conforming part is presented to verify automatic rejection before production is unlocked.

V. DISCUSSION

A. Human Vigilance Versus Engineered Poka-Yoke Gates

The shift in attribute agreement from $\kappa = 0.612$ to $\kappa = 0.954$ confirms that manual visual discrimination of micro-

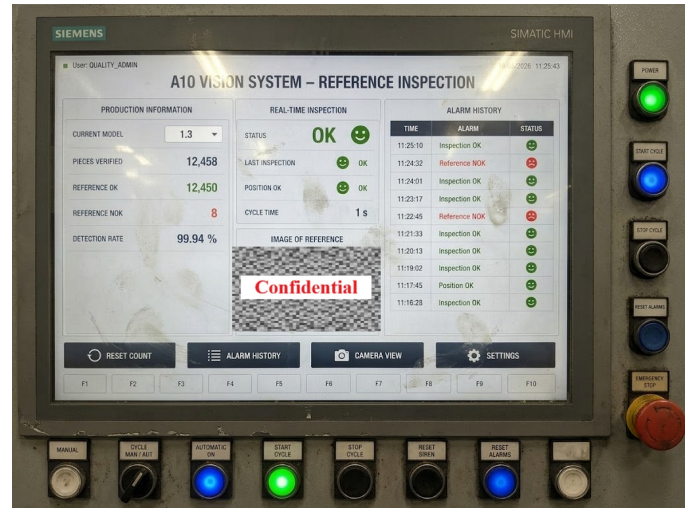


Fig. 15. Line-side HMI dashboard displaying real-time inspection counts, defect statistics, and alarm histories.

printed characters at line cadence is fundamentally limited by cognitive fatigue. Reducing the Detection score from $D = 7$ to $D = 1$ substituted a variable human task with an automated Poka-Yoke gate [49]. During the six-month production run, the system intercepted 5 true reference mix-ups that had breached upstream procedural clearance, demonstrating that procedural discipline alone is insufficient in high-mix facilities.

B. Economic Analysis and Comprehensive Return on Investment

Historical baseline COPQ losses were €225,600 in 2025. Accounting for operating expenses (OPEX)—including annual optics maintenance (€2,500), bi-monthly calibration checks (€1,200), and false-alarm technician review time (14 cumulative downtime hours over six months, valued at €3,360)—the net annual financial recovery is calculated as:

$$\begin{aligned} \text{Net Annual Recovery} &= \text{€}225,600 - \text{€}7,060 \\ &= \text{€}218,540/\text{year} \end{aligned} \quad (15)$$

Because the industrial robot and PLC were existing assets, the initial capital expenditure (CAPEX) was limited to the Cognex camera, lens, diffuse illumination, and software integration (€18,000). The resulting payback period was achieved in approximately one month:

$$\text{Payback Period} = \left(\frac{\text{€}18,000}{\text{€}218,540/12} \right) \approx 0.99 \text{ months} \quad (16)$$

C. Trade-Off Between Sensitivity and Overkill

The observed overkill rate of 0.044% (310 false rejections out of 700,000 parts) reflects a deliberate safety-first configuration. In safety-critical automotive glazing, false rejections routed to technician review carry minimal operational penalties relative to the catastrophic warranty and containment costs of an escape.

D. Technical Limitations

Three operational limitations are recognized:

1) *Program management*: Introducing new windshield references requires generating new region-of-interest templates and syntax strings, adding engineering setup time [50].

2) *Optical reflection*: Residual curvature reflections can occasionally cause false rejections on high-gloss coatings [52], [51].

The single-plant case design means financial and cycle time gains depend on the specific line layout and existing automation infrastructure.

E. Secondary Quality Capabilities

An unexpected benefit of the deployment was the incidental detection of ceramic screen-printing anomalies. Faded ceramic ink, character clipping, and logo smudging caused the OCR engine to fail string verification, flagging 30 marking defects and functioning as a secondary print-quality gate without additional capital expenditure [53].

VI. CONCLUSION

This study demonstrated the structured application of the DMAIC framework to eliminate reference-mixing defects in automotive windshield manufacturing. By deploying an automated Poka-Yoke quality gate integrating a Cognex machine vision camera, Siemens PLC, and ABB sorting robot, reference escapes were reduced from 47 incidents per year to zero across a six-month monitoring run of 700,000 windshields.

Attribute measurement reliability improved from $\kappa = 0.612$ to $\kappa = 0.954$, and the baseline RPN decreased from 196 to 14. Net annual COPQ savings reached €218,540, recovering the initial €18,000 capital investment in under one month. Future work will investigate integrating deep learning-based OCR architectures to further suppress false rejections on low-contrast ceramic prints while maintaining absolute defect containment.

REFERENCES

- [1] M. Ronchi, M. Gamberi, C. Cafarella, A. Caporale, F. G. Galizia, et al., "Automatic visual inspection in automotive assembly lines: a techno-economic assessment for the configuration check of exterior components," in *Proc. Summer School Francesco Turco*, 2024, pp. 1–6.
- [2] V. Gurav and A. Upadhyay, "Quality assurance in mixed-model assembly lines through vision-based deep learning," *Industrial Engineering Journal*, vol. 54, no. 1, 2025, doi: 10.13140/RG.2.2.19639.64161.
- [3] C. A. de Souza Silva and E. P. Paladini, "Smart machine vision system to improve decision-making on the assembly line," *Machines*, vol. 13, no. 2, p. 98, 2025.
- [4] H.-D. Lin, H.-L. Wu, and C.-H. Lin, "A deep transfer learning-based visual inspection system for assembly defects in similar types of manual tool products," *Sensors*, vol. 25, no. 6, p. 1645, 2025.
- [5] R. Y. Alsada and Y. Kumar, "A measurement of quality costs in industrial organizations," *Cogent Business & Management*, vol. 9, no. 1, p. 2128253, 2022.
- [6] C. Ashley and S. Varki, "Loyalty and its influence on complaining behavior and service recovery satisfaction," *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior*, vol. 22, pp. 21–35, 2009.
- [7] N. Ngoc Quang and D. C. Thuy, "Justice and trustworthiness factors affecting customer loyalty with mediating role of satisfaction with complaint handling: Zalo OTT Vietnamese customer case," *Cogent Business & Management*, vol. 10, no. 2, p. 2211821, 2023.
- [8] A. Rocha, A. Pedregal, C. Maia, G. Soares, H. Cardoso, and M. Fonseca, "Complaints management: quality of response to customer complaints in an automotive company," *International Journal of Productivity and Quality Management*, vol. 44, no. 1, pp. 18–39, 2025.
- [9] M. Martin, X. Centelles, A. Sole, C. Barreneche, A. I. Fernández, and L. F. Cabeza, "Polymeric interlayer materials for laminated glass: A review," *Construction and Building Materials*, vol. 230, p. 116897, 2020.
- [10] A. Mareška, T. Kordová, M. Havlík Míka, et al., "Relaxation of polyvinyl butyral film with non-uniform thickness," *Manufacturing Technology*, vol. 22, no. 1, pp. 45–58, 2022.
- [11] S. B. Jha and R. F. Babiceanu, "Deep CNN-based visual defect detection: Survey of current literature," *Computers in Industry*, vol. 148, p. 103911, 2023.
- [12] H. A. Khorshidi, I. Gunawan, and F. Esmaeilzadeh, "Implementation of SPC with FMEA in less-developed industries with a case study in car battery manufactory," *International Journal of Quality and Innovation*, vol. 2, no. 2, pp. 148–157, 2013.
- [13] F. Sumasto, Y. A. Nugroho, E. S. Solih, A. W. Arohman, D. Agustin, and A. K. Permana, "Enhancing quality control in the Indonesian automotive parts industry: A defect reduction approach through the integration of FMEA and MSA," *Instrumentation, Measures, Metrologies*, vol. 23, no. 1, 2024.
- [14] R. Godina, J. Matias, and S. Azevedo, "Quality improvement with statistical process control in the automotive industry," *International Journal of Industrial Engineering and Management*, vol. 7, no. 1, p. 1, 2016.
- [15] R. Godina, C. Pimentel, F. Silva, and J. C. Matias, "Improvement of the statistical process control certainty in an automotive manufacturing unit," *Procedia Manufacturing*, vol. 17, pp. 729–736, 2018.
- [16] L. Cepova, A. Kovacikova, R. Cep, P. Klaput, and O. Mizera, "Measurement system analyses—Gauge repeatability and reproducibility methods," *Measurement Science Review*, vol. 18, no. 1, pp. 20–27, 2018.
- [17] I. A. Memon, Q. B. Jamali, A. S. Jamali, M. K. Abbasi, N. A. Jamali, and Z. H. Jamali, "Defect reduction with the use of seven quality control tools for productivity improvement at an automobile company," *Engineering, Technology & Applied Science Research*, vol. 9, no. 2, pp. 4044–4047, 2019.
- [18] J. Doshi and D. Desai, "Application of failure mode & effect analysis (FMEA) for continuous quality improvement-multiple case studies in automobile SMEs," *International Journal for Quality Research*, vol. 11, no. 2, p. 345, 2017.
- [19] M. Soković, D. Pavletić, and E. Krulčić, "Six Sigma process improvements in automotive parts production," *Journal of Achievements in Materials and Manufacturing Engineering*, vol. 19, no. 1, pp. 96–102, 2006.
- [20] N. Vamsi Krishna Jasti and A. Sharma, "Lean manufacturing implementation using value stream mapping as a tool: A case study from auto components industry," *International Journal of Lean Six Sigma*, vol. 5, no. 1, pp. 89–116, 2014.
- [21] A. M. Reis, A. Dall-Orsoletta, E. Nunes, L. Costa, and S. Sousa, "Quality costs and Industry 4.0: inspection strategy modelling and reviewing," *The International Journal of Advanced Manufacturing Technology*, vol. 136, no. 9, pp. 3883–3897, 2025.
- [22] K. Knop, E. Olejarz, and R. Ulewicz, "Evaluating and improving the effectiveness of visual inspection of products from the automotive industry," in *Int. Scientific-Technical Conf. MANUFACTURING*, Springer, 2019, pp. 231–243.
- [23] Y. Chen, Y. Ding, F. Zhao, E. Zhang, Z. Wu, and L. Shao, "Surface defect detection methods for industrial products: A review," *Applied Sciences*, vol. 11, no. 16, p. 7657, 2021.
- [24] E. Indasyah, F. Ibrahim, D. F. Syahbana, and F. Istiqomah, "Automated visual inspection system of gear surface defects detection using faster RCNN," in *2023 Int. Conf. Advanced Mechatronics, Intelligent Manufacturing and Industrial Automation (ICAMIMIA)*, IEEE, 2023, pp. 899–904.
- [25] A. Pacana, K. Czerwińska, and R. Dwornicka, "Analysis of quality control efficiency in the automotive industry," *Transportation Research Procedia*, vol. 55, pp. 691–698, 2021.
- [26] J. Buckley and R. Servent, "Improvements in ultrasonic inspection of resistance spot welds," *Insight-Non-Destructive Testing and Condition Monitoring*, vol. 51, no. 2, pp. 73–77, 2009.

- [27] KEYENCE America, "Glass inspection for the automotive industry," <https://www.keyence.com>, 2024.
- [28] J. Carroll, "Machine vision system detects antenna trace defects on automotive glass," *Vision Systems Design*, vol. 24, p. 16, 2019.
- [29] P. Ding and L. Yang, "Glass defect detection with improved data augmentation under total reflection lighting," *Applied Sciences*, vol. 14, no. 13, p. 5658, 2024.
- [30] Z. Chen, S. Huang, H. Lv, Z. Luo, and J. Liu, "Defect detection in automotive glass based on modified YOLOv5 with multi-scale feature fusion and dual lightweight strategy," *The Visual Computer*, vol. 40, no. 11, pp. 8099–8112, 2024.
- [31] S. Lee, B. Kim, and H. Lee, "Deep learning-based glass detection for smart glass manufacturing processes," *Computers, Materials and Continua*, vol. 84, no. 1, pp. 1397–1415, 2025.
- [32] F. Sari and A. B. Ulas, "Deep learning application in detecting glass defects with color space conversion and adaptive histogram equalization," *Traitement du Signal*, vol. 39, no. 2, p. 731, 2022.
- [33] C.-C. Ho, H.-P. Wang, and Y.-C. Chiao, "Machine vision-based cutting process for LCD glass defect detection system," *The International Journal of Advanced Manufacturing Technology*, vol. 123, no. 5, pp. 1477–1498, 2022.
- [34] A. El Mazgualdi, H. Masrour, A. El Hassani, and J. El Mhamdi, "Visual inspection and scratch detection on glass panels using convolutional neural networks," *Journal of Glass Science and Technology*, vol. 42, no. 3, pp. 115–124, 2023.
- [35] E. Adán and A. Adán, "Computer vision for glass waste: Technologies and sensors," *Sensors*, vol. 25, no. 21, p. 6634, 2025.
- [36] T. Yamaura, K. Kobayashi, and M. Watanabe, "Depth estimation of internal latent flaws in glass substrates using light-scattering imaging and machine learning," *Optical Engineering*, vol. 64, no. 2, p. 023101, 2025.
- [37] Q. Zhou, R. Chen, B. Huang, C. Liu, J. Yu, and X. Yu, "An automatic surface defect inspection system for automobiles using machine vision methods," *Sensors*, vol. 19, no. 3, p. 644, 2019.
- [38] N. Hütten, R. Meyes, and T. Meisen, "Vision transformer in industrial visual inspection," *Applied Sciences*, vol. 12, no. 23, p. 11981, 2022.
- [39] Y.-T. Jou, R. M. Silitonga, M.-C. Lin, R. Sukwadi, and J. Rivaldo, "Application of Six Sigma methodology in an automotive manufacturing company: a case study," *Sustainability*, vol. 14, no. 21, p. 14497, 2022.
- [40] L. M. Monday, "Define, measure, analyze, improve, control (DMAIC) methodology as a roadmap in quality improvement," *Global Journal on Quality and Safety in Healthcare*, vol. 5, no. 2, pp. 44–46, 2022.
- [41] V. Gupta, R. Jain, M. Meena, and G. Dangayach, "Six-sigma application in tire-manufacturing company: a case study," *Journal of Industrial Engineering International*, vol. 14, no. 3, pp. 511–520, 2018.
- [42] M. Bhargava and S. Gaur, "Process improvement using six-sigma (DMAIC process) in bearing manufacturing industry: a case study," in *IOP Conf. Series: Materials Science and Engineering*, vol. 1017, 2021, p. 012034.
- [43] R. G. Schroeder, K. Linderman, C. Liedtke, and A. S. Choo, "Six Sigma: Definition and underlying theory," *Journal of Operations Management*, vol. 26, no. 4, pp. 536–554, 2008.
- [44] Y. H. Kwak and F. T. Anbari, "Benefits, obstacles, and future of six sigma approach," *Technovation*, vol. 26, no. 5–6, pp. 708–715, 2006.
- [45] V. Grecu and C. Deneş, "The hidden factory: Quantifying informational waste and operational capacity loss in manufacturing," *Acta Universitatis Cibiniensis. Technical Series*, vol. 77, no. 1, pp. 55–64, 2025.
- [46] H. Rødseth, P. Schjøberg, and A. Marhaug, "Deep digital maintenance," *Advances in Manufacturing*, vol. 5, no. 4, pp. 299–310, 2017.
- [47] V. Tuominen, "Cost modeling of inspection strategies in automotive quality control," *Engineering Management Research*, vol. 1, no. 2, p. 33, 2012.
- [48] M. L. McHugh, "Interrater reliability: the kappa statistic," *Biochemia Medica*, vol. 22, no. 3, pp. 276–282, 2012.
- [49] D. Romero, P. Gaiardelli, D. J. Powell, and M. Zanchi, "Intelligent poka-yokes: error-proofing and continuous improvement in the digital lean manufacturing world," in *IFIP Int. Conf. Advances in Production Management Systems*, Springer, 2022, pp. 595–603.
- [50] N. Alsaadi, "Roadblocks in integrating Lean Six Sigma and Industry 4.0 in small and medium enterprises," *Systems*, vol. 12, no. 4, p. 125, 2024.
- [51] M. Maślanka, D. Jancarczyk, and J. Rysinski, "Integration of machine vision and PLC-based control for scalable quality inspection in Industry 4.0," *Sensors*, vol. 25, no. 20, p. 6383, 2025.
- [52] M. Hussain, "Sustainable machine vision for Industry 4.0: a comprehensive review of convolutional neural networks and hardware accelerators in computer vision," *AI*, vol. 5, no. 3, 2024.
- [53] O. Morales Matamoros, J. G. Takeo Nava, J. J. Moreno Escobar, and B. A. Ceballos Chávez, "Artificial intelligence for quality defects in the automotive industry: A systemic review," *Sensors*, vol. 25, no. 5, p. 1288, 2025.