



Original Research Article

A Risk-Based Precision Measurement and Inspection Framework for Quality Assurance in Saudi Industrial Manufacturing

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Abstract: The increasing reliance on the ability to accurately decide where, when, and how to measure in industrial manufacturing, rather than on an indiscriminate expansion of inspection, is highlighted in this review. By drawing on evidence from the field of metrology, Quality 4.0, zero-defect manufacturing, automated visual inspection, digital twins, and risk-based inspection, a risk-based framework for precision measurement and inspection in Saudi industrial manufacturing is developed. The synthesis argues for linking three decision levels—product and process criticality, measurement capability and uncertainty, and inspection evidence with closed-loop corrective action. However, recent literature shows that the benefits of advanced sensing, on-machine measurement, machine vision, and data-driven prediction depend on metrological traceability, validated measurement systems, controlled decision rules, data integrity, and qualified quality staff. Studies carried out in Saudi Arabia also point out that organizational readiness, investment limitations, system integration, and capability building influence the adoption of Industry 4.0. The framework in question bases inspection intensity on consequence and detectability, ties acceptance decisions to uncertainty, and sees digital technologies as a way of producing evidence rather than as a replacement for metrological control. It also suggests that governance should be achieved through the use of risk registers, critical-to-quality characteristics, measurement system analysis, traceability records, escalation rules, and regular reviews. This method could allow for local manufacturing within the framework of Vision 2030 by allocating quality resources to the failure modes that have the greatest operational, safety, reliability, and reputational consequences, while at the same time making conformity decisions that are defensible. The research priorities are sector-specific validation in Saudi Arabia, the economic optimisation of inspection efforts, trustworthy artificial intelligence, interoperable digital calibration records, and long-term evidence on quality performance.

Keywords: Risk-Based Inspection, Precision Measurement, Quality Assurance, Metrological Traceability, Quality 4.0, Saudi Manufacturing, Measurement Uncertainty, Zero-Defect Manufacturing.

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1. INTRODUCTION

Saudi Arabia is increasing its efforts to carry out technology-heavy manufacturing as a component of its strategy for economic diversification. Recent

research into the automotive, petrochemical, cement, and other manufacturing sectors of Saudi Arabia indicates a greater emphasis on Industry 4.0, localisation, digital integration, and achieving

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sustainable operational performance (Aljuaid *et al.*, 2024; Ghaithan *et al.*, 2021; Mahnashi *et al.*, 2023). However, the fact that a factory is digitally enabled does not mean that it is a high-quality factory. Product conformity still relies on the decisions regarding what to measure—such as which characteristics are important, what methods can be used to measure them, how uncertainty influences acceptance, which defects require inspection, and how the evidence is turned into corrective action. These questions become all the more significant as Saudi manufacturers move into higher-value supply chains in the areas of aerospace, automotive, energy equipment, precision components, and advanced materials, since dimensional, surface, and functional failures in such cases can have effects that extend beyond a single part. Literature of a high quality has shifted from relying on end-of-line detection to incorporating prevention, prediction, and learning at an integrated level. Quality 4.0 involves combining traditional quality management principles with connected sensing, analytics, and automation, yet reviews point out that introducing technology without altering the processes, having reliable data, and possessing the necessary managerial skills can merely digitise existing weak controls (Escobar *et al.*, 2021; Dias *et al.*, 2022; Sader *et al.*, 2022; Sony *et al.*, 2020). In a similar way, zero-defect manufacturing treats inspection as part of a system that detects, repairs, predicts, and prevents defects rather than as a final sorting activity (Psarommatis *et al.*, 2020a; Psarommatis *et al.*, 2020b). This change is particularly important in the context of precision manufacturing since measurement serves a dual function: it verifies the output and also provides process knowledge.

There is a special kind of risk associated with precision measurement. The value obtained from a measurement is not the actual value; it is an estimate accompanied by uncertainty. The decision as to whether a measurement conforms is influenced by factors such as traceability, the use of calibrated standards, the environmental conditions, the probing strategy, the behaviour of the sensor, and how the data is processed. Because advanced manufacturing needs more than just accurate instruments, it calls for a metrology system which maintains both uncertainty and traceability from the calibration stage right through to the production decisions (Carmignato *et al.*, 2020; Hall and White, 2021). Uncertainty that is specific to a given task on the manufacturing floor can have a significant impact on whether a part is accepted when it is close to the specification limits. The use of on-machine probing leads to effects due to covariance, thermal effects, and machine geometry that must not be ignored (Sato *et al.*, 2021; Sepahi-Boroujeni *et al.*, 2021).

Inspection also faces a similar issue concerning the allocation of resources. In the case of certain safety-critical characteristics, 100% inspection can be considered reasonable. But when the measurement capability is poor, carrying out 100% inspection may prove to be wasteful, slow or even misleading. On the other hand, reduced inspection can be cost-effective for well-established and stable processes but could be dangerous when the potential consequences of a failure are high. Studies on risk-based maintenance and pipeline inspection have demonstrated the benefits of combining the probability of failure or the likelihood of degradation with the consequences in order to prioritise limited inspection resources (for example Leoni *et al.*, 2021; Sözen *et al.*, 2022). The same approach should be applied to manufacturing quality; the level of evidence required should be determined by the criticality and the measurement capability should decide whether that evidence is reliable.

The review addresses the gap that exists among three areas of literature which are frequently dealt with in isolation: risk-based inspection, manufacturing metrology, and digital quality. It combines these into a framework appropriate for use in Saudi industrial manufacturing. The aim is not to suggest a general numerical risk formula or to promote inspection intervals that apply across different sectors. Rather, the paper puts forward a decision architecture that connects risk ranking, critical-to-quality characteristics, measurement-system capability, uncertainty-aware decision rules, automated inspection, and closed-loop learning. On this basis, it sees quality assurance as consisting of a controlled distribution of evidence, rather than as a choice between conventional metrology and digital technology.

2. AIM OF THE STUDY

The aim of the study is to create an evidence-based conceptual framework which will deal with the allocation of precision measurement and inspection effort in accordance with manufacturing risk in Saudi Arabia. It includes the latest research in the areas of metrological traceability, measurement uncertainty, risk-based inspection, automated visual inspection, digital twins, zero-defect manufacturing, and Quality 4.0. The expected contribution will be a practical method of determining what level of product criticality, process risk, measurement capability, and digital data should be taken into account before a manufacturer decides to accept, reject, escalate or improve a production process.

3. RESEARCH OBJECTIVES

1. To look at recent evidence for precision measurement, inspection automation,

- Quality 4.0, and risk-based prioritization as they relate to industrial quality assurance.
2. To assess the impact of metrological traceability on the uncertainty of measurement and on the measurement system's capability with regard to the critical characteristics of manufacture when making conformity decisions.
3. The method for converting a risk ranking into different levels of inspection intensity, choice of method, and escalation requirements.
4. We should evaluate the potential and limitations of machine vision, on-machine measurement, digital twins and data-driven prediction within a risk-based quality system.
5. Suggest an appropriate implementation framework and research programme for Saudi manufacturers who are interested in localisation, digital transformation and achieving reliable quality performance.

4. RESEARCH QUESTIONS

What are the technical and organizational risks that have the greatest influence on the reliability of precision measurement and inspection in modern manufacturing?

RQ2: In what way should the factors of consequence, occurrence, detectability, and measurement uncertainty be combined conceptually in order to establish the level of inspection? What functions should machine vision, on-machine measurement, digital twins, and predictive analytics carry in a metrologically controlled quality system?

RQ4: What are the specific priorities for implementation or the restrictions concerning a risk-based precision measurement framework in the Saudi manufacturing sector?

RQ5: What governance mechanisms and further research are required if evidence-based conformity decisions are to be maintained and continuous quality improvement is to take place?

5. REVIEW METHODOLOGY

The research problem involves metrology, production engineering, reliability, quality management, and digital manufacturing, which is why a structured integrative review approach was selected. A focused systematic review of just one technology would not adequately capture the decision relationships as shown in the proposed framework; that is why the review protocol incorporated concept-driven searching together with critical thematic synthesis. The scholarly databases and publisher indexes used were Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, SpringerLink, Emerald Insight, Taylor & Francis Online and MDPI. The search expressions were based

on combinations of the following terms: "precision measurement", "manufacturing metrology", "measurement uncertainty", "metrological traceability", "risk-based inspection", "quality assurance", "Quality 4.0", "zero defect manufacturing", "automated inspection", "machine vision", "on-machine measurement", "digital twin", "Saudi manufacturing", and "Industry 4.0 Saudi Arabia". The searches covered the literature from 2020 to 2025, with a particular focus on online publications that were issued before the issue year if those publications were highly relevant and directly related to current practice.

Eligibility was based on journal relevance rather than on branding. The inclusion criteria were peer-reviewed journal articles or reviews that dealt with industrial measurement, inspection, risk prioritization, digital quality, or the transformation of manufacturing in Saudi Arabia and that made a methodological or conceptual contribution to the development of the framework. Studies which looked only at the general accuracy of artificial intelligence, without considering a context of manufacturing-quality decision-making, were excluded. The evidence base did not contain purely commercial material, unreviewed web pages, patents, summaries of standards, or papers lacking adequate bibliographic verification. Since this manuscript is an integrative review of a framework and not a registered meta-analysis, it does not report any fabricated figures regarding identification, exclusion, or screening. We have deliberately decided not to include a artificially constructed flow diagram; instead, reproducibility is achieved through clear concepts, criteria, and verified references, rather than through made-up numerical claims.

The quality was evaluated along five different dimensions: the clarity of the manufacturing or measurement problem; the transparency of the methods; the relevance to conformity, inspection, or process control; the evidence supporting the conclusions stated; and the degree to which the findings could be applied in risk-based decision-making. In order to identify field-level patterns, review articles and empirical studies were employed to examine the measurement, inspection or quality-management value of the technologies in question. The Saudi studies were assessed individually with regard to their contextual implications, such as localization, investment, organizational readiness and digital capability (Alsaadi, 2022; Mahnashi *et al.*, 2023; Mahin *et al.*, 2024).

The synthesis consisted of four steps. In the first step, the papers were grouped into the following categories: metrology and uncertainty; risk prioritization; automated inspection; predictive or

digital-twin quality; and organizational implementation. In the second step, the recurring failure mechanisms were identified, these being inadequate traceability, insufficient measurement capability, weak inspection prioritization, data-quality problems, model drift, and skills gaps. In the third step, the failure mechanisms were linked to the decisions that a quality system has to make—namely, what to measure, how to measure, how often to inspect, how to interpret borderline results, and when to escalate. In the fourth step, these decisions were incorporated into a closed-loop framework, as shown in Figure 1, and also into the operational tiers, a summary of which is given in Table 2.

In order to enhance interpretative reliability, the synthesis incorporated different types of sources rather than relying on review articles as a stand-in for primary engineering evidence. The claims regarding inspection technologies were compared with actual manufacturing applications and the claims about organisational readiness were compared with those from studies of the Saudi sector. Contradictory results were kept whenever they indicated different operating contexts, especially in cases where laboratory accuracy could not ensure robustness in production. No weighting scores were given to journals, countries or technologies since the aim of the review was decision integration rather than bibliometric ranking. This method tends to favour causal reasoning in that each item included in the framework must be linked to a quality, metrology, reliability or implementation problem and the recommended control for that item must directly deal with the problem in manufacturing practices.

The framework also treats measurement records as comprising controlled-quality evidence by retaining the calibration identifiers, the software versions, the environmental conditions, the status of the operator or automated system, and the versions of the decision rules associated with each result, in order that investigations may be able to reproduce the reasons for a conformity decision.

The bibliographic details and DOI strings were verified by referring to the publishers' websites or to other reliable records indexed in the DOI system for the final set of references. We kept 30 peer-reviewed references in order to ensure that the review remained focused and could be audited. The method does have some limitations: it does not provide estimates of the pooled effect sizes, it does not aim to cover every sector in full, and it is unable to eliminate the publication bias that favours successful digital applications. The limitations are clearly dealt with in the limitations section and are not concealed under the guise of pseudo-precision.

6. THEMATIC LITERATURE REVIEW AND CRITICAL ANALYSIS

6.1 Risk-Based Quality Assurance in the Saudi Manufacturing Transition

Saudi research into manufacturing always describes digital transformation as a means of achieving localization, increased productivity, and sustainability. It also states that the decision to adopt such technologies is based on the organization's existing capabilities. Research concerning localization in the automotive sector associates Industry 4.0 with flexible and customized production as well as with the development of capabilities (Aljuaid *et al.*, 2024). Evidence from the petrochemical and plastics industry shows that combining Industry 4.0 with lean practices leads to better sustainability performance, meaning that technology provides value only when it is incorporated into the way operations are run, not when it is simply installed as standalone equipment (Ghaithan *et al.*, 2021). Studies on the adoption of digital technologies in Saudi manufacturing have highlighted the need for investment, the requirement to reconfigure systems, and the existence of limitations in data security and capability. The cement sector has been examined using the approach of organizational diagnostics and by applying the iterative Plan-Do-Check-Act cycle. The above findings imply that a quality framework in Saudi Arabia should not start by buying sensors; instead, it should begin with considering the effects of nonconformity and with the institutional ability to handle those effects.

The interpretation is supported by Quality 4.0 reviews. Rather than replacing current quality practices, digital instruments complement them (Sader *et al.*, 2022; Dias *et al.*, 2022). The benefits of these digital tools are best realized when leadership, strategy, skills, process integration, and analytics all develop together (Sony *et al.*, 2020; Mahin *et al.*, 2024). It is therefore necessary for quality staff to be competent in both digital technologies and in traditional quality methods, covering areas such as communication, data interpretation, and change leadership (Santos *et al.*, 2021). With regard to risk-based precise measurement, governance must be understandable to both engineers and managers: the model should explain why inspections are intensified, what evidence justifies release, and who is responsible for escalation.

Table 1 presents the literature in the form of evidence domains together with the associated framework implications. The pattern is that the more recent technologies address different aspects of the quality problem: metrology offers defensible measurement, risk assessment methods draw attention to issues, automated inspection provides

greater coverage and consistency, and predictive systems reduce the amount of feedback. None of

these alone, however, eliminates the possibility of blind spots.

Table 1: Evidence synthesis for a risk-based precision measurement and inspection system

Evidence domain	What recent literature establishes	Main quality risk if unmanaged	Framework implication
Metrology and uncertainty	Traceability, calibrated artefacts, task-specific uncertainty and covariance affect conformity decisions.	False acceptance/rejection; unverifiable measurement history.	Validate measurement capability before changing inspection frequency; preserve uncertainty and traceability.
Risk prioritization	Likelihood/consequence logic directs scarce inspection and maintenance resources toward critical items.	Uniform inspection effort unrelated to failure consequence.	Assign assurance intensity by CTQ/failure-mode criticality, then define escalation.
Automated inspection	Machine vision and in-line automation expand coverage and consistency but depend on realistic validation.	Dataset shift, false negatives, false positives and uncontrolled operating conditions.	Treat automated inspection as a measurement/evidence system with validated performance and monitoring.
Digital twins and prediction	Connected process data can anticipate quality abnormalities and accelerate root-cause learning.	Model drift or prediction used as unqualified release authority.	Use predictive outputs as risk evidence unless validated decision rules justify direct release.
Saudi implementation	Localization and Industry 4.0 value depend on investment, skills, integration and organizational readiness.	Technology acquisition without assurance maturity or sustainable governance.	Stage digital quality investment around critical risks, capability development and auditable controls.

6.2 Precision Measurement, Traceability and Decision Risk

Metrological traceability is what makes a conformity assessment defensible by establishing an unbroken chain of calibration that links measurements taken in production to recognised reference standards. Even as measurements become more digital or are incorporated directly into machines, calibrated dimensional artefacts will always be necessary (Carmignato *et al.*, 2020). While digitalisation does not affect the need for traceability information, it does alter the way this information is presented and shared. "Digital infrastructures have to contain meaningful uncertainty information, not merely transmit a result without its uncertainty components" (Hall and White, 2021). Barbosa *et al.*, also see digital metrology as a strategic challenge for smart manufacturing, especially when it comes to machine-readable records, large volumes of data, communication, and automated assessment (Barbosa *et al.*, 2022).

Quality risk is most apparent close to the specification limits. Even if the instrument seems to give numerically correct readings, uncertainty can result in false acceptances or false rejections when a measured feature is near a tolerance limit. An examination of geometric dimensioning and tolerancing carried out on the manufacturing floor indicates that task-specific uncertainty is necessary since the machine's structure, the environment, and

the measurement strategy all affect each result in different ways (Sato *et al.*, 2021). The use of on-machine probing introduces extra complexity, because the correlations between machine-axis errors and probe positions can cause the actual risk of a decision to be either underestimated or overestimated under simplified uncertainty models (Sepahi-Boroujeni *et al.*, 2021). This is in agreement with a framework rule in that inspection frequency cannot make up for a measurement method which is either incapable or not well characterised. Simply repeating uncertain evidence more frequently does not improve the decision.

The precision is also affected by the production system; studies on the geometric errors of ultra-precision machine tools indicate that modelling, measurement and compensation make up a connected calibration procedure, with sensor reproducibility and error decomposition still representing major challenges (Geng *et al.*, 2021). On-machine measurement is able to reduce delay since parts can be measured while they remain in the machine, but investigations into touch-trigger probing highlight the importance of matching hardware, software, calibration and application requirements to the particular stage of manufacturing (Zhuang *et al.*, 2024). Although smart sensors provide improved connectivity and adaptivity, risks relating to quality such as sensor drift, interoperability, environmental robustness and

digital traceability have to be managed (Varshney *et al.*, 2021).

The framework suggested makes a distinction between product risk and evidence risk. Product risk refers to the likelihood and impact of a feature not conforming to specifications, while evidence risk is the risk that the measurement or inspection system will reach an incorrect conclusion. When a high-criticality feature has a weak measurement capability, method improvement, the use of additional measurements, or controlled escalation should be carried out before increasing the production volume. On the other hand, reduced sampling can be accepted for a low-criticality feature which has shown a stable capability. This approach prevents a typical managerial mistake, which is to use the risk ranking merely as a reason for changing the sample size without looking at the reliability of the measurement method.

6.3 Risk-Based Inspection and Differentiated Evidence Intensity

The principle offered by research into risk-based inspection is helpful when it comes to prioritisation. Most of the existing literature concentrates on process assets rather than on individual manufacturing activities. Risk-based maintenance methods evaluate components according to the combined significance of the probability of failure and the consequences thereof, and assign maintenance resources to those devices which are most responsible for system risk (Leoni *et al.*, 2021). Also, when planning inspections of pipelines, decisions about when to carry out an inspection are made on the basis of defect and fatigue data rather than by sticking to a fixed interval (Sözen *et al.*, 2022). In a manufacturing environment, the unit of analysis becomes a critical-to-quality characteristic, a process step, the condition of the tooling, or a defect mode.

A manufacturing risk score should therefore act as a trigger for decision-making, not as a seemingly precise prediction. Although traditional rankings of severity, occurrence, and detectability can be of some help in terms of prioritisation, the same ordinal scores may mask very different risk profiles. We suggest retaining the component ratings and also introducing two explicit qualifiers: measurement capability and evidence maturity. Where the observed occurrence is low but the characteristic is severe and difficult to detect, it should lead to more rigorous or redundant inspection. On the other hand, a stable characteristic resulting from a capable process and confirmed by a capable measurement system can then move towards statistically justified sampling, provided that trend monitoring is continued.

This is in keeping with the principle of zero-defect manufacturing. As stated in the literature, the difference is made between detection, repair, prediction and prevention, and it maintains that quality performance is enhanced when these approaches work in conjunction with one another rather than being carried out as separate projects (Psarommatis *et al.*, 2020a). Industry 4.0 can promote this kind of integration by connecting measurements to process feedback and to redesign (Psarommatis *et al.*, 2020b). The aim, therefore, is not to achieve 'maximum inspection'. Instead, it is to establish an inspection burden that is both cost-effective and operationally justified while at the same time minimising the residual quality risk.

6.4 Automated Inspection, Machine Vision and Digital Twins

Automated inspection is able to enhance consistency and completeness, in particular when it comes to surface or assembly features which are difficult to check by manual means at production speed. Studies on machine vision indicate rapid advances in imaging, lighting, algorithms, and their application to product quality (Sioma 2023). Reviews of deep learning point to considerable progress in the detection of surface defects. Yet these depend on the use of representative datasets, balanced classes, the quality of the labeling, the domain conditions, and the performance metrics. Additional research into PCB inspection shows that the whole system includes image acquisition, processing, recognition, performance evaluation, and feedback to manufacturing, not just a classification model (Zhou *et al.*, 2023).

This point is essential in the context of risk-based quality assurance since the accuracy of a model based on a curated data set does not indicate its ability to measure in actual production conditions. In the case of a safety-critical defect, false negatives can have severe consequences, while false positives result in excess scrap and the need for further investigation. For this reason, the inspection system must be validated under real-world lighting conditions, at realistic speeds, and with defect variation frequencies that are typical. Guha *et al.*, (2023) demonstrate the value of this method by showing that machine vision can serve as a measurement-capable in-process control for key device characteristics and by linking automated inspection to statistical verification rather than to visual plausibility. Likewise, reviews of in-line automation point out that integration with manufacturing processes and the incorporation of manufacturing feedback are vital to attaining zero-defect results (Azamfirei *et al.*, 2023).

Digital twins take feedback from detection and move it towards prediction. In the case of die-casting, digital-twin and data-driven approaches combine real-time process information with defect prediction (Liu *et al.*, 2022). In research into aerospace assembly, digital-twin systems have been used in conjunction with predictive and associative methods to predict quality abnormalities and to identify the factors that contribute to them (Zhuang *et al.*, 2022). Although these studies suggest potential for moving inspection earlier in the process, predictive outputs should be regarded as indications of risk rather than as automatic authorization for release, unless measurement traceability, model validation, and decision rules justify such a use. A predicted probability of conformity cannot take the place of the necessary physical verification when the

model has not been proven to remain calibrated amid changes in material, tooling wear, or the introduction of new product variants.

Figure 1 therefore places digital inspection and prediction within a governed evidence loop, the level of assurance needed being determined by risk ranking, the measurement strategy setting the traceability and uncertainty, the inspection technologies providing the evidence, the conformity rules converting the evidence into decisions, and the feedback improving the process controls and updating the risk register. The design of the architecture is meant to prevent an artificial intelligence model from weakening the metrology controls merely because it is fast.

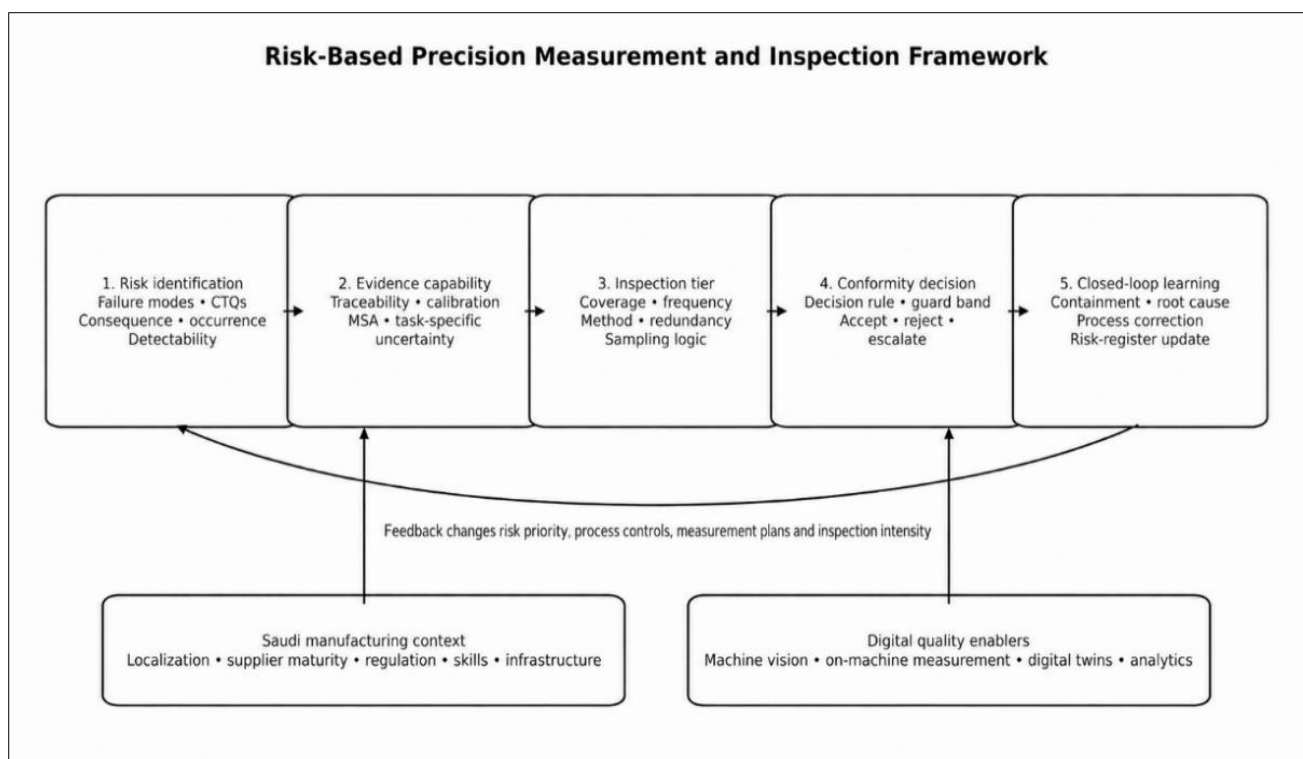


Figure 1: Proposed risk-based precision measurement and inspection framework for Saudi industrial manufacturing

6.5 Framework Synthesis: From Criticality to Closed-Loop Assurance

The framework suggested starts off by determining the failure modes and the critical-to-quality characteristics at both the product and process levels. For each of these items, the consequence, occurrence or exposure, and detectability are evaluated, taking into account the implications related to regulatory requirements, safety, customers, reliability, and reputation. In the second step, the evidence capability is assessed by looking at calibration status, traceability, resolution, repeatability, reproducibility, task-specific uncertainty, sensitivity to environmental factors,

software validation, and data integrity. The third step involves assigning an inspection tier; higher tiers call for earlier detection, stronger evidence from the measurement system, greater coverage, the use of redundant methods where this is justified, tighter escalation procedures, and more frequent review, while lower tiers can make use of sampling provided that process capability and trend stability have been demonstrated.

As part of the fourth step, an uncertainty-aware conformity rule is applied. According to the established policy, guard bands, remeasurement, the use of alternative methods, or an engineering review

are required, instead of forcing measurements at the borderline into a state of binary certainty. In the fifth step, the results of the inspection are connected to process learning. Rather than remaining as isolated quality records, risk assessments are updated to take into account nonconformities, trends approaching limits, shifts in model confidence, and changes in the measurement systems. This enables prediction and prevention, not merely repeated detection.

The synthesis also sets apart governance in terms of "technology readiness" and "assurance readiness": a plant may have cameras, connected probes, and analytics but still lack a calibration procedure, master data, model-change control, or staff who are capable of interpreting uncertainty. In such a case the plant is technology ready but not assurance ready. Hence, Saudi manufacturers who wish to speed up localisation should base their digital quality investments on having demonstrable control over key risks. This is in line with the findings of Saudi adoption research, which indicates that the value of Industry 4.0 investments is determined by an organisation's diagnostic capabilities and the degree of system integration (Alsaadi, 2022; Mahnashi *et al.*, 2023).

7. DISCUSSION

The main conclusion of this review is that risk-based precision measurement is not mainly a matter of how often inspections are carried out; it is rather a matter of evidence governance. The level of assurance required is determined by the risk involved, while metrology is responsible for the trustworthiness of the evidence and digital technologies enable the speed and extent with which evidence can be generated and interpreted. In cases where these functions are separated, organisations tend to make up for uncertainty by increasing the number of inspections, or compensate for limited inspections by placing too much trust in analytical tools. The suggested framework, on the other hand, requires that all three questions be answered before any release: how serious the consequences of a wrong decision are; how reliable the measurement or inspection method is; and what action is to be taken on the basis of the evidence.

This way of looking at the issue resolves a number of the tensions found in the existing literature. Those in favour of Quality 4.0 are correct to stress connectivity, analytics, and faster learning, while metrology research focuses on traceability and uncertainty. These are complementary rather than opposing priorities. If sensors drift and the definitions are not consistent, high-frequency data have little use for quality control. Yet a perfectly traceable result from a laboratory can still arrive too late to prevent a batch of defects. The aim should be

to produce traceable, decision-relevant information at process speed. The development of digital representations of uncertainty and advances in smart-metrology research are helping to achieve this convergence (Hall and White, 2021; Barbosa *et al.*, 2022).

The same reasoning resolves the apparent contradiction between 100 per cent inspection and statistical sampling. Complete inspection is not always the better option. This is the case when the criticality of the item, the variability of the process, the ability to detect defects, and economic considerations all support it, and when the inspection system is capable. Although automated machine vision can evaluate a large number of visual features with high coverage, the literature on deep learning indicates that performance can vary according to the data and operating conditions (Ameri *et al.*, 2024; Zheng *et al.*, 2021). Therefore, the framework achieves high coverage by means of validation and monitoring. The processes are capable and the measurements are reliable, which allows for reduced sampling. Lower-risk characteristics still require no less than adequate quality control.

The fact that the Saudi situation has strategic significance means that localization leads to the establishment of new supplier relationships, new requirements for the workforce, and manufacturing processes which may not have a long history of stable performance. Research into the automotive and petrochemical sectors indicates a great deal of interest in digitalised and sustainable manufacturing, while studies in the cement and general manufacturing sectors point to organizational and investment obstacles (Aljuaid *et al.*, 2024; Ghaithan *et al.*, 2021; Mahnashi *et al.*, 2023; Alsaadi, 2022). Within this kind of setting, risk-based assurance can help to prevent two expensive extremes: importing costly inspection technologies in the absence of a clear risk case and depending on outdated sampling rules that do not take into account the importance of the new locally produced products.

Table 2 breaks down the framework into four practical levels. The tiers are intentionally left qualitative since numerical thresholds would have to be determined on a sector by sector basis and confirmed in light of the consequences of the product, the regulatory requirements, and the process data. Tier 1 covers characteristics which are catastrophic or safety-critical; Tier 2 consists of major reliability and customer-critical characteristics; Tier 3 comprises standard functional characteristics having a stable capability; and Tier 4 includes attributes of low consequence. A change in tier should be based on evidence; a characteristic should be upgraded if there is a deterioration in capability, if the issues with the

measurement system remain unresolved, if new suppliers are brought in, or if there are repeated results near the limit. Conversely, de-escalation can

be justified by sustained capability and by validated controls.

Table 2: Proposed inspection tiers for risk-based manufacturing quality assurance

Tier	Typical risk profile	Measurement and inspection strategy	Decision / escalation rule
Tier 1 - Critical	Safety, regulatory or catastrophic functional consequence; weak detectability is unacceptable.	Validated high-capability method; very high or 100% coverage where feasible; redundancy for selected CTQs; tight traceability.	Predefined guard bands; automatic hold for ambiguous results; engineering review and documented release authority.
Tier 2 - Major	Major reliability, customer or costly downstream consequence.	High in-process coverage or intensified sampling; capability monitoring; automated inspection where validated.	Escalate on trend shift, near-limit clustering, supplier/process change or measurement-system degradation.
Tier 3 - Controlled	Moderate consequence with demonstrated process and measurement capability.	Statistically justified sampling plus SPC/trend monitoring; periodic measurement-system verification.	Increase tier if capability deteriorates or recurring nonconformity appears; reduce only after sustained evidence.
Tier 4 - Routine	Low consequence, mature process, stable historical capability.	Reduced sampling, audit checks or attribute verification appropriate to the characteristic.	Maintain traceability and change control; escalate when design, supplier, tooling or process conditions change.

As shown in Figure 2, the governance cycle is outlined. Strategic management is responsible for setting the risk appetite, meeting regulatory commitments, and establishing localization priorities. Tactical quality engineering then turns these into critical characteristics, measurement plans, inspection levels, and acceptance criteria. The operational systems carry out the measuring and

inspecting, collect the evidence, and trigger containment or correction. The performance data are then passed back to management for review. It is important to have this separation of responsibilities since, otherwise, automated systems might result in opaque decisions lacking a clear owner. The framework based on risk must still be auditable even if the evidence is produced by complex software.

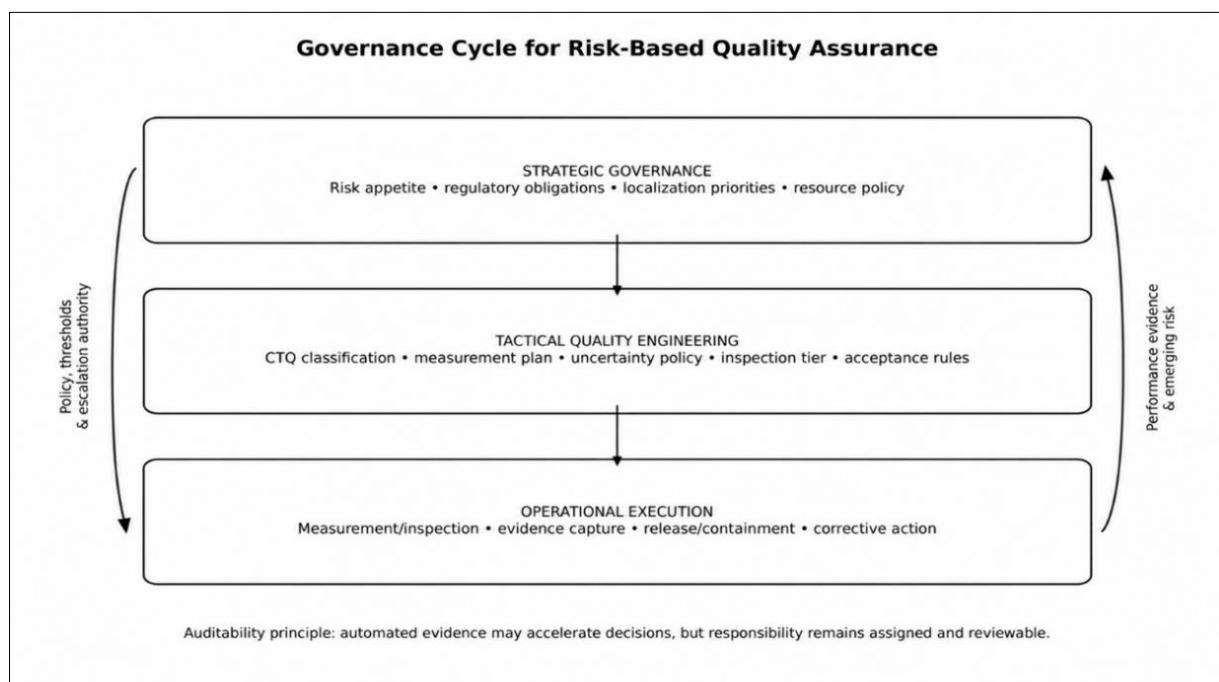


Figure 2: Governance cycle linking strategic policy, tactical quality engineering and operational evidence

The framework doesn't take professional judgement away; on the contrary it makes it clearer and puts such judgements open to review—human expertise remains necessary if new failure modes are to be assessed, conflicting evidence is to be interpreted and changes to the inspection strategy are to be approved. Research into Quality 4.0 skills supports the combination of digital proficiency with leadership ability (Santos *et al.*, 2021). The practical aim therefore is better quality engineering, automation being in charge of obtaining evidence repeatedly and recognising patterns, while qualified individuals are in charge of the risk model, metrological validity and the release policy.

8. RESEARCH GAPS AND FUTURE RESEARCH

The five most important gaps should be given priority. Firstly, there is a lack of published evidence to validate risk-based precision measurement frameworks in Saudi production lines. Studies tailored to each sector should compare baseline inspection methods with risk-tiered approaches in the case of automotive components, fabricated energy equipment, petrochemical products, and emerging aerospace supply chains. While model accuracy is not the only criterion that should be considered, the studies should also take into account escape rates, false rejection rates, inspection time, the cost of quality, and process learning.

Secondly, economic optimisation is still in an immature stage. In order to carry out risk-based inspection, the trade-off between the cost of measurement, the delay caused by inspection, the consequences of defects and the remaining uncertainty should be quantified. Future research should combine quality-loss functions, process capability and uncertainty in order to set defensible escalation thresholds.

Thirdly, reliable artificial intelligence needs to have better metrological treatment. This should involve research into machine-vision and predictive models concerning calibration drift, dataset shift, uncertainty representation and traceable validation. The research should separate classification confidence from measurement uncertainty and should indicate when it is appropriate to release an algorithm rather than merely use it for screening. Fourthly, digital traceability depends on the use of interoperable data formats. The digital calibration certificates, the machine-readable uncertainty, and the equipment history should be able to interface with manufacturing execution and quality-management systems including provenance. Although recent reviews have identified the metrology-digitalization agenda and have thus provided a foundation, the implementation standards

and industrial demonstrations remain uneven (Barbosa *et al.*, 2022; Hall and White, 2021).

Fifth, organisational research should look at the level of assurance achieved during the Saudi localisation process. Longitudinal studies could be used to examine how supplier development, workforce skills, leadership, and cybersecurity influence the long-term reliability of measurement. This would take the existing Saudi Industry 4.0 studies from a focus on technology adoption to one that addresses measurable quality outcomes.

9. PRACTICAL, MANAGERIAL AND POLICY IMPLICATIONS

What this means for manufacturers is that they should prioritize the critical characteristics when purchasing any additional inspection technology. Each measurement plan must take into account the associated failure consequence, the required capability, the way in which uncertainty is to be handled, the sampling or coverage rule, the escalation procedure, and the data-retention requirement. Measurement system analysis should be carried out again following any major changes to the tooling, software, fixtures, probes, cameras, or environmental conditions. View the implementation of digital inspection as part of a quality-management-system effort rather than as an information-technology project. When preparing business cases, one should consider residual risk and quality costs, not merely the speed of automation. In the case of localized supply chains, a shared definition of acceptable evidence must be established. Supplier quality agreements should specify the requirements relating to traceability, calibration evidence and the decision rules for critical measurements.

Support for localisation should involve metrological infrastructure, accredited calibration facilities, the development of the workforce, and the use of interoperable quality data, all for the benefit of policy-making and industrial-development organisations. Incentives for smart manufacturing should be linked to assurance readiness – that is, to demonstrable traceability, validated measurement systems, cybersecurity, data governance and the development of competence. This approach would ensure that investment in digital factories corresponds with the reliability requirements of international value chains, rather than viewing the adoption of technology as the final objective.

10. LIMITATIONS

The review is conceptual and integrative and not a statistical meta-analysis. Since the literature reviewed includes a variety of manufacturing sectors, measurement tasks, and risk models, the numerical inspection thresholds cannot be generalized. The

empirical evidence from Saudi Arabia is still concentrated on Industry 4.0 adoption and on certain sectors rather than on precision-metrology results. There is a possibility that successful digital applications have been subject to publication bias. Inspection algorithms could change quickly, and publication in journals may fail to keep up. The framework must be validated in each sector before it is put into use.

11. CONCLUSION

A precision measurement and inspection system based on risk assessment should base its level of assurance on the likely consequences and have to back up each of its decisions with reliable, traceable, and awareness-of-uncertainty evidence. As shown by the literature review, standardized metrology, risk prioritization, automated inspection, digital twins, and Quality 4.0 are most effective when they are integrated rather than used separately. The framework being proposed allows for adaptation to the circumstances of Saudi manufacturing without requiring a trade-off between thorough measurement and fast digitalization. The assurance needed is determined by the criticality; the reliability of the evidence is determined by the measurement capability; the inspection technologies provide the coverage; and closed-loop governance converts the results into measures for prevention and learning. The following stage will be to empirically validate the approach in the production environments of Saudi Arabia using as criteria quality, cost, reliability, and decision-risk outcomes.

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