



## China Scholarship Council / Université de Lyon Scholarships for doctoral mobility

### Call for Thesis subjects 2026

**RESEARCH SUBJECT TITLE:**

Human-Centered Artificial Intelligence for Quality 4.0: Adaptive and Generative Approaches to In-Process Manufacturing Quality

**University / Institution:** University Lumiere Lyon 2

**Name of the laboratory:** Decision and Information Systems for Production systems (DISP UR 4570)

Website: <https://www DISP-lab.fr/>

**Name of the research team:** research axis Information Systems and Data

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**Name of the supervisors:** Prof. Nejib MOALLA, Dr. M.-Lounes BENTAHA

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**Doctoral School:** InfoMaths (ED 512)

**Lab Language:** English and French

**Minimum language level required:**

- English: B2

**Expected duration of the thesis:** 36 months

**Keywords:** Industry 4.0, Manufacturing quality, Human-machine collaboration, AI-driven decision support, Generative AI, In-process monitoring

### **Abstract:**

Manufacturing quality is undergoing a significant shift as Industry 4.0 technologies introduce new ways to monitor, predict, and prevent defects directly in the production process. Classical methods such as Statistical Process Control or Six Sigma address manufacturing issues at a later stage, while current AI-based solutions still struggle with limited contextual data, high variability, and low trust from operators, especially in SMEs. This research explores how AI can be optimized for human-centered manufacturing quality by combining real-time sensor data with operator feedback to create adaptive learning loops. Algorithms are continuously updated through reliability scores and transfer learning, ensuring that the system evolves with the production environment and remains aligned with operator insights. In doing so, the approach integrates process- and product-related perspectives while making advanced quality monitoring more practical and accessible on the shop floor.

A novelty lies in using generative AI to mediate communication between algorithms and humans. Instead of delivering opaque outputs, generative models can explain predictions, contextualize anomalies, and engage operators in conversational validation of results. This interaction not only improves transparency and trust but also enhances the quality of labeling and feedback, creating a virtuous cycle of collaboration between humans and machines. By focusing on clarity, adaptability, and inclusiveness, this direction positions AI not just as a technical layer for automation, but as a partner for human expertise in shaping more resilient and proactive quality practices in manufacturing.

### **Problem Statement and Motivation**

The ability to maintain consistent product quality is central to competitiveness and sustainability in manufacturing. However, several persistent barriers limit the potential of AI in quality management:

1. **Limited adaptability:** Models often degrade under high variability or non-stationary environments (Gross et al., 2024; Marín Díaz, 2025).
2. **Low operator trust:** Most quality-AI models remain “black boxes,” providing limited interpretability (Ribeiro et al., 2016; Gross et al., 2024).
3. **SME adoption barriers:** Resource limitations demand lightweight and human-inclusive systems (Ferraz et Gonçalves, 2025).
4. **Human-AI disjunction:** While AI excels at pattern recognition, operators contribute tacit knowledge, intuition, and situational awareness that are rarely captured (Rožanec et al., 2023; Passalacqua et al., 2024).

The emerging Industry 5.0 paradigm emphasizes human-centric, resilient, and sustainable manufacturing, highlighting the need for collaborative human-AI approaches (Ghobakhloo et al., 2024; Yang et al., 2024).

### **Preliminary Research Gap Analysis**

Existing literature reveals three critical gaps:

1. **Adaptability Gap:** Defect detection research in manufacturing has largely focused on deep learning segmentation and classification methods. However, these models remain brittle in dynamic environments, lacking mechanisms for incremental or transfer learning.
2. **Human-AI Interaction Gap:** Reviews on Industry 5.0 stress the centrality of human-machine collaboration, but most quality research treats the operator as a passive data source rather than an active collaborator. Emerging HITL-XAI (human-in-the-loop and explainable AI) approaches in predictive maintenance and automotive inspection show promise but remain underexplored in quality management.
3. **Transparency & Generative Interaction Gap:** While explainable AI methods improve interpretability, most are static visualizations or feature-based explanations. The potential of generative AI to provide contextualized, conversational, and adaptive explanations in manufacturing quality is largely untapped.

## Research Questions

**Main RQ:** How can Human-Centered Artificial Intelligence (HCAI), enhanced by generative interaction mechanisms, improve in-process manufacturing quality monitoring and decision-making under the Quality 4.0 and Industry 5.0 paradigms?

### Sub-questions:

**RQ1:** How can adaptive learning loops (reliability scoring, transfer learning) ensure robustness in variable manufacturing environments?

**RQ2:** What forms of generative AI interaction (contextual explanations, conversational validation) enhance operator trust and decision-making?

**RQ3:** How does operator feedback impact data quality, model performance, and overall defect detection efficiency?

**RQ4:** How can SMEs adopt lightweight HCAI-driven Quality 4.0 systems sustainably?

## Objectives

1. **Conceptual:** Define a human-centered Quality 4.0 framework integrating adaptive AI, generative explanations, and operator collaboration.
2. **Technical:** Develop prototypes combining real-time sensor streams, adaptive defect detection algorithms, and generative conversational interfaces.
3. **Empirical:** Validate the framework through simulation and pilot studies, measuring accuracy, transparency, trust, and workload.
4. **Prescriptive:** Provide adoption guidelines and a maturity model tailored to SMEs.

## High-level Methodology

1. **Systematic literature review:** on HCAI, Industry 5.0, and generative AI in manufacturing quality.
2. **Prototype development:** adaptive AI algorithms (transfer/incremental learning) + generative explanation interface.
3. **Evaluation:** controlled experiments with operators + case study applications.

4. **Analysis & synthesis:** empirical findings + guidelines for adoption.

### Expected Contributions

- **Theoretical:** Extend Quality 4.0 by embedding generative human-AI interaction as a new pillar of transparency and collaboration.
- **Technical:** Deliver adaptive, conversational quality monitoring prototypes.
- **Empirical:** Provide evidence on how generative explanations improve trust and feedback quality.
- **Practical:** Roadmap for SMEs to adopt lightweight, human-centered AI quality systems.

### Application

For application in this PhD position, applicants are invited to communicate:

- An updated CV
- A motivation letter with explicit interest in this research project
- The last academic transcripts
- The last report produced
- At least two recommendation letters

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