

AI-Driven Quality Optimization for Defect Detection and Defect Reduction in Smart Manufacturing Processes: An Empirical Study

PATIL JAYENDRA DATTATREY

Research Scholar

NIILM University Kaithal, Haryana

RESEARCH GUIDE

Dr. Bholu Kumar

Associate Professor, Ph.D Mechanical engineering

NIILM University Kaithal, Haryana

Abstract

Purpose – Manufacturing defects continue to consume material, machine time and inspection effort even in plants with mature quality systems, because conventional inspection confirms non-conformities after value has already been added to the product. Artificial intelligence (AI) offers an alternative in which models read process and image data continuously and flag deviations before defective output accumulates. What remains unclear is how far such practices have actually reached the shop floor and how the professionals who run these processes judge their contribution. **Design/methodology/approach** – A cross-sectional survey of 200 manufacturing professionals drawn from production, quality, operations and engineering roles was conducted using a structured questionnaire and purposive sampling. Responses were recorded on a three-point agreement scale and analysed with percentage distributions, derived frequencies, weighted mean scores, ranking, chi-square goodness-of-fit tests and effect sizes. **Findings** – AI-based defect detection was the most widely reported practice (65% agreement), followed by automated AI-based quality inspection (62%) and AI-based process optimization (61%); real-time production monitoring (59%) and predictive quality analysis (56%) lagged behind. Perceived contribution ran consistently ahead of reported use: 74% of respondents agreed that AI improves overall manufacturing quality and 72% that it helps identify defects early, against a mean adoption level of 60.6% and a mean perception level of 70.0%. Every item departed strongly from a uniform response distribution ($p < 0.001$; effect size $w = 0.50-0.87$). **Originality/value** – The study treats five AI-enabled quality practices as a single integrated quality-management bundle and reports practitioner-level evidence rather than single-line case results. **Limitations** – The findings represent reported practice and perception, not independently measured defect rates; the design is cross-sectional and the sample non-probability.

Keywords: Artificial intelligence; smart manufacturing; quality management; defect detection; predictive quality analysis; Industry 4.0; zero-defect manufacturing; survey research

1. Introduction

1.1 Background: smart manufacturing and the cost of poor quality

Every factory lives with a fixed arithmetic. Material that is scrapped, parts that return for rework, machines that stand idle while an inspector settles a borderline surface, and warranty claims that arrive months after shipment are the visible part of the cost of poor quality, and they persist even in plants with disciplined statistical process control. The reason is structural: conventional inspection confirms defects rather than preventing them. Smart manufacturing changes the inputs to this arithmetic. Connected machines, sensors, vision stations and manufacturing execution software produce a continuous record of how a process is actually behaving, and Industry 4.0 architectures make that record available for analysis in near real time (Kusiak, 2018; Sahoo and Lo, 2022). Quality management is one of the functions where the record pays for itself earliest, because deviation from specification usually leaves a trace in process data well before it becomes a rejected part (Gunasekaran, Subramanian and Ngai, 2019).

1.2 Artificial intelligence in manufacturing quality management

Artificial intelligence converts that trace into a decision. Machine learning models trained on historical process data learn the conditions under which defects tend to appear; computer-vision systems compare each unit against a learned image of an acceptable part; predictive models estimate the likelihood that the present process state will yield non-conforming output. Reviews of the field converge on a similar picture: learning methods are already applied across monitoring, diagnosis and optimisation tasks in manufacturing, and quality-related applications are among the more mature of these (Wuest et al., 2016; Rajesh, Prabhuswamy and Krishnasamy, 2022). The practical attraction is a shift in timing. Inspection at the end of the line discovers defects that have already absorbed material and machine time, whereas a model that watches the process discovers the conditions that create them (Gao et al., 2022).

1.3 Manufacturing defects and why they escape conventional control

Defects arrive from several directions at once: variation in incoming material, tool wear and machine condition, drift in process parameters, handling and assembly errors, ambient conditions, and inspection systems that are themselves inconsistent between appraisers and shifts. The resulting non-conformities — dimensional, surface, assembly and material defects — are typically caught by sampling inspection performed by people, at a station, after the operation is complete. Human inspection is slow, tiring and variable, and sampling by construction allows some defective units to pass. Detection therefore happens after the cost has been incurred, and the feedback that reaches the process is delayed by hours or by whole batches.

1.4 Problem statement

Three linked problems motivate the present study. The first is detection latency: in many plants the first reliable signal that a process has drifted is a failed final inspection or a customer complaint. The second is inspection capability: manual visual inspection of high-volume output cannot hold a stable decision threshold across shifts, and appraiser variation is a recurring audit finding. The third is an evidence gap. The engineering literature demonstrates what AI-based inspection and prediction can achieve on specific lines and datasets (Singh and Desai, 2023; Mewada et al., 2022), but practitioner-level evidence on which of these practices are actually in use across firms, and on how experienced manufacturing professionals judge their contribution, is comparatively thin. A quality manager planning an investment cannot rely on laboratory accuracy figures alone; peers' deployment experience and perceived benefit are part of the decision input.

1.5 Research gap

The detailed statement of the gap follows the literature review (Section 2.7). In brief, prior work is rich in technology-specific demonstrations and thin in integrated, practitioner-level evidence on the adoption of multiple AI-enabled quality practices and on the relationship between reported use and perceived contribution.

1.6 Objectives of the study

The study pursues five objectives.

- (1) To examine the reported adoption of AI-based quality optimization practices in smart manufacturing.
- (2) To assess the perceived contribution of AI-based defect detection and automated inspection to the early identification of manufacturing defects.
- (3) To examine the perceived contribution of AI to reducing defective products, inspection errors, rework and material waste.
- (4) To assess the reported use of real-time monitoring and predictive quality analysis.
- (5) To identify the organizational and technological requirements associated with implementing AI-based quality-management systems.

1.7 Research questions

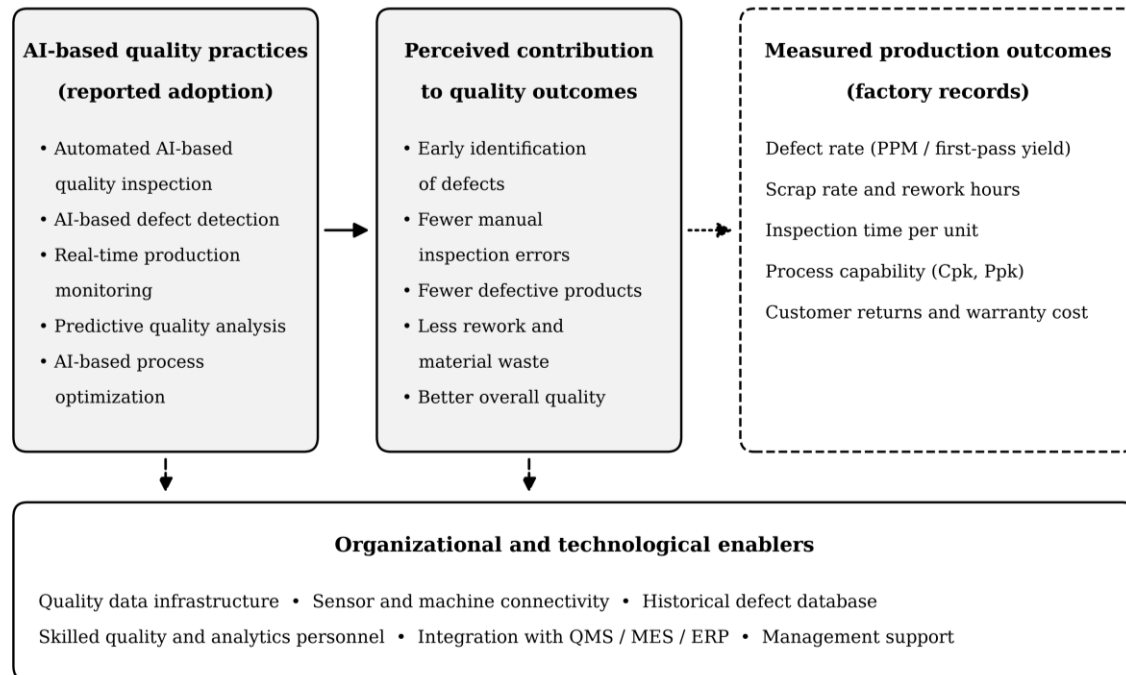
Each objective is operationalised as a research question.

- (1) What is the reported level of adoption of AI-based quality practices in smart manufacturing?
- (2) How do manufacturing professionals perceive the contribution of AI to early defect detection?
- (3) How do respondents perceive the contribution of AI to reducing defective products, inspection errors, rework and material waste?
- (4) What is the reported use of real-time monitoring and predictive quality analysis?

- (5) Which technological and organizational factors are perceived as important for successful AI-based quality implementation?

1.8 Scope, conceptual framework and contribution

The study covers five AI-enabled quality practices — automated AI-based quality inspection, AI-based defect detection, real-time production monitoring, predictive quality analysis and AI-based process optimization — and five perceived contributions of these practices to quality outcomes. Figure 1 sets out the conceptual framing used throughout the paper: reported practices map onto perceived quality outcomes, both conditioned by organizational and technological enablers, while validation against measured production outcomes is deliberately left outside the present dataset.



Solid arrow: relationship examined here from survey evidence. Dashed arrows: enabling conditions reported by respondents. Dotted arrow: validation step against factory records, outside the scope of the present dataset.

Figure 1. Conceptual framework of the study. Reported adoption of AI-based quality practices and perceived contribution to quality outcomes are examined from survey evidence; enabling conditions and the validation step against factory records frame the interpretation and the future research agenda. The contribution of the paper is fourfold. It provides an integrated, multi-practice view of AI in quality management at practitioner level rather than a single-technology demonstration. It reports a perception-based dataset transparently, including an explicit statement of what the data can and cannot support. It derives quantitative indicators — weighted means, ranks, dispersion, goodness-of-fit statistics and an adoption–perception gap — from the reported distributions without adding assumptions beyond the published percentages. And it translates the findings into an implementation-oriented set of implications for quality managers.

2. Review of Literature

The review is organised thematically rather than study by study, so that the position of the present survey within the field can be stated precisely at the end of the section.

2.1 Artificial intelligence in smart manufacturing

Smart manufacturing is commonly described as the integration of cyber-physical systems, industrial internet-of-things devices, cloud services and analytics into production, so that operating decisions rest on data rather than on schedule and habit (Kusiak, 2018; Sahoo and Lo, 2022). Within that framing, AI is the layer that extracts usable patterns from the accumulated record. Rajesh, Prabhuswamy and Krishnasamy (2022) review machine learning applications across conventional and non-conventional machining and argue that learning methods now touch process monitoring, prediction and parameter optimisation along the whole machining chain. Gunasekaran, Subramanian and Ngai (2019) place quality management itself on an Industry 4.0 trajectory in which real-time

data and analytics progressively displace periodic, sample-based quality routines. The common thread across these accounts is not any single algorithm but the availability of process data at a granularity that earlier quality systems never possessed.

2.2 AI-based automated inspection

Automated inspection is the oldest and most visible AI quality application. Vision systems capture images of parts and classify them against learned representations of acceptable appearance, removing the fatigue and inconsistency inherent in human viewing. Harishyam et al. (2023) report a machine-learning pipeline for visual inspection of mechanical components in which image acquisition and classification are automated end to end, and they identify image quality as a governing factor in detection performance. Dattani et al. (2023) describe an automated inspection system for cast products covering visual, material and dimensional checks, with the stated aims of reducing manpower, raising inspection throughput and shortening the inspection cycle. Arora (2023) positions image-processing-based defect detection as a core quality-control function of Industry 4.0 and contrasts it with the error rates and cycle times of manual inspection. Stojanovic, Miladinovic and Gligorijevic (2022) survey smart manufacturing applications in inspection and quality assurance and observe that inspection is usually automated early, because its inputs — images and measurements — are already digital.

2.3 Machine learning and deep learning for defect detection

Detection research has moved from hand-crafted features to deep architectures. Singh and Desai (2023) build an automated surface defect detection framework on a fine-tuned ResNet-101 convolutional network and address two recurring industrial constraints, scarce labelled defect images and limited compute, through transfer learning. Gao et al. (2022) review vision-based defect recognition and trace a shift toward industrial intelligence, in which detection models feed scheduling and maintenance decisions instead of merely raising alarms. Process-specific work shows the same pattern in additive manufacturing: Wang, Yang and Moghaddam (2022) connect process modelling in laser powder bed fusion to defect detection and quality control through machine learning, and Fu et al. (2022) review detection algorithms for metal laser-based additive manufacturing while noting data scarcity and class imbalance as standing obstacles. Kumar et al. (2023) widen the scope to production control, reviewing machine learning across design, process and production control in additive manufacturing. Mewada et al. (2022) take a diagnostic angle, embedding a machine-learning expert system in a forging process so that defect signatures are recognised at the process rather than at final inspection.

2.4 Predictive quality analysis

Predictive quality asks a different question from detection: not whether this part is defective, but whether the process is about to produce defective parts. The methodological lineage lies in predictive maintenance, where multiple-classifier and regression models estimate the remaining useful life of assets (Susto et al., 2015; Carvalho et al., 2019) and where model output schedules intervention before failure (Susto, Beghi and De Luca, 2015). Transferred to quality, the same logic predicts non-conformance from process signatures. Msakni, Risan and Schütz (2023) demonstrate machine learning prediction models for quality control in an automotive setting, and Latham and Giannetti (2023) combine expert knowledge with machine learning for defect detection and root-cause analysis in a hot strip mill, a hybrid design that keeps process engineers in the loop. These studies share a dependency that detection studies feel less strongly: a prediction is only as good as the historical, labelled record of process states and their quality outcomes.

2.5 Real-time process monitoring

Real-time monitoring sits between detection and prediction. Streaming process data — temperatures, forces, vibrations, pressures, vision frames — are compared against learned envelopes of normal operation so that excursions are flagged while the affected units are still on the line. Reviews of machine learning in manufacturing consistently list monitoring among the earliest successful applications (Wuest et al., 2016), and monitoring is the substrate on which both detection and prediction depend: without a continuous, time-stamped process record, neither models nor operators can see drift. In practice, monitoring maturity varies widely between plants because it demands sensor coverage, machine connectivity and data pipelines before a single model can be trained.

2.6 Zero-defect manufacturing

Zero-defect manufacturing (ZDM) provides the theoretical endpoint of these practices. Psarommatis et al. (2020) define ZDM as a paradigm in which detection, prediction, prevention and repair strategies are combined so that defects do not reach the customer, and they catalogue the shortcomings of current implementations; Psarommatis et al. (2022) update the picture and list open challenges, including data availability, model generalisation and integration with existing production systems. Quality 4.0 reviews reach a similar conclusion from the management side: digital technologies extend rather than replace established quality management practice, and their value depends on how they are embedded in the quality system (Oliveira, Alvelos and Rosa, 2024). ZDM is useful in the present paper as an ordering principle: detection and monitoring are its entry-level capabilities, prediction and prevention its advanced ones.

2.7 Summary of the literature and research gap

Table 1 summarises the reviewed studies by focus, method and type of evidence. Read together, they describe a field that is rich in technology-specific demonstrations and thin in practitioner-level synthesis. Existing research has investigated AI-enabled visual inspection, machine learning-based defect detection, predictive quality monitoring and intelligent manufacturing systems in considerable depth. These studies, however, typically examine a single technology, a single process or a single plant. There is comparatively less emphasis on how manufacturing professionals perceive the adoption of several AI-enabled quality practices — automated inspection, defect detection, real-time monitoring, predictive quality analysis and process optimization — as one integrated quality-management approach, and on how perceived contribution compares with reported use. The present study addresses that gap through a survey of 200 manufacturing professionals.

Table 1. Summary of the reviewed literature and its relevance to the present study

Study	Focus	Method / evidence	Relevance to this study
Rajesh et al. (2022)	Machine learning in smart machining	Review of ML algorithms across machining processes	Establishes ML as a cross-cutting manufacturing capability
Singh and Desai (2023)	Surface defect detection	Fine-tuned ResNet-101 CNN on image data	Benchmark for automated visual inspection
Mewada et al. (2022)	Forging defect diagnosis	ML expert system embedded in a forging process	Shows detection moving from final inspection to the process
Harishyam et al. (2023)	Visual inspection of components	Automated image acquisition plus ML classification	Highlights image quality as a governing factor
Arora (2023)	Image processing for QC in Industry 4.0	Conceptual / technical review	Frames automated detection as a core QC function
Dattani et al. (2023)	Automated inspection of cast products	System description: visual, material, dimensional checks	Illustrates manpower and cycle-time motivation
Wang et al. (2022); Fu et al. (2022)	Defect detection in additive manufacturing	State-of-the-art reviews	Identify data scarcity and class imbalance as obstacles
Kumar et al. (2023)	ML in additive manufacturing	Review across design, process and production control	Links detection to production control decisions
Gao et al. (2022)	Vision-based defect recognition	Review towards industrial intelligence	Positions detection as input to wider decisions
Susto et al. (2015); Carvalho et al. (2019)	Predictive maintenance	Classifier studies and systematic review	Methodological lineage of predictive quality
Msakni et al. (2023); Latham and Giannetti (2023)	Predictive quality in automotive and steel	Case studies with ML models	Show prediction working on labelled plant data
Stojanovic et al. (2022)	Smart inspection and QA applications	Survey of applications	Explains why inspection is automated first
Psarommatis et al. (2020; 2022)	Zero-defect manufacturing	State-of-the-art reviews	Provide the detection–prediction–prevention ladder
Oliveira et al. (2024)	Quality 4.0	Systematic literature review	Anchors AI practices in quality management theory

3. Research Methodology

3.1 Research design

The study uses a descriptive, cross-sectional survey design with quantitative analysis. A single wave of data collection captures reported practice and perception at one point in time; there is no

experimental manipulation and no before–after comparison. The design estimates levels and patterns of agreement, and it is deliberately not used to estimate causal effects of AI on defect rates.

3.2 Target population

The target population comprises professionals employed in manufacturing organizations who work in production, quality control or assurance, operations, process or maintenance engineering, or plant management, and who have direct exposure to, or working knowledge of, the quality practices under study. Supervisors, engineers, quality-control personnel and managers are all in scope, because adoption decisions and day-to-day experience with AI quality tools are distributed across these roles.

3.3 Sample size

The study is based on 200 respondents. For descriptive percentage analysis of a heterogeneous professional population this sample gives reasonably stable proportion estimates: at a 95% confidence level the margin of error for a proportion of 0.5 is approximately ± 6.9 percentage points, and it is narrower for proportions further from 0.5. The sample size was not derived from a power analysis for multivariate modelling, and the paper makes no multivariate claims.

3.4 Sampling technique

Purposive (judgemental), non-probability sampling was used. Respondents were selected on the basis of their role and their experience of manufacturing operations, quality management, automation or AI-enabled manufacturing systems. The reason is practical: no sampling frame exists for “professionals with exposure to AI-based quality practices”, so random sampling of the target population was not feasible. The consequence is equally clear, and is carried into the limitations: the results describe the sampled professionals and cannot be projected onto a national or sector-wide population.

3.5 Instrument and constructs

Data were collected with a structured questionnaire in two parts. Part A contains five statements on the reported use of AI-based quality practices. Part B contains five statements on the perceived contribution of AI to quality outcomes. The items were drafted from the constructs identified in the literature review and worded as statements for agreement rating, so that each research question is answered by a defined item set. Table 2 lists the constructs, the corresponding items and their literature anchors.

Table 2. Constructs, questionnaire items and measurement

Construct	Questionnaire item (as administered)	Scale	Literature anchor
Adoption: automated inspection	Automated AI-based quality inspection is used in our production/quality processes	3-point agreement	Harishyam et al. (2023); Dattani et al. (2023)
Adoption: defect detection	AI-based defect detection is used in our production/quality processes	3-point agreement	Singh and Desai (2023); Arora (2023)
Adoption: real-time monitoring	Real-time production monitoring supported by AI is used in our plant	3-point agreement	Wuest et al. (2016)
Adoption: predictive quality	Predictive quality analysis using AI/ML is used in our plant	3-point agreement	Msakni et al. (2023); Carvalho et al. (2019)
Adoption: process optimization	AI-based process optimization is used in our production processes	3-point agreement	Rajesh et al. (2022)
Perception: early detection	AI helps identify defects at an early stage	3-point agreement	Gao et al. (2022)
Perception: inspection errors	AI reduces manual quality-inspection errors	3-point agreement	Stojanovic et al. (2022)
Perception: defective output	AI supports reduction in defective products	3-point agreement	Mewada et al. (2022)
Perception: rework and waste	AI reduces rework and material waste	3-point agreement	Psarommatis et al. (2020)
Perception: overall quality	AI improves overall manufacturing quality	3-point agreement	Oliveira et al. (2024)

3.6 Measurement scale

Each statement in Parts A and B was rated on a three-point agreement scale: agree, neutral, disagree. The three-point format was chosen for a busy professional audience because it forces a direction of

judgement while retaining an explicit neutral option, and because it reduces differences in scale-use habit between respondents with different survey experience. Its cost is coarseness: it cannot separate mild from strong agreement, and the neutral category absorbs both indifference and lack of knowledge. For the derived statistics reported in Section 4, responses were coded agree = 3, neutral = 2, disagree = 1; percentages remain the primary reporting statistic.

3.7 Data collection procedure

The questionnaire was administered in a single wave; invitations reached respondents through professional and industry contacts, and completed responses were returned electronically. A screening question confirmed that each respondent worked in a manufacturing role covered by Section 3.2. Participation was voluntary, no incentive was attached to responses, and no personally identifying information was recorded against individual answers.

3.8 Data analysis plan

Analysis proceeded in seven steps. First, frequencies and percentages were computed for every item. Second, because the sample size is fixed at 200, observed counts were derived exactly from the reported percentages (count = percentage $\times$ 2). Third, weighted mean scores were computed from the percentage distribution of each item on the 3–2–1 coding, together with a normalised index on a 0–100 scale. Fourth, items were ranked by agreement percentage and described by their agree–disagree spread. Fifth, a chi-square goodness-of-fit test compared each item’s response distribution with a uniform distribution across the three categories ($df = 2$), with the effect size $w = \sqrt{(\chi^2/n)}$. Sixth, an exact binomial test examined whether the proportion agreeing exceeded one half. Seventh, the adoption and perception item sets were compared through their mean agreement levels, giving an adoption–perception gap.

One point of transparency is important here. Item-level response records were not available for this analysis, only the aggregated percentage distributions. Internal consistency (Cronbach’s alpha), correlation and regression therefore were not estimated, and no reliability coefficient is claimed. The derived statistics above are deterministic functions of the reported distributions; they add no new information, but they make the information that exists easier to interpret and to compare with other studies. Table 3 maps each research question to its data source, analysis and exhibit.

Table 3. Research questions, data sources and analysis plan

Research question	Items	Analysis	Exhibit
RQ1 Reported adoption of AI quality practices	Part A (5 items)	Percentages, derived counts, weighted mean, rank, χ^2 , binomial test	Tables 4–5; Figure 2
RQ2 Perceived contribution to early detection	Part B items 1–2	Percentages, weighted mean, χ^2 , binomial test	Tables 6–7; Figure 3
RQ3 Perceived contribution to defect, error, rework and waste reduction	Part B items 2–4	Percentages, weighted mean, χ^2 , binomial test	Tables 6–7; Figure 3
RQ4 Reported use of monitoring and predictive analysis	Part A items 3–4	Percentages, rank, binomial test	Tables 4–5; Figure 2
RQ5 Organizational and technological requirements	Synthesis of Sections 4–5 against the literature	Descriptive synthesis against the literature	Section 5; Table 9
Cross-cutting: adoption versus perception	Part A vs Part B	Mean agreement levels; adoption–perception gap	Table 8; Figure 4

3.9 Ethical considerations

The study involved an anonymous, voluntary questionnaire completed by working professionals in the course of their employment; it included no intervention, no incentive, no vulnerable participants and no collection of personally identifying information. Respondents were informed of the purpose of the study before participating, and return of a completed questionnaire was treated as consent. Response records were held by the authors and used solely for this analysis.

4. Results

4.1 Respondent profile

The analysis dataset comprises the ten item distributions reported in the following sections. Respondent-level profile characteristics were not retained in analysable form, so the sample is described here by its size, by the eligibility criteria of Section 3.4 and by the item distributions themselves. Subgroup comparisons by designation, industry sector or organization size are therefore outside the scope of this paper; they are recorded as a limitation in Section 7 and as a future step in Section 8.

4.2 Reported adoption of AI-based quality practices (RQ1, RQ4)

Table 4 and Figure 2 present the distribution of responses to the five adoption statements. AI-based defect detection was the most widely reported practice, with 65% of respondents agreeing that it is used in their processes. Automated AI-based quality inspection followed at 62%, and AI-based process optimization at 61%. Real-time production monitoring was reported by 59% of respondents, and predictive quality analysis by 56%, the lowest of the five. Neutral responses occupied a substantial band of 22–28% across the items, and disagreement stayed between 13% and 16%.

Table 4. Reported adoption of AI-based quality optimization practices (n = 200)

AI-based quality practice	Agree (%)	Neutral (%)	Disagree (%)
Automated AI-based quality inspection	62	24	14
AI-based defect detection	65	22	13
Real-time production monitoring	59	26	15
Predictive quality analysis	56	28	16
AI-based process optimization	61	25	14

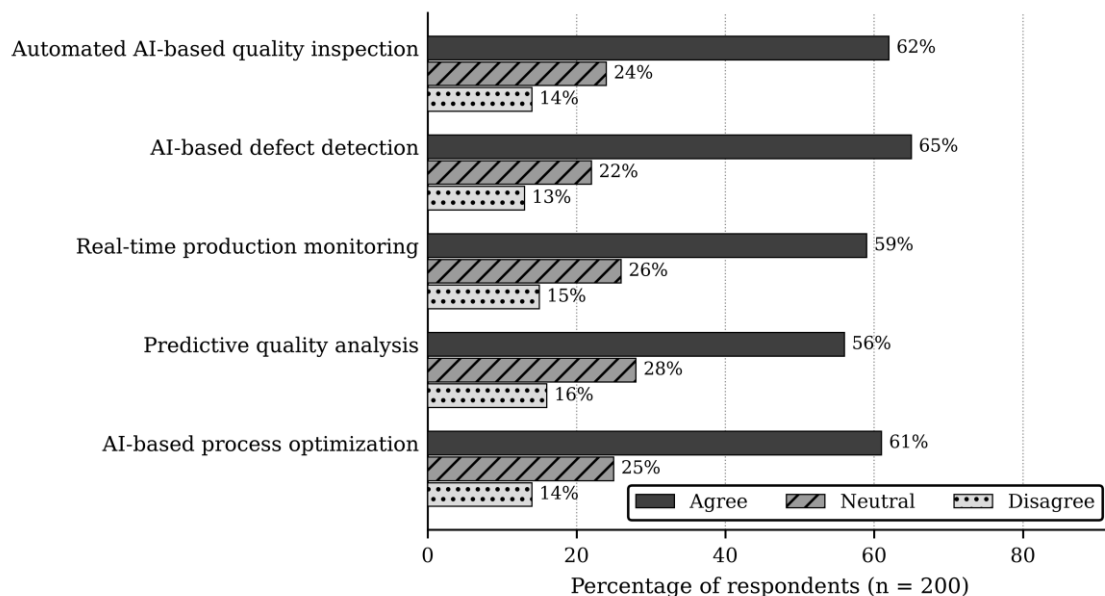


Figure 2. Distribution of responses to the five adoption statements (n = 200). Bars are ordered as in Table 5.

Two features of the pattern deserve comment. The ordering places the two inspection-related practices first and the prediction-related practice last, which is the same ordering that the technology-readiness argument in Section 2 predicts: vision-based detection is comparatively self-contained and its benefit is visible on a single line, whereas predictive analysis needs a labelled historical record before it can say anything useful. The wide neutral band is the second feature. Between roughly a fifth and a quarter of respondents neither confirmed nor denied each practice, a response profile that reads as an aware-but-not-deployed middle rather than as settled rejection.

4.3 Derived statistics for the adoption items

Table 5 converts the percentage distributions into the derived indicators described in Section 3.8. Every item's response distribution departs strongly from a uniform spread across the three categories (χ^2 between 50.6 and 92.7 on 2 df; $p < 0.001$ in all cases), and the effect sizes ($w = 0.50$ – 0.68) are

large by conventional standards. The exact binomial test adds a finer distinction: for four of the five practices the proportion agreeing is significantly above one half at the 5% level, whereas predictive quality analysis (56% agreement, one-tailed $p = 0.052$) is the single practice whose reported use cannot be statistically separated from an even split of opinion. Its last-place rank is therefore not only a descriptive observation but also the weakest signal in the adoption set.

Table 5. Derived statistics for the adoption items ($n = 200$)

Item	Counts (A/N/D)	Weighted mean (3–1)	Index (0–100)	Rank	Spread (A–D)	χ^2 (df = 2)	w	p (χ^2)	p (binom.)
Automated inspection	124/48/28	2.48	74.0	2	48	76.96	0.62	<0.001	0.0004
Defect detection	130/44/26	2.52	76.0	1	52	92.68	0.68	<0.001	<0.001
Real-time monitoring	118/52/30	2.44	72.0	4	44	62.92	0.56	<0.001	0.007
Predictive quality analysis	112/56/32	2.40	70.0	5	40	50.56	0.50	<0.001	0.052
Process optimization	122/50/28	2.47	73.5	3	47	72.52	0.60	<0.001	0.001

Note: Counts are derived exactly from the reported percentages of $n = 200$. Weighted means use the coding agree = 3, neutral = 2, disagree = 1. χ^2 tests the null hypothesis of a uniform distribution across the three categories; the binomial p -value is the exact one-tailed probability of observing at least the reported number of 'agree' responses under $p = 0.5$.

4.4 Perceived contribution of AI to quality outcomes (RQ2, RQ3)

Table 6 and Figure 3 report the perception items. Agreement that AI improves overall manufacturing quality was the strongest response in the entire questionnaire (74%). Agreement that AI helps identify defects at an early stage stood at 72%, that AI supports a reduction in defective products at 70%, that AI reduces manual quality-inspection errors at 68%, and that AI reduces rework and material waste at 66%. Disagreement never exceeded 11% on any perception item.

Table 6. Perceived contribution of AI to defect reduction and quality outcomes ($n = 200$)

Statement on AI contribution	Agree (%)	Neutral (%)	Disagree (%)
AI helps identify defects at an early stage	72	18	10
AI reduces manual quality-inspection errors	68	21	11
AI supports reduction in defective products	70	20	10
AI reduces rework and material waste	66	23	11
AI improves overall manufacturing quality	74	17	9

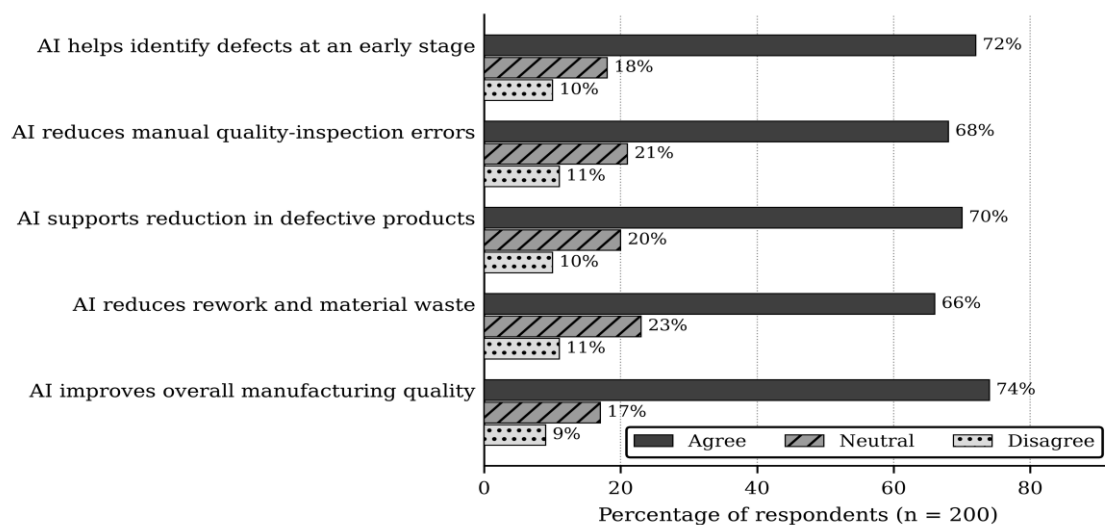


Figure 3. Distribution of responses to the five perceived-contribution statements ($n = 200$).

A gradient within these five items is worth noting. The most abstract judgement — overall quality improvement — attracted the highest agreement, while the most concrete and auditable claim — less rework and material waste — attracted the lowest. Respondents appear willing to endorse the direction of AI's contribution while reserving judgement on hard, countable savings. This is exactly the pattern one would expect if perceived benefit is formed partly by direct experience and partly by expectation.

4.5 Derived statistics for the perception items

The derived indicators for the perception set (Table 7) show the same statistical signature as the adoption set but with larger magnitudes: χ^2 between 100.4 and 150.8 on 2 df ($p < 0.001$), effect sizes $w = 0.71$ – 0.87 , and exact binomial probabilities far below 0.001 for every item. On the 3–1 coding the weighted means run from 2.55 (rework and waste) to 2.65 (overall quality), against 2.40–2.52 for the adoption items.

Table 7. Derived statistics for the perceived-contribution items ($n = 200$)

Item	Counts (A/N/D)	Weighted mean (3–1)	Index (0–100)	Rank	Spread (A–D)	χ^2 (df = 2)	w	p (χ^2)	p (bino m.)
Early defect identification	144/36/20	2.62	81.0	2	62	136.48	0.83	<0.001	<0.001
Fewer manual inspection errors	136/42/22	2.57	78.5	4	57	111.16	0.75	<0.001	<0.001
Fewer defective products	140/40/20	2.60	80.0	3	60	124.00	0.79	<0.001	<0.001
Less rework and material waste	132/46/22	2.55	77.5	5	55	100.36	0.71	<0.001	<0.001
Better overall quality	148/34/18	2.65	82.5	1	65	150.76	0.87	<0.001	<0.001

Note: As for Table 5, counts are derived exactly from the reported percentages of $n = 200$ and the binomial p -values are exact one-tailed probabilities under $p = 0.5$.

4.6 The adoption–perception gap

Comparing the two item sets produces the clearest single result of the study. The mean agreement level across the five adoption statements is 60.6%; across the five perception statements it is 70.0%. Perceived contribution therefore runs 9.4 percentage points ahead of reported use (weighted means 2.60 against 2.46). The same ordering holds for matched pairs: agreement that AI identifies defects early (72%) exceeds reported use of AI-based defect detection (65%) by seven points, and agreement that AI reduces manual inspection errors (68%) exceeds reported use of automated AI-based inspection (62%) by six points. Table 8 and Figure 4 summarise the comparison.

Table 8. Comparison of reported adoption and perceived contribution

Indicator	Adoption items (Part A)	Perception items (Part B)	Difference
Mean agreement across the five items (%)	60.6	70.0	+9.4
Weighted mean score (3–1 coding)	2.46	2.60	+0.14
Highest item (%)	65 (defect detection)	74 (overall quality)	+9
Lowest item (%)	56 (predictive quality analysis)	66 (rework and waste)	+10
Matched pair: early detection (%)	65 (defect detection)	72 (early identification)	+7
Matched pair: inspection errors (%)	62 (automated inspection)	68 (fewer manual errors)	+6

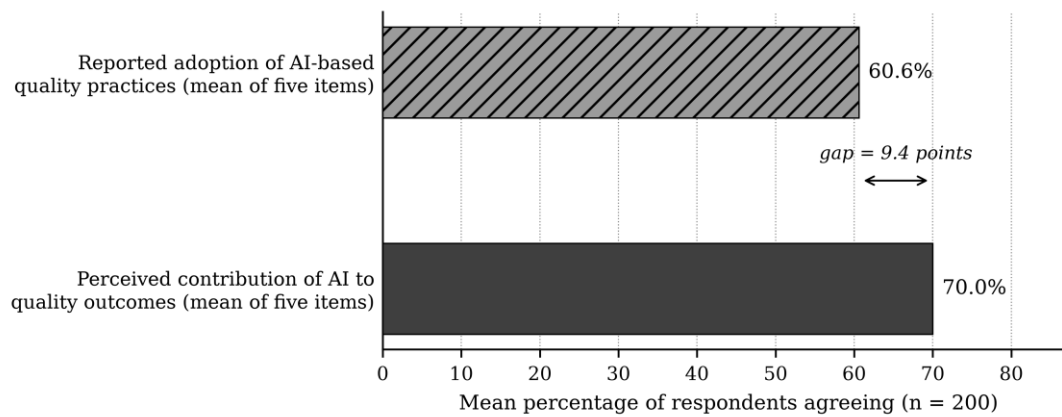


Figure 4. Mean agreement levels for the adoption and perceived-contribution item sets (n = 200).

5. Discussion

The results answer the research questions in a consistent pattern, and the pattern says as much about the diffusion of AI in quality management as about AI itself.

On RQ1 and RQ4, adoption is detection-led. The two inspection-related practices occupy the top ranks, real-time monitoring sits in the middle and predictive quality analysis brings up the rear, statistically indistinguishable from an even split of opinion. This ordering matches the technical argument developed in Section 2: a vision-based detection cell needs images, a labelled sample of defects and compute, and its payoff is visible on one line within weeks (Singh and Desai, 2023; Arora, 2023). Predictive quality needs a time-stamped, labelled history of process states and their quality outcomes, plus the data engineering to keep that history usable — precisely the obstacles flagged in the additive-manufacturing and zero-defect literature (Fu et al., 2022; Psarommatis et al., 2022). The survey, in other words, reproduces at practitioner level the readiness ladder that the engineering literature describes at technology level.

On RQ2 and RQ3, perceived contribution is uniformly positive but internally graded. The holistic judgement (overall quality, 74%) outranks the mechanical ones (early identification, 72%; fewer defective products, 70%), which in turn outrank the claims that a cost accountant could verify from plant records (fewer inspection errors, 68%; less rework and waste, 66%). Read against the zero-defect manufacturing literature, this gradient is reasonable: detection and monitoring are the entry-level capabilities of the ZDM ladder and the ones most respondents have actually seen working (Psarommatis et al., 2020). Claims about rework and waste depend on prevention and on process-level integration, which fewer plants have reached.

The adoption–perception gap of 9.4 points is the finding with the most managerial content. Practitioners believe in the technology somewhat more than they report using it. Two readings are compatible with the data. Expectation may be formed externally, by vendor demonstrations, conference cases and pilot publicity, before deployment catches up. Or expectation may be formed internally, by a successful pilot on one line that respondents generalise to the technology as a whole. The survey cannot separate these readings, and the paper does not pretend otherwise. What the gap does establish is that perceived benefit in this sample is anticipatory as much as experiential — which is why the conclusion is phrased in terms of reported practice and perceived contribution rather than measured defect reduction.

On RQ5, the enablers named by the literature reappear in the respondents' own framing of what AI quality work requires: reliable production data, sensor and machine connectivity, a usable historical defect record, trained people, and integration of model output with existing quality-management, MES and ERP workflows. This is the Quality 4.0 argument in operational clothing: the technology extends the quality system rather than replacing it (Oliveira, Alvelos and Rosa, 2024). The hybrid designs reported in the steel and automotive literature make the same point from the technical side — keeping process engineers in the loop converts a black-box alarm into a diagnosis someone can act on (Latham and Giannetti, 2023; Msakni, Risan and Schütz, 2023).

Finally, what this evidence does not show should be stated as plainly as what it does show. No defect rate was measured. Perception is vulnerable to salience and recency: a dramatic early catch by a vision system is more memorable than a month of quiet false alarms. And a cross-sectional design

cannot separate cause from selection — plants with a stronger data culture may both adopt AI earlier and run better quality, without AI being the difference. These are reasons for the cautious wording used throughout the paper, not footnotes to it.

6. Practical Implications

The findings translate into six implications for manufacturers considering, or extending, AI-based quality systems. Table 9 links each implication to the evidence in this study and to a concrete action.

Table 9. Practical implications, supporting evidence and suggested actions

Implication	Evidence in this study	Suggested action
Start where detection pays	Defect detection (65%) and automated inspection (62%) are the most reported practices and score high on perceived contribution	Pilot a vision-based inspection cell on one high-value line; pre-define miss rate, false-alarm rate and inspection time as acceptance criteria
Treat data readiness as the gate for prediction	Predictive quality analysis is the least reported practice (56%) and the only item not significantly above an even split	Build a defect taxonomy and time-stamped process records before purchasing prediction tools; audit label quality first
Instrument the process before promising savings	Perceived contribution exceeds reported adoption by 9.4 points; the rework-and-waste claim attracts the lowest agreement	Baseline first-pass yield, scrap, rework hours and inspection hours; re-measure on the same definitions after deployment
Keep humans in the loop	Agreement that AI reduces manual inspection errors is high but not universal (68%)	Define escalation rules and appraiser cross-checks; schedule periodic model audits and drift reviews
Integrate, do not isolate	Respondents name data, sensors, skills and system integration as requirements (RQ5)	Route model output into QMS/MES workflows: non-conformance records, SPC charts, maintenance triggers
Build skills alongside models	A 22–28% neutral band on adoption indicates an aware-but-not-deployed middle	Train quality staff in data handling and model interpretation; pair engineers with QC staff on pilot teams

7. Limitations

Six limitations qualify the findings. First, the data capture reported practice and perception, not independently measured defect rates, scrap rates or inspection times; nothing in this paper should be read as a measured reduction in defects. Second, the design is cross-sectional and single-wave, so it describes a moment and cannot track change. Third, purposive sampling means the results characterise the sampled professionals and support no projection to a wider population. Fourth, the three-point scale is coarse: it cannot separate mild from strong agreement, and its neutral category conflates indifference with lack of knowledge. Fifth, because only aggregated percentage distributions were available for this analysis, internal consistency, correlation and regression could not be estimated; the derived statistics in Section 4 inherit the rounding of the published percentages. Sixth, self-reported responses carry the usual risks of salience and social desirability, and, because respondent-level profile records were not retained in analysable form, heterogeneity across industry sectors, organization sizes and professional roles could not be controlled in the analysis.

8. Future Research

The limitations define the agenda. The most valuable next step is to link survey responses to factory records — defect rate, scrap rate, rework hours, inspection time and process capability indices — at firm level, so that perceived contribution can be tested against measured outcomes. Longitudinal before–after designs around a specific implementation would separate anticipation from experience in the adoption–perception gap. At instrument level, a multi-item construct battery on a five-point scale with a separate ‘not applicable’ option would permit reliability assessment, correlation and regression analysis, and would allow the enablers of RQ5 to be modelled as mediators of adoption. Multi-group comparisons by organization size, sector and AI maturity would test whether the

readiness ladder observed here holds across contexts, and qualitative case studies of plants where predictive quality works — and of plants where it was abandoned — would identify the conditions under which the top of the zero-defect ladder becomes reachable.

9. Conclusion

This study set out to examine how far AI-based quality practices have reached manufacturing practice and how professionals judge their contribution. Among the 200 respondents, AI-based defect detection (65%), automated AI-based quality inspection (62%) and AI-based process optimization (61%) were the most reported practices, while real-time production monitoring (59%) and predictive quality analysis (56%) trailed them; perceived contribution ran consistently higher, from 66% for reduced rework and waste to 74% for overall quality improvement, leaving a mean adoption–perception gap of 9.4 percentage points. The interpretation we draw is that AI-based quality practice is diffusing in the order the technology readiness argument predicts — detection first, prediction last — and that belief in its benefit is currently ahead of deployed experience. The caution belongs with the finding: these are reported practices and perceived contributions, not measured reductions in defect rates, and successful implementation depends on data availability, sensor infrastructure, skilled people and integration with existing quality-management processes. Manufacturers that treat those conditions as part of the investment, rather than as prerequisites to be assumed, are the ones most likely to convert perception into measured quality performance.

References

- Arora, M. (2023) ‘AI-driven Industry 4.0: advancing quality control through cutting-edge image processing for automated defect detection’, *International Journal of Computer Science and Mobile Computing*, 12(8), pp. 16–32. doi: 10.47760/ijcsmc.2023.v12i08.003.
- Carvalho, T.P., Soares, F.A.A.M.N., Vita, R., Francisco, R.P., Basto, J.P. and Alcalá, S.G.S. (2019) ‘A systematic literature review of machine learning methods applied to predictive maintenance’, *Computers & Industrial Engineering*, 137, 106024.
- Dattani, K., Koli, M., Kini, M. and Dongre, P. (2023) ‘Automated system for manufacturing defects detection’, *VIVA-Tech International Journal for Research and Innovation*, 1(6), Article 17, pp. 1–5.
- Fu, Y., Downey, A.R.J., Yuan, L., Zhang, T., Pratt, A. and Balogun, Y. (2022) ‘Machine learning algorithms for defect detection in metal laser-based additive manufacturing: a review’, *Journal of Manufacturing Processes*, 75, pp. 693–710.
- Gao, Y., Li, X., Wang, X.V., Wang, L. and Gao, L. (2022) ‘A review on recent advances in vision-based defect recognition towards industrial intelligence’, *Journal of Manufacturing Systems*, 62, pp. 753–766.
- Gunasekaran, A., Subramanian, N. and Ngai, E.W.T. (2019) ‘Quality management in the 21st century enterprises: research pathway towards Industry 4.0’, *International Journal of Production Economics*, 207, pp. 125–129.
- Harishyam, B., Jenarthanan, M.P., Rishivanth, R., Rajesh, R. and Sai Girish, N. (2023) ‘Visual inspection of mechanical components using visual imaging and machine learning’, *Materials Today: Proceedings*, 72, pp. 2557–2563.
- Kumar, S., Gopi, T., Harikeerthana, N., Gupta, M.K., Gaur, V., Krolczyk, G.M. et al. (2023) ‘Machine learning techniques in additive manufacturing: a state of the art review on design, processes and production control’, *Journal of Intelligent Manufacturing*, 34, pp. 21–55.
- Kusiak, A. (2018) ‘Smart manufacturing’, *International Journal of Production Research*, 56(1–2), pp. 508–517.
- Latham, S. and Giannetti, C. (2023) ‘A tool to combine expert knowledge and machine learning for defect detection and root cause analysis in a hot strip mill’, *SN Computer Science*, 4, 628.
- Mewada, S., Saroliya, A., Chandramouli, N., Kumar, T.R., Lakshmi, M., Mary, S.S.C. and Jayakumar, M. (2022) ‘Smart diagnostic expert system for defect in forging process by using machine learning process’, *Journal of Nanomaterials*, 2022(1), 2567194.

- Msakni, M.K., Risan, A. and Schütz, P. (2023) 'Using machine learning prediction models for quality control: a case study from the automotive industry', *Computational Management Science*, 20, 14.
- Oliveira, D., Alvelos, H. and Rosa, M.J. (2024) 'Quality 4.0: results from a systematic literature review', *The TQM Journal*, 37(2), pp. 379–456.
- Psarommatis, F., May, G., Dreyfus, P.-A. and Kiritsis, D. (2022) 'Towards zero defect manufacturing paradigm: a review of the state-of-the-art methods and open challenges', *Computers in Industry*, 134, 103548.
- Psarommatis, F., Sousa, J., Mendonça, J.P. and Kiritsis, D. (2020) 'Zero-defect manufacturing: state-of-the-art review, shortcomings and future directions in research', *International Journal of Production Research*, 58(1), pp. 1–17.
- Rajesh, A.S., Prabhuswamy, M.S. and Krishnasamy, S. (2022) 'Smart manufacturing through machine learning: a review, perspective, and future directions to the machining industry', *Journal of Engineering*, 2022, 9735862, pp. 1–6.
- Sahoo, S. and Lo, C.-Y. (2022) 'Smart manufacturing powered by recent technological advancements: a review', *Journal of Manufacturing Systems*, 64, pp. 236–250.
- Singh, S.A. and Desai, K.A. (2023) 'Automated surface defect detection framework using machine vision and convolutional neural networks', *Journal of Intelligent Manufacturing*, 34(4), pp. 1995–2011.
- Stojanovic, V., Miladinovic, L. and Gligorijevic, N. (2022) 'Smart manufacturing applications for inspection and quality assurance processes', *Procedia Computer Science*, 198, pp. 536–541.
- Susto, G.A., Beghi, A. and De Luca, C. (2015) 'A predictive maintenance system for the optimization of manufacturing processes', *IEEE Transactions on Automation Science and Engineering*, 12(4), pp. 1140–1150.
- Susto, G.A., Schirru, A., Pampuri, S., McLoone, S. and Beghi, A. (2015) 'Machine learning for predictive maintenance: a multiple classifier approach', *IEEE Transactions on Industrial Informatics*, 11(3), pp. 812–820.
- Wang, P., Yang, Y. and Moghaddam, N.S. (2022) 'Process modeling in laser powder bed fusion towards defect detection and quality control via machine learning: the state-of-the-art and research challenges', *Journal of Manufacturing Processes*, 73, pp. 961–984.
- Wuest, T., Weimer, D., Irgens, C. and Thoben, K.-D. (2016) 'Machine learning in manufacturing: advantages, challenges, and applications', *Production & Manufacturing Research*, 4(1), pp. 23–45.