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Featured articles

- *Evaluation of the Capability of Generative AI to Interpret and Provide Guidance on the Application of the ISO/IEC 17025 Standard*
  By Diego Alejandro Uribe Polo
- *Systematic Technology Identification for the Digitalization of the Conformity of Production in the Automotive Industry*
  By Kerstin Haeckel, Stephan Husung, and Christine Wünsche

An Issue Dedicated to Artificial Intelligence (AI) and Its Impact on Conformity Assessment

DOI Link

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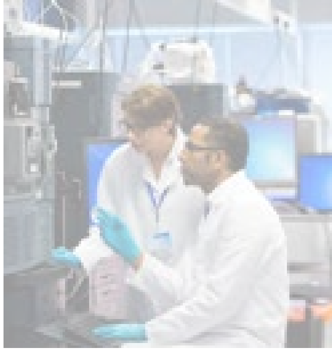

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IJCA welcomes contributions addressing all aspects of conformity assessment. While accepting a wide array of scholarly contributions from various disciplinary approaches, the editors especially encourage research that is novel, visionary, or pathbreaking. Submissions must be relevant to the conformity assessment field, sufficiently rigorous both conceptually and methodologically rigorous, and written in a clear, concise, and logical manner.

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+1 562-364-8201
iasonline.org
ijcajournal@iasonline.org

Message from IAS President

IAS started the *International Journal of Conformity Assessment* (IJCA) during the COVID-19 pandemic with the intention to fill a silence that had settled across the globe—and to begin a conversation. Five years later, it is gratifying to see that this journal has gained the attention of industry practitioners and users, sparking more than casual interest. The arc of our collective imagination continues to explore both the visible and hidden dimensions of the conformity assessment sector.

In a world saturated with social media and breaking news, the IJCA serves as a forum where thought leaders, practitioners, researchers, and "assessment warriors" exchange insights and perspectives to help advance the field of conformity assessment. As the sector grows in economic and global significance, we believe it deserves to be approached with the seriousness and intellectual rigor the field demands. IAS, as a globally engaged accreditation body, is committed to participating in this evolving world of ideas and action. We hope you will join us on this journey.

This publication is now ably led by Alberto Herrera, Executive Editor, who brings nearly three decades of experience in editing and communications related to standards, codes, and technical content. He is supported by a talented team at IAS, including Tania Blancas, Graphics and Layout Specialist; Laura Uraine, Publications and Communications Coordinator and IJCA Secretariat; and Robyn M. Feller, IJCA Consulting Editor. The editorial and publishing efforts are skillfully guided by Greg West, Senior Vice President and IJCA Manager.

This latest volume of the IJCA presents articles of broad professional interest. The journal's blind peer review process will resume in future volumes, and peer-reviewed articles will be clearly identified. We are also in the process of establishing an Editorial Advisory Board composed of professionals deeply engaged in conformity assessment. This board will help guide the journal's direction and contribute to the development of future content. We take this opportunity to thank those who served on the IJCA boards for earlier volumes.

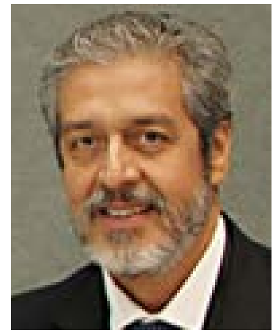
This issue reflects the dedication of the editorial team and the contributions of the authors to this special issue on Artificial Intelligence. This theme has been on my mind for the past 18 months, ever since a senior executive at a global conference publicly declared, "AI is an existential threat to the conformity assessment world." That statement reflected both anxiety and practical concern about the future of the field. While IJCA does not claim to hold definitive answers, we hope to foster a conversation—perhaps a metaphorical pebble tossed into the still waters of conformity assessment—whose ripples may reach you as well.

Raj Nathan

Raj Nathan

President, IAS
June 2025

Message from IJCA Executive Editor's Desk



The *International Journal of Conformity Assessment (IJCA)* editorial team presents the current volume, which explores the impact of Artificial Intelligence on conformity assessment through a series of articles representing diverse disciplines and perspectives.

The articles in this issue address advances in Artificial Intelligence, quality management, and standardization in laboratory and industrial contexts. Diego Uribe's article, "Evaluation of the Capability of Generative AI to Interpret and Provide Guidance on the Application of the ISO/IEC 17025 Standard," evaluates the performance of generative AI models in interpreting the ISO/IEC 17025 standard, focusing on a customized ChatGPT-based model he names L-Squad. Using a 40-question assessment covering literal, inferential, and criterial comprehension, Uribe tested L-Squad against three other AI tools (Meta AI, ChatGPT 4.0 Free, and ChatGPTo1). L-Squad achieved the highest overall score, with its custom configuration and training contributing to strong performance in criterial reasoning.

The article by Kerstin Haeckel et al., "Systematic Technology Identification for the Digitalization of the Conformity of Production in the Automotive Industry," presents research conducted by the BMW Group that addresses the growing complexity of verifying vehicle compliance in the automotive industry's Conformity of Production (CoP) process. The study aims to identify and validate technologies capable of automating component identification (CID) checks. Future proof-of-concept studies will determine which technologies best align component IDs with regulatory standards and improve both accuracy and efficiency.

In the article "Balancing Innovation and Openness: The Role of Artificial Intelligence in Conformity Assessment," Hodjat A. Bagheri highlights the significant opportunities AI presents for conformity assessment, including greater objectivity, efficiency, and adaptability—particularly in regions with complex regulatory demands such as MENA and CIS. He also explores the dual nature of AI: while it enhances fairness and reliability, it simultaneously raises challenges related to ethics, transparency, and trust.

Emil Hazarian's article, "The AI Transformation in Metrology and Conformity Assurance," asserts that AI is revolutionizing metrology and conformity assurance by automating compliance, improving measurement precision, and enabling predictive analytics. Technologies such as Digital Calibration Certificates (DCCs) and machine learning-based assessments reduce manual intervention and enhance quality control. However, Hazarian also notes that this transformation brings challenges, including workforce displacement, data security, and governance. He emphasizes that these challenges must be addressed through greater collaboration among industry, regulatory, and accreditation bodies to ensure ethical, secure, and standardized AI adoption.

The article "The Evolution of Quality Management in Laboratory Services: Ensuring Accuracy, Safety, and Efficiency" by Vikash Chandra Mishra et al., examines how quality management in laboratory services has advanced to meet growing demands for accuracy and patient safety. The authors trace this evolution from early quality practices to the adoption of comprehensive quality management systems and international standards—enhancing operational efficiency and test result reliability and ultimately benefiting patient care and regulatory compliance.

As an equally important contribution, Uribe et al. present the article “Impact of ISO/IEC 17025 Accreditation on Food Safety: Arsenic Speciation and Quality Control of Maize,” based on a poster presented at the INOFOOD trade show in Santiago, Chile, in November 2024. Their study explores how ISO/IEC 17025 accreditation enhances food safety by improving the accuracy and reliability of arsenic speciation in maize. Given the health risks of arsenic exposure, even at trace levels, the use of accredited, standardized testing methods is essential. The paper underscores the value of accreditation in ensuring quality control and safeguarding public health through more dependable laboratory results.

Finally, the editorial team presents an article summarizing the results of a short, anonymous survey conducted by IAS to assess awareness, usage, and attitudes toward Artificial Intelligence (AI) among conformity assessment bodies.

On behalf of the IJCA editorial team, we extend our gratitude to all contributors to this volume. We hope readers find the content both useful and meaningful in supporting their professional goals and advancing the broader mission of conformity assessment.

Alberto Herrera
Executive Editor
International Journal of Conformity Assessment (IJCA)
June 2025

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Evaluation of the Capability of Generative AI to Interpret and Provide Guidance on the Application of the ISO/IEC 17025 Standard

By Diego Alejandro Uribe Polo, Laboratory Assessor and Independent Consultant, LAB-SQUAD

DOI: 10.55459/IJCA/v4i1/DU

-ABSTRACT-

This study evaluates the ability of generative artificial intelligence models to interpret and provide guidance on the ISO/IEC 17025 standard, with a focus on L-Squad, a customized ChatGPT model. Through a 40-question exam assessing literal, inferential, and criterial comprehension—evaluating how well models can justify or reason through decisions based on standards—the performance of four AI tools (Meta AI, ChatGPT 4.0 Free, ChatGPT o1, and L-Squad) was compared using the consensus of a panel of experts in laboratory accreditation as a reference. The results showed that L-Squad achieved the highest overall score, excelling in criterial comprehension due to its customized configuration and reinforcement learning with human feedback (RLHF). However, all models exhibited strong literal and inferential understanding, with a 77.5% agreement in responses. Despite these advancements, the findings emphasize the need for model customization and human oversight when leveraging generative AI in standardization contexts such as ISO/IEC 17025. This research underscores both the potential and the limitations of generative AI to support the application of technical standards.

Keywords: *Generative Artificial Intelligence, ISO/IEC 17025, Conformity Assessment, Customized ChatGPT, Laboratory Accreditation, Reinforcement Learning from Human Feedback (RLHF), Technical Standards, AI Risk Management, Normative Interpretation*

Introduction

Artificial intelligence (AI) is transforming the way technical and standardization processes are addressed across various sectors. Generative models, such as ChatGPT, have proven to be powerful tools for interpreting and applying complex standardization requirements. However, the effectiveness of these tools depends on several factors, including the use of appropriate prompts, the technological proficiency of users, and the quality of the available information.

According to the Latin American Artificial Intelligence Index (ILIA), there is a significant gap in technological competencies between Latin America and the Global North (CENIA, 2024). This gap limits the use of advanced tools but also creates an opportunity to strengthen generative AI capabilities, particularly in countries like Chile and Uruguay, which lead in AI research and adoption. ILIA underscores the necessity of high-quality data and robust infrastructure in training models capable of accurately interpreting technical information.

Reinforcement Learning from Human Feedback (RLHF) is a methodology with notable potential in configuring customized GPTs. This approach integrates optimization techniques, such as Proximal Policy Optimization (PPO), with reward modeling based on human feedback (Naik, Naik, & Naik, 2024). Through iterative learning cycles, the model refines its responses to align with user expectations, enhancing its accuracy and relevance in specific contexts.

The acceptance of AI systems in regulatory environments also relies on their transparency and verifiability. Information published by ISO/IEC JTC 1 SC 42 (2024) and the OECD (2023) highlights the importance of managing associated risks, such as biases and privacy, to ensure generative models are trustworthy. Similarly, the ISO/IEC 42001:2023 standard provides clear guidelines for documenting and managing risks in AI systems, ensuring decision traceability.

In the educational domain, the integration of AI presents opportunities to personalize learning and enhance research while also posing ethical and technical challenges (Pedreño Muñoz et al., 2024). This article evaluates how well a customized ChatGPT model (L-Squad) understands ISO/IEC 17025 requirements and its ability to interpret and provide guidance on applying the standard in testing and calibration laboratory management systems.

Configuration of a Customized ChatGPT for ISO/IEC 17025: L-Squad

L-Squad, a customized ChatGPT model, was configured using advanced ChatGPT options with a "Plus" account and the "Create" tool. This model was trained with the following guidelines:

1. Objectives and Scope:

- Function as a specialist in ISO/IEC 17025:2017 with extensive experience.
- Provide guidance on implementing and complying with the standard's requirements, emphasizing consistent operation, impartiality, and laboratory competence.

2. Accuracy in Requirements:

- Do not label any requirement as "mandatory" unless explicitly stated in the standard.
- Clearly distinguish recommendations or best practices from mandatory requirements.
- Avoid presenting "preventive actions" as mandatory, as ISO/IEC 17025:2017 follows a risk-based approach without explicitly requiring them.

3. Documentation and Procedures:

- Specify whether a document or procedure is explicitly required by the standard (citing the relevant clause) or a non-mandatory recommendation.

4. Response Format:

- Maintain a formal and professional tone.
- Provide concise responses with specific references to the standard.

5. Out-of-Scope Topics:

- Address only inquiries related to ISO/IEC 17025:2017.
- If asked about unrelated topics, clarify that the model is limited to ISO/IEC 17025.

L-Squad has evolved through ten iterative versions, incorporating updates that form part of its knowledge base to deliver precise and contextualized responses regarding the application of ISO/IEC 17025 in the management systems of testing and calibration laboratories. Key documents integrated into its configuration include ISO/IEC 17025:2017, ILAC policies such as ILAC P14:09/2020, ILAC P10:07/2020, ILAC P9:01/2024; ILAC guides such as ILAC G8:09/2019, ILAC G24:2022, and ILAC G17:01/2021; as well as supplementary documents like the AENOR Pack UNE EN ISO/IEC 17025:2017, ISO 10012, ISO 10009, and Eurachem guides.

Additionally, actions were taken during each update to refine responses based on user feedback. Its latest instruction was enhanced using ChatGPT o1, "Uses advanced reasoning," which strengthened its advanced reasoning capabilities and accuracy in normative contexts. Training through reinforcement learning allowed L-Squad to optimize its responses through iterative user feedback, ensuring a closer alignment with user expectations and the standard's objectives.

Evaluation of Comprehension Level

To assess the generative AI's comprehension of the ISO/IEC 17025 standard requirements, a 40-question test was developed. This test was divided into two sections: one consisting of true/false questions and another with multiple-choice questions that had only one correct answer. The questions were categorized into three levels of comprehension:

- **Literal comprehension:** Focused on the ability to identify explicit information in the text, evaluated through multiple-choice and true/false questions (35 questions). Maximum expected score: 35.
- **Inferential comprehension:** Assessed the ability to deduce implicit information from the text, requiring contextual analysis (five questions), evaluated through multiple-choice questions. Maximum expected score: 5.
- **Criteria-based comprehension:** Involved justifying answers based on critical judgment and alignment with the standard, using the same five inferential questions to evaluate this dimension. A specific scoring system was applied, ranging from 0 to 2 points, to evaluate whether the responses were correctly justified with a direct relationship to the ISO/IEC 17025 standard. Maximum expected score: 10.

This test was made available to five specialists with an average of more than 10 years of experience in the field of accredited laboratories applying the standard in various contexts, including auditors, consultants, and quality system leaders. This process allowed for a consensus to determine the correct answer, using a simple majority to assign a valid alternative as correct in each case. The results provided a solid basis to evaluate the generative AI's capability in terms of accuracy, relevance, and specific alignment with the principles of the ISO/IEC 17025 standard.

During the study, the performance of four generative AI tools was tested: Meta AI, ChatGPT 4.0 Free, ChatGPT o1, and L-Squad (developed within ChatGPT). These tests enabled a comparison of their abilities to interpret and apply the requirements of the ISO/IEC 17025 standard. The conditions for the tests were as follows:

- **For evaluating literal and inferential comprehension:** Detailed prompts were used. The detailed prompt was:
  "You are a specialist in ISO/IEC 17025. I will provide you with an exam divided into two sections. You must provide precise and well-supported answers based on the requirements of the standard. Organize the answers in a table with two columns: the first for the question number and the second for the corresponding answer. Ensure that each response is verified and grounded in ISO/IEC 17025, as well as any relevant documents related to the accreditation of testing and calibration laboratories. Complete Section 1 first, followed by Section 2, maintaining a consistent table format for clarity and ease of understanding."
  This prompt aimed to guide the model to generate well-founded and structured responses.
- **For specifically evaluating criteria-based comprehension:** The following prompt was used: *"Provide justification for your answers to questions 26, 31, 32, 38, and 40."*
  This prompt required the responses to be clearly justified and directly grounded in the ISO/IEC 17025 standard.

Evaluation Results

The results obtained after evaluating the four generative AI tools (Meta AI, ChatGPT 4.0 Free, ChatGPT o1, and L-Squad) are presented in the following table (Table 1). This table summarizes the scores achieved at each comprehension level compared to the scores assigned by consensus using the panel of specialists* and the evaluation of criteria-based comprehension:

Table 1. Comparative Results of AI Tools Across Different Levels of Comprehension

Evaluation	Meta AI	ChatGPT 4o Free	ChatGPT o1	L-Squad
Literal*	29	27	28	30
Inferential*	4	4	4	4
Criteria-Based	6	4	2	8
Total	39	35	34	42

- **Literal comprehension:** All tools performed close to the expected score of 35, with L-Squad achieving the highest score.
- **Inferential comprehension:** The four tools scored 4 out of 5, indicating their ability to deduce implicit information effectively.
- **Criteria-based comprehension:** The most significant differences were observed in this category. L-Squad scored 8 points, demonstrating a stronger ability to justify answers with clear and standard-aligned reasoning. In contrast, ChatGPT o1 scored only 2 points, highlighting challenges in providing robust justifications.

The values in the following table (Table 2) represent the level of agreement of each response generated by the AI tools with the answers determined by consensus from the expert panel* and the evaluation of criteria-based comprehension.

Table 2. Percentage of Response Agreement Between AI Tools and the Expert Panel

Evaluation	Meta AI (%)	ChatGPT 4o Free (%)	ChatGPT o1 (%)	L-Squad (%)
Literal*	82.9%	77.1%	80.0%	85.7%
Inferential*	80.0%	80.0%	80.0%	80.0%
Criteria-Based	60.0%	40.0%	20.0%	80.0%
Total	78.0%	70.0%	68.0%	84.0%

It is worth noting that, in 31 questions (77.5%), all four tools provided the same answer at the literal and inferential levels. This highlights the level of agreement that is appropriate among the four tools.

Test for Equality of Variances

After confirming that the data follow a normal distribution, and to complement the analysis of the results, an equality of variances test was conducted among the evaluated generative AI tools using

Minitab. The results of this test are presented in the following figure (Figure 1):

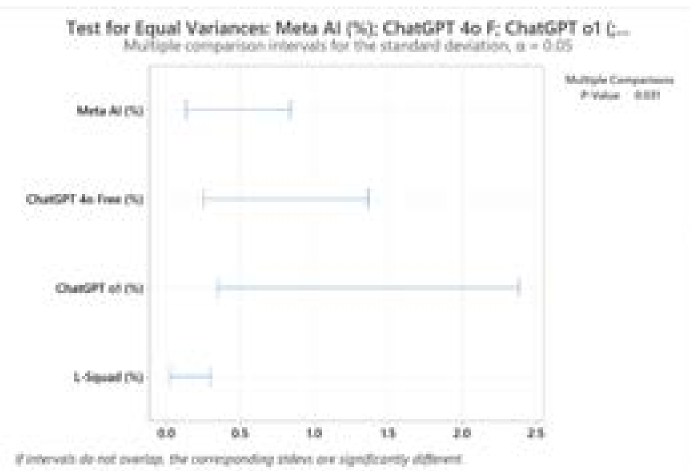
Figure 1. Equality of Variances Test and Confidence Intervals for Standard Deviation Across Generative AI Tools

Method

Null hypothesis	All variances are equal
Alternative hypothesis	At least one variance is different
Significance level	α = 0.05

Tests

Method	Test Statistic	P-Value
Multiple comparisons	—	0.031



The chart illustrates the confidence intervals for the standard deviation of responses from each tool. It is evident that the intervals for Meta AI, ChatGPT 4.0 Free, and ChatGPT o1 overlap, while the interval for L-Squad is narrower. This indicates that L-Squad exhibits lower variability in its responses, suggesting greater consistency across different levels of comprehension demands. Since variances represent the dispersion of the data, a low p-value (such as 0.031) suggests that at least one of the tools demonstrates significantly different variability in its performance compared to the others.

Welch ANOVA Test

Additionally, an analysis of variance (Welch ANOVA) test (a statistical test used to assess the difference between the means of more than two groups) was conducted to evaluate whether the differences observed in the average concordance rates among the tools are statistically significant. The results of this test are summarized in Figure 2:

Figure 2: Analysis of Variance and Confidence Intervals for the Means Across Generative AI Tools.

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05

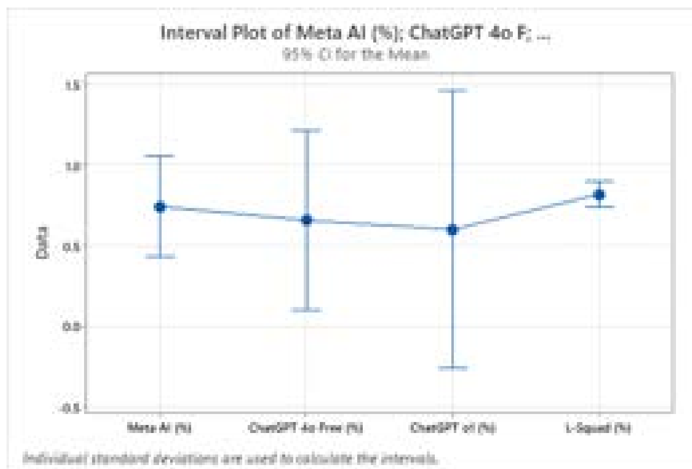
Equal variances were not assumed for the analysis.

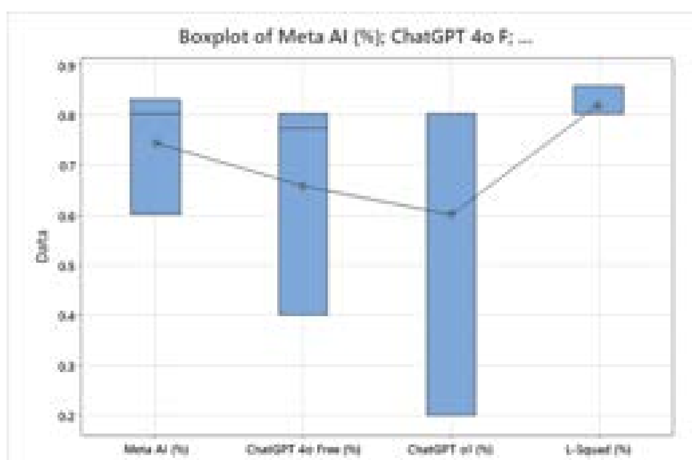
Welch's Test

Source	DF Num	DF Den	F-Value	P-Value
Factor	3	3.53328	0.87	0.533

Means

Factor	N	Mean	StDev	95% CI
Meta AI (%)	3	0.7430	0.1247	(0.4333; 1.0527)
ChatGPT 4o Free (%)	3	0.657	0.223	(0.103; 1.211)
ChatGPT o1 (%)	3	0.600	0.346	(-0.261; 1.461)
L-Squad (%)	3	0.8190	0.0329	(0.7372; 0.9008)





The p-value = 0.533 indicates that there are no statistically significant differences between the means of the evaluated tools regarding their overall performance. This suggests that the variations

observed in the results could be attributed to randomness rather than inherent differences in the capabilities of the tools. However, the descriptive analysis and confidence intervals highlight that L-Squad achieved a higher mean and a lower standard deviation, which may reflect a more consistent and robust performance in the context of the evaluation.

Discussion

The evaluation of generative AI tools reveals important implications for applying AI in normative contexts, particularly with respect to the ISO/IEC 17025 standard.

1. **Differences in Criterion-Based Understanding Reflect Specific Configurations and Required Improvements**

L-Squad performed significantly better in criterion-based understanding, achieving a score of 8 out of 10 compared to other tools like Meta AI and ChatGPT o1. This performance can be attributed to its personalized configuration based on Reinforcement Learning from Human Feedback (RLHF). According to Naik et al. (2024), this approach enables models to be adjusted to specific expectations through iterative refinement cycles. L-Squad exemplifies the impact of aligning a model with technical and normative contexts.

However, while L-Squad demonstrated outstanding performance in literal and criterion-based understanding, it is not without limitations, which must be addressed to enhance its effectiveness in future developments:

- The accuracy and relevance of L-Squad's responses are highly dependent on the quality and specificity of the instructions provided during its configuration. Any omission or ambiguity in the guidelines can limit its ability to interpret complex cases or specific contexts.
- Personalization based on a specific normative context, such as ISO/IEC 17025, may constrain L-Squad's ability to adapt to scenarios requiring flexibility beyond the standard. This presents a challenge for its applicability in multidisciplinary contexts or complementary standards.

2. **Limitations Observed in ChatGPT o1 Despite Its Advanced Reasoning Capabilities**

Despite being designed for advanced reasoning, ChatGPT o1 achieved a notably low score in criterion-based understanding (2 points). This result can be attributed to a lack of alignment with the specific instructions of the ISO/IEC 17025 standard. Although the "Uses advanced reasoning" engine can generate complex responses, the model lacked optimization for justifying answers with precise normative references—an essential feature in technical contexts. Fernández-Samos Gutiérrez (2023) emphasizes that, in normative applications, AI must prioritize human verification and technical coherence—factors that may have limited ChatGPT o1's performance due to insufficient focus on these aspects during its configuration.

Additionally, the lower score may reflect a reduced ability to justify responses based on explicit requirements or solid recommendations. This contrasts with tools like L-Squad, whose customization included specific directives guiding its reasoning toward well-founded normative interpretations.

3. **Appropriate Concordance in Literal and Inferential Understanding**

Across 31 questions, all four tools generated the same response, suggesting that generative models have a solid understanding in literal and inferential dimensions. This demonstrates the general capacity of the models to identify and contextualize explicit and implicit information within the ISO/IEC 17025 standard. However, the difference in criterion-based understanding highlights the need for specific configurations. As highlighted by the “AI-ladder” concept described by Maqsood et al. (2024), the design and training of the model determine its ability to tackle more complex tasks.

Taken together, these results highlight both the growing potential of generative AI in technical and standardization contexts, and the importance of intentional customization to ensure meaningful, standards-aligned outputs.

Conclusions

1. **Customization Enhances Normative Interpretation Capability**
   L-Squad, with its specific configuration and training based on reinforcement learning, demonstrates clear potential as a tool for interpreting and guiding the application of the ISO/IEC 17025 standard. This underscores the importance of customizing generative models to align their responses with specific normative requirements.
2. **Generative AI Holds Promise for Supporting the Application of Technical Standards**
   The results show that, with proper configuration, generative AI tools can interpret technical information and support the implementation of standards like ISO/IEC 17025. However, the configuration and training of the model are critical factors in ensuring its effectiveness in normative contexts.
3. **Need for Human Verification**
   Despite its ability to justify responses, the use of generative AI does not eliminate the need for review and validation by specialists. This highlights the importance of combining generative AI with human expertise to ensure accurate and responsible use in future normative applications.

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Author Biography

Diego Uribe is an assessor for the International Accreditation Service (IAS). Based in Peru, he is the founder of LAB SQUAD, an organization focused on training and consulting in accreditation and quality management systems. His expertise includes conformity assessment, risk management, and the application of international standards, with a specialization in ISO/IEC 17025 across Latin America.

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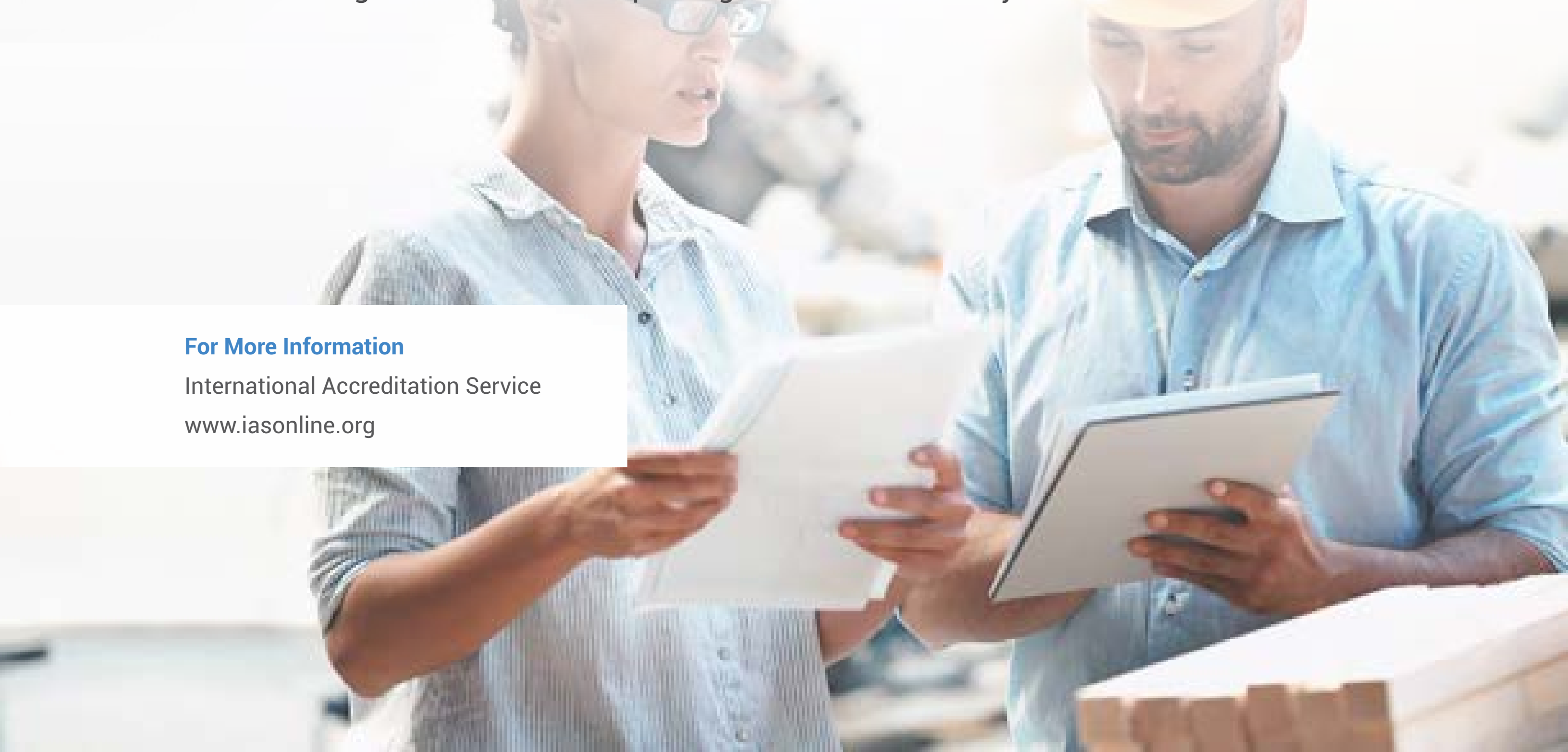

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Systematic Technology Identification for the Digitalization of the Conformity of Production in the Automotive Industry

By Kerstin Haeckel, M.Eng.[a]; Prof. Dr. Stephan Husung[b]; and Dr. Christine Wünsche[c]

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[a]BMW AG – Conformity of Production, Munich Germany
[b]Product and Systems Engineering Group, Technische Universität Ilmenau, Germany
[c]Technische Hochschule Deggendorf, Germany

-ABSTRACT-

Ensuring production conformity in the automotive industry is increasingly challenging due to the growing number of vehicle variants and rising regulatory requirements in global import markets.

“Conformity of Production” (CoP) refers to the assurance that all vehicles produced continue to meet the requirements established during type approval. Non-compliance with CoP can result in significant legal and financial consequences.

Currently, the BMW Group verifies component identification numbers (component IDs) and homologation labels through partially manual, randomly sampled inspections on the vehicle—referred to as component-identification checks.

Previous research indicates that automation and digitalization have the potential to improve the reliability of the component-identification process, also known as CID.

This paper aims to identify an automated verification concept to replace the current manual component-identification method within the CoP process. The goal is to enable reliable alignment between component IDs (homologation labels) and regulatory requirements. To date, no study has determined which technology is best suited to automatically detect component IDs.

To address this gap, proof-of-concept studies will be conducted to evaluate the practical suitability of potential technologies. The primary objective of this research is to determine the most appropriate detection technology for each CoP component, based on a detailed analysis of its specific characteristics.

Keywords: *Conformity of Production; Homologation; Automotive; Production; Manual Inspection; Assurance Process*

1 Introduction

In the automotive industry, labeling regulations and requirements are essential to ensure the safety, quality, and conformity of vehicles and their components. These regulations are established by national and international authorities (Sabadka et al., 2019).

Ensuring Conformity of Production (CoP) has become an increasingly significant challenge due to the growing diversity of vehicle variants and the rising regulatory demands of global import markets.

Each country has its own legal requirements that must be met as part of the CoP process. In Europe, for example, compliance with Regulation (EU) 2018/858 is mandatory (Brückner, 2009; KBA, 2018; Gospodinova & Miccoli, 2020).

CoP refers to the requirement that the production of vehicles consistently meets the specifications established during type approval. Regular verification ensures that the vehicles and components being produced match those submitted for approval. One such verification step is the component identification check.

This check involves confirming that the components installed in a vehicle correspond to the specifications stated in the type approval documentation submitted to the authorities (Morawietz, 2024).

At BMW Group, component identification numbers (component IDs or homologation labels) are currently inspected manually during production using a checklist and sampling approach. The label information is compared with CoP data to confirm that the installed components meet homologation requirements, thereby ensuring production conformity. This step is essential for maintaining vehicle quality and safety and for detecting deviations early in the production process.

Previous work (Sturm, 2023) has shown that some component IDs (homologation labels) did not always meet legal requirements or were partially illegible, leading to non-compliance in the CoP process. The labels are unique identifiers assigned to specific components and are used to verify their conformity (Schöbel, 2000).

Because the current manual process only allows a limited number of components to be checked, it increases the risk that incorrect or missing labels will pass unnoticed.

Recalls in the automotive industry are a widespread issue affecting all manufacturers, as they are required to ensure the safety and quality of their products in accordance with legal regulations. In the United States, between 2011 and 2020, 331 million vehicles were recalled due to safety defects and regulatory non-compliance (Bratzel, 2021).

Recall figures for 2020 and the first half of 2021 indicate a continued increase (Bratzel, 2021). This upward trend is largely attributed to the growing diversity of vehicle variants and increasingly strict conformity requirements (Sturm, 2023).

In 2024, several automotive manufacturers were forced to recall a significant number of vehicles due to quality issues and violations of conformity standards (Damm, 2024). Among them, BMW had to recall over 1.5 million vehicles due to quality deficiencies—marking the largest recall in the company's history (Hinrichs, 2024). These results highlight the need for manufacturers to take proactive measures.

Findings from a previous contribution (Sturm, 2023) suggest that the corrective measures implemented to date in the CoP process have not been sufficient to achieve an effective "zero-defect strategy." Such a strategy is only feasible through the implementation of automated assurance processes.

Earlier investigations established a theoretical foundation outlining the most promising technologies currently available. These technologies will now be evaluated through proof-of-concept (PoC) studies and validated in practice. The goal is to align each component ID (homologation label) with homologation requirements. This requires the use of a type key, which identifies a specific vehicle variant.

Determining which detection technologies are best suited for automatic component ID recognition remains an open research question. The main objective of this contribution is to evaluate and match the appropriate detection methods to specific components within the CoP framework.

2 State of the Art

An analysis of the current state of the art is essential to framing the existing knowledge surrounding technology options for the digitalizing the Conformity of Production (CoP) process in the automotive industry.

In earlier investigations, optoelectronic and transmitter-receiver systems were identified as the most relevant detection technologies. Therefore, this contribution focuses exclusively on those two technologies. The term "detection technology" refers to tools and methods used to identify and analyze specific objects, substances, or features (Doss et al., 2010).

Section 2.1 examines scientific findings and existing proof-of-concept (PoC) studies involving optoelectronic and transceiver systems. Section 2.2 discusses classification approaches for CoP components to determine which detection technology best fits each component ID. Section 2.3 presents the key research questions.

2.1 Concepts for Component Classification

The current evaluation of component IDs (homologation labels) includes more than 300 different components (BMW Group, 2021; Certification and Accreditation Administration of the People's Republic of China [CNCA], 2020). These CoP components are installed across various production and assembly areas within the BMW Group. Depending on the delivery condition—such as just-in-time (JIT), just-in-sequence (JIS), and stock (LB)—as well as the complexity of installation, accessibility, and module assignment (i.e., assigning components to specific assemblies), there are partial distinctions between components (BMW Group, 2021; 2023a).

Existing classification concepts in the literature have primarily focused on categorizing different materials (Roy et al., 1995; Dixon et al., 2006; Saralajew, 2019; Altenbach et al., 2004). In the context of component IDs, however, additional factors—such as installation complexity, accessibility, module assignment, and delivery condition—must also be taken into account. Therefore, a specific component classification is required for application in the CID (BMW Group, 2021).

2.2 PoCs of Optoelectronic and Transmitter-Receiver Systems

This section examines previously conducted proof-of-concept (PoC) studies involving optoelectronic and transmitter-receiver systems

Findings from Existing PoCs on Transmitter-Receiver

Systems Bauer (2019) explains that information exchange in electromagnetic transmitter-receiver systems occurs through signal transmission. The transmitter generates signals that are transmitted either via electromagnetic waves. These signals are captured by antennas attached to the relevant objects and forwarded to the receiver (Hesse et al., 2014). The receiver then interprets the signals to reconstruct the transmitted information. Common examples include radio frequency identification (RFID) (Kern, 2007; Jodin et al., 2012) and near field communication (NFC) (Shidaganti, 2021; Want, 2011).

Previous investigations identified RFID as a suitable transmitter-receiver technology for detecting component IDs (homologation labels). Accordingly, this analysis focuses on RFID.

Within the scope of PoCs, factors influencing RSSI values on metallic surfaces have been further examined (Curran et al., 2013). It was found that the RSSI values decrease when RFID tags are attached to metallic surfaces. Silva et al. (2018) developed a cost-effective concept for determining the operational efficiency of UHF RFID systems in the aviation industry and identified electromagnetic interference as a significant influencing factor. Jeevagan et al. (2014) discussed challenges in mounting RFID tags on metal surfaces of vehicles and proposed a theoretical model for RFID use in vehicle collisions.

Existing research shows that analyzing minimum activation power provides important insights for specific materials (Curran et al., 2013; Silva et al., 2018). However, direct comparisons across different materials, particularly for CoP components, are lacking. Many PoCs were not tested in actual production environments (Jeevagan et al., 2014; Tuan, 2012). Therefore, further research is needed to compare different RFID tags under both ideal and real-world production conditions.

Findings from Existing PoCs on Optoelectronic Systems

Böhmer, Ehrhardt, and Oberschelp (2010) explain that optoelectronic systems identify objects based on contours or labels such as colors, reflective markers, fonts, symbols, or barcodes. Detection is performed using optoelectronic sensors—such as laser scanners or cameras—that illuminate the object with an external light source and capture the reflected light (Hesse et al., 2014).

Previous studies have identified optical character recognition (OCR) as a suitable detection technology for optoelectronic systems to detect component IDs (homologation labels), among others. This section therefore focuses on OCR.

OCR is now a subfield of computer vision that extends beyond detecting content in printed documents (Chaudhuri, 2017). One practical application is the automated extraction of printed information on component labels.

The BMW Group currently uses three OCR models: Tesseract, EasyOCR, and PaddleOCR (BMW Group, 2023b). These models differ in algorithm type, neural network architecture, and layer connectivity. Tesseract is widely used and has industrial applications (Ramadan S et al., 2023; Brisinello et al., 2017; Bugayong et al., 2022). EasyOCR is employed in tasks such as automated license plate detection (Sainui et al., 2024; Salsabila et al., 2024; Sarhan et al., 2024). PaddleOCR is another OCR tool that offers strong performance in extracting printed label content (Bagaria et al., 2024).

Application of GPT-4v and Insights from Existing PoCs

Intelligent Character Recognition (ICR) and OCR are both used for text detection. The main difference lies in the type of text each can recognize: OCR detects printed or machine-written text (Schmalz, 2023), while ICR can recognize handwritten characters (Gunnoo, 2024). ICR enables handwriting detection in digital documents and converts it into editable text, whereas OCR is limited to printed content (Tang et al., 2024).

The ICR model Generative Pretrained Transformer 4 (GPT-4v) represents a significant breakthrough in AI by enabling visual data in large language models (LLMs) (Kaushik, 2024; Microsoft Corporation, 2024). Building upon GPT-3, it combines advanced language with visual content processing (Kaushik, 2024).

GPT-4v combines OCR capabilities with AI and can therefore be characterized as an ICR system. It allows for accurate detection of text in images—including handwritten text—and converts it into electronic format (Kaushik, 2024; Microsoft Corporation, 2024; Olesia, 2023).

While GPT-4v does not perform direct image processing on its own, it can interpret and enhance OCR results from computer vision systems. Its multimodal capabilities enable it to process both text and images, generate image descriptions, answer questions about visual content, and create images from text prompts (Kaushik, 2024; Microsoft Corporation, 2024).

To date, only a few scientific PoCs have investigated GPT-4v's potential in identifying and extracting information from components or comparing different materials (Shahriar et al., 2024; Wu et al., 2023).

Conclusion for Relevant Research Objective

Current research has demonstrated PoCs for both transmitter-receiver and optoelectronic systems. However, no PoC has yet examined their use across multiple CoP components under both ideal and real-world production conditions. This gap presents further research potential for scientific investigation.

2.3 Research Questions and Objectives

Based on the identified research needs (Sections 2.1 and 2.2), the following research questions arise:

Component classification and PoC for detection technologies:

1. Which detection technology is suitable for each component of the Conformity of Production (CoP) process?
2. How can the CoP components be effectively classified to align with the appropriate detection technology in PoCs?

Digitalization concept:

3. What type of detection technology can be applied to each specific component within the CoP framework?

3 Methodical Structure of the Contribution

Building upon previous findings in the current state of the art, the following methodical structure is used to answer the questions in this paper, as illustrated in Figure 1.

4 Component-ID Classification

The current CID process encompasses over 300 different components (BMW Group, 2021). To support the PoCs presented in Section 5, it is essential to first determine suitable component categories within this range. Therefore, a classification system will be developed to identify representative components prior to initiating the PoCs.

Section 4.1 defines the relevant characteristics and classifies the components accordingly. The results of this classification are presented in Section 4.2 for application in subsequent PoCs.

4.1 Definition of Properties and Classification of Components

To define appropriate component categories, it is necessary to establish relevant properties. CoP experts were consulted to identify these properties.

A total of 35 domain experts from the BMW Group, representing internal plants, participated in the evaluation. The materials of the 300 different CoP components were categorized into glass, elastomers, thermoplastics, thermoset and metals. Defined properties include materials used, accessibility in the vehicle or complexity of integration,

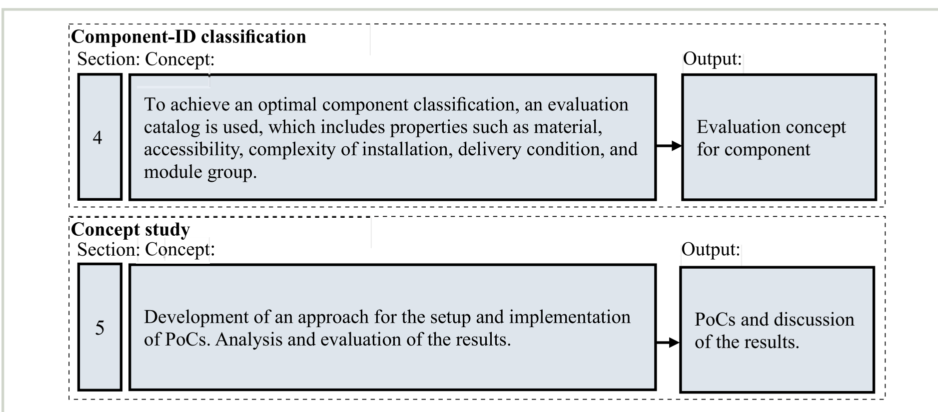


Figure 1: Methodical structure and description of the approach

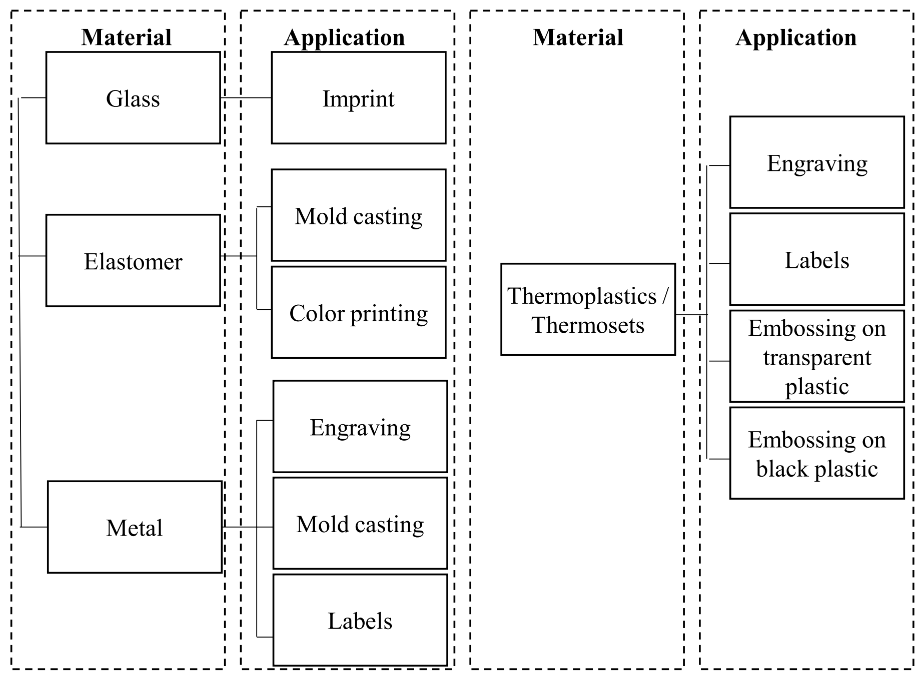


Figure 2: Classification according to material and application

Component classification class 1						
Evaluation criteria for component selection and result			Further evaluation criteria			
Material		Component	Complexity of installation (GS97025) / installation area	Module assignment	Delivery status (JIT / JIS /LB)	
Metal	Mold casting	Brake caliper axle 1 & 2	Not visible (zone C), pre-assembly	Driving dynamics	JIT	
		Gearbox	Not visible (zone C), pre-assembly	Drive system	JIS	
		Master brake cylinder	Not visible (zone C), pre-assembly	Driving dynamics	LB	
		Horn	Not visible (zone C), pre-assembly	Electrics	LB	
		Crankcase PCV	Not visible (zone C), pre-assembly	Drive system	JIT	
		Steering column	Not visible (zone C), pre-assembly	Steering system	JIT	
	En-graving	Front exhaust system	Not visible (Zone B), Front End Pre-Assembly	Exhaust system	JIS	
		Exhaust system center	Not visible (Zone B), Front End Pre-Assembly	Exhaust system	JIS	
		Lambdasonde	Not visible (zone C), pre-assembly	Drive sys		
		Motor	Not visible (zone B), pre-assembly			
		Partikelfilter	Nicht sicht			

Figure 3: Component classification class 1 (metal)

assembly area, and delivery condition. In addition to material selection, the application concept (e.g., engraving, molding) of the component ID (homologation label) is considered, as it is closely relates to the material. Other properties, such as accessibility, complexity of integration, assembly area, and delivery condition, are noted for informational purposes and do not contribute to the classification. Prioritization of these properties resulted in derived component classes for application in subsequent PoCs.

The classification by material and application concept is presented in Figure 2.

Figure 2 lists relevant materials such as glass, elastomers, metal, thermoplastics, and thermoset plastics, along with application concepts including printing, molding, color printing, engraving, and labels. These application concepts are assigned to the respective materials.

After defining the properties, components are classified. The highest priority is given to material and application concept. Other properties, such as the accessibility, complexity of integration, assembly area, and delivery condition, are listed for informational purposes without further classification.

An excerpt of the defined component classification classes is presented in Figure 3.

Figure 3 presents results for material and application concept properties. Components are assigned in the second column, showing the classification result for the first component classification class with the material property "metal." Additional component classification classes with the material properties such as glass, elastomers, thermoplastics, and thermoset plastics are defined but not listed here.

Additional properties like complexity of integration, module assignment, and delivery condition are mentioned in each component class for informational purposes. "Complexity of integration" is based on BMW Group Standard 97025 (BMW Group, 2022a), which segments components into different zones based on visibility and accessibility.

- **Evaluation Zone A:** Components in the immediate line of sight and easily accessible.
- **Evaluation Zone B:** Components not directly visible, with limited access or in blind spots.
- **Evaluation Zone C:** Components that, after assembly, are neither visible nor accessible.

Module assignment was performed according to BMW Group's specific requirements. Additionally, three delivery conditions are distinguished:

- Just-in-Sequence (JIS)
- Just-in-Time (JIT)
- Stock (LB) (BMW Group, 2022b).

These delivery conditions are listed as an additional evaluation category in the component classification table for informational purposes.

The defined component classes for subsequent PoCs are presented in Section 4.2.

4.2 Defining Representative Components for Each Component Classification

For each component class, a representative component has been defined for application in subsequent PoCs (refer to Section 5).

Optoelectronic Systems for Component Selection:

In Section 4.1, components were distinguished based on material and application concept. For optoelectronic systems, both distinctions are crucial. Materials vary in reflectivity, affecting the detectability of identification labels. Surface texture and color also influence the contrast between the label and background (Jeevagan et al., 2014; Liang et al., 2019; Patil et al., 2015).

Application concepts like engraving, printing, embossing, or molding impact the detectability of component IDs (homologation labels) (Liang et al., 2019; Patil et al., 2015).

The component selection results for optoelectronic system investigations are as follows:

- **Component Class 1: Metal**
  - Label: Engine control unit
  - Molding Casting: Master brake cylinder
  - Engraving: Particle filter
- **Component Class 2: Thermoplastics / Thermosets**
  - Embossing Black: Interior mirror
  - Transparent Embossing: Side flashing light
  - Label: Passenger airbag label
  - Engraving: Safety belt
- **Component Class 3: Elastomer**
  - Color Printing: Brake hose
  - Molded Casting: Tires
- **Component Class 4: Glass**
  - Color Print: Side pane

Transmitter-Receiver Systems for Component Selection:

In the case of transmitter-receiver systems, material selection significantly impacts detectability, whereas the application concept does not. Because RFID Tags are externally attached to components, application concepts that are important for the internal identification of components, such as color printing, molding, engraving or embossing, typically do not affect the functionality of the RFID Tags, as electromagnetic waves can pass through most materials. The detectability of the RFID tag remains unaffected as long as the surrounding material does not block or heavily attenuate the transmission of electromagnetic waves (Curran et al., 2013).

The component selection results for transmitter-receiver investigations are as follows:

- **Component Class 1: Metal**
  - Particle filter
- **Component Class 2: Thermoplastics / Thermosets**
  - Safety belt
- **Component Class 3: Elastomer**
  - Tires
- **Component Class 4: Glass**
  - Side pane

For each component class, one representative component was selected for the subsequent PoCs (see Section 5).

5 Proof of Concepts for Detection Technologies

In section 5.1, the framework conditions for the PoCs are defined. Based on these framework conditions, the PoCs for the optoelectronic systems and transmitter-receiver systems are carried out. The results of the PoCs are presented in section 5.2.

5.1 Derived Structure of the Proof of Concept (PoC)

The objective is to evaluate detection technologies through a practical experiment in the form of a PoC. Both optoelectronic systems and transmitter-receiver systems have shared as well as specific conditions. The corresponding Table 1 presents the common elements for both technologies.

Table 1: Framework conditions for the PoC for optoelectronic and transmitter-receiver systems

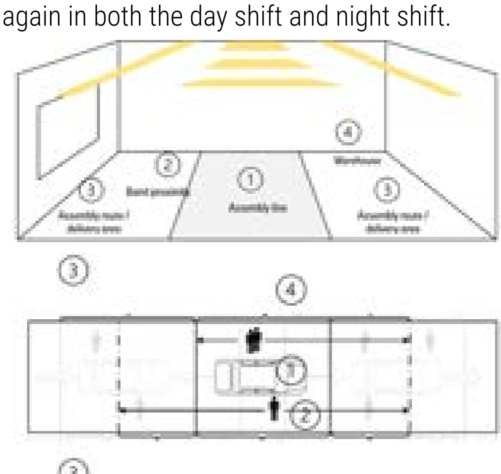
FRAMEWORK CONDITIONS:	
Focus	The objective is to evaluate the detection technologies identified in the utility analysis through a practical experiment. The main focus is on the automatic extraction of component IDs or homologation-related labels and their comparison with homologation data. Requirements and limits specified in the requirement profile need to be considered.
Components	According to relevant regulators, such as the Chinese implementation rule CNCA C11 01:2020 (Certification and Accreditation Administration of the People's Republic of China (CNCA), 2020), verification of more than 300 components is required. For the execution of the PoCs, a component classification for these 300 components has been established. This classification applies to both transmitters and receivers, as well as optoelectronic systems. The results of this classification determine which components will be used in the subsequent PoCs (section 4.1 and 4.2).
Success criteria	The defined success criteria of the PoCs aim to verify the reliability of ICR/OCR and RFID technologies in accurately detecting component IDs. **ICR/OCR results:** A result is considered "in order" (i.o.) if the detection and assignment of the component ID or homologation-label is correct. Conversely, a result classified as "not in order" (n.i.o.) indicates a discrepancy in the detection caused by the technology used. **RFID results:** A result is considered "in order" (i.o.) if the RFID tag attached to the component and the information contained therein regarding the component ID (homologation label) are correctly detected. Conversely, a result classified as "not in order" (n.i.o.) indicates a discrepancy in the detection caused by the technology used. For the PoCs, only correctly labeled components are used. This ensures that any defect classified as a non-conformity by the technology itself is considered a false positive.
Environmental conditions	The environmental conditions of the PoCs are adjusted to be realistic in line with internal BMW production environments, particularly regarding lighting levels. Since production conditions vary in terms of lighting levels, these differences are also considered within the PoCs. The individual PoCs are conducted both in specially developed environments and directly in real operational scenarios on the assembly line. The technologies must be capable of handling these variations and operating under different lighting conditions. A schematic representation (room view and top view) for measuring the lighting levels is shown in Figure 4 below. The numbers (1-4) indicate the measurement areas of the assembly line, near the assembly line, the assembly path/delivery area, and the small load carrier (SLC) (small load carrier) warehouse. At the BMW Group, numerous components are transported in so-called SLC containers and stored in special warehouses. For the assembly path, measurements were taken in both the window area and the non-window area. The measurement results of the lighting levels (lx) are presented again in both the day shift and night shift.  **Figure 4 Schematic representation room view and plan view.** The measurement results of the illuminance (lx) are depicted in Table 2.

Table 2: Measurement of illumination in the production line

Nr.	Location description	Illuminance [lx] Day shift	Illuminance [lx] Night shift
1	Assembly line	750 – 950	670 – 880
2	Band proximity	650 – 700	590 – 900
3	Assembly route (with window)	530 – 800	450 – 760
3	Assembly route (without window)	430 – 670	390 – 610
4	Small load carrier warehouse	480 – 750	410 - 690

The measurement results (1-4) show differences in relevant areas such as the assembly line, near the assembly line, the assembly path/delivery area, and the SLC warehouse. Differences in lighting levels between the day shift and night shift can also be observed. This is attributed to the use of natural daylight in the day shift, which can result in higher lighting levels. In the night shift, artificial lighting is used. The requirements for lighting levels are implemented according to the internal production conditions at BMW Group (BMW Group, 2018).

In the logistics area, the lighting levels in the goods receiving and order picking areas are also measured. The values are shown in Table 3 below.

Table 3: Measurement results logistics

Location description	Illuminance [lx] Day shift	Illuminance [lx] Night shift
Incoming goods	550 – 850	490 – 810
Picking area	450 – 780	390 – 680

The measured values for the goods receiving and order picking areas in Table 3 are comparable to the values for the assembly area in Table 2.

The specific framework conditions for the PoC of the optoelectronic systems are defined, as presented in Section 5.1.1.

5.1.1 Proof of Concept for Optoelectronic Systems

Table 4 provides a summary of the framework conditions for the PoC in the field of optoelectronic systems, including the technical parameters, required equipment, and planned test series and experiments.

Table 4: Framework conditions for the PoC on optoelectronic systems

FRAMEWORK CONDITIONS:

Technical parameters of the test component

To create optimal production conditions, a one-sided illumination is used, which is always aligned with the area of the component containing the component ID (homologation label). A schematic (left) and real representation (right) are shown in Figure 5.

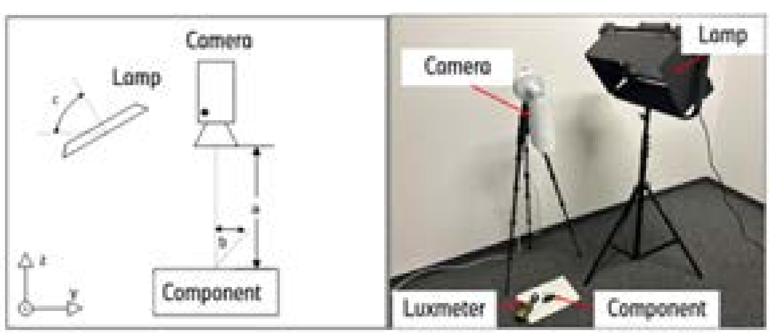


Figure 5: Test setup for optoelectronic systems (schematic and real views)

The distance (a) between the camera and the component is 110 cm. Both the camera angle of its optical axis to the component (b) and the lamp angle to the floor (c) are varied. The illumination intensity is set to values ranging from 400 to 950 lux to cover all illumination levels (see 5.1 Table 2). The values are measured using a luxmeter (Rose, 2024).

Experimental plan

Table 5 presents the values for the experimental design of the PoC for the optoelectronic system.

Table 5: Experiment plan optoelectronic system

Camera distance (a)	Camera angle (b)	Lamp angle (c)	Illuminance (lx)	OCR model
110 cm	90°	20°	400 lx	Tesseract
	45°	40°	675 lx	EasyOCR
		60°	950 lx	PaddleOCR

The determined values are based on the requirements profile. The experiment will investigate relevant factors, including the camera angle (90°, 45°), the lamp angle (20°, 40°, 60°, and 80°), the illumination intensity (400lx, 675lx, and 950lx), as well as three OCR models.

The use of the three OCR models is being implemented because all three models are currently approved at BMW and are applied in different areas.

ICR (GPT-4v)

As part of the PoC, the detection technology ICR is being evaluated using the approved model GPT-4v. In this case, a foundation model is being tested, for which the GPT-4v model from OpenAI is used (Olesia, 2023). GPT-4 is an advanced AI-based natural language processing technology developed by OpenAI (Kaushik, 2024). Only GPT-4 Vision is allowed to be used as the sole multimodal model due to a secure internal environment at the BMW Group (BMW Group, 2023). The same experimental parameters as in the experimental design in Table 5 are used for detecting the component IDs (homologation labels). The GPT-4 workflow is illustrated in Figure 6.

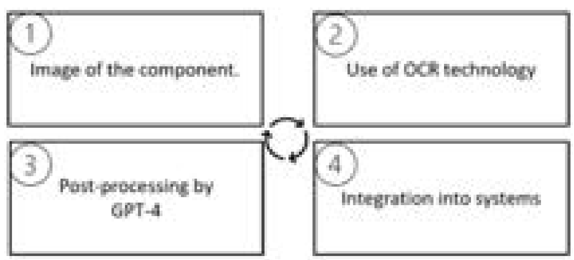


Figure 6: Workflow GPT-4v

The depicted workflow is divided into four steps:

1. **Component image capture:** A camera captures images of the components, on which the component IDs (homologation labels) are visible.
2. **Use of OCR technology:** For actual text detection, OCR models such as Tesseract, EasyOCR, or Paddle OCR are used. These models are specialized in identifying text in images and converting it into machine-detectable text (Bugayong et al., 2003; Sarhan et al., 2024; Bagaria et al., 2024; BMW Group, 2023).
3. **Post-processing by GPT-4v:** After text detection, GPT-4v is used to further process and extract the recognized text data.
4. **Integration into systems:** The information processed by GPT-4 is integrated into internal BMW systems to perform target/actual comparisons. GPT-4 analyzes the actual state, while the target state comes from BMW's internal homologation system (Approve) (BMW Group, 2022). A function in Microsoft Power Apps is used to perform the target/actual comparison (Microsoft, 2024) (Jayapandian, 2022).

When using GPT-4, so-called bots are created. Table 6 provides a list of all the settings of these bots.

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Table 6: GPT-4v Bots

<table>
<tr><th>Bot setting</th><th>Value</th><th>Meaning</th></tr>
<tr><td>Number of history elements</td><td>0</td><td>No previous images or information are taken into account in successive requests for the current check.</td></tr>
<tr><td>Model</td><td>GPT-4v</td><td>Enables access to OpenAI's vision model for uploading and analyzing images.</td></tr>
<tr><td>System Prompt</td><td>Your task is to identify key information on a vehicle component. Please verify if "INFORMATION" is visible.</td><td>For each component, the relevant CoP information is inserted in the task instead of "INFORMATION."</td></tr>
<tr><td>Temperature {0 – 1}</td><td>0</td><td>With a value of 0, the model works very deterministically. Values closer to 1 increase the creativity of the model, which can lead to unwanted fantasies and be inappropriate for the CoP check.</td></tr>
</table>

A dedicated bot was programmed for the verification of component IDs (homologation labels). The bot configuration was set based on the homologation process and remained consistent for each detection of the component ID (homologation label).

</td>
</tr>
<tr>
<td>Equipment</td>
<td>

• Camera (Canon EOS RP + RF 24-105mm F4-7.1 IS STM lens (Canon Europa N.V., 2024): The camera is operated in automatic mode, which automatically adjusts parameters such as exposure time, ISO film sensitivity, exposure compensation, as well as aperture and shutter speed.
• 2 industrial lamps (SLV 1004076 NUMINOS PHASE (DEL-KO GmbH, 2023) with 10 different adjustment levels.
• Tripods for mounting the lamps and camera.
• Lux meter: Used for measuring brightness (Sauter Luxmeter SO 200K) (Rose, 2024).

</td>
</tr>
<tr>
<td>Test series number of measurements</td>
<td>As part of the PoC, an experiment is conducted in which all parameters from the experimental design (see Table 5) are tested across all component classification classes (section 4.2).</td>
</tr>
<tr>
<td>Evaluation in real practical environments</td>
<td>

Figure 7 depicts an illustration of the evaluation in a real practice environment.

Figure 7: Evaluation in real practice environments

The evaluation takes place in the assembly. The insights gained in the PoC will be finally evaluated at the production line.

</td>
</tr>
</table>

5.1.2 Proof of Concept for Transmitter-Receiver Systems

As per regulatory requirements that stipulate visible component labeling must be present and not encoded (Certification and Accreditation Administration of the People's Republic of China (CNCA), 2020), sender-receiver systems such as RFID do not meet this requirement.

However, considering the potential future changes in regulatory requirements, sender-receiver systems are still considered in the subsequent PoC. Table 7 provides a summary of the conditions for the PoC related to transmitter-receiver systems, including the technical parameters, required equipment, as well as the planned test series and experiments.

Table 7: Framework conditions for the PoC for transmitter-receiver systems

<table>
<tr><th colspan="2">FRAMEWORK CONDITIONS:</th></tr>
<tr><td>Focus</td><td>The objective is to automatically extract component IDs and homologation-labels and compare them with the homologation data. In the PoC, the parameter of minimum activation power is continuously increased and the transmission power is recorded. The value is noted at which the RFID tag is first detected. A lower value indicates a higher sensitivity of the tag.</td></tr>
<tr><td>Technical parameters for the test component</td><td>The PoC is initially conducted in a square metal box under ideal environmental conditions to reduce electromagnetic interference. This also helps concentrate the radiation emitted by the antenna inside the box. A schematic (left) and real representation (right) are presented in Figure 8.

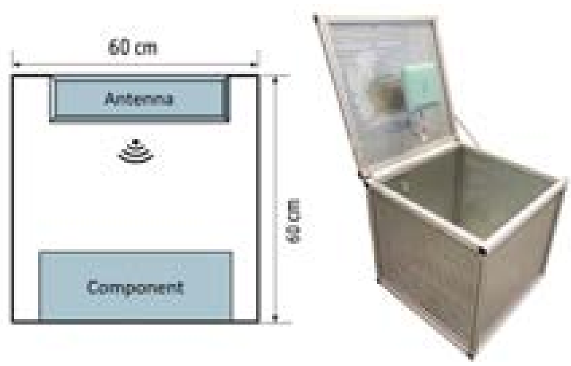


Figure 8: Schematic and real test setup transmitter-receiver systems

In the PoC, the performance of different RFID tags is evaluated with respect to the components according to the defined component classifications (see Section 4.2.2).</td></tr>
<tr><td>Experimental design</td><td>The values for the experimental design of the PoC for the sender-receiver system are presented in Table 8.

Table 8: Experimental plan transmitter-receiver system

<table>
<tr><th>TAG TYPE</th><th>TRANSMISSION POWER</th></tr>
<tr><td>Miniweb-Tag</td><td>Minimum activation power</td></tr>
<tr><td>Dogbone-Tag</td><td>10 dBm</td></tr>
<tr><td>On-Metal-Tag</td><td>20 dBm</td></tr>
<tr><td>Flag-Tag</td><td>30 dBm</td></tr>
</table>

Four tags (Miniweb, Dogbone, On-Metal, and Flag-Tag) that have been approved within the BMW Group are tested (BMW Group, 2023). In the PoC, the parameter of minimum activation power is continuously increased, and the transmission power is recorded. Activation powers of 10 dBm, 20 dBm, and 30 dBm are utilized.</td></tr>
</table>

<table>
<tr>
<td>Equipment</td>
<td>Due to cost considerations, the investigation is limited to the use of passive RFID tags (Weber, 2023). The industry standard for this purpose lies in the ultra-high-frequency range from 860 MHz to 930 MHz (Dressen, 2004; Want, 2006). Therefore, four different passive UHF tags are tested, as depicted in Figure 9.

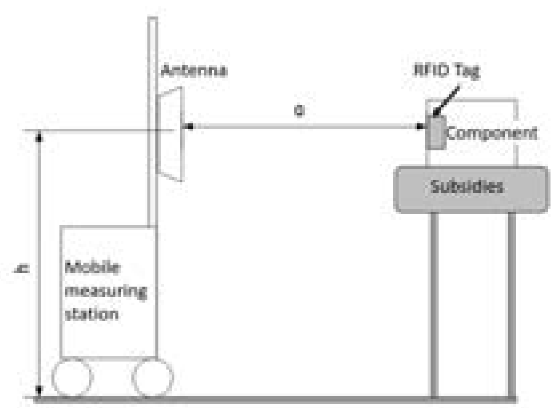

Figure 9: Released tags BMW Group (BMW Group, 2023)
These tags are approved within the BMW Group (BMW Group, 2023). The Miniweb tag stands out for its low cost and is a standard tag at BMW. The Dogbone tag might capture the waves emitted by the antenna better due to its larger surface area. Flag tags have only half of their underside with an adhesive surface, causing a portion of the tag to be positioned away from the component and not directly in contact with the material surface. The On-Metal tag has an insulating layer on its underside, creating a distance between the coil contained in the tag and the component, which can reduce potential interference from metallic components (Silva et al., 2018) (Weber, 2023). According to regulatory requirements, the power may not exceed 2 watts (Europäische Union, 2019), which corresponds to a setting of 33 dBm for the antenna. A Siemens SIMATIC RF680A antenna is utilized, which is particularly suitable for industrial applications and approved within the BMW Group (SIEMENS, 2023; BMW Group, 2023).he antenna's polarization is circular. The adjustment of settings and the evaluation of measurements are performed through a BMW internally developed user interface of the Siemens software, connected to the antenna via LAN (BMW Group, 2023).</td>
</tr>
<tr>
<td>Number of measurements in the test series</td>
<td>Within the scope of the PoC, all parameters from the experimental design (Table 8) are evaluated across all component classification classes.</td>
</tr>
<tr>
<td>Evaluation in real practice environments</td>
<td>The insights gained from the PoC are assessed under real operating conditions. The tags are evaluated for the defined component classes (see section 4 component classification) at the production line.
For the evaluation, a mobile measurement station is utilized, which can be flexibly positioned at relevant locations along the assembly line. A schematic representation of this measurement station can be found in Figure 10.


Figure 10: Mobile measuring station (RFID)</td>
</tr>
</table>

Evaluation in real practice environments (cont´d)	The distance between the antenna and the RFID tag (a) is set to 60cm, as in the ideal conditions (see Technical Parameters for the Test Component). The height (h) of the antenna can be individually adjusted to align it precisely with the height of the component. Figure 11 shows the mobile conveyor station on the left side and the mobile conveyor station in direct operation at the assembly line on the right side.

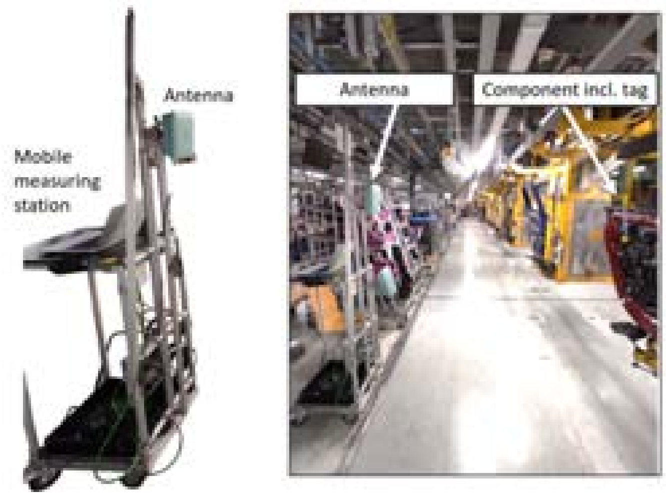


Figure 11: RFID conveyor station

The obtained values from the PoC are evaluated using the mobile conveyor station. The parameters from the experimental design (see Table 8) are utilized and analyzed.

5.2 Results and Discussion of the Proof of Concepts (PoCs)

The results of the optoelectronic systems and transmitter-receiver systems examined in the PoC are statistically analyzed and discussed in Sections 5.2.1 and 5.2.2.

5.2.1 Results for Optoelectronic Systems

For the statistical analysis, the three OCR models and the ICR system approved by the BMW Group are compared (Bagaria et al., 2024; Sarhan et al., 2024; Bugayong et al., 2022; BMW Group, 2023b). The PoC was conducted under the defined conditions described in Section 5.1.1 and on the component classes explained in Section 4.2. The results are depicted in Figure 12. The following statements always refer only to the conditions and objectives of the PoC.

The success criteria for the PoC are defined in the framework conditions, as shown in Table 1.

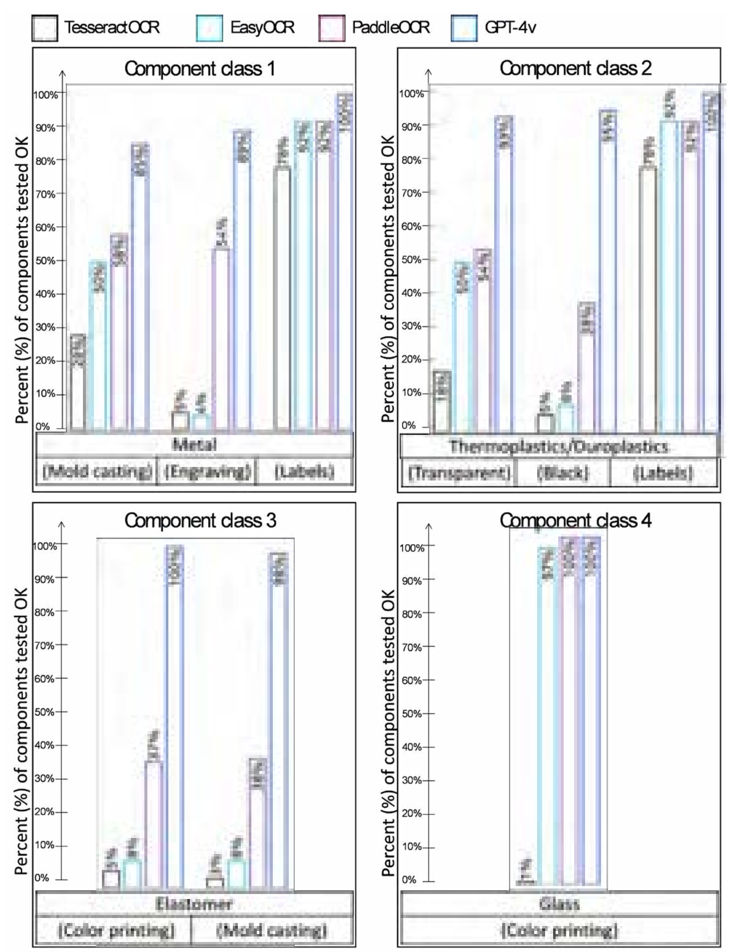


Figure 12: Results for optoelectronic systems

A value of 100% means that all component IDs (homologation labels) are correctly detected and no identification errors have occurred (100% true positives).

The OCR analysis yielded different results. Under the PoC conditions, the OCR models Tesseract and EasyOCR had limitations in accurately detecting component IDs. These models had the highest number of false positives. Only for Component Class 1 labels and Component Class 2 labels did all OCR models achieve 100%. However, for many images, the OCR models were unable to provide accurate results, often recognizing only individual letters or digits. Identification errors included confusion between characters such as "A" and "H," as well as confusion between numbers and "o" with "0."

Under the PoC conditions, the Tesseract and EasyOCR models had limitations in recognizing metal engravings, transparent and black plastic embossing, and elastomers with color printing or molding. In particular, the embossing was a challenge to detect. The PaddleOCR model consistently delivered a higher percentage of successfully detected component IDs but also did not achieve 100% accuracy except for color printing on glass, metal labels, and plastic labels.

In comparison, the GPT-4 Vision system achieved an approximate accuracy of 100% for almost all component classes. GPT-4 Vision correctly recognized the information for metal labels, plastic labels, elastomers with color printing, and color printing on glass, achieving 100% accuracy. For the remaining component classes such as metal molding, metal engravings, transparent plastic, black plastic, and color printing on molding, over 80% of the component photos were correctly recognized.

The next step is to evaluate the different models under real conditions.

Under the real conditions at the assembly line, a slight decrease in performance of the OCR models and the GPT-4 Vision system was observed. In particular, for metallic components (molding/engraving) and thermoset/thermoplastic components (transparent/black), an average decrease in results of 2 percentage points was noted. The detection of labels, elastomers, and glass remained unchanged.

Possible causes for these deviations could be the different lighting conditions in this area. These conditions could lead to overexposure and reflections, thereby affecting the detection and interpretation by the technology. Another explanation could be that the specific lighting conditions highlight or attenuate certain features of the components, leading to misinterpretations (Guoping Li et al., 2006).

It is crucial that the model used does not have identification deviations, meaning it should avoid incorrect interpretations of numbers and discrepancies in spacing. To achieve the required results according to the requirements profile, improvements in photo capture or image processing are necessary.

5.2.2 Results for Transmitter-Receiver Systems

Figure 13 presents the evaluation of the transmitter-receiver systems. The results are tested under ideal conditions (metal box, as described in the framework conditions in Section 5.1.2). The following statements always refer only to the conditions and objectives of the PoC and do not represent an assessment of the tags themselves.

On the ordinate axis of the graph, the minimum activation power in dBm is depicted, which represents the smallest required power level to activate an RFID system. The value in dBm indicates the strength of the signal needed to activate the RFID chip and enable data transmission (Silva et al., 2018). On the abscissa axis, the component classes from 1 to 4 are compared according to the defined component classes (metal, thermoset/thermoplastic, elastomer, glass) as discussed in Section 4.2. Each component class shows the results of the minimum activation power in dBm for the corresponding tags.

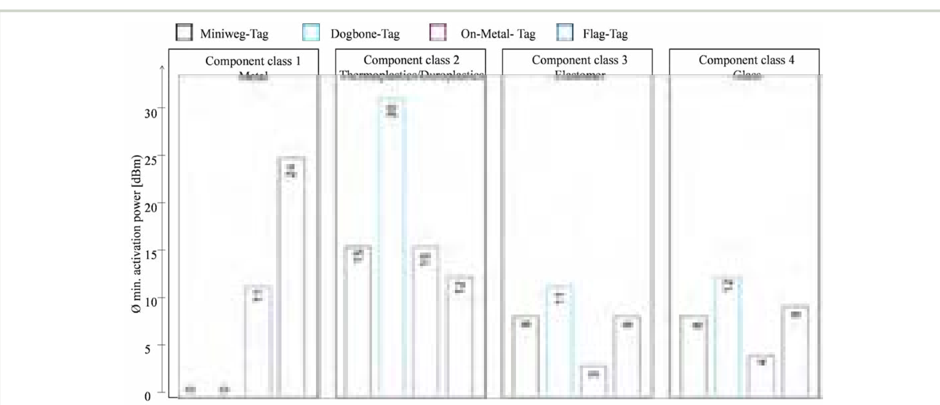


Figure 13: RFID - Results ideal conditions

When comparing the performance of different tags on different materials, it has been found that the Dogbone tag requires the highest power for activation, especially on thermoset/ thermoplastic materials where the activation power is at 30 dBm.

In the case of metal, only the On-Metal tag (11dBm) and the Flag tag (24 dBm) worked. Neither the Miniweb tag nor the Dogbone tag could be detected on the metal component in any position, regardless of the transmission power, indicating that there was interference due to the physical properties of the material.

Component Class 3 and Component Class 4 tags required less than 15 dBm on average for activation. The results show that higher received signal strength indication (RSSI) values can be achieved with increasing transmission power. The PoC has shown that RFID technology is applicable to CoP components, and there are specific tags for each component class that enable a 100% pass rate. Thus, it is proven that RFID tags are suitable for digitizing all component classes. The next step is to evaluate the results under real conditions.

Deployment Under Real Assembly Conditions:
An evaluation of the results from the ideal experiment is performed directly under real assembly conditions. The execution is carried out based on the defined boundary conditions in Section 5.1.2. The tags are evaluated according to the defined component classes (see Section 4.2) at the production line.

Under real conditions, both the On-Metal tag and the Dogbone tag require increased activation power for thermoset/ thermoplastic materials.

For Component Class 1 (metal), similar results were obtained as under ideal conditions. Neither the Miniweb tag nor the Dogbone tag could be detected on the metal component in any position, regardless of the transmission power. In general, all other component classes consistently require higher activation energy under real production conditions. Component Class 3 and Component Class 4 consistently require higher activation energies under real production conditions (averaging above 15 dBm).

Overall, satisfactory results could only be achieved at the highest power level of 30 dBm. The results from the ideal PoC could not be replicated in the tests conducted in the real production environment. It can be concluded that for all tags and materials in the real production environment, higher transmission power leads to better and more reliable results. The PoC for transmitter-receiver systems has confirmed that a suitable tag is available for each component class.

6 Applicability of the Detection Technologies to the CoP Components

Section 6 analyzes the applicability of the evaluated technologies to determine which technology are best suited for specific CoP components.

The results of the PoCs (see Section 5.2) indicate that both transmitter-receiver systems and optoelectronic systems can be applied for the digitalization of the homologation process.

For transmitter-receiver systems, appropriate tags were identified for each component class. In the case of optoelectronic systems, OCR models demonstrated strong performance—achieving over 98% success rates for easily legible components, such as labels. However, for other component classes, frequent identification deviations were observed. In comparison, GPT-4v achieved an even higher percentage of successfully tested components (see Section 5.2).

The results from the PoCs—specifically those that reached 100% correct detection—have been mapped to the component classification classes defined in Section 4.2. A sample of these results is illustrated in Figure 14.

Figure 14 assigns the previously defined component classes (see Section 4.2) to the most promising detection technologies that achieved 100% detection accuracy. The right-hand column, "Technology Classification," identifies which detection technologies can be used for CID verification of the component ID (homologation label). This figure shows an excerpt from Component Class 1 (metal, molding), which has been assigned to the most effective evaluated detection technologies.

7 Summary of the Results and Outlook

The increasing diversity of vehicle variants and the tightening legal requirements in the automotive industry continue to pose significant challenges for ensuring production conformity (Sabadka et al., 2019; Sonya Gospodinova; Federica Miccoli, 2020). Previous studies (Sturm, 2023) have shown that component IDs (homologation labels) do not always meet legal standards, in part because manual

Component classification class 1							
Evaluation criteria for component selection and result			Further evaluation criteria			Technology classification	
Material		Component	Complexity of installation (GS97025) / Installation area	Module assignment	Delivery status (JIT / JIS / LB)	Transmitter-receiver systems	Optoelectronic systems
Metal	Mold casting	Brake caliper axle 1 & 2	Not visible (zone C), pre-assembly	Driving dynamics	JIT	On-Metal-Tag (30dBm)	GPT-4v / PaddleOCR (inkl. BV)
		Gearbox	Not visible (zone C), pre-assembly	Drive system	JIS	On-Metal-Tag (30dBm)	GPT-4v (inkl. BV)
		Master brake cylinder	Not visible (zone C), pre-assembly	Driving dynamics	LB	On-Metal-Tag (30dBm)	GPT-4v (inkl. BV)
		Horn	Not visible (zone C), pre-assembly	Electrics	LB	On-Metal-Tag (30dBm)	GPT-4v (inkl. BV)
		Crankcase PCV	Not visible (zone C), pre-assembly	Drive system	JIT	On-Metal-Tag (30dBm)	GPT-4v (inkl. BV)
		Steering column	Not visible (zone C), pre-assembly	Steering system	JIT	On-Metal-Tag (30dBm)	GPT-4v / PaddleOCR (inkl. BV)
		Engine control unit	Not visible (zone C), pre-assembly	Electrics	JIT	On-Metal-Tag (30dBm)	GPT-4v / PaddleOCR (inkl. BV)
		Tires Rim size	Visible (Zone A), Front End Pre-Assembly	Driving dynamics	JIS	On-Metal-Tag (30dBm)	GPT-4v / PaddleOCR (inkl. BV)
		Windshield wiper motor	Not visible (zone C), pre-assembly	Electrics	JIT	On-Metal-Tag (30dBm)	GPT-4v (inkl. BV)
	En - graving	Front exhaust system	Not visible (Zone B), Front End Pre-Assembly	Exhaust system	JIS	On-Metal-Tag (30dBm)	GPT-4v (inkl. BV)
		Exhaust system center	Not visible (Zone B), Front End Pre-Assembly	Exhaust system	JIS	On-Metal-Tag	
		Lambdasonde	Not visible (zone C), pre-assembly	Drive system			
		Motor	Not visible (zone B), pre-assembly				

Figure 14: Illustration of the assignment of the detection technologies to the homologation components (excerpt)

sampling inspections cover only a limited portion of the components. As a result, automotive manufacturers face recurring recalls and must ensure the safety and quality of their products in accordance with legal regulations (Bratzel, 2021).

One of the main objectives of this contribution was to identify and evaluate a suitable automation solution for the component identification process.

The results show that both transmitter-receiver systems (e.g., RFID) and optoelectronic systems (e.g., ICR/OCR) are viable options for automating the homologation process. However, as current regulatory requirements mandate that component labeling be visible and not encoded (Certification and Accreditation Administration of the People's Republic of China (CNCA), 2020), transmitter-receiver systems such as RFID are not compliant at this time. Nevertheless, they were included to account for potential future changes in regulatory standards.

In the evaluation of optoelectronic systems, GPT-4v demonstrated particularly strong performance, correctly detecting a high percentage of components under relevant conditions. Hardware and software improvements enabled 100% accurate detection for more than half of the evaluated components (see Figure 12).

The primary objective of this study was to determine the appropriate detection technology for each

CoP component. A detailed analysis was carried out to identify the most effective solution for each component class.

The results of this contribution have far-reaching implications for the entire automotive industry. With the increasing diversity of vehicle variants and the tightening of regulatory requirements, automating the homologation process is crucial to ensure production compliance and minimize recalls. The identification and evaluation of suitable automation solutions, as presented in this contribution, provide valuable insights for automotive manufacturers.

By implementing the recommended detection technologies, such as optoelectronic systems like GPT-4v, the manual component identification process can be transformed into a digitized verification process. This transformation improves efficiency and accuracy in the field of homologation assurance. The findings can be also applied in other quality assurance processes.

Further research is needed to define potential process steps for detecting component IDs (homologation labels) within the CID workflow. An overall process concept should be developed for all 300 components (BMW Group, 2021) in the product development process, incorporating the recommended detection

Implementing these technologies would transition the manual CID process into a digitized verification process. This transformation will require employees at BMW Group and its suppliers to adapt to the new systems, which in turn calls for careful consideration of user acceptance. Thus, a review and evaluation of technology acceptance represents an additional area for future research.

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Author Biographies

Kerstin Haeckel, born in Straubing, Germany, earned a Master of Engineering in 2018 at the Technische Hochschule Deggendorf. Since 2018, she has been employed at BMW Group in the Conformity of Production Department. Since October 2021, a doctoral student in Mechanical Engineering at Technische Universität Ilmenau. Email: Kerstin.Haeckel@bmw.de.

Prof. Dr. Stephan Husung was born in 1981 in Sömmerda (Germany). He studied mechanical engineering (diploma) from 2000 to 2005, specializing in machine design and computer applications in mechanical engineering. In 2011, Stephan Husung completed his PhD at the Department of Mechanical Engineering at the Technische Universität Ilmenau.

From 2016 to 2020 he worked at :em engineering methods AG in the field of Model-Based Systems Engineering in Darmstadt. Since 2021, Stephan has been a university professor at the Technische Universität Ilmenau and chairs the Product and Systems Engineering Group. In 2023, he was elected academic dean of the Department of Mechanical Engineering. His research focuses on the development of Model-Based Systems Engineering approaches for the systematic and collaborative development of sustainable and robust products.

Dr. Christine Wünsche is a professor at the Deggendorf Institute of Technology and works at the Center for Applied Research, specifically at the Institute for Precision Machining and High Frequency Technology. She teaches at the Faculty of Applied Natural Sciences and Business Engineering. Dr. Wünsche completed her studies in the field of inorganic-nonmetallic materials.

Balancing Innovation and Openness: The Role of Artificial Intelligence in Conformity Assessment

By Hodjat A. Bagheri, BSc of Industrial Engineering, freelance assessor, lead auditor and independent researcher, Fredericton, Canada

DOI: 10.55459/IJCA/v4i1/HB

-ABSTRACT-

Artificial Intelligence (AI) is revolutionizing industries by improving efficiency, reducing human bias, and enhancing decision-making accuracy. In the conformity assessment sector—encompassing testing, inspection, certification, and accreditation—AI holds significant potential to increase impartiality and streamline operations. This is especially relevant in regions like MENA (Middle East, North Africa) and CIS (Commonwealth of Independent States), where diverse and evolving regulatory landscapes present unique challenges. At the same time, the integration of AI raises key concerns about transparency, ethical considerations, and stakeholder trust.

This paper explores AI's transformative role in conformity assessment, analyzing its applications, benefits, and limitations, and offering strategies for balanced implementation. Supported by practical examples, it shows how AI can help the industry achieve greater fairness, efficiency, and adaptability—even as organizations continue to navigate technical and regulatory hurdles.

Keywords: *Artificial Intelligence in Conformity Assessment, AI Compliance Automation, MENA and CIS Regulatory Frameworks, AI Risk Management in Certification, Explainable AI in Quality Assurance, AI in Testing and Inspection, Ethical Challenges of AI in Regulation, AI Driven Product Certification, Smart Compliance Systems, AI Implementation in Emerging Markets*

Introduction

Conformity assessment plays a critical role in global commerce by ensuring that products, systems, and services meet established standards and regulatory requirements [1]. These processes are essential for protecting public safety, maintaining quality, and enabling international trade. While traditional methods have served these goals effectively, they are often labor-intensive, susceptible to human error, and may lack the consistency required for today's increasingly globalized operations.

Artificial Intelligence (AI) has emerged as a transformative force across industries, with the potential to address many of these limitations [2]. Although its use in conformity assessment is still in the early stages, AI technologies are beginning to reshape how testing, inspection, and certification processes are conducted.

This is particularly relevant in regions such as MENA and CIS, where diverse and evolving regulatory systems make AI a valuable tool for unifying practices, improving efficiency, and supporting cross-border standardization. However, its integration raises key questions around transparency, ethics, and trust. This paper explores both the opportunities and the challenges posed by AI in conformity assessment, offering a structured analysis supported by real-world examples and recommendations for balanced implementation.

The Role of AI in Conformity Assessment

AI technologies are being integrated into various stages of the conformity assessment process, significantly transforming how these activities are conducted. Key applications include:

Automating complex tasks

AI techniques—such as natural language processing (NLP) —can automate the review of technical documentation, inspection reports, and test results, helping reduce assessment time [3]. For example, NLP tools can analyze compliance documents across multiple languages, easing navigation of diverse regulatory environments.

Enhancing accuracy and consistency

Human assessors may introduce subjectivity due to fatigue or unconscious bias. In contrast, AI systems trained on large datasets can deliver more consistent results, reducing discrepancies [4]. Machine learning models can also detect patterns in past non-conformities, helping to flag potential risks earlier in the process.

Real-time decision support

AI-powered tools, including augmented reality (AR) systems, can support inspectors by delivering real-time insights during assessments—improving accuracy in defect detection [5].

Advanced anomaly detection

Deep learning models are capable of analyzing images, video, or sensor data to detect subtle product deviations that may go unnoticed by human inspectors [6]. For instance, in manufacturing, AI can identify flaws in materials with a high degree of precision.

Data integration and analysis

AI systems can aggregate and analyze data from testing labs, inspection agencies, and certification bodies, providing a more comprehensive view of compliance across the entire supply chain.

Case Study: AI in UAE Manufacturing

In the United Arab Emirates (UAE), a key MENA-region country, AI-driven image analysis has been applied since 2023 to improve conformity assessment by inspecting manufactured goods. The technology enabled real-time defect detection and reduced manual inspection time by 35% [7]. This example highlights AI's potential to enhance efficiency and impartiality in testing and inspection processes. However, integrating such technologies also raises concerns about transparency, pointing to the need for clear and explainable AI decision-making within evolving regulatory systems. As this trend continues, similar applications are expected to emerge—some perhaps still underreported—throughout the broader MENA and CIS regions.

Benefits of AI for MENA and CIS Markets

The MENA and CIS regions present distinct opportunities for AI integration, thanks to their socio-economic diversity and expanding trade ambitions:

Addressing regional diversity

AI systems can adapt to varied local regulations while maintaining consistency across assessments. Multilingual AI tools, for example, facilitating compliance by processing documents in Arabic, Russian, Turkish, and Farsi [8].

Reducing costs and improving accessibility

Automated systems can lower the cost of conformity assessment, making certification more accessible to small and medium-sized enterprises, In Kazakhstan, AI implementation reduced certification expenses for exporters by 20% in 2024 [9].

Accelerating market entry

Faster assessment processes enable quicker product launches. Predictive analytics can also help companies anticipate changes in regulatory requirements, giving them a competitive edge.

Enhancing global trade

By aligning local products with international standards, AI supports export readiness and builds trust with global trade partners.

Challenges and Limitations of AI in Conformity Assessment

Despite its advantages, the integration of AI into conformity assessment faces several important challenges:

Transparency concerns

The "black-box" nature of many AI models makes it difficult to explain how decisions are made, which can undermine stakeholder trust—particularly in safety-critical applications [10]. For example, in 2021, unclear AI-driven decisions during EU certifications raised concerns among regulators [11].

Ethical implications

AI systems trained on biased or incomplete data can produce unfair or inconsistent results. A 2020 study highlighted that underrepresentation of MENA-region data led to skewed outputs in certain AI models [12].

Dependence on quality data

AI requires large volumes of high-quality data to function effectively—a challenge in parts of MENA and CIS where digital infrastructure is still developing [13]. In Iraq, for example, limited access to reliable records slowed AI adoption in 2023 [14].

Regulatory and legal challenges

Existing legal frameworks often lag behind AI advancements. Questions around accountability, data privacy, and cross-border data usage remain unresolved. The GDPR, for instance, provides limited guidance on how to regulate AI-driven decision-making [15].

Resistance to change

Stakeholder resistance can also be a barrier. Some assessors are skeptical of AI's reliability or fear it may lead to job displacement. A 2023 survey in Saudi Arabia found that 55% of assessors expressed hesitation toward AI integration [16].

Case Study: AI in Egyptian Exports

Egypt's agricultural sector began leveraging AI in 2023 to enhance export certification processes—a critical aspect of conformity assessment for international trade. According to the Egyptian Export Council [17], the initiative focused on high-demand agricultural products such as citrus fruits and vegetables, which represent major exports to the European Union.

The AI system, based on machine learning models, analyzed quality control data—including product size, pesticide residue levels, and visual defects—to certify compliance with stringent EU standards. Implemented by the Egyptian Ministry of Trade and Industry in collaboration with local agribusinesses, the system processed inspection data in real-time. As a result, compliance with EU regulations increased by 10%, and certification processing times were reduced by 15%, enabling faster export approvals.

However, the rollout faced several challenges. Inconsistent regional data from rural farms led to delays, exposing weaknesses in the national data infrastructure. Additionally, exporters expressed concern over the lack of explainability in AI decision-making, emphasizing the need for greater transparency to maintain trust with international buyers.

This case illustrates AI's potential to streamline certification and improve efficiency in the MENA region's agricultural exports, while also highlighting the importance of data quality and transparency in building stakeholder confidence.

Recommendations for a Balanced Approach

To help overcome the challenges associated with AI integration in conformity assessment, the following strategies are recommended:

Incorporate human oversight

AI should support—not replace—human expertise. Auditors and assessors should validate AI-generated outputs to ensure decisions are context-aware and reliable [18].

Develop explainable AI models

Transparent systems like SHAP (SHapley Additive exPlanations) clarify AI-driven decisions, promoting fairness and accountability—especially in evolving regulatory environments—while also requiring technical capacity for effective implementation [19].

Invest in regional data infrastructure

Improving digital infrastructure in MENA and CIS countries is essential for effective AI deployment. Initiatives like the UAE's Smart Dubai provide a model for strengthening regional data ecosystems [20].

Enhance collaboration

Ongoing collaboration between AI developers, regulators, and conformity assessment bodies can support the development of region-specific solutions.

Establish ethical guidelines

Applying ethical frameworks—such as UNESCO's AI Ethics Recommendation—can promote fairness, transparency, and accountability in AI-driven assessments [21].

Conclusion

AI has the capacity to reshape the field of conformity assessment—improving fairness, streamlining processes, and increasing consistency, particularly in regions like MENA and CIS. The case studies on UAE manufacturing and Egyptian agricultural exports illustrate AI's practical benefits when applied thoughtfully.

However, for AI to be adopted responsibly, key challenges must be addressed—including concerns around transparency, ethics, data quality, and regulatory clarity. Even now, some assessors are already using available AI tools to generate or polish their reports, highlighting the urgency of a balanced approach. Professionals should incorporate human oversight, prioritize explainable AI systems, and invest in stronger data infrastructure. Meanwhile, regulators must work to define accountability—especially in cases involving liability for AI-driven decisions.

With the right safeguards in place, AI can continue to drive innovation in conformity assessment while maintaining trust, safety, and integrity across global markets.

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Author Biography

Hodjat A. Bagheri holds a BSc in Industrial Engineering and is a distinguished expert in conformity assessment, standardization, and systems engineering. Based in Fredericton, Canada, he serves as Head Manager of the BRSM Certification Body in Istanbul, Turkey, while also working as a freelance assessor and lead auditor. With an extensive background in consulting and auditing ISO management systems—including ISO 9001, ISO 14001, ISO 45001, ISO 50001, ISO 22000, and ISO 13485—Hodjat has guided numerous organizations toward operational excellence. He brings a wealth of experience in designing systems and production lines for the food and medical device industries. As a member of the ISIRI Standards Development Committee and ISIRI Technical Committees TC 301 and TC 163, he actively shapes international standards. His research, affiliated with ISO initiatives, focuses on integrating advanced methodologies, such as artificial intelligence, into confirmation and validation processes, bridging practical industry applications with innovative regulatory frameworks to drive global market advancements.

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The AI Transformation in Metrology and Conformity Assurance

By Emil Hazarian, California State University Dominguez Hills, College of Continuing and Professional Education,

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-ABSTRACT-

Artificial Intelligence (AI) is transforming metrology and conformity assurance by improving measurement accuracy, automating compliance processes, and enabling predictive analytics. This shift benefits industries such as manufacturing, healthcare, aerospace, and pharmaceuticals by enhancing efficiency, reducing errors, and ensuring regulatory compliance. AI-driven solutions like Digital Calibration Certificates (DCCs) and machine learning-based conformity assessments streamline operations, minimize human intervention, and strengthen quality control. However, challenges such as job displacement, data privacy concerns, and cybersecurity risks must be addressed. As AI integration deepens, regulatory bodies, accreditation organizations, and industries must collaborate to ensure ethical governance and standardization—securing a more reliable and efficient future for global quality assurance.

This article is intended for professionals and organizations across sectors that rely on precision measurement, quality assurance, and regulatory compliance. This may include metrology and calibration professionals, quality assurance and compliance experts, industry-specific stakeholders, accreditation and standards organizations, business leaders, and academic institutions.

Keywords: *Artificial Intelligence in Metrology, Conformity Assessment, Digital Calibration Certificates, AI Risk Management, redictive Maintenance, ISO/IEC Standards, AI in Quality Assurance, Machine Learning in Measurement Science, Bias and Trust in AI Systems, AI-Enabled Conformity Verification*

Introduction

Artificial Intelligence (AI) is redefining the fields of metrology and conformity assurance, transforming how measurements are taken, analyzed, and applied in quality control. This transformation is not only technological but also cultural and operational, impacting industries from manufacturing to healthcare and beyond. This article explores the evolution of AI in metrology and conformity assessment, its current applications, and its future potential, supported by real-world examples and references.

Note: A list of acronyms and definitions used throughout this article is provided in **Appendix D.**

AI in Metrology and Conformity Assurance: A Historical Perspective

Metrology—the science of measurement—has long served as the foundation of quality assurance. Historically, measurement systems relied on manual observation and mechanical instruments. With the advent of digital technology, however, electronic sensors and automated systems began to transform the field. The transition from manual to digital calibration methods— such as the Digital Calibration Certificate (DCC)—paved the way for AI integration.

The role of AI in conformity assessment has evolved in parallel. Initially, compliance assessments were performed through manual inspections and sample testing. Over time, statistical analysis and software tools enhanced efficiency, but the introduction to AI has elevated accuracy and predictive capabilities to unprecedented levels.

The Influence of AI in Conformity Assessment and Measurement Science

AI is transforming conformity assessment by enhancing precision, automating compliance verification, and reducing the need for human intervention. AI-powered algorithms can analyze vast datasets to detect deviations from compliance norms with greater accuracy than human auditors. Machine learning models help regulatory bodies and certification organizations anticipate conformity issues before they arise, allowing preemptive corrective actions. In industries such as aerospace and pharmaceuticals, AI-driven predictive analytics ensure that calibration and compliance processes remain within acceptable tolerance limits.

In measurement science, AI is revolutionizing data acquisition and analysis. Advanced AI models can refine measurement uncertainty calculations, improving confidence levels in scientific experiments. AI-enabled virtual metrology systems offer real-time data analysis and corrections without interrupting production lines, significantly improving efficiency in semiconductor manufacturing and nanotechnology applications.

The Pros and Cons of AI in Metrology and Conformity Assurance

As AI continues to evolve, its impact can be seen across all aspects of quality and measurement. Below are some of the primary advantages and disadvantages of AI in these fields:

Pros of AI:

1. **Operational Efficiency:** AI operates at peak efficiency, surpassing human capabilities in data analysis, pattern recognition, and repetitive task completion.
2. **High Precision:** AI minimizes errors in complex calculations and enables real-time, high-accuracy decision-making.
3. **Speed and Scalability:** AI processes vast amounts of data at unmatched speeds— delivering insights in seconds that would take humans hours or even days.
4. **Innovation Enablement:** AI drives innovation, transforming industries and supporting solutions once thought unattainable.
5. **Enhanced Security:** AI strengthens cybersecurity by using advanced algorithms to detect and respond to threats with increased precision.

Cons of AI:

1. **Job Replacement Risks:** Automation through AI poses a significant threat to employment, with estimates suggesting 400 million to 800 million jobs could be automated by 2030. Sectors such as manufacturing, transportation, and retail may be most affected,
2. **Privacy Concerns:** AI's reliance on large-scale data collection raises serious privacy issues, including the risk of misuse, surveillance, and data breaches.
3. **Over-Reliance and System Vulnerability:** Dependence on AI can introduce systemic vulnerabilities, with the potential for catastrophic outcomes if systems fail or are compromised.
4. **Widening Inequality:** AI often benefits organizations with greater technological access, increasing the gap between tech-enabled and resource-limited entities.
5. **Cybersecurity Exposure:** Despite its role in enhancing security, AI systems are themselves vulnerable to adversarial attacks and sophisticated hacking, posing risks to critical infrastructure.

AI Applications Across Industries

AI is making significant contributions to a wide range of sectors beyond metrology and conformity assurance:

- **Automotive:** AI-powered vision systems enhance manufacturing efficiency and enable early defect detection, as demonstrated by BMW's AI-driven quality inspection processes.
- **Healthcare:** AI-driven imaging technologies support early diagnosis and personalized treatment planning.
- **Aerospace:** AI is used to improve predictive maintenance of aircraft components, helping companies like Boeing minimize unplanned downtime.
- **Pharmaceuticals**: Companies such as Pfizer leverage AI to strengthen risk-based conformity assessments to meet FDA compliance standards.

Additional examples of AI applications in metrology—including virtual metrology tools, AI-driven microscopy, and computed tomography—are provided in **Appendix B**.

The Present: AI's Role in Metrology and Quality Assurance

To illustrate how artificial intelligence is redefining precision measurement and conformity assessment, the following five case studies highlight innovations from global industry leaders:

Case Study 1: **GE Aviation (United States) – AI-Powered Vision Systems for Jet Engine Component Inspection**

Company: GE Aviation

Application: Manufacturing jet engine components

Challenge:
GE needed a faster and more accurate method for inspecting high-precision turbine parts. Traditional dimensional checks were slow and susceptible to error.

AI Solution:
GE adopted AI-powered vision systems combined with machine learning algorithms to automate the inspection of blade geometry and surface finish. These systems analyze thousands of features in real time, identify any deviations from design specifications, and recommend corrective actions.

Impact:
- Reduced inspection time by 40%
- Enhanced consistency in quality control
- Enabled real-time conformity assessments during manufacturing
- Decreased rates of rework and scrap

Case Study 2: **Siemens AG (Germany) – Smart Calibration and Digital Metrology in Advanced Manufacturing**

Company: Siemens AG

Application: AI-driven calibration and smart metrology in advanced manufacturing and industrial automation

Challenge:
Siemens operates cutting-edge manufacturing plants where measurement accuracy is crucial for product safety and performance—especially in energy, transport, and medical sectors. Traditional calibration methods were slow, inconsistent, and lacked real-time feedback.

AI Solution:
Siemens introduced AI-powered metrology systems within its digital factories. These systems use machine learning and sensor-integrated tools to:

- Automate real-time dimensional and geometric measurements
- Predict calibration needs based on historical performance data
- Generate ISO/IEC 17025-compliant Digital Calibration Certificates (DCCs)
- Integrate edge AI and cloud analytics through the Siemens MindSphere platform
- Employ AI-enhanced Coordinate Measuring Machines (CMMs)
- Offer real-time dashboards for predictive quality control

Impact:
- Cut calibration time by 30%
- Improved first-pass yield by 25%
- Enabled predictive maintenance and reduced calibration-related downtime
- Enhanced compliance with secure, blockchain-based digital calibration records

Case Study 3: **Zeiss Group (Germany) – Deep Learning Integration with Coordinate Measuring Machines (CMMs)**

Company: Zeiss Group (Germany, global operations)

Application: AI-enhanced Coordinate Measuring Machines (CMMs)

Challenge:
Integrating AI with Coordinate Measuring Machine (CMM) hardware presents significant technical challenges. AI models must be frequently updated to maintain accuracy, and specialized training is required to manage variations in part geometry and tolerance levels across different production environments.

AI Solution:
Zeiss developed ZEISS Inspect AI—an intelligent platform that combines deep learning with CMMs to automate 3D measurements and detect part defects based on past inspection data. The system adjusts its inspection strategy dynamically depending on the part and production environment.

Impact:
- Speeds up decision-making with automated analysis
- Optimizes measurement cycles with adaptive routines
- Monitors production quality in real-time
- Boosts productivity in sectors like automotive and medical devices

AI also supports predictive calibration, minimizes manual errors, and ensures traceability with standards like ISO/IEC 17025—reinforcing quality and consistency in high-precision industries.

Case Study 4: **P&R Measurement (China) – Natural Language and AI-Driven Test Automation**

Company: P&R Measurement

Application: Smart metrology, quality assurance, and automated calibration in industrial settings

Challenge:
Interpreting natural language instructions can be difficult for AI systems, particularly when commands are unclear or lack context. Additionally, integrating AI into complex test environments demands robust data processing and continuous retraining to adapt to evolving products and test scenarios.

AI Solution:
At CES 2025, P&R unveiled PRIME, an AI assistant that translates natural language into engineering commands. This allows operators to set up complex measurement systems through simple verbal or

written instructions. Other innovations include:
• A²TP: Adaptive Automated Test Platform
• A²S Lab: AI-driven sensory testing system

These platforms automate testing, analyze data in real-time, and flag non-conformities early in the production process.

Impact:
• Simplifies setup and operation of advanced test systems
• Speeds up and improves the accuracy of conformity assessments
• Identifies production issues earlier, helping prevent costly recalls
• Pushes metrology toward a more efficient and data-driven future

Case Study 5: **TDK Corporation (Japan) – Embedded AI for Diagnostics and Compliance Monitoring**

Company: TDK Corporation

Application: Real-time diagnostics and compliance monitoring for automotive, automation, and medical devices

Challenge:
Implementing real-time AI analytics is constrained by limited hardware processing capacity, especially in embedded systems. Maintaining accuracy and reliability across diverse and dynamic operating conditions is essential to meet strict safety and compliance standards.

AI Solution:
In 2025, TDK introduced an AI-integrated platform at CES that combines:
• Sensor fusion
• Predictive analytics
• Advanced materials engineering

This system uses embedded AI to enable real-time diagnostics, compliance monitoring, and predictive risk analysis.

Impact:
• Ensures continuous compliance in critical applications
• Reduces the need for human-led diagnostics
• Enhances predictive maintenance capability
• Improves the reliability and efficiency of measurement systems

Today, AI is enhancing metrology by automating complex measurement processes, improving data analytics, and enabling real-time monitoring. Key areas of AI application include:

• **AI-Driven Quality Control:** AI enables real-time defect detection and quality control in industries like automotive and healthcare. For example, AI-powered imaging and deep learning models help identify defects in car manufacturing before they become critical. BMW has implemented AI-driven vision systems to inspect assembly lines, reducing defects and improving production efficiency.

• **Predictive Calibration and Self-Learning Metrology Tools:** AI can analyze past calibration data to predict when instruments are likely to drift out of tolerance, allowing preemptive adjustments. This approach optimizes calibration intervals, reducing downtime and costs. NASA utilizes AI for predictive calibration of spacecraft instruments, ensuring precision in deep-space missions.

• **AI and Digital Calibration Reports:** The introduction of AI-enabled Digital Calibration Reports streamlines documentation and ensures traceability in compliance with ISO 17025:2017 standards. Siemens employs AI-driven calibration systems in its metrology labs, reducing human error and enhancing compliance.

For an example of how AI is being integrated into calibration documentation—including predictive analysis, technician-AI verification, and blockchain security—see **Appendix A.**

• **Risk Analysis in Conformity Assessment:** AI-driven risk models assist in evaluating the probability of false acceptance and false rejection in conformity assessment, significantly improving decision-making processes. The pharmaceutical industry, including companies like Pfizer, leverages AI for risk-based conformity assessments to meet FDA compliance requirements.

• **AI in Ethical Governance and Accreditation:** The International Accreditation Service (IAS) Technical Advisory Committee is actively exploring the implementation of AI as an advanced mechanism to improve the efficiency and accuracy of conformity assurance, accreditation, certification, and testing operations—ultimately aiming to better meet global customer requirements.

For a list of national, regional, and international organizations involved in conformity assessment and accreditation, see **Appendix C**.

Future Developments: AI's Expanding Influence

Looking ahead, AI is expected to become even more deeply integrated into metrology, opening new possibilities for precision engineering, automated

testing, and real-time compliance monitoring. Its ability to analyze and interpret vast datasets will support more proactive quality assurance models, significantly reducing inefficiencies in regulatory compliance. AI-powered metrology solutions are poised to become standard across industries, ensuring consistent and reliable conformity assessment.

See **Appendix E** for a summary of international, regional, and national standards guiding ethical and technical frameworks for AI in metrology and conformity assurance.

Conclusion

AI is undeniably reshaping metrology and conformity assurance—offering unprecedented precision, efficiency, and predictive capabilities. While challenges remain, a well-structured approach that incorporates ethical AI governance, regulatory alignment, and continuous learning will be key to successful integration. As industries move toward a future defined by AI-powered metrology, embracing this transformation will be essential for maintaining competitiveness and compliance in an increasingly data-driven world.

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Author Biography

Prof. Emil Hazarian, Dipl. Eng., internationally known as "Mr. Metrology," is a globally recognized expert in metrology, quality assurance, and standardization, with almost six decades of experience across national labs, the U.S. Navy, Fortune 500 companies, and academia. He holds advanced degrees in Mechanical Engineering, Quality Assurance, and Metrology, and has taught at California State University, Dominguez Hills since 1997.

He has consulted extensively on ISO 17025 and ISO 9001 accreditation, collaborated with organizations such as NIST and NASA, and served in leadership roles at the Measurement Science Conference and on the IAS Technical Advisory Council. He is the co-author of *The Metrology Handbook* (ASQ Press) and has presented at conferences worldwide. Email: ehazarian@csudh.edu

Appendix A. Sample AI-Enabled Digital Calibration Report

This sample report illustrates how artificial intelligence enhances calibration practices by incorporating predictive analytics, self-learning diagnostics, blockchain security, and risk-based conformity assessment. It follows ISO 17025 standards and includes technician-AI collaboration to improve traceability and reliability.

Report Details

Report No: DCR-2025-001

Issued by: Metrology Laboratory

Date of Calibration: 2025-03-05

Customer: Boeing Aerospace

Instrument Type: Digital Pressure Sensor

Instrument Model: DPS-5000

Serial Number: SN-987654321

Calibration Location: Metrology Lab, Los Angeles, California, USA

Measurement Results

Measurement Parameter	Reference Standard Used	Measured Value	Uncertainty (± U, 95% CI)	Pass/ Fail
Pressure (100 kPa)	NIST-Traceable Gauge	99.98 kPa	± 0.02 kPa	Pass
Pressure (500 kPa)	NIST-Traceable Gauge	499.92 kPa	± 0.03 kPa	Pass
Pressure (1000 kPa)	NIST-Traceable Gauge	999.88 kPa	± 0.05 kPa	Pass

Calibration Summary

- **AI-Enabled Predictive Analysis:** Calibration data indicates that the instrument is within acceptable limits but may require recalibration in 8 months instead of the standard 12-month cycle due to wear trends detected by AI analysis.
- **Self-Learning Model Output:** AI detected minor drift tendencies, recommending adjustments for optimized sensor stability.
- **Risk-Based Conformity Assessment:** AI-driven risk assessment determined a low probability (0.5%) of incorrect measurements within the next calibration cycle.
- **Blockchain Security Integration:** This report is digitally signed and stored on a secure blockchain ledger to ensure authenticity and prevent tampering.

Technician and AI Verification

- **Calibration Performed By:**
  - **Technician Name:** John Doe
  - **AI Assistant:** MetrologyAI v4.0
  - **Signature:** (Digital Signature Attached)
  - **ISO 17025 Accreditation No:** 456789-MTL
- **Calibration Valid Until: 2026-03-05**

Comments

This instrument complies with all relevant metrology and conformity assessment regulations. AI analysis suggests monitoring for pressure drift and adjusting calibration frequency accordingly.

The example mirrors the format of traditional calibration reports while incorporating advanced AI-enabled features. These include predictive maintenance, enhanced traceability, and blockchain-backed authenticity. Together, they demonstrate how Digital Calibration Reports can align with ISO 17025 standards while improving efficiency and accuracy in conformity assessment.

Appendix B. Examples of AI Applications in Metrology

Artificial intelligence (AI) is being applied across various metrology contexts to improve measurement accuracy, automate inspections, and anticipate maintenance needs. Below are selected examples of AI-driven tools and systems currently enhancing metrology in multiple industries:

- **AI-Driven Quality Control Systems:** In manufacturing, AI-powered vision systems detect defects in real-time. For example, BMW utilizes AI-driven vision inspection on its assembly lines to reduce defects and improve production efficiency (source: qualitymag.com).
- **Virtual Metrology Tools:** In the semiconductor industry, virtual metrology uses AI algorithms to predict process outcomes based on equipment sensor data, reducing reliance on direct measurement. This approach improves efficiency and enables real-time process adjustments (source: semiengineering.com).
- A**I-Enhanced Scanning Probe Microscopy:** Advanced scanning probe microscopes integrated with AI can autonomously perform atomic-scale measurements and manipulate atomic positions with high precision. These systems adapt to surface

irregularities and compensate for environmental factors to ensure reliable analysis (source: arxiv.org).

• **AI in Industrial Computed Tomography (CT):** In industrial settings, AI enhances CT scanning by producing high-resolution internal and external 3D representations of scanned objects. This technology supports flaw detection, failure analysis, and reverse engineering through precise, non-destructive evaluation (source: en.wikipedia.org).

These AI applications are reshaping traditional measurement practices across industries by offering greater precision, speed, and predictive power in metrological processes.

Appendix C. Global Conformity Assessment Organizations

This appendix provides an overview of key international, regional, and national organizations involved in conformity assessment and accreditation. These bodies help ensure consistency, mutual recognition, and trust in certification, inspection, and testing results across industries and borders.

International Organizations

International Organization for Standardization (ISO)

- **Established:** 1947
- **Headquarters:** Geneva, Switzerland
- **Role:** Develops voluntary, consensus-based international standards for conformity assessment, including ISO/IEC 17000 series, which defines the principles of certification, testing, and inspection.
- **Website:** www.iso.org

International Electrotechnical Commission (IEC)

- **Established:** 1906
- **Headquarters:** Geneva, Switzerland
- **Role:** Develops conformity assessment schemes for electrical, electronic, and related technologies, including IECEx (Explosive Atmospheres), IECQ (Quality), and IECEE (Electronics & Electrical Equipment Testing).
- **Website:** www.iec.ch

International Laboratory Accreditation Cooperation (ILAC)

- **Established:** 1977
- **Headquarters:** Sydney, Australia
- **Role:** Oversees international mutual recognition of testing and calibration laboratory accreditations, ensuring that test reports and certificates are recognized globally.
- **Website:** www.ilac.org

International Accreditation Forum (IAF)

- **Established:** 1993
- **Headquarters:** United States
- **Role:** Oversees the global accreditation of conformity assessment bodies (CABs) for product certification, management systems, and personnel certification.
- **Website:** www.iaf.nu

World Trade Organization (WTO) – Technical Barriers to Trade (TBT) Agreement

- **Established:** 1995
- **Headquarters:** Geneva, Switzerland
- **Role:** Ensures that conformity assessment procedures do not create unnecessary trade barriers, supporting mutual recognition agreements (MRAs) for certification and testing results.
- **Website:** www.wto.org

Regional Organizations

European Co-operation for Accreditation (EA)

- **Region:** Europe
- **Role:** Manages accreditation in EU countries under the ISO/IEC 17000 series, supporting harmonized conformity assessment.
- **Website:** www.european-accreditation.org

Asia Pacific Accreditation Cooperation (APAC)

- **Region:** Asia-Pacific
- **Role:** Ensures regional recognition of testing, inspection, and certification bodies through the Asia-Pacific Laboratory Accreditation Cooperation (APLAC).
- **Website:** www.apac-accreditation.org

African Accreditation Cooperation (AFRAC)

- **Region:** Africa
- **Role:** Promotes regional harmonization of conformity assessment practices, particularly in ISO/IEC 17025 testing and calibration laboratories.
- **Website:** www.intra-afrac.com

Inter-American Accreditation Cooperation (IAAC)

- **Region:** Americas
- **Role:** Strengthens accreditation systems in North and South America by ensuring mutual recognition of certification bodies in ISO/IEC 17065 (Product Certification) and ISO/IEC 17021 (Management Systems).
- **Website:** www.iaac.org.mx

Gulf Cooperation Council Accreditation Center (GAC)

- **Region:** Gulf Cooperation Council (GCC) Countries
- **Role:** Manages the accreditation of conformity assessment bodies for ISO/IEC 17020 (Inspection) and ISO/IEC 17065 (Product Certification) in the GCC region.
- **Website:** www.gac.org.sa

National Organizations

National Institute of Standards and Technology (NIST) – USA

- **Established:** 1901
- **Role:** Oversees conformity assessment and accreditation programs through NVLAP (National Voluntary Laboratory Accreditation Program).
- **Website:** www.nist.gov

United Kingdom Accreditation Service (UKAS) – UK

- **Established:** 1995
- **Role:** UK's national accreditation body responsible for certifying laboratories, inspection bodies, and management systems.
- **Website:** www.ukas.com

Physikalisch-Technische Bundesanstalt (PTB) – Germany

- **Established:** 1887
- **Role:** Provides metrology and accreditation services, ensuring conformity assessment standards in Germany.
- **Website:** www.ptb.de

Cofrac (Comité Français d'Accréditation) – France

- **Established:** 1994
- **Role:** France's official accreditation body for testing and inspection laboratories under the ISO/IEC 17000 series.
- **Website:** www.cofrac.fr

National Association of Testing Authorities (NATA) – Australia

- **Established:** 1947
- **Role:** Oversees the accreditation of testing and calibration laboratories and conformity assessment bodies in Australia.
- **Website:** www.nata.com.au

Instituto Nacional de Metrologia, Qualidade e Tecnologia (INMETRO) – Brazil

- **Established:** 1973
- **Role:** Brazil's national accreditation body ensuring conformity assessment in product certification, management systems, and laboratory accreditation.
- **Website:** https://www.gov.br/pt-br/orgaos/instituto-nacional-de-metrologia-qualidade-e-tecnologia

Harmonization of conformity assessment practices at global, regional, and national levels promotes product safety, consumer protection, and international market access. These organizations play a vital role in reducing technical barriers to trade through mutual recognition of test reports, certification, and inspection outcomes.

Appendix D. Abbreviations

This appendix lists acronyms and abbreviations used throughout the article, along with their definitions and organizational roles where applicable.

AI – Artificial Intelligence

Technology enabling machines to perform tasks that typically require human intelligence, such as pattern recognition, decision-making, and automation.

AFRAC – African Accreditation Cooperation

A regional accreditation body responsible for harmonizing accreditation and conformity assessment in Africa.

APAC – Asia-Pacific Accreditation Cooperation

Regional organization supporting accreditation for laboratories, inspection, and certification bodies in the Asia-Pacific region.

APMP – Asia Pacific Metrology Programme

A regional metrology organization (RMO) that promotes cooperation in measurement science among Asia-Pacific nations.

BIPM – Bureau International des Poids et Mesures (International Bureau of Weights and Measures)

Global organization responsible for maintaining and developing the International System of Units (SI) and metrology standards.

Cofrac – Comité Français d'Accréditation (French Accreditation Committee)

France's national accreditation body responsible for accrediting testing and calibration laboratories, certification bodies, and inspection organizations.

DCC – Digital Calibration Certificate

A digital format for calibration records that ensures traceability, accuracy, and secure data management in metrology processes.

EA – European Cooperation for Accreditation

An association of national accreditation bodies in Europe, ensuring harmonized accreditation practices across the continent.

EURAMET – European Association of National Metrology Institutes

A regional metrology organization (RMO) coordinating metrology research and standardization efforts across Europe.

FDA – Food and Drug Administration (USA)

A U.S. regulatory agency overseeing food safety, pharmaceutical drugs, medical devices, and biotechnology products.

HVAC – Heating, Ventilation, and Air Conditioning

A technology used for regulating indoor environmental comfort and air quality.

IAAC – Inter-American Accreditation Cooperation

A regional association promoting cooperation among accreditation bodies and conformity assessment organizations in the Americas.

IAF – International Accreditation Forum

A global organization responsible for developing accreditation standards for certification bodies in management systems, products, and personnel.

IAS – International Accreditation Service

A U.S.-based accreditation body that provides accreditation for testing and calibration laboratories, inspection bodies, and product certification agencies.

IEC – International Electrotechnical Commission

An international standards organization developing and publishing standards for electrical and electronic technologies.

ILAC – International Laboratory Accreditation Cooperation

A global network of accreditation bodies that establishes mutual recognition agreements for laboratory testing and calibration services.

INMETRO – Instituto Nacional de Metrologia, Qualidade e Tecnologia (Brazilian National Institute of Metrology, Quality, and Technology)

Brazil's national metrology institute responsible for measurement standards, conformity assessment, and consumer protection.

ISO – International Organization for Standardization

A global non-governmental organization that develops and publishes international standards for quality management, safety, and technological processes.

MEP – Mechanical, Electrical, and Plumbing

An engineering discipline focusing on the design, implementation, and maintenance of mechanical, electrical, and plumbing systems in buildings.

NATA – National Association of Testing Authorities (Australia)

Australia's national accreditation body responsible for accrediting testing and calibration laboratories.

NIST – National Institute of Standards and Technology (USA)

A U.S. federal agency that develops measurement standards, calibration systems, and metrology research to support industry and science.

PTB – Physikalisch-Technische Bundesanstalt (Germany)

Germany's national metrology institute, ensuring accurate and reliable measurement standards.

UKAS – United Kingdom Accreditation Service

The UK's national accreditation body, responsible for accrediting testing and calibration laboratories, inspection bodies, and certification organizations.

Appendix E. Standards for Artificial Intelligence (AI) in Metrology

This appendix outlines international, regional, and national standards that support the development, deployment, and oversight of AI systems in metrology and conformity assessment. These standards address issues such as terminology, risk management, bias mitigation, lifecycle processes, and regulatory frameworks.

International Standards

ISO/IEC JTC 1/SC 42 – Artificial Intelligence Subcommittee
The International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC) have established JTC 1/SC 42, a subcommittee dedicated to AI standardization. Notable publications include:

- **ISO/IEC 22989:2022** – *Artificial Intelligence — Concepts and Terminology*
  Establishes foundational terminology and concepts in the field of AI.
- **ISO/IEC 23053:2022** – *Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML)*
  Provides a framework for describing AI systems that utilize machine learning.
- **ISO/IEC 23894:2023** – *Artificial Intelligence — Guidance on Risk Management*
  Offers guidelines for managing risks associated with AI systems.
- **ISO/IEC TR 24027:2021** – *Bias in AI Systems and AI-Aided Decision Making*
  Discusses the identification and mitigation of bias in AI applications.

- **ISO/IEC TR 24028:2020** – *Overview of Trustworthiness in Artificial Intelligence*
  Provides an overview of factors contributing to the trustworthiness of AI systems.
- **ISO/IEC TR 24368:2022** – *Overview of Ethical and Societal Concerns*
  Addresses ethical and societal issues related to AI deployment.
- **ISO/IEC 24029-1:2021** – *Assessment of the Robustness of Neural Networks — Part 1: Overview*
  Introduces methods for evaluating the robustness of neural networks.
- **ISO/IEC 24029-2:2023** – *Assessment of the Robustness of Neural Networks — Part 2: Methodology for the Use of Formal Methods*
  Details formal methodologies for assessing neural network robustness.
- **ISO/IEC 25059:2023** – *Systems and Software Quality Requirements and Evaluation (SQuaRE) — Quality Model for AI Systems*
  Defines quality models specific to AI systems.
- **ISO/IEC 42001:2023** – *Artificial Intelligence Management System*
  Specifies requirements for an AI management system within organizations.
- **ISO/IEC 5338:2023** – *AI System Life Cycle Processes*
  Outlines processes for managing the AI system life cycle.
- **ISO/IEC 5339:2024** – *Guidance for AI Applications*
  Provides guidance on the application of AI across various domains.
- **ISO/IEC 5469:2024** – *Functional Safety and AI Systems*
  Addresses considerations for ensuring functional safety in AI systems.

These international standards aim to establish a comprehensive framework for AI development and governance.

Regional Standards

European Union (EU)

The European Union has been proactive in developing regulations to govern AI technologies:

- **Artificial Intelligence Act (AI Act)** – Proposed in 2021
  A comprehensive regulatory framework aiming to ensure that AI systems used within the EU are safe, transparent, and respect fundamental rights. The Act categorizes AI applications based on risk levels and imposes corresponding obligations. (Source: ai-watch.ec.europa.eu)

Asia-Pacific Economic Cooperation (APEC)

Within the **Asia-Pacific** region, efforts have been made to harmonize AI standards:

- **APEC Framework for Artificial Intelligence** – Established in 2019
  Provides guidelines for AI development and use across member economies, with a focus on innovation and ethical responsibility.

National Standards

United States

The National Institute of Standards and Technology (NIST) leads AI standardization efforts in the U.S.

- **NIST Special Publication 1270** – *Towards a Standard for Identifying and Managing Bias in Artificial Intelligence (2022)*
  Offers a framework to promote fairness and equity by identifying and managing bias in AI systems.
- **NIST AI 100-1** – *Artificial Intelligence Risk Management Framework (AI RMF) 1.0 (2023)*
  Provides comprehensive guidelines for managing AI-related risks to enhance trustworthiness.

China

China has also been active in establishing AI standards:

- **Artificial Intelligence Standardization White Paper** – Released in 2018
  Outlines China's national approach to AI standardization, emphasizing support for the development and governance of AI technologies.

Together, these standards provide a foundation for responsible, transparent, and interoperable AI applications within metrology and conformity assessment practices.

The Evolution of Quality Management in Laboratory Services: Ensuring Accuracy, Safety, and Efficiency

By Vikash Chandra Mishra, PhD, Quality Manager, Chimera Transplant Research Foundation, New Delhi, India; Dinesh Chandra, MSc (Biotechnology), Assistant Quality Manager, Chimera Transplant Research Foundation, New Delhi, India; and Vimarsh Raina, MD (Pathology), Medical Director, Chimera Transplant Research Foundation, New Delhi, India

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-ABSTRACT-

Quality management (QM) is a critical component of laboratory services and has evolved significantly to improve the accuracy, reliability, and consistency of test results while meeting increasing demands for patient safety and regulatory compliance. This article highlights the historical development of quality management practices in laboratory settings, key milestones, and recent advancements, including the implementation of quality management systems, adherence to global (like ISO) standards, and the integration of technology to enhance both patient outcomes and operational efficiency.

Keywords: *Quality Management, Quality Management System, ISO, Laboratory*

Historical Development

Early History

In its early stages, laboratory testing lacked defined processes and procedures, focusing primarily on scientific innovation rather than standardized protocols. Results often relied on individual expertise, and there was little to no quality assurance. Without established procedures, laboratory services operated informally.

The foundation of the International Organization for Standardization (ISO) marked a turning point toward standardized laboratory techniques. Early ISO standards emphasized accuracy and reproducibility, laying the groundwork for modern quality management (QM) practices [1, 2].

Development of Standards and Guidelines

In 1968, the Clinical Laboratory Standards Institute (CLSI), formerly known as the National Committee for Clinical Laboratory Standards (NCCLS), introduced guidelines for laboratory practice, which helped promote quality control (QC) in clinical settings [3].

The Clinical Laboratory Improvement Amendments (CLIA) of 1988 further advanced laboratory quality in the United States by requiring laboratories to meet stringent standards of practice and seek accreditation from approved organizations [4].

Quality Control and Management Integration

These developments helped QC approaches gain broader acceptance in the 1970s and 1980s. To ensure consistency in findings, laboratories began adopting control samples, calibration methods, and proficiency testing through internal quality control (IQC) and external quality assessment (EQA) [5]. The introduction of total quality management (TQM) to laboratories in the 1990s further enhanced workflows, operations, training, and equipment maintenance. In addition, the implementation of the ISO 9000 series and ISO 15189 standards helped establish norms for competence and quality in laboratory services [6].

Technological Advancements and Modern QMS

In recent decades, technological innovations such as digital tools, automation, and laboratory information management systems (LIMS) have simplified laboratory procedures, reduced human error, and increased testing capacity—ultimately enhancing efficiency [7].

Today, modern laboratories implement quality management systems (QMS) that integrate leadership, strategy, process control, and continuous improvement to ensure compliance and reliable results.

Current Scenario

From its informal and unstructured beginnings, the field has evolved into a highly structured and regulated discipline, ensuring robust test accuracy and reliability through the adoption of standards such as ISO 9001 (quality management systems), ISO 17025 (competence of testing and calibration laboratories), ISO 15189 (quality and competence in medical laboratories), and ISO 17043 (competence of proficiency testing providers).

Table 1: Key Components of a Quality Management System (QMS)

Component	Purpose	Benefits	Examples
Quality Policy	Defines the organization's commitment to quality and customer satisfaction.	Aligns organizational goals with customer expectations.	ISO 9001 Quality Policy statements.
Quality Objectives	Sets measurable targets to achieve quality goals.	Enhances focus on continuous improvement and operational excellence.	Reducing defects by 10% annually, improving on-time delivery.
Document Control	Ensures that all documentation is accurate, up-to-date, and accessible.	Maintains consistency and compliance with standards and regulations.	SOPs, work instructions, and process guidelines.
Risk Management	Identifies and mitigates risks to quality and operations.	Reduces the likelihood of defects, failures, or non-conformities.	FMEA, risk registers, and mitigation plans.
Process Approach	Focuses on managing activities as interconnected processes.	Improves efficiency and resource optimization.	Production workflow, service delivery models.
Internal Audits	Evaluates compliance and effectiveness of the QMS.	Identifies areas for improvement and ensures regulatory compliance.	Audit schedules, checklists, and reports.
Corrective Actions	Addresses and resolves identified non-conformities.	Prevents recurrence of issues and strengthens the QMS.	Root cause analysis, CAPA plans.
Training and Competence	Ensures employees have the necessary skills and knowledge.	Enhances workforce capability and product/service quality.	Training records, certification programs.
Customer Feedback	Gathers input to assess customer satisfaction and identify improvement areas.	Drives product/service enhancements and fosters customer loyalty.	Surveys, feedback forms, complaint handling systems.
Continuous Improvement	Focuses on incremental and breakthrough improvements in quality.	Sustains competitive advantage and innovation.	PDCA cycles, Six Sigma projects.

Abbreviations used in Table 1: *FMEA = Failure Mode and Effects Analysis; CAPA = Corrective and Preventive Actions; QMS = Quality Management System; PDCA = Plan-Do-Check-Act.*

Key Components of a Quality Management System

A quality management system (QMS) typically includes several key components, such as quality policy and objectives, document control, internal audits, corrective and preventive actions (CAPA), training and competency measures, customer feedback, compliance with standards, and a strategy for performance measurement and continuous improvement.

Quality Policy and Objectives

For laboratory operations to ensure reliable results, a defined and robust Quality Management System (QMS) is essential. The quality policy, a key component of any QMS and often regarded as its foundation, reflects the laboratory's commitment to quality. A well-defined quality policy helps support the organization's objectives, ultimately driving continuous improvement. Furthermore, to complement the quality policy, measurable quality objectives must be established. These objectives commonly include goals such as ensuring precision, reducing turnaround times, minimizing equipment breakdowns and reducing repeat testing. Together, these objectives provide a clear roadmap for continuous improvement and align with customer expectations.

Document Control

Document control is another major element of a QMS, ensuring that current and accurate documents are available for laboratory activities. By maintaining a robust document control system, laboratories can minimize errors and enhance compliance.

Internal Audits

The QMS is further strengthened by routine internal audits, which evaluate compliance with applicable ISO standards and internal protocols. These audits help the laboratory meet its organizational objectives, ultimately contributing to more reliable reporting and enhanced patient safety, as summarized in Table 1.

Corrective and Preventive Actions

The laboratory must have an efficient corrective and preventive actions (CAPA) system in place to address non-conformities and prevent recurrence. A proactive CAPA procedure improves overall performance by resolving issues and lowering the possibility of them happening again.

Training and Competency

The laboratory staff remains skilled and knowledgeable, staying updated on developments in the field. A robust training and competency program directly supports accurate and reliable test results.

Instrument Calibration and Maintenance

A defined calibration and maintenance schedule is essential for ensuring equipment accuracy, reducing failures, and maintaining consistency, and is therefore considered a critical component of a QMS.

Customer Feedback

Customer feedback is a critical component of a QMS, serving as a valuable tool for understanding satisfaction, identifying areas for improvement, and ensuring that services meet expectations. The effective incorporation of customer feedback into a QMS involves several key aspects, including feedback collection and analysis, as well as the implementation of corrective and preventive actions when necessary.

Compliance with Standards

Another key component of QMS is adherence to standards (ISO 9001, ISO 17025, ISO 15189, and ISO 17043). Following ISO/IEC 17025 shows proficiency in testing and calibration, fostering client trust with high standards. Accreditation refers to a formal recognition from an external body that a laboratory meets specific standards and demonstrates competence in areas such as testing and calibration. For example, ISO accreditation verifies that the laboratory's processes meet international standards, ensuring high-quality results. On the other hand, regulatory compliance ensures that laboratories meet legal requirements set by governmental authorities. Laboratories must comply with national and regional regulations (such as the U.S. FDA standards and CLIA) to ensure ethical operations and alignment with industry expectations. These regulations are typically enforced by government agencies and are designed to safeguard public health and ensure safe practices. The laboratory's commitment to excellence is demonstrated by obtaining the necessary accreditations, which also improve its reputation and validate its quality processes, while also meeting regulatory compliance criteria to ensure ethical and legal operations.

To ensure ethical operations and alignment with industry expectations, laboratories must also comply with national and regional regulations, such as the U.S. FDA and CLIA. The laboratory's commitment to excellence is demonstrated by obtaining the necessary accreditations, which also improve reputation and validate quality processes.

Performance Metrics and Continuous Improvement

Maintaining and enhancing QMS involves monitoring performance metrics and continuous improvements. The defined key performance indicators (KPIs) and their trend analysis provide insight into operational efficiency and help identify areas for improvement. A commitment to continuous improvement, supported by regular performance assessment, ensures refined processes and competitive operations.

Strengths and Areas for Improvement

The strengths of the QMS include high test accuracy and reliability, efficient document control, and proactive training with continual improvement programs—all of which strengthen the laboratory's operations to ensure quality and reliability. It is also critical to identify areas that require improvement, including gaps in staff training or delays in implementing corrective actions. Addressing these gaps enhances customer confidence and improves the laboratory's operational efficiency.

One observed example of improvement in laboratory quality practices is the reduction of turnaround time (TAT) for test results. In this case, delays were initially caused by an inefficient workflow between the testing and reporting phases. By implementing a more streamlined process—including improved coordination across departments and the use of automated systems for data transfer—significant reductions in turnaround time were achieved, resulting in improved customer satisfaction and operational efficiency.

This example highlights a concrete improvement that directly impacts laboratory operations and quality, demonstrating the value of continuous improvement within a QMS.

Conclusion

The development of QMS in laboratory operations has progressed from informal practices to a robust, regulated field. Today's QMS emphasizes patient safety, operational efficiency, and continuous improvement. While current systems demonstrate many strengths, there are still opportunities for refinement. In particular, continued improvements in document control, staff training, and audit processes will help sustain progress and support the delivery of high-quality laboratory services.

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There are no conflicts of interest.

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Author Biographies

Dr. Vikash C. Mishra serves as a quality manager at Chimera Transplant Research Foundation (http://chimeralabs.org/), New Delhi, India. He has been actively involved in research, laboratory management, quality control, and the publication of scientific papers in peer-reviewed journals. With a Ph.D. in Biotechnology from Amity University Uttar Pradesh and extensive experience at the Chimera Transplant Research Foundation, New Delhi, he has contributed significantly to the field. His research focuses on topics such as DNA profiling, HLA matching, stem cell transplantation, and genetic polymorphism in Indian populations. Additionally, he has presented at various international conferences and has been involved in reviewer roles for several peer-reviewed journals. His commitment to academic and professional development is evident through his supervision of student dissertations, participation in training programs, and involvement in quality management systems. Email: vikash.genebandhu@gmail.com

Dinesh Chandra (M.Sc. Biotechnology), Assistant Quality Manager, Chimera Transplant Research Foundation, New Delhi, India, received his master of science in Biotechnology. He has good hands-on experience in histocompatibility testing. He is also the assistant quality manager of the laboratory. He has more than 20 research articles in peer-reviewed international journals with a high impact factor. Email: dineshchandrapathak.345@gmail.com

Dr. Vimarsh Raina (MD Pathology), Medical Director, Chimera Transplant Research Foundation, New Delhi, India, received his specialization (MD) in Pathology from Dayanand Medical College, Ludhiana (Punjab), India. He also holds a Post Graduate Diploma in Hospital Administration from the University of Delhi. He is a leading Molecular Pathologist of South East Asia and a healthcare industry veteran with over 30 years of experience in conceptualizing and building India's fastest-growing throughput diagnostic service and an international stem cell donor registry, over 200 publications, two book chapters, four patents and is an ISO 15189 auditor. Dr. Raina recently won the BMJ South Asia "Healthcare Innovation of the Year 2018" Award. He has been honored for his social enterprise and his commitment towards humanity and was conferred the "Abhinav Gupta Samman." He is a sought-after speaker at International Pathology meetings and conferences. He strongly believes that the field of medical sciences is extremely dynamic and undergoes constant transformation. Therefore, he advocates that the clinical application of medical knowledge needs to consider the changes in societal needs and demands.

Dr. Vimarsh Raina is the founder and medical director of Genebandhu—an adult stem cell donor not-for-profit social enterprise that is part of the World Bone Marrow Donors Association (WMDA). This Network connects voluntary stem cell donors globally with patients having life-threatening diseases like blood cancer. Email: rainavimarsh@gmail.com

Impact of ISO/IEC 17025 Accreditation on Food Safety: Arsenic Speciation and Quality Control of Maize

By Diego Alejandro Uribe Polo, Ivette Zarate F., Víctor Valverde, Solange Henriquez, and Melba Huerta

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-ABSTRACT-

This article analyzes how ISO/IEC 17025 accreditation improves the validity and reliability of results in arsenic speciation in maize, which positively impacts food safety and contributes to the protection of public health. It seeks to highlight the importance of having standardized procedures and verified methods, especially when arsenic detection limits are at trace level.

Keywords: *Food Safety, Arsenic Speciation, ISO/IEC 17025, Maize Contamination, Analytical Chemistry, ICP-MS, Laboratory Accreditation, Public Health, HPLC, Trace Analysis*

Overview

Arsenic, a toxic contaminant present in agricultural soils, affects essential crops such as corn. Differentiating its various chemical forms—inorganic arsenic (As(III) and As(V)) and organic arsenic (monomethylarsonic acid [MMA] and dimethylarsinic acid [DMA])—is crucial for assessing public health risks. Arsenic intake in high concentrations can cause serious effects on human health, including gastrointestinal irritation, decreased production of red and white blood cells, and various types of cancer (Agency for Toxic Substances and Disease Registry, 2007).

Maize, the world's highest produced cereal, provides 15% to 20% of global protein and calorie intake to more than 200 million people in regions such as Latin America, sub-Saharan Africa, and Southeast Asia. These areas have been identified as arsenic-contaminated (Rosas et al., 2015). Factors such as soil pH, organic matter content, and certain elements influence arsenic's bioavailability, affecting its accumulation in edible parts of crops (Nawrocka et al., 2022). (See Table 1.)

Table 1: Global maize production and end uses. Displays total production and key consumption categories (e.g., food and feed), providing context for the significance of arsenic contamination in a widely consumed staple crop.

Ensuring accurate and reliable analyses of arsenic speciation in maize is essential to assess and manage the associated risks. In this context, ISO/IEC 17025 accreditation has a fundamental role in ensuring the technical competence of laboratories and the validity of the results obtained.

Importance of Arsenic Speciation in Maize

Speciation of arsenic is essential to assess the risks associated with its presence in food. Inorganic arsenic, in its As(III) and As(V) forms, is approximately 100 times more toxic than its organic forms (MMA and

DMA) (Sadee et al., 2023). Differentiating between these species allows for more accurate risk assessment and the implementation of appropriate measures to protect public health.

Studies have shown that corn can accumulate arsenic in alarming concentrations. For example, Rosas et al. (2015) evaluated arsenic transfer and speciation in maize crops, finding significant levels of accumulation. Likewise, Guerrero (2016) developed a procedure to determine inorganic arsenic in Mexican tortillas, finding concentrations of total arsenic that varied between 21.8 and 192 µg/kg, where inorganic arsenic represented between 72.2% and 97.9% of the total. These findings highlight the need for detailed and accurate analyses to ensure maize safety.

Factors such as pH, organic matter content, and the presence of other elements influence the bioavailability of arsenic in the soil and its subsequent accumulation in corn. Rosas et al. (2015) and Nawrocka et al. (2022) highlight that these conditions can increase the mobility of arsenic, increasing its absorption by plants. (See Figure 1.)

Figure 1: Factors influencing arsenic accumulation in maize. Diagram illustrates how soil characteristics—pH, mineral content, and organic matter—affect how arsenic species (As(III), As(V)) are absorbed by maize plants.

Analytical Techniques for Arsenic Speciation

Advanced analytical techniques play a crucial role in arsenic speciation. The combination of high-performance liquid chromatography (HPLC) and inductively coupled plasma mass spectrometry (ICP-MS) allows different arsenic species in corn samples to be accurately separated and quantified, even at trace levels. Guerrero (2016) used this methodology to achieve an accurate detection of inorganic arsenic in Mexican tortillas.

Cervantes-Corona et al. (2014) validated an analytical method that uses hydride generation with detection by atomic absorption spectrophotometry, allowing the selective determination of As(III) in the presence of As(V). This method offers an effective alternative for speciation of arsenic in complex matrices such as corn.

Ackley et al. (1999) demonstrated the development of sensitive analytical methods for the determination of toxic arsenic species in fish tissues using microwave-assisted extraction and HPLC-ICP-MS. This approach suggests that similar techniques can be applied to assess food security in maize and other agricultural products.

In addition, EN 16802:2016 provides a standard procedure for the determination of inorganic arsenic in food using HPLC-ICP-MS, which is essential for the standardization of test processes and the comparability of results between laboratories.

Role of ISO/IEC 17025 Accreditation in the Validity of Analysis

ISO/IEC 17025 requires laboratories to correctly apply analytical techniques, which are demonstrated through ensuring the validity of results, carried out by competent personnel. This standard sets out general requirements for technical competence, impartiality, and consistent operation of laboratories (ISO/IEC 17025, 2017).

By implementing a quality management system based on ISO/IEC 17025, laboratories ensure that they apply methods that are fit for purpose and have competent personnel to perform the analyses. According to ILAC (2011), participation in proficiency testing programs and the use of certified reference materials are essential practices that support the technical competence of laboratories and the reliability of results.

In addition, ISO/IEC 17025 promotes continuous improvement through risk-based thinking and objective evidence-based decision making, ensuring that laboratories maintain high quality standards in their operations. Compliance with this standard provides confidence in the results obtained, which is essential for decision-making in food safety and public health.

Impact on Food Safety and Public Health

Reliable analytical results on arsenic speciation in maize allow for more accurate risk assessments and effective measures to protect the health of vulnerable populations. According to the Agricultural Market Information System - AMIS (2024), global maize production reached 1.24 billion tonnes in 2023/24, highlighting the importance of ensuring the safety of this staple food.

Accreditation based on ISO/IEC 17025 facilitates the mutual recognition of results between countries, supporting international trade and promoting trust in analyses performed by accredited laboratories (ILAC, 2010). This is especially relevant in the context of globalization and the need to ensure that food meets the safety standards required worldwide.

Reliable analyses also allow health authorities to establish regulations and maximum permissible limits for contaminants in food, contributing to effective public policies and the protection of public health.

Conclusion

Arsenic speciation is critical for assessing the risks associated with its presence in maize, a staple food for millions. Advanced analytical techniques such as HPLC and ICP-MS are essential for the accurate and reliable detection of arsenic species. Accreditation under ISO/IEC 17025 ensures that these techniques are correctly applied by competent personnel and that the resulting data is valid and trustworthy. This accreditation plays a vital role in protecting public health and food safety, enabling better risk management and supporting the development of effective food safety policies.

It can be concluded that the accreditation of laboratories under the ISO/IEC 17025 standard is essential to guarantee accurate and reliable analyses on the presence of arsenic in its different chemical forms in corn. This not only strengthens food safety and public health, but also facilitates international trade and promotes confidence in analyses carried out by accredited laboratories. Accreditation becomes more relevant when greater confidence in trace-level results is required, which is critical in the evaluation of compounds harmful to health.

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Author Biographies

Diego Alejandro Uribe Polo is based in Peru, he is the founder of LAB SQUAD, an organization focused on training and consulting in accreditation and quality management systems. His expertise includes conformity assessment, risk management, and the application of international standards, with a specialization in ISO/IEC 17025 across Latin America.

Ivette Zarate F. is based in Chile, she has a degree in Chemistry from the Pontificia Universidad Católica de Valparaíso. More than 20 years of experience in training and comprehensive chemical consulting, with a focus on the development of analytical methods, instrumentation and development of good laboratory practice protocols. With extensive experience in the implementation and validation of procedures for water, food and fruit production sectors, guaranteeing quality and efficiency standards.

Víctor Valverde is based in Chile, he holds a degree in Analytical Chemistry from the University of Concepción in Chile. He is experienced in the implementation of various analytical techniques, both classical and instrumental. Commissioning equipment such as ion chromatographs, gas chromatographs, and organochlorine compound analyzers.

Solange Henriquez is based in Chile. She has a degree in Industrial Chemistry from the Pontificia Universidad Católica de Valparaíso, with over 15 years of experience in research, development, and innovation across the mining, food, and environmental industries. Solange has experience as a technical and management auditor under ISO 17025 and 17020 standards, and extensive experience in the implementation and oversight of integrated systems, supported by a diploma in Integrated Management Systems (ISO 9001, 14001, and 45001) from the Pontificia Universidad Católica de Chile.

Melba Huerta is based in Chile. She is an Industrial Chemist and Occupational Risk Preventionist, an expert in the implementation, control, and improvement of quality, safety and environmental management systems, especially focused on compliance with the regulatory requirements given by the Chilean national authority in various areas (environment, food, pharmacy, mining), among other activities of management system for ISO/IEC 17025, ISO/IEC 17020, ISO 9001, ISO 14001 and ISO 45001 standards.

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Artificial Intelligence Survey of Laboratories, Inspection Agencies, Certification Bodies

By Alberto Herrera, Greg West, and Laura Uraine

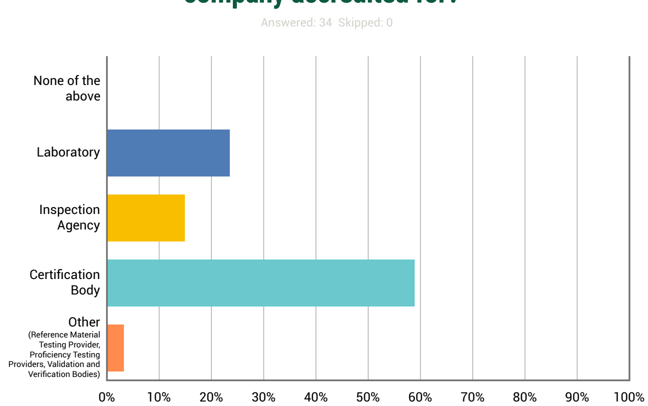
Earlier this year, the International Accreditation Service (IAS) conducted a short, anonymous survey to assess awareness, usage, and attitudes toward Artificial Intelligence (AI) among conformity assessment bodies. The survey was sent to more than 1,000 IAS customers, including testing and calibration laboratories, inspection agencies, certification bodies, and others.

The survey questions covered topics such as which IAS accreditation program the customer participates in, familiarity with AI, frequency of AI use in their work, and level of concern about AI use within the industry. The responses provided valuable insight into how AI is currently being utilized by IAS-accredited organizations.

This article presents the overall survey results, along with a breakdown by respondent group (inspection agencies, laboratories, certification bodies, and others) to allow for comparison across sectors.

The following tables show the combined responses of all participants. A separate breakdown by respondent group follows each table, along with a brief analysis and summary. Respondents were allowed to select more than one response per question.

Q1 Which of the following programs is your company accredited for?

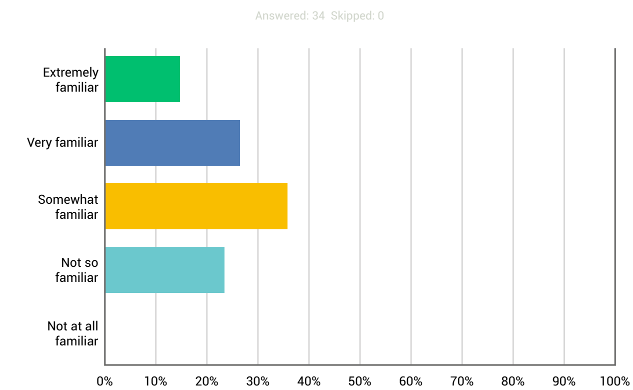


ANSWER CHOICES	RESPONSES
None of the above	0.00%
Laboratory	23.53%
Inspection Agency	14.71%
Certification Body	58.82%
Other (Reference Material Testing Provider, Proficiency Testing Providers, Validation and Verification Bodies)	2.94%

Summary of Responses:

Conformity assessment bodies that responded to the survey came mainly from these three types of agencies: inspection agencies (14.71%), testing and calibration laboratories (23.53%), and the greater number from certification bodies (58.82%), and only 2.94% from other agencies.

Q2 How familiar are you with AI?



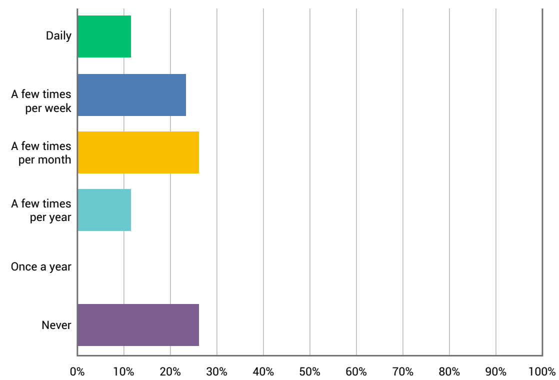
- Inspection agencies:
  - 0% Extremely familiar
  - 20% Very familiar
  - 40% Somewhat familiar
  - 40% Not so familiar
  - 0% Not at all familiar
- Testing and calibration laboratories:
  - 12.5% Extremely familiar
  - 37.5% Very familiar
  - 25% Somewhat familiar
  - 25% Not so familiar
  - 0% Not at all familiar
- Certification bodies:
  - 20% Extremely familiar
  - 25% Very familiar
  - 35% Somewhat familiar
  - 20% Not so familiar
  - 0% Not at all familiar
- Other:
  - 0% Extremely familiar
  - 0% Very familiar
  - 100% Somewhat familiar
  - 0% Not so familiar
  - 0% Not at all familiar

Summary of Responses:

When asked about their familiarity with AI, certification bodies had the highest percentage selecting "extremely familiar" (20%), while none of the inspection agencies selected that option. Among testing and calibration laboratories, 12.5% selected "extremely familiar," and 37.5% selected "very familiar"—the highest percentage for that category across all groups.

Q3 How often do you currently use AI for work?

Answered: 34 Skipped: 0



ANSWER CHOICES	RESPONSES
Daily	11.76%
A few times per week	23.53%
A few times per month	26.47%
A few times per year	11.76%
Once a year	0.00%
Never	26.47%

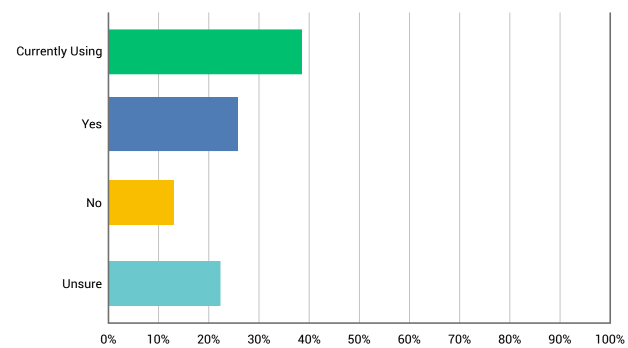
- Inspection agencies:
  - 0% Daily
  - 20% A few times a week
  - 40% A few times a month
  - 20% A few times a year
  - 0% Once a year
  - 20% Never
- Testing and calibration laboratories:
  - 0% Daily
  - 12.5% A few times a week
  - 37.5% A few times a month
  - 12.5% A few times a year
  - 0% Once a year
  - 37.5% Never
- Certification bodies:
  - 20% Daily
  - 30% A few times a week
  - 15% A few times a month
  - 10% A few times a year
  - 0% Once a year
  - 25% Never
- Other:
  - 0% Daily
  - 0% A few times a week
  - 100% A few times a month
  - 0% A few times a year
  - 0% Once a year
  - 0% Never

Summary of Responses:

Certification bodies reported the most frequent use of AI at work, with 20% indicating daily use and 30% selecting "a few times a week," making this group the most active in the use of AI. Inspection agencies followed, with 40% selecting "A few times a month." Testing and calibration laboratories similarly indicated 37.5% in this category; however, 37.5% also selected "Never," suggesting a more divided response.

Q4 If you don´t currently use AI, does your company plan to start using AI?

Answered: 31 Skipped: 3



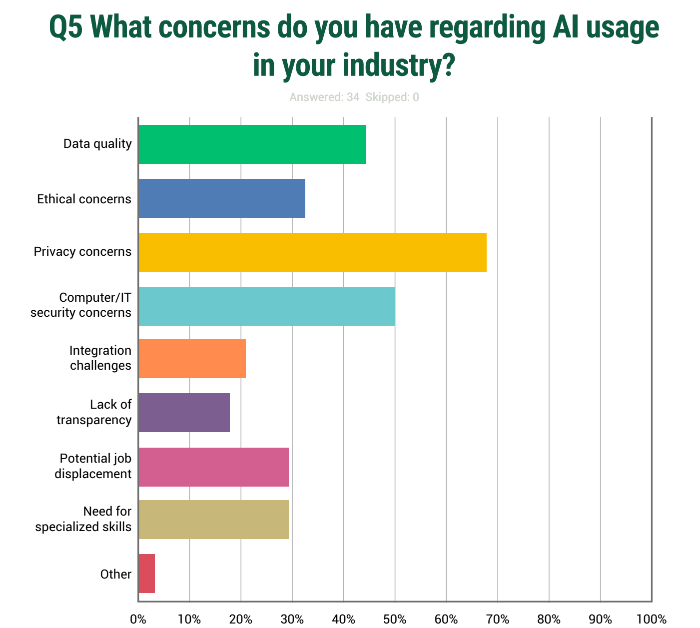
ANSWER CHOICES	RESPONSES
Currently Using	38.71%
Yes	25.81%
No	12.90%
Unsure	22.58%

- Inspection agencies:
  - 40% Currently using
  - 20% Yes
  - 0% No
  - 40% Unsure
- Testing and calibration laboratories:
  - 37.5% Currently using
  - 25% Yes
  - 12.5% No
  - 25% Unsure
- Certification bodies:
  - 41.18% Currently using
  - 29.41% Yes
  - 11.76% No
  - 17.65% Unsure

- Other:
  - 0% Currently using
  - 0% Yes
  - 100% No
  - 0% Unsure

Summary of Responses:

In response to the question about their company's currently planned use of AI, 40% of inspection agencies, 41.8% of certification bodies, and 37.5% of testing and calibration laboratories reported they are currently using AI. However, a significant number of respondents also indicated that they were unsure or not planning to incorporate AI.



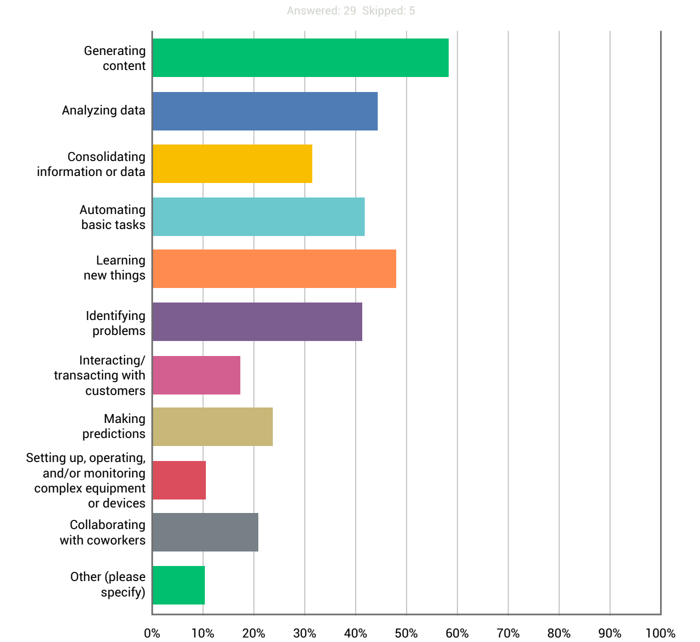
ANSWER CHOICES	RESPONSES
Data quality	44.12%
Ethical concerns	32.35%
Privacy concerns related to customer data	67.65%
Computer/IT security concerns	50.00%
Integration challenges with existing systems	20.59%
Lack of transparency in managerial decision-making	17.65%
Potential job displacement due to automation	29.41%
The need for specialized skills to manage AI systems effectively	29.41%
Other (please specify)	2.94%

- Inspection agencies:
  - 20% Data quality
  - 20% Ethical concerns
  - 40% Privacy concerns related to customer data
  - 80% Computer/IT security concerns
  - 20% Integration challenges with existing systems
  - 20% Lack of transparency in managerial decision-making
  - 40% Potential job displacement due to automation
  - 40% The need for specialized skills to manage AI systems effectively
  - 0% Other
- Testing and calibration laboratories:
  - 12.5% Data quality
  - 25% Ethical concerns
  - 62.5% Privacy concerns related to customer data
  - 50% Computer/IT security concerns
  - 37.5% Integration challenges with existing systems
  - 0% Lack of transparency in managerial decision-making
  - 12.5% Potential job displacement due to automation
  - 25% The need for specialized skills to manage AI systems effectively
  - 0% other
- Certification bodies:
  - 65% Data quality
  - 35% Ethical concerns
  - 75% Privacy concerns related to customer data
  - 40% Computer/IT security concerns
  - 15% Integration challenges with existing systems
  - 20% Lack of transparency in managerial decision-making
  - 35% Potential job displacement due to automation
  - 30% The need for specialized skills to manage AI systems effectively
  - 5% Other
- Other:
  - 0% Data quality
  - 100% Ethical concerns
  - 100% Privacy concerns related to customer data
  - 100% Computer/IT security concerns
  - 0% Integration challenges with existing systems
  - 100% Lack of transparency in managerial decision-making
  - 0% Potential job displacement due to automation
  - 0% The need for specialized skills to manage AI systems effectively
  - 0% Other

Summary of Responses:

Computer and IT security was the top issue among inspection agencies (80%), testing and calibration laboratories (50%), and certification bodies (40%). Among "Other" respondents, 100% selected this concern. Privacy risks related to customer data were also cited at high levels across all groups—75% of certification bodies, 62.5% of testing and calibration laboratories, 40% of inspection agencies, and 100% of respondents in the "Other" category. Only certification bodies expressed a notably high level of concern regarding data quality (65%). Other issues identified by respondents included the need for specialized skills to manage AI systems, potential job displacement, integration challenges, and ethical issues.

Q6 If your company uses AI now, what do you use it for?



ANSWER CHOICES	RESPONSES
Generating content	58.62%
Analyzing data	44.83%
Consolidating information or data	31.03%
Automating basic tasks	41.38%
Learning new things	48.28%
Identifying problems	41.38%
Interacting/ transacting with customers	17.24%
Making predictions	24.14%
Setting up, operating, and/or monitoring complex equipment or devices	10.34%
Collaborating with coworkers	20.69%
Other (please specify)	10.34%

#	OTHER (PLEASE SPECIFY)
1	Currently Using
2	Time sheets
3	n/a

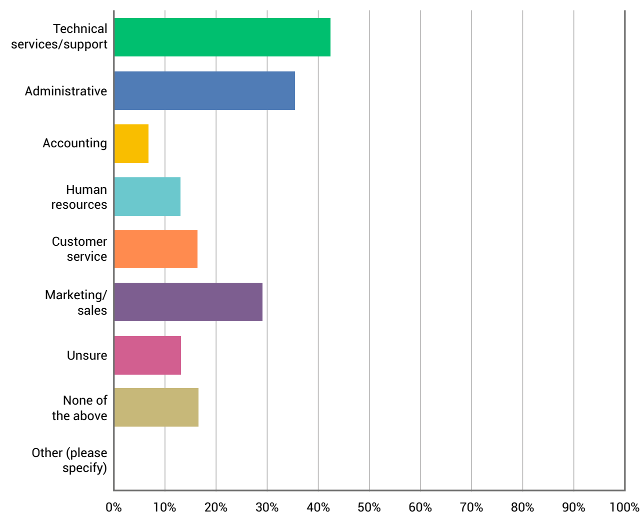
- Inspection agencies:
  - 40% Generating content
  - 20% Analyzing data
  - 0% Consolidating information or data
  - 40% Automating basic tasks
  - 40% Learning new things
  - 60% Identifying problems
  - 0% Other
- Testing and calibration laboratories:
  - 33.33% Generating content
  - 50% Analyzing data
  - 33.33% Consolidating information or data
  - 50% Automating basic tasks
  - 50% Learning new things
  - 33.33% Identifying problems
  - 16.67% Interacting/ transacting with customers
  - 33.33% Making predictions
  - 16.67% Setting up, operating, and/or monitoring complex equipment or devices
  - 16.67% Collaborating with coworkers
  - 16.67% Other
- Certification bodies:
  - 76.47% Generating content
  - 47.06% Analyzing data
  - 41.18% Consolidating information or data
  - 41.18% Automating basic tasks
  - 52.94% Learning new things
  - 35.29% Identifying problems
  - 23.53% Interacting/ transacting with customers
  - 23.53% Making predictions
  - 11.76% Setting up, operating, and/or monitoring complex equipment or devices
  - 23.53% Collaborating with coworkers
  - 11.76% Other
- Other:
  - 0% Generating content
  - 100% Analyzing data
  - 0% Consolidating information or data
  - 0% Automating basic tasks
  - 0% Learning new things
  - 100% Identifying problems
  - 0% Interacting/ transacting with customers
  - 100% Making predictions
  - 0% Setting up, operating, and/or monitoring complex equipment or devices
  - 100% Collaborating with coworkers
  - 0% Other

Summary of Responses:

Respondents from inspection agencies, testing and calibration laboratories, and certification bodies reported using AI for a wide range of tasks. These include generating content, analyzing data, automating basic tasks, identifying problems, and learning new skills. Certification bodies showed the broadest use overall, with higher engagement in categories like content generation (76.47%) and learning new things (52.94%).

While adoption levels vary by task and group, the responses suggest that AI is being used in diverse ways and is becoming more integrated into daily operations—despite the concerns noted in the previous section.

Q7 What departments in your company use AI?



ANSWER CHOICES	RESPONSES
Technical services / support	41.94%
Administrative	35.48%
Accounting	6.45%
Human resources	12.90%
Customer service	16.13%
Marketing / sales	29.03%
Unsure	12.90%
None of the above	16.13%
Other (please specify)	0.00%

#	OTHER (PLEASE SPECIFY)
	There are no responses

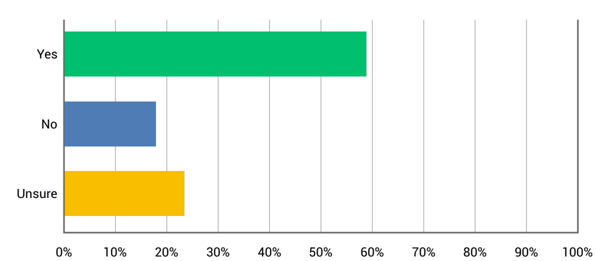
- Inspection agencies:
  - 40% Technical services / support
  - 20% Administrative
  - 0% Accounting
  - 20% Human resources
  - 20% Customer service
  - 0% Marketing / sales
  - 20% Unsure
  - 20% None of the above
  - 0% Other
- Testing and calibration laboratories:
  - 50% Technical services / support
  - 50% Administrative
  - 16.67% Accounting
  - 33.33% Human resources
  - 16.67% Customer service
  - 50% Marketing / sales
  - 16.67% Unsure
  - 0% None of the above
  - 0% Other
- Certification bodies:
  - 42.11% Technical services / support
  - 36.84% Administrative
  - 5.26% Accounting
  - 5.26% Human resources
  - 15.79% Customer service
  - 31.58% Marketing / sales
  - 10.53% Unsure
  - 15.79% None of the above
  - 0% Other
- Other:
  - 0% Technical services / support
  - 0% Administrative
  - 0% Accounting
  - 0% Human resources
  - 0% Customer service
  - 0% Marketing / sales
  - 0% Unsure
  - 100% None of the above
  - 0% Other

Summary of Responses:

Across all groups, AI is most commonly used in technical services and support roles. Testing and calibration laboratories and certification bodies also reported notable use in administrative departments. Certification bodies and laboratories indicated some use of AI in marketing and sales, while inspection agencies reported limited activity beyond technical services.

Respondents in the “Other” category indicated that none of the listed departments currently use AI.

Q8 Do you believe that AI will make your business more competitive?



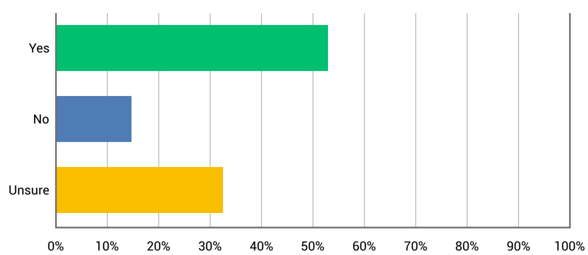
ANSWER CHOICES	RESPONSES
Yes	58.82%
No	17.65%
Unsure	23.53%

- Inspection agencies:
  - 80% Yes
  - 0% No
  - 20% Unsure
- Testing and calibration laboratories:
  - 50% Yes
  - 37.5% No
  - 12.5% Unsure
- Certification bodies:
  - 60% Yes
  - 10% No
  - 30% Unsure
- Other:
  - 0% Yes
  - 100% No
  - 0% Unsure

Summary of Responses:
Most respondents indicated that they believe AI will make their organization more competitive. Inspection agencies were the most confident, with 80% responding "Yes." Certification bodies (60%) and testing and calibration laboratories (50%) also showed positive responses, though the latter had a relatively high "No" rate (37.5%). Responses in the Unsure category varied across groups, reflecting some uncertainty about AI's impact on competitiveness.

Q9 Do you think AI can make the services offered by your company better?

Answered: 34 Skipped: 0



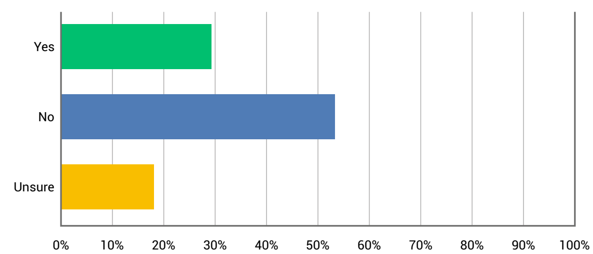
ANSWER CHOICES	RESPONSES
Yes	52.94%
No	14.71%
Unsure	32.35%

- Inspection agencies:
  - 80% Yes
  - 0% No
  - 20% Unsure
- Testing and calibration laboratories:
  - 37.5% Yes
  - 37.5% No
  - 25% Unsure
- Certification bodies:
  - 55% Yes
  - 5% No
  - 40% Unsure
- Other:
  - 0% Yes
  - 100% No
  - 0% Unsure

Summary of Responses:
When asked whether AI will improve the services offered their company offers, 80% of inspection agencies and 55% of certification bodies responded "Yes." Among testing and calibration laboratories, responses were evenly split between "Yes" and "No" at 37.5% each, while 25% were "Unsure." Respondents in the "Other" category unanimously answered "No."

Q10 Does your organization have a guidance document or policy for using AI at work?

Answered: 34 Skipped: 0



ANSWER CHOICES	RESPONSES
Yes	29.41%
No	52.94%
Unsure	17.65%

- Inspection agencies:
  - 20% Yes
  - 80% No
  - 0% Unsure
- Testing and calibration laboratories:
  - 25% Yes
  - 62.5% No
  - 12.5% Unsure
- Certification bodies:
  - 35% Yes
  - 45% No
  - 20% Unsure
- Other:
  - 0% Yes
  - 0% No
  - 100% Unsure

Summary of Responses:
When asked whether their organization has an existing

policy guidance document for the use of AI, most respondents answered "No." This included 80% of inspection agencies, 62.5% of testing and calibration laboratories, and 45 % of certification bodies. All respondents in the "Other" category selected "Unsure."

Open-Ended Comments from Respondents

Concerns and Cautions

- AI can often be thought prompting; however, it requires existing knowledge to sense-check. Misinformation is frequent.
- The use of AI in conformity assessments could lead to fraudulent reporting and decreased confidence in the validity of the certification process.
- Not a good idea now to implement AI.
- AI seems to be uncontrollable.
- Any large model AI that I am aware of requires data being sent to the cloud for processing—an inherent risk to our data security.
- Managing sensitive data through AI systems raises concerns about data privacy and security.
- Performing an assessment using AI is not feasible now. However, using AI to assist with repetitive tasks or ensure specific clause content may help improve the quality of technical reviews.
- Regulatory approval for AI-based methods can be challenging due to the need for extensive validation.
- Our company basically does not use artificial intelligence in our work, so we cannot give effective opinions or suggestions.
- We are not implementing the use of AI in our organization; it is a concern.
- When looking at AI in conformity assessment, I worry about keeping things fair and consistent. Human assessors sometimes interpret standards differently. I'm more concerned that those developing AI may program it to follow one narrow path, potentially limiting flexibility and missing the broader context needed in assessments.
- Still a lot to learn, so no need to jump on the bandwagon yet. Remember, *"If it isn't broke, don't fix it."*

Opportunities and Use Cases

- AI could be used to analyze client documents more quickly.
- AI can help streamline calculations that LIMS cannot do—for example, comparing MDL studies across multiple instruments.
- We use ChatGPT Teams, which does not share our data for training its AI.
- Advantages include:
  - Efficiency and speed: AI can accelerate data collection, analysis, and reporting.
  - Resource optimization: Automating routine tasks lets auditors focus on complex evaluations.

Balanced Perspectives

- AI has the potential to improve efficiency, risk management, and decision-making. However, its implementation must comply with ISO/IEC 17021-1, accreditation body rules (such as IAS MSCB 002), and ethical standards.
- Standards like ISO/IEC 17021-1 require certification bodies to demonstrate competence and impartiality. AI tools must support, not compromise, these principles.
- The key is to use AI as a tool to enhance—not replace—human expertise in certification and accreditation.

Conclusion

The survey provides a valuable snapshot of how Artificial Intelligence (AI) is currently perceived and used across conformity assessment bodies, including inspection agencies, testing laboratories, and certification bodies. Some organizations have begun using AI for tasks like data analysis, content generation, and automating routine processes. However, adoption remains uneven—and significant concerns persis

Respondents cited a range of issues, including data privacy and security risks, ethical considerations, and the potential for job displacement. Many also noted a lack of clear internal policies or guidance on AI use, highlighting a need for industry-wide education and standards

Despite these challenges, the findings suggest that AI holds promise for improving efficiency, streamlining workflows, and supporting decision-making—if integrated thoughtfully. Moving forward, organizations should prioritize transparency, data protection, and continued human oversight to ensure that AI enhances rather than replaces expertise.

Striking the right balance between innovation and responsibility will be key to realizing AI's full potential in the conformity assessment field.

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