A conceptual model for interactive visual inspection and labeling to bridge automation and human quality control

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Abstract

Advancements in automation and increasingly capable AI models are transforming industrial quality control and shift the human involvement toward higher-level tasks. This development brings both risks and opens up potentials, requiring a careful and conscious shaping of this change to ensure an optimal outcome. In this position paper, we approach this challenge from the perspective of human potential loss and reflect on our engagement with industry stakeholders from the automotive, aerospace, and coating domains. We outline key principles for both preserving human expertise and engagement in hybrid workflows and active building of new skills, proposing a conceptual model for interactive visual inspection and labeling. In addition, we discuss initial visualization interface considerations and outline research directions for enhancing human-AI collaboration in quality control.

Keywords

Human in the Loop, Industry 5.0, Human Automation, Visual Analytics

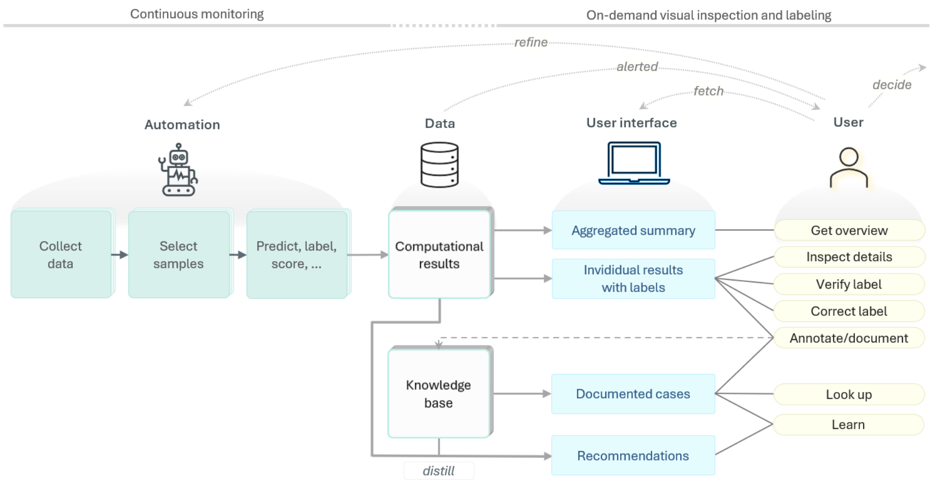

Figure 1: Proposed conceptual model for hybrid quality control. The left side represents continuous monitoring, primarily automated by AI, while the right side illustrates human collaboration through on-demand visual inspection and labeling.

1. Introduction

Automation is widely used in industrial quality control (QC) to enhance consistency and efficiency while reducing manual labour. Traditional automated inspection systems often rely on predefined rules and threshold-based evaluations. Advancements in machine learning and deep learning now enable the automation of more complex QC tasks [1, 2], which were once thought to require human expertise exclusively [3]. As a result, human intervention in QC shifts even more toward higher-level tasks, such as decision-making, defining corrective actions in production, and refining inspection criteria.

AutomationXP25: Hybrid Automation Experiences, April 27, 2025, Yokohama, Japan. In conjunction with ACM CHI'25.
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This shift reinforces the need to actively preserve, utilize and augment human expertise in quality control processes [4, 5]. Effective collaboration between humans, as inspectors and decision makers, and AI systems is necessary to balance automation efficiency with human judgment, especially when managing trade-offs between accuracy, reliability, and throughput. Industry 5.0 emphasizes a shift toward sustainable, human-centered, and resilient manufacturing [6]. In this context, it is essential to design workflows and systems that enhance human potential rather than diminish it.

In this work, we reflect on findings from a large-scale industry project with multiple partners, including technology providers and manufacturing companies from sectors such as automotive, aerospace, and coatings. By analyzing workflows and challenges, we investigate how human-AI collaboration in quality control can be strengthened. Specifically, we explore how interactive visual analytics can support human oversight, intervention, and knowledge transfer while advancing AI-driven automation.

We outline ten key principles to enhance human potential (Sec. 2), propose a conceptual model for interactive visual inspection and labeling (Sec. 3), and discuss initial visualization design considerations (Sec. 4). Finally, we outline research directions to improve hybrid human-AI quality control (Sec. 5).

2. Enhancing Human Potential

Growing automation heightens the risk of human potential loss, a major concern for industry. While automation enhances efficiency, it can lead to disengagement, knowledge erosion, and reduced adaptability among workers [7]. In the context of hybrid QC, we define *human potential* as the ability to effectively apply domain expertise, adapt to new challenges, and actively contribute in continuous process improvement.

Strengthening human potential is essential for maintaining expertise and decision-making quality, but has also critical links to employee satisfaction, workforce stability, and long-term value creation [8]. When workers feel engaged, valued, and able to develop skills alongside automation, they are more likely to remain in their roles [9]. A key challenge in AI-driven workflows is the risk of deskilling [10]. The long-standing question of whether AI serves as a multiplier—disproportionately favoring experienced workers over novice employees—remains relevant. However, as AI models become more advanced, there is a growing risk that workers become overly dependent on automation, and gradually lose the ability to question decisions, diagnose issues, and solve problems [11]. At the same time, AI offers opportunities to reshape and expand skills, serving as a tool to enhance employee's cognitive and technical abilities [12]. Hybrid human-AI collaboration depends on actively fostering skill development and problem-solving capabilities to counteract the risk of deskilling and support upskilling [13].

Over two years, we collaborated with industry stakeholders, including technology providers and manufacturers, and conducted a series of workshops and interviews on human-centric aspects of zero-defect manufacturing [14]. Based on this engagement and a review of related work, we derived ten principles to enhance human potential:

P1. **Active Human-AI Engagement**. Processes and systems should be designed to foster a mindset where users see AI as an augmenting tool rather than a replacement. Users should be actively engaged, critically assess AI decisions, and act as collaborators rather than passive operators who risk to become mere assistants to AI-driven QC.

P2. **Transparent and Trustworthy Decision-Making**. AI outputs should be interpretable to help users build trust, improve oversight, and develop expertise [15]. It should facilitate bidirectional knowledge exchange, where both AI and human workers continuously learn from each other [16].

P3. **Role Clarity in Hybrid Workflows**. AI should enhance, not undermine, worker autonomy [8]. Clearly defined roles and collaborative decision-making mechanisms ensure that human workers remain in control throughout the process.

P4. **Reducing Ergonomic Strain**. Automation and AI should be used to alleviate repetitive and high-strain QC tasks, to allow human workers focus on higher-level decision-making.

P5. **Situational Assistance**. AI should provide context-aware recommendations and synthesize knowledge to support workers in both routine and non-routine tasks [17]. Beyond executing predefined automation pipelines, AI can act as an adaptive guide at various decision points.

P6. **Adaptive Training**. AI-assisted QC interfaces should incorporate training mechanisms [18] that adapt to user expertise levels to reduce onboarding time and promote continuous skill development. To maintain engagement and prevent "explanation fatigue", interfaces should dynamically adapt and avoid redundant explanations.

P7. **Knowledge Documentation and Sharing**. Findings and interventions should be systematically recorded to support organizational learning and efficient problem resolution. Knowledge retention should not be outsourced to the AI but should remain accessible and transferable.

P8. **Capturing Tacit Knowledge**, which is often difficult to articulate and embedded in daily practice, should be systematically recorded across different levels of interactions. In addition to traditional documentation and training approaches, methods such as behavior-oriented data collection and gamification can help surface implicit expertise and support continuous learning.

P9. **AI-Assisted Pattern Recognition**. Revealing patterns and root causes of quality issues can help to anticipate failures and optimize production processes [19].

P10. **AI Literacy and Oversight**. AI should help workers understand its strengths and limitations, fostering overall AI literacy [20].

3. Conceptual Model: Human-AI Quality Control Workflow Abstraction

Building on these *human potential* principles, we propose a conceptual model that integrates human expertise into AI-driven QC. This model, illustrated in Fig. 1, structures human-AI collaboration into two interrelated processes (*P3*): *continuous monitoring*, which runs mostly automatically, and *on-demand visual inspection and labeling*, performed by users. Since our focus is on human interaction, we provide a high-level overview of the continuous monitoring before detailing the user's role in the workflow.

3.1. Continuous Monitoring

Throughout the production monitoring process, data is collected automatically and continuously (*P4*). Depending on the setup—which varies by domain and product—samples are taken at fixed intervals, at specific stages, or based on other predefined conditions. These samples may include images, infrared scans, structured sensor data, or other modalities. A machine learning model processes each sample, predicts and assigns a label, which may take the form of a numerical score, a boolean value, or a categorical assessment. The results, along with timestamps and, ideally, confidence scores, are saved in a database. While automated quality control has existed for years, earlier systems often relied on rule-based checks and frequently required human involvement to interpret results. With advances in deep learning, these processes are now largely autonomous and allow the AI to perform more complex analyses and detect quality issues (*P9*). This three-step process of data collection, sample selection, and AI-based labeling may be repeated across different products and QC workflows.

3.2. On-Demand Visual Inspection and Labeling

User involvement in this process occurs through two mechanisms: *alerts*, which are system-triggered notifications, and manual *fetching*, where users actively request information. Interaction takes place through dedicated user interfaces with embedded visualizations (*P1*). These interfaces support various user tasks, which we outline here, while preliminary design considerations are discussed in Sec. 4.

Aggregated Summary. This interface enables users to assess the overall state of the AI-driven monitoring process, as schematically shown in Fig. 2. Users analyze temporal patterns, KPIs, and interpret explainability features (e.g., feature importance analysis; see *P2*). This supports high-level situational awareness (*P5*) and aligns with the typical overview-first, details-on-demand approach [21]. Users can quickly evaluate the number of inspections performed, detect anomalies, and identify areas

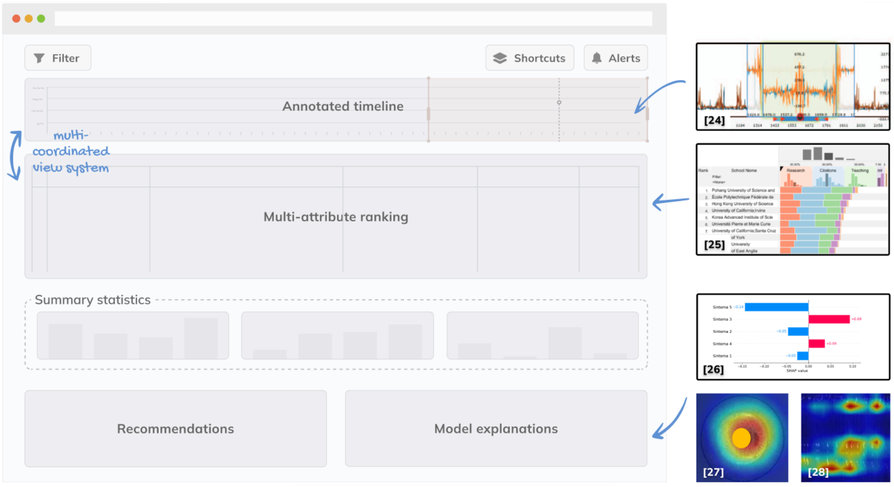

Figure 2: High-level interface concept to provide overview and analysis capabilities, integrating multiple aspects of the QC process. The illustration includes example visualization techniques: ChronoLenses [24] for time-series data, LineUp [25] for ranking heterogeneous data, feature importance plots [26], and attention maps [27, 28].

that require further investigation. Alerts and recommendations guide users toward critical incidents (*P6*), while filtering options help them refine their focus.

Individual Results with Labels. By reviewing individual samples, users compare AI-generated labels with their domain expertise to confirm or override model results, as illustrated in Fig. 3. This is done for spot checks, regulatory compliance, trust calibration, model improvement, or learning from AI insights, among other reasons (*P1*). Depending on the QC tasks, users assess simple visual cues like color deviations or cracks [2] or more complex deficiencies [22, 23]. A sample may have a single overall label or a fine-grained annotation consisting of multiple labels. Combined with custom notes, this supports both AI learning and knowledge management.

Documented Cases. Users can retrieve, review, and contribute to past cases, including previous quality issues and per-sample interventions (*P7*). In addition, they can document broader corrective actions and best practices, such as those addressing recurring quality issues.

Recommendations. The AI system synthesizes computational results (e.g., predicted labels) with information from the knowledge base to generate actionable recommendations (*P5*, *P6*). These may include checklists, suggested machine or process adjustments, and other decision-support elements.

Users also play an active role in refining the automated monitoring process by applying insights from inspections, making corrective decisions, and changing broader aspects of the production process.

4. Visualization Design Considerations

We highlight visualization and interaction techniques that may be adapted for the QC context. While the conceptual model outlines hybrid collaboration, its effective implementation relies on well-designed interface components. These approaches represent initial ideas that must be refined and complemented by additional visualizations and interface components to support all outlined human potential principles.

4.1. Integrating Multi-Attribute Rankings with Temporal Analysis

A core objective is to provide users with a high-level overview while enabling them to explore subsets and patterns before inspecting individual samples. Inspired by LineUp [25] and related techniques [29, 30], we propose a multi-attribute ranking, in combination with an annotated timeline, and embedded in a coordinated multiple-views system [31], as illustrated in Fig. 2. The multi-attribute ranking allows users to analyze heterogeneous attributes by ranking samples based on predicted labels, confidence scores, or other QC-relevant metrics. Each row can represent an individual sample or a group of

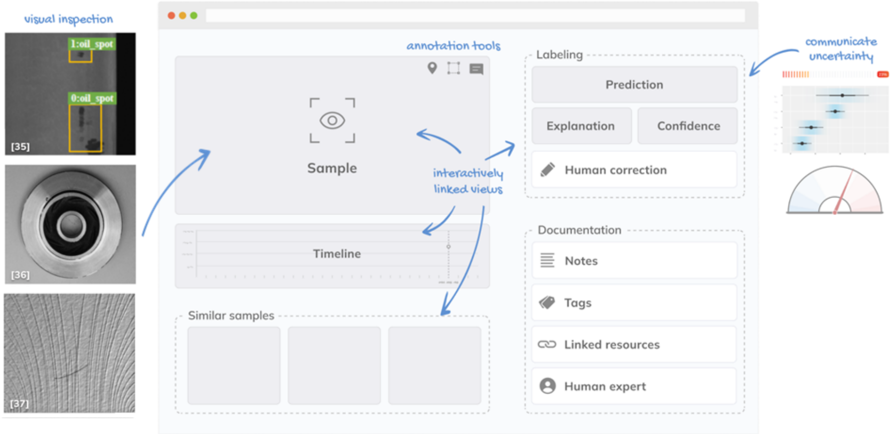

Figure 3: Interface concept for per-sample visual inspection and labeling. The center displays the sample data, which may include images, infrared scans, video clips, or other modalities depending on the quality control task. Users can review prediction results with uncertainty information, make corrections, add annotations, and document findings. (Image sources: Dabhi et al. [35], Lv et al. [36], and Wieler et al. [37])

samples. To further support pattern recognition and anomaly detection, word-scale visualizations can be embedded within each row [32]. However, a limitation of traditional ranking techniques is their lack of temporal context, which is essential for QC. Identifying temporal patterns [33], such as defects occurring at regular intervals or systematic issues, but also AI-judgment mistakes and factors relating to these, can provide critical insights and support AI oversight capabilities. Additionally, understanding when users override AI predictions helps in refining models and workflow processes. Thus, we suggest the integration of an annotated timeline that highlights user corrections, and system-detected anomalies, and other essential events. The timeline is interactively linked with the ranking and allows users to correlate data attributes with temporal trends. In large-scale time series data, where samples may be collected at high frequencies, temporal guidance mechanisms [34] become essential.

4.2. Feature Importance and Attention Plots

Feature importance and attention visualizations help to extract high-level insights from data. While displaying raw or aggregated data is essential for certain tasks, visualizations should also reveal key patterns to support deeper analysis. This becomes particularly relevant when working with large datasets and in settings where AI models perform a high degree of automation. Feature importance visualizations help users understand which variables most influence the model's decision-making process. Methods such as SHAP explanations can highlight key features, but they must be presented in a way that is understandable for lay users [38, 26]. For image-based QC tasks, additional visualizations can indicate why a model made a certain prediction or, for instance, highlight regions of interest with AI-human mismatches. Examples include heatmaps [39], contour plots [40], or attention maps [27], which can reveal typical patterns the model associates with defects or quality issues.

4.3. Uncertainty and Human-AI Alignment

Uncertainty visualization is essential for reliable and transparent decision-making, as well as for building trust in AI [41]. In addition to helping users learn from AI decisions and develop their skills, it also supports a better understanding of AI limitations, fostering AI literacy regarding its strengths and constraints in the QC context. To support this, uncertainty quantification and model explainability techniques [42] should be integrated at both the overview level and in per-sample inspections.

This directly connects to human-AI alignment. Explainable AI and uncertainty displays should also incorporate human feedback. For instance, when the AI lacks confidence, the system could present similar cases labeled by both AI and human inspectors to aid comparison. Mismatches between human and AI labels should be factored into future uncertainty assessments. Additional overviews of alignment patterns could highlight areas where AI consistently performs well or struggles.

5. Discussion

The increasing automation of industrial QC through more capable models presents both opportunities and challenges. While AI can enhance efficiency and accuracy, human expertise remains critical for ensuring reliability, adaptability, resilience, and long-term knowledge transfer.

From technology push and societal needs to a concept. We approach this challenge from the perspective of human potential loss and have compiled a set of principles to address it. Building on these principles and insights from QC across various sectors, we developed a workflow abstraction to guide our thinking about human-AI collaboration and support discussions with stakeholders.

These represent an initial, opportunistic sample rather than a definitive framework. We welcome active dialogue and will continue to refine both the principles and conceptual model through iterative engagement with industry stakeholders.

From conceptual model to interface design. A major challenge lies in translating workflow abstractions into usable interaction paradigms and interactive visualization techniques [43]. We outlined initial considerations for overview and detail page designs to support human oversight, intervention, and knowledge transfer. However, further research is needed to refine these interface ideas, increase their level of fidelity and evaluate their effectiveness in real-world settings. Key research questions are: *How can QC interfaces support the systematic capture and transfer of tacit knowledge (P8)? How can QC interfaces dynamically adjust based on user expertise, confidence levels, or task complexity (P5)? How should AI uncertainty be communicated (P2)? How can a system distill actionable recommendations from AI predictions and the knowledge base, and how should these be presented (P6, P7)?*

From interface to counterpart. Integrating AI into QC workflows is not just about building models and interfaces but about fostering hybrid teams where humans and AI collaborate effectively (*P1*) [44]. Besides the interface design, successful human-AI collaboration depends on cultural and organizational considerations that extend beyond HCI and visualization research (*P3*).

Quality issues often emerge later in the production cycle or post-production [45] which requires systems to integrate feedback from multiple stages. Research is needed to explore how AI-assisted QC can support this long-term traceability. In general, the transition to hybrid workflows requires a deeper understanding of the human role in QC [46]. Designing *intelligent automation* in a way that supports human engagement, trust, and skill development is essential to ensure that workers remain active participants rather than passive overseers, supporting the development of resilience both on an organizational and an employee-level.

6. Conclusion

In this position paper, we explored effective human-AI collaboration in industrial quality control. We emphasized the importance of preserving human potential and outlined a conceptual model to support this goal. We plan to develop prototypes and engage further with industry stakeholders to refine our approach and validate assumptions. Additionally, we aim to assess whether our proposed workflow and design ideas effectively support human-AI collaboration in real-world quality control settings.

While our focus has been on industrial QC, we believe many ideas are transferable to other hybrid environments where humans and AI systems must interact effectively. Therefore, this work shall also serve to encourage further research on human-centered AI collaboration across different domains.

Acknowledgments

This work is part of the ZERO3 project (FO999896399), funded by the Austrian Research Promotion Agency (FFG). The authors thank Profactor, i-RED Infrarot Systeme, and the other project partners for their valuable contributions.

Declaration on Generative AI

The authors used GPT-4o for grammar and spelling checks. After using these services, the authors reviewed and edited the content and take full responsibility for the publication's content.

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