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RESTRUCTURING INDUSTRIAL COGNITION: AN AI-ENABLED PERCEPTUAL ALIGNMENT FRAMEWORK FOR QUALITY INSPECTION

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Abstract

Artificial intelligence (AI) is increasingly embedded in manufacturing systems, reshaping not only operational efficiency but also the epistemological foundations of quality decision-making (Brynjolfsson & McAfee, 2017; Porter & Heppelmann, 2014). While prior studies have emphasized the technical advantages of AI-driven inspection systems, limited attention has been given to how such systems transform perceptual judgment and redefine the boundary between human and machine cognition in industrial contexts (Gambino et al., 2020; Longoni et al., 2019). Addressing this gap, this study proposes an AI-enabled perceptual alignment framework for spherical surface inspection, integrating skeleton-based feature matching with three-dimensional (3D) pose estimation to mitigate perceptual uncertainty in high-precision manufacturing environments. Drawing on impression integration theory (Anderson, 1981; Kunda & Thagard, 1996), this research conceptualizes quality inspection as a perceptual integration process in which cognitive and visual cues are synthesized to form defect judgments. Traditional inspection systems—heavily reliant on human operators—are prone to variability due to fatigue, subjective bias and the inherent complexity of curved surfaces. Using a real-world case of golf ball surface inspection, this study demonstrates how AI-mediated perception can standardize judgment by reconstructing object orientation, correcting geometric distortions and enabling consistent feature recognition under variable conditions.

Empirical findings indicate that the proposed framework significantly reduces inspection variability, lowers false detection rates and enhances yield stability. More importantly, the results reveal a structural shift from human-centric to AI-mediated decision-making, in which perceptual authority is redistributed from individual operators to algorithmic systems. This transformation contributes to the emergence of more data-driven forms of quality governance and more traceable decision processes within manufacturing systems. Theoretically, this study extends impression integration theory to human–AI interaction in industrial settings by demonstrating how AI systems not only replicate but also recalibrate perceptual judgment processes. Practically, it offers a scalable and modular solution for spherical object inspection with broader applicability across precision manufacturing domains. By positioning AI as a mediator of perception, this research provides new insights into the evolving role of intelligent systems in shaping industrial cognition and decision-making.

Keywords

Artificial Intelligence; Quality Inspection; Perceptual Alignment; Smart Manufacturing; Visual Inspection; AI-Mediated Decision-Making

1. Introduction

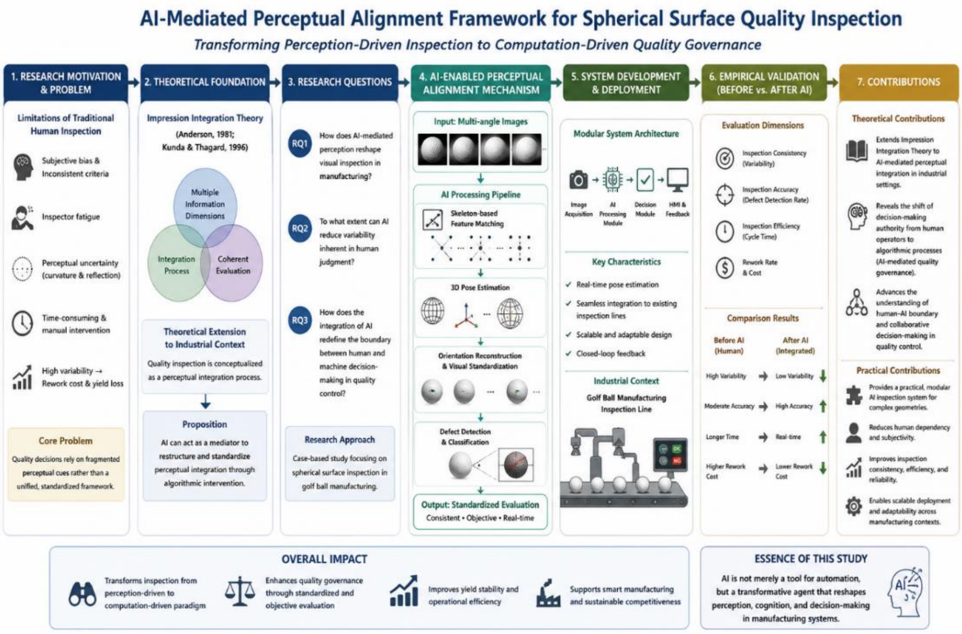
The rapid advancement of artificial intelligence (AI) has fundamentally transformed manufacturing systems, shifting them from labor-intensive processes toward data-driven and algorithmically optimized operations (Brynjolfsson & McAfee, 2017). In recent years, AI-based approaches have been increasingly adopted in quality inspection and manufacturing analytics, with prior work showing their potential to improve defect detection, process visibility and inspection efficiency (Sundaram & Zeid, 2023). However, a more profound transformation is underway beyond these operational enhancements. AI is increasingly redefining how decisions are made, particularly in contexts that rely heavily on human perception and judgment (Gambino et al., 2020).

Quality inspection represents one of the most cognitively demanding processes in manufacturing. Traditionally, inspection tasks have relied on human visual perception supported by optical devices. While such approaches are effective to a certain extent, they are inherently constrained by subjective bias, fatigue and inconsistency in judgment criteria (Longoni et al., 2019). These limitations become particularly pronounced in the inspection of spherical objects, where surface curvature and reflective properties introduce substantial perceptual uncertainty.

In conventional spherical surface inspection systems, multiple imaging stations are typically employed to compensate for orientation variability and ensure coverage of the object surface. Despite these efforts, the process remains inefficient and often requires manual intervention to resolve ambiguous cases. As a result, inspection outcomes are time-consuming and prone to variability, undermining yield stability and increasing rework costs. More importantly, the reliance on human interpretation means that quality decisions are often shaped by fragmented perceptual cues rather than a unified and standardized evaluation framework.

This study argues that these limitations are not merely technical but fundamentally perceptual. To address this issue, it introduces an AI-enabled perceptual alignment framework that reconfigures the inspection process from a perception-driven paradigm to a computation-driven paradigm. Specifically, the proposed system integrates skeleton-based feature matching with 3D pose estimation to reconstruct object orientation and standardize visual representation.

To provide a theoretical foundation, this study draws on impression integration theory, which posits that individuals form judgments by integrating multiple dimensions of information into a coherent evaluation (Anderson, 1981; Kunda & Thagard, 1996). Extending this perspective to industrial settings, the study conceptualizes quality inspection as a perceptual integration process. By introducing AI as a mediator of this process, it examines how perceptual integration can be restructured through algorithmic intervention, drawing on the view that judgments are formed through the integration of multiple cues into a coherent evaluation (Anderson, 1981; Kunda & Thagard, 1996).



Accordingly, this research addresses the following questions: How does AI-mediated perception reshape visual inspection in manufacturing? To what extent can AI reduce variability inherent in human judgment? And how does the integration of AI redefine the boundary between human and machine decision-making in quality control processes? To answer these questions, this study employs a case-based approach focusing on spherical surface inspection in golf ball manufacturing. The proposed framework is implemented as a modular system that can be integrated into existing inspection lines, enabling real-time pose estimation, feature alignment and defect detection. By comparing performance before and after AI integration, the study evaluates the impact of the system on inspection consistency, efficiency and reliability.

The findings contribute to both theory and practice in several ways. First, they extend impression integration theory by demonstrating how perceptual judgment can be externalized and restructured through AI systems in industrial contexts. Second, they reveal a shift in decision-making authority from human operators to algorithmic processes, highlighting the emergence of AI-mediated quality governance. Third, they provide practical insights into the design of scalable and adaptable inspection systems for complex geometries. In doing so, this study moves beyond viewing AI as a tool for automation and instead positions it as a transformative agent that reshapes perception, cognition and decision-making in manufacturing systems.

2. Literature Review and Theoretical Foundation

2.1 AI in manufacturing and the transformation of decision-making

AI has become a central enabler of smart manufacturing, improving efficiency and enabling advanced data-processing capabilities (Brynjolfsson & McAfee, 2017; Sundaram & Zeid, 2023). Recent work suggests that AI is not merely a tool for enhancing operational efficiency but a transformative force that reshapes how decisions are generated, validated and executed (Brynjolfsson & McAfee, 2017). In particular, AI systems are increasingly capable of performing tasks that traditionally relied on human perception, such as anomaly detection and visual judgment. This shift implies a redistribution of decision authority from human operators to algorithmic systems, raising important questions about the nature of cognition and judgment in industrial environments.

Despite these developments, the literature remains fragmented in its treatment of AI-driven decision transformation. Technical studies emphasize algorithmic performance, whereas management studies discuss digital transformation at an organizational level. There is a lack of integrative frameworks that connect AI capabilities with the cognitive processes underlying human judgment. This gap is particularly evident in quality inspection contexts, where decision-making is inherently perceptual and involves the integration of multiple uncertain visual cues.

2.2 Perceptual uncertainty in visual inspection

Visual inspection involves subjective interpretation and is influenced by human cognitive limitations. In curved surface inspection, perceptual uncertainty is amplified due to orientation variability and image distortion. The challenge becomes more pronounced in the inspection of spherical objects, where surface curvature introduces additional complexity. In such contexts, visual information is highly sensitive to object orientation, lighting conditions and reflective properties. Traditional inspection systems attempt to mitigate these issues through multi-angle imaging and predefined threshold-based algorithms. However, these approaches often result in redundant data and still require human intervention for ambiguous cases.

From a cognitive perspective, visual inspection can be understood as a process of perceptual integration, in which operators synthesize multiple visual cues to form a judgment (Anderson, 1981). When these cues are incomplete, distorted or inconsistent—as is often the case in curved surface inspection—the resulting judgments become unstable. This instability manifests as variability in inspection outcomes, leading to inconsistent quality standards and increased operational costs. Although AI-based inspection systems have been proposed to address these challenges, existing studies tend to treat perception as a purely technical problem, focusing on image-recognition accuracy rather than the underlying cognitive process of judgment formation. Consequently, the role of AI in restructuring perceptual integration remains underexplored.

2.3 Human–AI boundary in perceptual judgment

As AI systems become more capable of performing perceptual tasks, the boundary between human and machine cognition is increasingly blurred. In traditional manufacturing settings, humans are regarded as the ultimate decision-makers, with machines serving as tools to assist or augment their capabilities. However, the growing sophistication of AI challenges this paradigm by enabling machines to independently interpret data and make judgments. Research suggests that people may remain cautious about AI-based judgment even when algorithmic systems demonstrate strong performance, particularly when decisions are perceived as requiring individualized understanding (Longoni et al., 2019). This perception shapes how AI is adopted in decision-making contexts.

In industrial contexts, this boundary is not merely psychological but operational. The delegation of decision-making to AI systems raises critical questions regarding trust, accountability and standardization. For instance, when AI systems consistently outperform human operators, organizations may increasingly rely on algorithmic decisions, thereby reducing human involvement in the inspection process. This shift represents a transition from human-centric to AI-mediated decision-making, with significant implications for quality governance. However, existing studies have largely examined human–AI boundaries in consumer or service settings, with limited attention to manufacturing environments. In particular, the role of AI in redefining perceptual judgment—where decisions are based on visual and contextual cues—remains insufficiently understood.

2.4 Theoretical foundation: Impression integration in AI-mediated perception

To address the limitations of existing literature, this study adopts impression integration theory as a conceptual lens to examine how perceptual judgments are formed and transformed in AI-enabled environments (Anderson, 1981; Kunda & Thagard, 1996). Impression integration theory explains how multiple cues are synthesized into a unified judgment. Although originally developed in the context of social perception, this framework provides a useful foundation for understanding visual inspection in manufacturing, where operators combine various visual signals—such as shape, texture and alignment—to assess product quality.

The introduction of AI fundamentally alters this process. By reconstructing object orientation through 3D pose estimation and standardizing feature representation, AI systems effectively restructure the input space of perceptual integration. In doing so, they reduce ambiguity and enable more consistent judgment outcomes. This transformation can be understood as a shift from human-based impression integration to AI-mediated perceptual alignment. Building on this perspective, this study proposes that AI does not merely replicate human perception but reconfigures the process by which perceptual judgments are formed. Specifically, AI acts as an intermediary that filters, aligns and enhances visual information before it is evaluated, thereby reshaping the cognitive foundation of decision-making.

2.5 Research gap and contribution

Based on the above discussion, three key gaps can be identified. First, prior studies on AI in manufacturing have largely focused on performance metrics, overlooking the transformation of perceptual and cognitive processes underlying decision-making. Second, research on visual inspection has emphasized technical solutions without adequately addressing perceptual uncertainty and judgment variability. Third, studies on human–AI interaction have rarely examined industrial contexts, particularly in relation to perceptual tasks. This study addresses these gaps by integrating AI technology with a cognitive theoretical framework to examine how perceptual judgment is restructured in manufacturing environments. By proposing an AI-enabled perceptual alignment model and validating it through a real-world case, this research contributes to a deeper understanding of the evolving relationship between human cognition, machine intelligence and industrial decision-making.

3. Conceptual Framework and Hypotheses Development

3.1 Conceptualizing AI-mediated perceptual alignment

Building on the preceding discussion, this study conceptualizes quality inspection as a perceptual integration process in which multiple sources of visual information are synthesized to form defect judgments. In traditional manufacturing environments, this process is largely human-centered, relying on operators to interpret fragmented and often uncertain visual cues. Such reliance introduces variability because human perception is inherently influenced by cognitive limitations, fatigue and subjective bias.

To address this issue, this study introduces the concept of AI-mediated perceptual alignment, defined as the process by which artificial intelligence systems restructure and standardize perceptual inputs to enable consistent and reliable judgment outcomes. Rather than merely automating inspection tasks, AI functions as a mediator that transforms how visual information is organized, interpreted and evaluated.

Specifically, the proposed framework integrates skeleton-based feature matching with three-dimensional (3D) pose estimation to reconstruct the orientation of spherical objects and align them into a standardized reference frame. This alignment reduces perceptual ambiguity by ensuring that defect-related features are consistently represented across inspection instances.

Accordingly, the conceptual framework consists of three core components:

1. Perceptual uncertainty – variability and ambiguity in visual information caused by factors such as object orientation, surface curvature and lighting conditions.
2. AI-mediated alignment capability – the system's ability to reconstruct object pose, standardize feature representation and reduce noise in visual data.
3. Inspection outcome transformation – improvements in consistency, accuracy and reliability of quality judgments, as well as broader shifts in decision-making structures.

This framework extends impression integration theory by incorporating AI as an active agent that reshapes the inputs of perceptual integration, thereby altering the resulting judgments.

3.2 Perceptual uncertainty and inspection variability

Perceptual uncertainty disrupts judgment stability because unstable or ambiguous cues weaken the integration process through which evaluations are formed (Anderson, 1981; Kunda & Thagard, 1996). From this perspective, uncertainty in input cues is expected to increase variability in inspection outcomes. In manufacturing settings, this instability manifests as fluctuations in defect classification, increased false positives and negatives, and reliance on manual re-inspection.

H1: Perceptual uncertainty is positively associated with inspection variability.

3.3 AI-mediated alignment and reduction of perceptual uncertainty

AI-mediated alignment addresses perceptual uncertainty by transforming how visual information is structured. Through 3D pose estimation, the system reconstructs the spatial orientation of objects, enabling consistent alignment regardless of initial positioning. In addition, skeleton-based feature matching ensures that critical features are accurately identified and mapped across different inspection instances. By standardizing the representation of visual inputs, AI reduces ambiguity and enhances the clarity of defect-related information. This process effectively stabilizes the perceptual integration mechanism, allowing for more consistent judgment outcomes.

H2: AI-mediated alignment capability is negatively associated with perceptual uncertainty.

3.4 AI-mediated alignment and inspection consistency

Beyond reducing uncertainty, AI-mediated alignment directly influences the consistency of inspection outcomes. By providing a standardized reference frame for evaluation, AI systems minimize the influence of contextual variations and human subjectivity. In traditional inspection processes, different operators may interpret the same visual information differently, leading to inconsistent results. AI systems, in contrast, apply uniform decision rules across all instances, ensuring that similar inputs yield similar outputs. Thus, AI-mediated alignment is expected to enhance inspection consistency.

H3: AI-mediated alignment capability is positively associated with inspection consistency.

3.5 Inspection consistency and yield stability

Inspection consistency plays a critical role in determining overall production performance. Inconsistent judgments can lead to misclassification of products, resulting in unnecessary rework or the release of defective items. Over time, such inconsistencies contribute to fluctuations in yield rates and increased operational costs. By improving the reliability of defect detection, consistent inspection processes help stabilize production outcomes and enhance overall quality performance.

H4: Inspection consistency is positively associated with yield stability.

3.6 AI-mediated alignment and decision authority shift

The introduction of AI into perceptual tasks has implications beyond performance improvement. As AI systems become more reliable in generating consistent judgments, organizations may increasingly rely on algorithmic outputs rather than human interpretation. This shift represents a redistribution of decision authority, where the role of human operators transitions from primary decision-makers to supervisors or validators of AI outputs. Such a transformation reflects a broader trend toward AI-mediated governance in manufacturing systems. Consequently, stronger AI-mediated alignment capability is expected to accelerate the shift in decision authority from humans to machines.

H5: AI-mediated alignment capability is positively associated with the shift from human-centric to AI-mediated decision-making.

3.7 Decision authority shift and quality governance transformation

The redistribution of decision authority has significant implications for quality governance. In traditional systems, quality control relies on human expertise and tacit knowledge, which are often difficult to standardize and scale. In contrast, AI-mediated systems enable the codification of decision rules and the creation of traceable and auditable processes. This transformation enhances transparency, accountability and scalability in quality management, facilitating the development of data-driven governance structures.

H6: The shift toward AI-mediated decision-making is positively associated with the development of data-driven quality governance.

3.8 Summary of the conceptual model

Based on the proposed hypotheses, this study presents a conceptual model in which AI-mediated alignment reduces perceptual uncertainty, enhances inspection consistency and ultimately improves yield stability. In parallel, it drives a structural transformation in decision-making authority, contributing to the emergence of AI-enabled quality governance. This dual-path model—capturing both operational performance and governance transformation—provides a comprehensive framework for understanding the role of AI in reshaping manufacturing systems.

4. Methodology

4.1 Research design

This study adopts a case-based empirical research design to investigate how AI-mediated perceptual alignment reshapes visual inspection and decision-making in manufacturing environments. Given the focus on both operational performance and cognitive transformation, a real-world implementation context is essential to capture the complexity of human–AI interaction in industrial settings.

Accordingly, a single-case embedded design is employed, focusing on a high-precision manufacturing environment involving spherical surface inspection. The case was selected based on three criteria:

1. The presence of significant perceptual uncertainty in inspection tasks.
2. The integration of AI technologies into existing inspection systems.
3. The availability of longitudinal performance data before and after AI implementation.

The research design follows a quasi-experimental before–after comparison, enabling the evaluation of changes in inspection performance and decision structures following the introduction of AI-mediated alignment. This approach is particularly suitable in industrial contexts where controlled experimentation is not feasible but real operational data are available.

4.2 Research context and case description

The empirical setting of this study is a golf ball manufacturing facility that employs a multi-station automated optical inspection system for surface quality control. The inspection process involves multiple imaging stations designed to capture different surface angles of spherical objects in order to compensate for orientation variability.

Despite the use of automated equipment, the system exhibits several structural limitations. First, the orientation of incoming objects is inherently random, resulting in inconsistent visibility of critical features. Second, surface curvature and reflective properties introduce visual distortions that complicate defect detection. Third, the system relies on predefined thresholds and requires frequent manual calibration, leading to variability in inspection outcomes. Finally, ambiguous cases are often escalated to human operators for re-evaluation, increasing labor intensity and reducing efficiency.

To address these challenges, an AI-enabled perceptual alignment module was integrated into the existing inspection system. The module combines skeleton-based feature matching and 3D pose estimation to reconstruct object orientation and standardize visual representation prior to defect analysis. Importantly, the system is designed as a modular add-on, allowing seamless integration without requiring a complete overhaul of existing infrastructure.

4.3 Data collection

Data were collected from the production line over two phases.

1. Pre-AI phase (baseline period).During this phase, inspection relied on the original multi-station optical system combined with manual verification. Data collected included defect detection outcomes, false positive and false negative rates, manual re-inspection frequency and yield rates.
2. Post-AI phase (intervention period).After integrating the AI module, the same set of indicators was recorded to enable comparison. Additional data related to AI system performance were also collected, including pose estimation accuracy, feature alignment consistency and system decision logs.

To ensure comparability, data were collected over equivalent production volumes and operating conditions across both phases. The dataset consists of batch-level and unit-level observations, allowing both aggregated and fine-grained analyses.

4.4 Measurement of variables

To empirically test the proposed hypotheses, key constructs were operationalized as follows.

- Perceptual uncertainty.Measured as variability in visual input conditions, including indicators such as reflection-intensity variance and inconsistency in feature visibility. These indicators were aggregated to reflect the overall level of uncertainty in inspection inputs.
- AI-mediated alignment capability.Measured using system-level performance indicators, including pose estimation accuracy (alignment error rate), feature-matching precision and the consistency of standardized representations across instances. Higher values indicate stronger alignment capability.
- Inspection variability.Captured by variance in defect classification across repeated inspections, disagreement rates between system and human judgments in the pre-AI phase and inconsistency across inspection stations.
- Inspection consistency.Measured as reductions in classification variance, stability of defect detection results across batches and repeatability of inspection outcomes.
- Yield stability.Measured by the fluctuation range of yield rates across production batches, defect leakage rate and rework frequency. Lower variability and lower defect leakage indicate higher yield stability.
- Decision authority shift.Operationalized through reductions in manual re-inspection rates, the proportion of decisions made solely by the AI system and the frequency of operator intervention.
- Quality governance transformation.Measured using indicators of decision-log traceability, the standardization of inspection criteria and the consistency of quality reporting across production cycles.

4.5 Data analysis approach

To test the proposed conceptual model, this study employs a two-stage analytical strategy. First, a before–after comparative analysis is conducted to evaluate changes in key performance indicators following AI implementation. Statistical tests such as paired-sample t-tests and variance analysis are used to assess the significance of differences between the pre-AI and post-AI phases.

Second, a structural equation modeling (SEM) approach is employed to examine the relationships among constructs and test the proposed hypotheses. SEM is particularly suitable for this study because it allows simultaneous estimation of multiple relationships among latent variables and captures both direct and indirect effects within the conceptual framework. A partial least squares SEM (PLS-SEM) method is adopted, given the exploratory nature of extending impression integration theory into manufacturing contexts and the complexity of the model. This approach is appropriate for complex models with relatively small sample sizes and emphasizes prediction and theory development.

4.6 Reliability and validity

Several steps are taken to establish reliability and validity and to ensure the robustness of the analysis. Construct reliability is assessed using internal-consistency measures, including composite reliability and Cronbach's alpha. Convergent validity is evaluated through average variance extracted (AVE), which ensures that indicators adequately represent their respective constructs. Discriminant validity is tested using the Fornell–Larcker criterion and cross-loading analysis.

For system-generated data, consistency checks are performed to validate the accuracy of AI outputs, including cross-validation with manually verified samples. In addition, triangulation is achieved by combining system logs, production records and operator feedback to enhance data credibility.

4.7 Summary

The use of a case-based design and a quasi-experimental before–after comparison is consistent with prior studies examining AI implementation in real-world contexts. The adoption of PLS-SEM is also aligned with methodological recommendations for exploratory research involving complex models and emerging theoretical frameworks. By integrating real-world industrial data with a theoretically grounded analytical framework, and by combining before–after analysis with structural modeling, the study provides a comprehensive evaluation of AI-mediated perceptual alignment in manufacturing contexts.

5. Results

5.1 Descriptive results and performance comparison

A comparative analysis between the pre-AI and post-AI phases reveals substantial improvements across multiple performance indicators following the implementation of the AI-enabled inspection module.

First, inspection variability was significantly reduced. In the pre-AI phase, defect classification exhibited notable inconsistency across inspection stations and operators, reflecting the influence of perceptual uncertainty. After the introduction of AI-mediated alignment, classification variance decreased markedly, indicating that the system was able to standardize visual inputs and stabilize judgment outcomes.

Second, false detection rates showed a clear decline. Both false positives (incorrectly identifying non-defective items as defective) and false negatives (failing to detect actual defects) were reduced. This suggests that the AI system enhanced the accuracy of defect identification. The improvement can be attributed to the system's ability to reconstruct object orientation and align features prior to analysis, thereby minimizing ambiguity in visual interpretation.

Third, yield stability improved significantly. In the pre-AI phase, yield rates fluctuated across production batches due to inconsistent inspection outcomes and rework processes. After AI implementation, yield variability decreased and the proportion of stable, high-quality output increased. This result highlights the role of consistent inspection in enhancing overall production performance.

Finally, manual intervention was substantially reduced. The frequency of manual re-inspection declined as the AI system demonstrated reliable performance in handling previously ambiguous cases. This reduction not only improved efficiency but also signaled a shift in decision-making responsibility from human operators to the AI system.

5.2 Hypothesis testing results

The proposed hypotheses were tested using structural equation modeling. The results provide strong support for the conceptual framework.

H1 predicted that perceptual uncertainty is positively associated with inspection variability. The analysis confirms this relationship, showing that higher levels of input uncertainty—such as orientation dispersion and image distortion—are associated with greater variability in inspection outcomes. This finding reinforces the notion that instability in perceptual inputs disrupts judgment consistency.

H2 proposed that AI-mediated alignment capability is negatively associated with perceptual uncertainty. The results support this hypothesis, indicating that the AI system effectively reduces uncertainty by reconstructing object orientation and standardizing visual features. This demonstrates that AI does not merely process visual data but also actively restructures the perceptual input space.

H3 predicted that AI-mediated alignment capability positively influences inspection consistency. The findings strongly support this relationship. The alignment mechanism ensures that similar inputs are evaluated under consistent conditions, thereby enhancing repeatability and reliability in inspection outcomes.

H4 proposed that inspection consistency positively affects yield stability. The results confirm that improved consistency in defect classification leads to more stable production outcomes. This finding underscores the operational importance of reliable inspection processes in maintaining product quality.

H5 predicted that AI-mediated alignment capability is positively associated with a shift toward AI-mediated decision-making. The analysis reveals a significant relationship: as AI systems become more capable and reliable, organizations increasingly rely on algorithmic decisions. This shift is evidenced by the reduced need for human intervention and the growing proportion of decisions made autonomously by the system.

H6 proposed that the shift toward AI-mediated decision-making contributes to the development of data-driven quality governance. The results support this hypothesis, showing that the adoption of AI enables the standardization and traceability of decision processes. System-generated logs and consistent decision rules facilitate the creation of auditable and scalable quality-management frameworks.

5.3 Structural model evaluation

The structural model demonstrates strong explanatory power. Key endogenous constructs, including inspection consistency and yield stability, exhibit substantial explained variance, indicating that the proposed framework captures critical drivers of performance improvement. Path coefficients are statistically significant and aligned with theoretical expectations, confirming the robustness of the relationships among constructs. In addition, the model reveals both direct and indirect effects of AI-mediated alignment, highlighting its central role in both operational and structural transformation.

5.4 Transformation of decision-making structure

Beyond performance improvements, the results reveal a deeper transformation in the decision-making structure of the inspection process. In the pre-AI phase, decision-making was distributed across multiple human operators, each applying individual judgment criteria to interpret visual information. This decentralized and perception-dependent structure contributed to variability and inefficiency.

In contrast, the post-AI phase is characterized by a centralized, system-driven decision architecture. The AI system functions as the primary decision-maker, applying standardized rules to all inspection instances, while human operators intervene mainly in exceptional cases and increasingly adopt a supervisory role. This shift represents a movement from human-centric perceptual judgment to AI-mediated decision-making and fundamentally alters how quality is defined, evaluated and controlled within the production system.

5.5 Summary of findings

Overall, the results demonstrate that AI-mediated perceptual alignment produces both operational and structural impacts. At the operational level, the system reduces perceptual uncertainty, enhances inspection consistency and improves yield stability. At the structural level, it redistributes decision authority and enables the emergence of more data-driven forms of quality governance. These findings confirm that AI is not merely an efficiency-enhancing tool but also a transformative agent that reshapes perception, cognition and decision-making in manufacturing environments.

6. Discussion

6.1 Reframing AI in manufacturing: From automation to perceptual mediation

The findings of this study suggest that the role of AI in manufacturing extends far beyond automation and efficiency enhancement. While prior research has largely framed AI as a tool for improving operational performance, this study demonstrates that AI fundamentally reshapes the perceptual and cognitive processes underlying decision-making. Specifically, the introduction of AI-mediated perceptual alignment transforms visual inspection from a human-dependent interpretive activity into a standardized computational process. This shift reframes AI not merely as a substitute for human labor but as a mediator of perception—an entity that reorganizes how information is structured and evaluated before judgment occurs.

This perspective contributes to a more nuanced understanding of AI adoption in industrial contexts. Rather than viewing AI simply as a means of replicating human capabilities, the results indicate that AI redefines the conditions under which perception itself takes place. In doing so, it alters the epistemological foundations of quality judgment by shifting from subjective interpretation to algorithmically structured evaluation.

6.2 Extending impression integration theory to industrial contexts

This study extends impression integration theory by demonstrating its applicability beyond human social perception to AI-mediated industrial environments. Traditionally, the theory explains how individuals integrate multiple dimensions of information to form holistic judgments. The findings here show that when AI systems intervene in this process, they do not merely participate in impression formation; they actively reshape its inputs.

In the context of visual inspection, human operators rely on fragmented and often ambiguous cues to form judgments about product quality. AI-mediated alignment restructures these cues by standardizing object representation and reducing perceptual noise. As a result, the integration process becomes more stable and less susceptible to variability. This transformation suggests a shift from human-based impression integration to AI-mediated perceptual alignment, in which the role of AI is not limited to decision execution but extends to the configuration of perceptual inputs.

6.3 Redefining the human–AI boundary in decision-making

Another key implication of this study lies in its contribution to the literature on human–AI boundaries. Existing research has often emphasized the distinction between human and machine cognition, focusing on users' perceptions of AI limitations. In contrast, this study provides empirical evidence of a structural shift in which AI systems assume an increasingly central role in decision-making processes.

The reduction in manual intervention observed in this study reflects a redistribution of decision authority, whereby human operators transition from primary decision-makers to supervisors of AI systems. This shift challenges traditional assumptions about the division of labor between humans and machines, particularly in tasks that involve perceptual judgment. Importantly, the findings suggest that the boundary between human and AI is not fixed but dynamically reconfigured through technological capability and organizational practice.

6.4 Implications for quality governance and industrial systems

The transformation observed in this study has broader implications for quality governance in manufacturing systems. Traditional quality control relies heavily on human expertise that is often tacit, context-dependent and difficult to standardize. This reliance creates challenges in ensuring consistency and scalability across production environments.

The adoption of AI-mediated inspection enables the codification of decision rules and the generation of traceable data, thereby facilitating the development of data-driven quality-governance structures. In such systems, decisions are no longer dependent on individual operators but are embedded within algorithmic processes that can be monitored, audited and continuously improved. This shift enhances transparency and accountability while also enabling organizations to scale quality-control practices more effectively. In this sense, AI not only improves inspection performance but also redefines the institutional mechanisms through which quality is managed and enforced.

6.5 Practical implications

The findings of this study offer several practical implications for manufacturing practitioners. First, organizations should recognize that the value of AI lies not only in performance improvement but also in its ability to standardize perception and reduce variability in decision-making. Investments in AI technologies should therefore focus on their capacity to restructure information flows and enhance consistency.

Second, the modular design of the AI system demonstrated in this study provides a viable pathway for integrating advanced technologies into existing production lines without significant disruption. This approach lowers the barrier to adoption and increases the scalability of AI solutions.

Third, the shift toward AI-mediated decision-making requires a redefinition of human roles within manufacturing systems. Rather than performing routine inspection tasks, human operators should be repositioned as system supervisors and analysts, focusing on exception handling and continuous improvement.

6.6 Limitations and future research

Despite its contributions, this study has several limitations. First, the research is based on a single-case study, which may limit the generalizability of the findings. Future research could examine multiple cases across different industries to validate the proposed framework. Second, other forms of decision-making in manufacturing—such as strategic planning and resource allocation—may involve different dynamics from those examined here. Extending the framework to these contexts would provide a more comprehensive understanding of AI's impact.

Third, the measurement of constructs such as perceptual uncertainty and decision-authority shift relies on operational proxies. Future studies could develop more refined measurement scales to capture these constructs with greater precision. Finally, ethical considerations related to accountability and transparency will become increasingly important as AI systems gain greater autonomy. Future research should explore these issues in greater depth, particularly in relation to industrial governance.

7. Conclusion

This study investigates how artificial intelligence reshapes perceptual judgment and decision-making in manufacturing contexts through the lens of AI-mediated perceptual alignment. By integrating skeleton-based feature matching with 3D pose estimation, the proposed framework addresses the fundamental challenge of perceptual uncertainty in spherical surface inspection. The findings demonstrate that AI not only improves inspection performance by reducing variability, enhancing consistency and stabilizing yield but also drives a structural transformation in decision-making.

Specifically, the study reveals a shift from human-centric perceptual judgment to AI-mediated decision-making, accompanied by the emergence of more data-driven forms of quality governance. Theoretically, this research extends impression integration theory by showing how AI systems restructure the inputs of perceptual integration and thereby alter judgment outcomes. It also contributes to the literature on human–AI interaction by providing empirical evidence of the dynamic reconfiguration of decision boundaries in industrial settings.

Practically, the study offers a scalable and modular solution for improving quality inspection in manufacturing, with potential applications across a wide range of industries involving complex geometries and high-precision requirements. In conclusion, this study positions AI not merely as a tool for automation but as a transformative agent that reshapes perception, cognition and governance in manufacturing systems. As industries continue to adopt intelligent technologies, understanding this transformation will be critical for designing effective and sustainable production systems.

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