

**Integrating Artificial Intelligence into Continuous Improvement:
An AI-Assistant Supporting 8D Problem-Solving in Automotive
Manufacturing**

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ABSTRACT

This work-in-progress paper examines how an AI-based assistant can be embedded within established continuous improvement processes to enhance value stream analysis in an automotive supplier environment. Drawing on a revelatory single-case study of a German automotive supplier that deployed an AI-Assistant in collaboration with a specialised German start-up, the research investigates the coupling of artificial intelligence with the 8D problem-solving methodology. Using a qualitative research design grounded in grounded theory principles, data were collected from multiple sources across the manufacturing operation and analysed through open, selective, and theoretical coding. Preliminary findings indicate that embedding the AI-Assistant into the 8D cycle produces substantial operational gains, including reductions in order lead time of at least 50 percent (reaching up to 90 percent in selected areas), an increase of at least 80 percent in the value creation rate for materials subjected to completed 8D measures, and meaningful reductions in manual scheduling effort, scrap, and work-in-progress. Beyond these quantifiable results, the integration yielded qualitative benefits in transparency, systematic problem identification, master data quality, and root-cause analysis speed. The paper contributes empirical evidence to the Industry 4.0 literature by demonstrating that AI technologies can augment rather than displace established lean methodologies, thereby addressing a critical gap identified in prior research on integrated AI-enabled manufacturing optimisation systems.

Keywords: Artificial Intelligence, Continuous Improvement, 8D Methodology, Value Stream Analysis, Automotive Manufacturing, Industry 4.0

INTRODUCTION

Contemporary manufacturing enterprises operate in environments defined by escalating complexity, volatile operational conditions, and unprecedented volumes of data emerging from manufacturing execution systems (MES) and enterprise resource planning (ERP) platforms. In such settings, value stream analysis—a foundational lean instrument for identifying and eliminating waste—has traditionally required substantial manual effort, which constrains both the frequency and the analytical depth of its application. The maturation of artificial intelligence technologies offers a novel avenue for addressing these constraints by enabling continuous, data-driven visualisation and interpretation of production flows.

This work-in-progress paper investigates the integration of an AI-Assistant into the continuous improvement architecture of a German automotive supplier. The initiative, launched on March 19, 2021 and running through December 20, 2021, was conceived as a vehicle for ongoing value stream transparency and for accelerating structured improvement cycles (KVP). Rather than positioning artificial intelligence as a replacement for established lean practice, the intervention deliberately embedded the AI-Assistant within the company's 8D problem-solving methodology, thereby creating a hybrid sociotechnical configuration in which algorithmic analysis and structured human problem-solving operate in tandem.

The remainder of the paper is organised as follows. The next section develops the theoretical foundation through a review of research on value stream analysis, AI-enabled manufacturing optimisation, and the integration of intelligent systems with continuous improvement practice. A research question is then derived from the identified gaps in this literature. The research methodology is subsequently described, followed by the presentation of preliminary results. The paper concludes with a discussion of theoretical and practical implications, limitations, and directions for further research.

THEORETICAL BACKGROUND

The Case for AI-Assisted Value Stream Optimisation

The embedding of AI-based assistants within value stream analysis constitutes an emerging frontier in manufacturing optimisation, responding to the need for dynamic, real-time identification and elimination of bottlenecks. A growing body of research argues that conventional value stream mapping approaches, although foundational to lean thinking, are increasingly misaligned with the variability and complexity characterising contemporary production environments (Luz, Tortorella, Narayanamurthy, Gaiardelli, & Sawhney, 2021; Thulasi, Faieza, Azfanizam, & Leman, 2022). The coupling of advanced AI technologies with established lean approaches has been positioned as an opportunity to re-engineer manufacturing efficiency through intelligent and adaptive systems (Horsthofer-Rauch et al., 2024; Okuyelu & Adaji, 2024). This imperative is reinforced by the trajectory of Industry 4.0, intensifying sustainability expectations, and the competitive pressures that characterise increasingly volatile markets (Lee et al., 2021; Shatiry et al., 2024).

Limitations of Conventional Value Stream Mapping

Despite its widespread diffusion and its demonstrated effectiveness in exposing waste and optimising flow, value stream mapping in its conventional form exhibits limitations that become pronounced in contemporary manufacturing contexts. The essentially static character of traditional VSM renders it ill-suited to the variability intrinsic to modern production systems (Luz et al., 2021; Thulasi et al., 2022). This limitation is particularly salient in high-variety, low-volume production settings, where variability itself operates as a form of waste that cannot be adequately captured through static mapping techniques (Araibi, Ishak, & Shadhar, 2023).

The incipient literature on stochastic approaches to value stream analysis reflects an awareness of these constraints. A systematic review of stochastic value stream research concludes that the field remains in an early developmental stage and that existing contributions

have not yet integrated uncertainty systematically into traditional mapping procedures (Luz et al., 2021). This limitation assumes growing importance as production systems become more intricate and as real-time adaptability becomes a precondition for sustained performance.

Manual effort constitutes a further source of inefficiency in conventional mapping exercises, particularly in volatile and high-variance manufacturing environments (Horsthofer-Rauch et al., 2024). The time required to complete a traditional mapping exercise can be sufficient for underlying operational conditions to shift, reducing the relevance of the resulting analysis or even rendering derived improvements counterproductive. This temporal disconnect between analysis and implementation creates an opening for more dynamic approaches to value stream optimisation.

The Emergence of AI-Driven Manufacturing Optimisation

Artificial intelligence has reshaped quality management and process optimisation across numerous industrial settings (Okuyelu & Adaji, 2024). Real-time monitoring systems that combine machine learning algorithms with sensor data and IoT connectivity now support continuous oversight of production parameters, facilitating early fault prognosis, minimising disruption, and reducing the likelihood of substandard output (Okuyelu & Adaji, 2024; Vasquez, Drake, & Bramante, 2024). This constitutes a transition from reactive to predictive manufacturing management, in which emerging problems can be addressed before they materialise as performance losses.

Recent work on edge-deployed AI systems has demonstrated the feasibility of processing complex multivariate sensor signals in real time, notably in semiconductor manufacturing, where precision and responsiveness are especially important (Vasquez et al., 2024). Executing AI models at the edge, rather than through centralised servers, addresses latency concerns that are critical in time-sensitive applications such as real-time fault detection and process control. This architectural pattern provides a conceptual template for similar deployments in value stream optimisation, where rapid response to changing conditions is essential for sustaining flow.

Evidence from workplace studies further suggests that AI-based assistants can enhance productivity and reduce administrative burden (Jackson & Panteli, 2024). By automating routine tasks, digital assistants free human workers to concentrate on value-adding activity, generating measurable efficiency gains. At the same time, the same literature identifies controllability, transparency, and trust as central concerns that must be deliberately managed when AI systems are introduced into work environments (Jackson & Panteli, 2024).

Digital and Simulation-Based Value Stream Mapping

The turn toward digital value stream mapping represents a significant response to the limitations of static approaches. Research in the oil and gas construction sector has illustrated the implementation of Digital Value Stream Mapping frameworks for productivity monitoring and tracking, drawing on IoT technologies to provide continuous visibility into process flows and to enable the systematic identification and elimination of labour and material waste (Shatiry et al., 2024).

A parallel development is the integration of process mining with value stream mapping (Horsthofer-Rauch et al., 2024). By automatically discovering and analysing process flows from event data, process mining substantially reduces the manual effort historically associated with value stream mapping while simultaneously producing more timely and accurate insights into process performance.

Simulation-based approaches offer a further route to enhancing the dynamic capabilities of value stream mapping (Chaudhary, Elahi, Thulasi Das, Varotaria, Jain, & Rathod, 2025). When value stream mapping is combined with system simulation, key performance indicators such as utilisation, throughput, and reliability can be analysed under alternative scenarios. This supports both the identification of inefficiencies and the ex-ante testing of candidate improvements, thereby lowering implementation risk.

The Imperative of Real-Time Bottleneck Identification

As production systems grow in complexity and variability, the real-time identification of bottlenecks becomes increasingly critical. Traditional bottleneck analysis, which relies on periodic assessment and manual interpretation, struggles to keep pace with dynamic production environments in which bottlenecks migrate rapidly in response to shifts in demand, equipment behaviour, and resource availability (Chaudhary et al., 2025; Okuyelu & Adaji, 2024).

AI-driven approaches to quality monitoring and process optimisation demonstrate the feasibility of continuous real-time analysis of production parameters (Okuyelu & Adaji, 2024). Machine learning algorithms can interrogate large volumes of sensor data, detect patterns and anomalies that signal emergent bottlenecks, and support proactive intervention. Such capabilities are particularly valuable where multiple interdependent processes must be coordinated to sustain flow.

Real-time defect detection systems based on machine learning offer a further illustration of the potential of AI-enabled manufacturing optimisation (Kumar & Satyarthi, 2024). Although developed in the context of additive manufacturing, the architectural logic of such systems—continuous observation, pattern recognition, and immediate corrective action—maps naturally onto the challenge of real-time bottleneck identification in more general production settings.

Industry 4.0 and the Shift in Manufacturing Intelligence

The Industry 4.0 transition represents a paradigmatic shift in manufacturing, characterised by the convergence of cyber-physical systems, IoT technologies, and artificial intelligence into autonomous production architectures (Lee et al., 2021; Shatiry et al., 2024). This transformation creates both the conditions and the imperative for more sophisticated approaches to value stream optimisation that can meaningfully exploit the data generated by modern production environments.

Sustainability has assumed increasing importance in this context, prompting interest in value stream mapping approaches capable of optimising not only economic performance but also environmental and social outcomes (Horsthofer-Rauch et al., 2024; Lee et al., 2021). Incorporating sustainability metrics into value stream analysis demands analytical capabilities able to balance multiple, and at times competing, objectives. AI-assisted approaches offer the computational and analytical sophistication required to address this multidimensional optimisation challenge.

The emergence of sustainability-integrated value stream mapping combined with process mining illustrates how multiple performance dimensions can be incorporated into real-time optimisation systems (Horsthofer-Rauch et al., 2024). Such approaches simultaneously discover process flows and track sustainability indicators, supporting optimisation across the triple bottom line.

Technological Foundations and Implementation Concerns

Realising AI-assisted value stream optimisation requires a technological infrastructure capable of supporting real-time data acquisition, processing, and analysis. Recent developments in edge computing and AI deployment have demonstrated the feasibility of embedding intelligent systems directly at the point of production, thereby enabling rapid response to changing conditions without the latency associated with cloud-based processing (Vasquez et al., 2024).

The parallel development of interactive AI assistants capable of perceiving, reasoning, and collaborating with humans in real-world environments constitutes a further enabling advance (Wang et al., 2023). Such systems provide the human–machine interface required for effective AI-assisted value stream optimisation, allowing operators and managers to engage with intelligent systems in a manner that preserves appropriate levels of human oversight and control.

Implementation in manufacturing environments, however, raises substantial challenges relating to trust, transparency, and ethics (Gabriel et al., 2024). Prior research emphasises that the effective adoption of AI assistants depends on careful attention to value alignment, privacy, and

the potential for unintended consequences—considerations that are especially pressing in manufacturing settings where decisions taken by AI systems may have immediate implications for production performance and worker safety.

Research Gaps and Derivation of the Research Question

Although the literature reviewed above documents meaningful advances in AI technologies and digital value stream mapping, important gaps remain in understanding how such approaches can be effectively integrated for real-time manufacturing optimisation. Research on stochastic value stream analysis highlights the underdeveloped treatment of uncertainty in value stream analysis and the absence of systematic engagement with the interaction of multiple uncertainty sources (Luz et al., 2021).

A more specific gap concerns AI-assisted value stream optimisation as an integrated system. Although AI-driven quality monitoring, digital value stream mapping, and real-time process optimisation have each been studied in isolation, research on the integrated systems required to deliver comprehensive real-time value stream optimisation remains limited (Horsthofer-Rauch et al., 2024; Okuyelu & Adaji, 2024). Closely related is the absence of established methodologies and metrics for evaluating AI assistants in manufacturing contexts, where traditional performance measures may be inadequate to capture the complex interactions between human operators, AI systems, and production processes (Gabriel et al., 2024; Wang et al., 2023).

These gaps, taken together, indicate a need for empirical evidence on how AI technologies can be embedded within established continuous improvement practices and on what operational outcomes such integration can produce. This leads to the central research question guiding the present study:

How can an AI-based assistant be integrated with the 8D continuous improvement methodology to enhance value stream analysis and operational performance in

automotive supplier manufacturing?

The question is explicitly oriented toward integration rather than substitution: it treats the AI-Assistant as a component of a broader sociotechnical system in which established lean practice continues to play a central role.

RESEARCH METHODOLOGY

Rationale for a Qualitative Case Study Design

The study adopts a qualitative case study design to investigate the complexities associated with introducing artificial intelligence into an industrial setting. Qualitative case research is particularly well suited to the exploration of contemporary phenomena that are emergent, nuanced, and embedded in real-world contexts (Eisenhardt, 1989; Yin, 2018). A case study approach, rooted in empirical evidence and supported by data drawn from multiple sources and at multiple levels of analysis, enables the development of a rich understanding of the phenomenon under investigation (Creswell, 2018).

A single-case design was selected deliberately in order to examine a novel and specific phenomenon—namely, the development and deployment of AI-based assistants by a German start-up on behalf of its clients. The design is justified by the unique and revelatory nature of the case, which provides access to a phenomenon that has not previously been systematically examined through social-scientific inquiry (Yin, 2018). The focal start-up specialises in AI-based assistants for applications including purchasing, supply chain management, and production planning, and thus offers a rare opportunity to study both the developmental and the implementation stages of AI technologies within a single organisational setting. This orientation aligns with the study's broader objective of exploring the interplay between technological innovation and organisational practice.

Methodological principles articulated by Creswell (2018) informed the alignment of the research approach with the research question and objectives. The revelatory value of case-based inquiry for generating new theoretical insight in settings where prior knowledge is limited is further supported by Eisenhardt and Graebner (2007).

Case Selection

Beyond the innovative deployment of AI, the selection criteria for the case encompassed several further considerations. These included the start-up's openness to research collaboration, its pioneering role within the German AI landscape, and the potential transferability of insights generated in this setting to comparable business contexts. This selection process was designed to ensure that the case would offer both the depth and the detail required to contribute meaningfully to the broader discussion of AI in business (Glaser & Strauss, 2017; Miles, Huberman, & Saldaña, 2014).

The case study approach adopted here is intended to generate insights into the implementation of AI-based assistants in business that have both theoretical and practical value. The methodology prioritises empirical evidence and in-depth qualitative analysis in order to surface the dynamics of collaboration, adjustment, and innovation that arise when AI-based assistants are introduced into operational settings.

Data Analysis

Data analysis was organised as an iterative process structured around grounded theory principles. Drawing on the foundational work of Glaser and Strauss (2017), grounded theory is well suited to exploratory studies such as the present research, whose aim is to generate novel theoretical insights into the implementation of AI-based assistants within a specific business context.

Application of Grounded Theory.

Analysis began with open coding, through which the data were rigorously examined in order to identify the categories, themes, and concepts emerging directly from the material (Charmaz, 2014). This initial phase was essential for reducing a substantial body of data into analytically manageable components. A phase of selective coding followed, in which the initial codes were filtered according to their relevance to the core phenomena of the study and their alignment with the research objectives. This phase was guided by the principles of Glaser and Strauss (2017), which emphasise focusing analytical attention on categories that contribute to the development of grounded theory.

The final analytical phase was theoretical coding, in which the selected codes were woven into a coherent theoretical account. This phase consolidated the various strands of analysis into an integrated framework that illuminates the dynamics of AI-assistant implementation (Glaser, 1978).

Iterative Character of the Analysis.

Consistent with the grounded theory tradition, the analysis was iterative: it was refined continuously as new data were collected from the field. This ongoing interaction between data collection and analysis enabled the approach to remain adaptive and to incorporate emerging insights while revising earlier constructs (Miles et al., 2014). This iterative logic was critical for developing a comprehensive, theory-informed understanding of the case, consistent with the exploratory orientation of the research.

Ethical Considerations

The analytical process was underpinned by strict adherence to ethical standards of research. Confidentiality and data integrity were maintained at every stage of coding and analysis, consistent with established guidance on ethical qualitative research (Creswell, 2018). The resulting analysis contributes to a deeper understanding of the interplay between

technological advancement and organisational practice and adds to the broader academic conversation on the implementation of technology in organisations.

FINDINGS

The presentation of findings is organised in four parts. The first describes the analytical approach embodied in the AI-Assistant. The second documents its integration with the company's continuous improvement process through the 8D methodology. The third summarises the quantitative and qualitative improvements observed in the pilot area. The fourth describes the multiple roles assumed by the AI-Assistant and the trajectory of planned future development.

The Analytical Approach of the AI-Assistant

The AI-Assistant fulfils its core function by digitally capturing and representing value streams. It draws on production data from multiple sources, including the company's SAP system and the FORCAM manufacturing execution system. The principal data inputs include SAP material data (material number, description, lot sizes, process times, indices, and ABC classifications) and manufacturing order data (order number, start and end dates and times, machine number, and scrap). From FORCAM, the AI-Assistant retrieves machine availability data, including Overall Equipment Effectiveness (OEE) at the machine level. Information from work plans—in particular concerning machine assignments and planned times for individual process steps—is also incorporated.

The analytical process comprises four stages:

- *Data Analysis.* A neural network is used to analyse production steps and performance on the basis of the collected data. This entails comparing actual production data with planned data drawn from SAP and the work plans.
- *Value Stream Visualisation.* The AI-Assistant automatically generates visualisations of value streams, with representations organised by product and by temporal unit (day,

week, month).

- *Cause–Effect Identification.* The AI-Assistant constructs cause-and-effect logic to identify potential improvement opportunities. Such relationships are represented at multiple levels, including order, period, machine, and value stream, and the AI-Assistant contributes to making these relationships transparent.
- *Problem Identification.* Drawing on the analysis, the AI-Assistant identifies problems within the production process or value stream, in particular by detecting irregularities through the correlation of data from different sources.

Integration with the 8D Continuous Improvement Process

A central feature of the implementation is the integration of the AI-Assistant into the company's established continuous improvement process, operationalised through the 8D problem-solving methodology.

- *Problem Escalation.* Problems identified by the AI-Assistant are fed into the 8D process.
- *Structured Improvement Activities.* 8D measures are executed on a regular cycle, typically every fourteen days, with the involvement of a core team and relevant subject-matter experts. The AI-Assistant contributes by identifying concrete, material- and process-specific problems that form the basis of effective 8D work.
- *Action Recommendations.* The AI-Assistant functions as an advisor, diagnosing both weaknesses and strengths of the production system and deriving concrete action recommendations. It additionally provides rule-based recommendations intended to accelerate implementation.
- *Digitalisation of the 8D Process.* A key development was the introduction of digital 8D forms integrated into the AI-Assistant, enabling 8Ds to be executed directly within the system. This digital approach also supports organisational learning.

- *Monitoring and Learning.* The AI-Assistant monitors the effectiveness of implemented 8D measures. On the basis of executed and documented 8Ds, the AI-Assistant is designed to develop a contextual understanding of which actions are effective in particular situations—a structural learning of effective measures that forms a central planned capability of the system.

Observed Improvements and Preliminary Results

The initial pilot implementation in the mechanical fabrication area produced significant and broad-based improvements. The combination of continuous, transparent value stream representation and the proactive pursuit of measures by company personnel generated both quantifiable and qualitative gains.

Quantifiable Results.

Across all completed 8D measures in the pilot area, order lead time (DLZ) was reduced by at least 50 percent, with reductions of up to 90 percent observed in selected areas. The share of time devoted to value-adding activities increased by at least 80 percent for materials for which 8D measures had been completed. While specific percentage improvements for delivery reliability are not universally quantified in the project documentation, the reports indicate a positive trajectory. Expected efficiency gains additionally included a reduction in manual activities such as scheduling by more than 80 percent, a scrap reduction of more than 15 percent, and a reduction in work-in-progress of more than 10 percent.

Qualitative Improvements.

Several qualitative benefits were documented. First, the AI-Assistant delivered enhanced transparency, providing a detailed view of value streams that fostered a more systematic understanding of processes and interdependencies among employees. Second, it supported systematic problem identification, surfacing issues that would have been difficult to detect through manual analysis in light of the data volume and process complexity. Third, the

comparison of data from different sources (in particular historical booking data and planned data) contributed to improvements in master data quality over time as inconsistencies and deviations were corrected on the basis of the system's indications; the resulting alignment of SAP planning parameters with real-world conditions further enhanced planning accuracy and process stability. Fourth, root cause analysis was accelerated substantially: identifying the actual root cause of problems became significantly faster and more efficient than under previous, highly manual procedures.

Roles of the AI-Assistant and Future Development

Within the organisation, the AI-Assistant occupies multiple roles: Assistant (data collection, analysis, and reporting), Tool (information display, database, and learning), Colleague (feedback exchange), and Advisor (process visualisation, diagnostics, and recommendations). This multi-role positioning reflects the hybrid human–AI configuration that characterises the intervention.

Several directions for further development were articulated. Geographic expansion envisages a stepwise rollout to additional manufacturing areas, including implementations in the United States and Polish plants and, subsequently, in assembly operations at the German plant; analyses for the US and Polish sites have already been initiated on the basis of available data. A broader future outlook points to the development of the AI-Assistant as an integrated application, potentially linked to the company's cascade KPI system. Finally, work was initiated to establish automated, secure data exchange via Azure and to prepare automated SAP data downloads, with the aim of further reducing manual effort in data provisioning.

DISCUSSION

Theoretical Contribution

This study contributes to the literature on Industry 4.0 and AI-enabled manufacturing in three principal ways. First, it provides empirical support for the theoretical proposition that AI-assisted systems can help to overcome the static limitations of traditional value stream mapping noted by Luz et al. (2021) and Thulasi et al. (2022). Second, by demonstrating the coupling of an AI-Assistant with a structured 8D cycle, it substantiates the feasibility of the convergence between AI technologies and lean methodologies highlighted by Horsthofer-Rauch et al. (2024). Third, it shows that the AI-Assistant can bridge the temporal disconnect between analysis and implementation that has historically constrained traditional VSM, thereby addressing a specific limitation emphasised in the prior literature.

Practical Implications

The operational gains observed in the pilot—order lead time reductions of 50 to 90 percent and an increase of at least 80 percent in the value creation rate—are of immediate relevance to manufacturing organisations seeking to protect or extend their competitive position. Equally important, the embedding of the AI-Assistant within the company's 8D process illustrates that the introduction of AI need not disrupt established improvement methodologies: on the contrary, it can enhance and accelerate them. This finding is likely to be particularly relevant for practitioners who value continuity with proven continuous improvement practice.

Engagement with Identified Research Gaps

The study speaks to several of the research gaps identified in the theoretical background. It addresses the call by Okuyelu and Adaji (2024) for empirical evidence on integrated AI-enabled manufacturing optimisation systems by demonstrating a working integration of AI-driven analysis, digital value stream representation, and real-time improvement activity. It also

engages with the concerns raised by Gabriel et al. (2024) and Jackson and Panteli (2024) regarding trust, transparency, and human–machine collaboration, illustrating how the positioning of the AI-Assistant as a complement to—rather than a substitute for—human problem-solving activity can contribute to productive collaboration.

Limitations and Directions for Further Research

Several limitations of the present work-in-progress should be acknowledged. First, as a single-case study, the research offers analytic rather than statistical generalisation; further investigation across additional organisational and industry contexts will be required to assess the transferability of the findings. Second, the temporal horizon of the study limits insight into the long-term sustainability of the documented improvements, pointing to the value of longitudinal follow-up research on the evolution of human–AI collaboration over time. Third, the study underscores the need for evaluation frameworks capable of capturing the complex interactions between human operators, AI systems, and production processes in line with the arguments of Gabriel et al. (2024) and Wang et al. (2023). Fourth, while the pilot results are encouraging, questions of scalability across different production environments and organisational sizes remain open and warrant systematic further investigation.

CONCLUSION

This work-in-progress paper provides preliminary empirical evidence that an AI-based assistant can be effectively integrated with the 8D continuous improvement methodology to enhance value stream analysis in automotive supplier manufacturing. The case of a German automotive supplier demonstrates that such integration can deliver substantial operational improvement—most notably in order lead times and value creation rates—while simultaneously advancing qualitative dimensions of performance, including transparency, problem-identification systematicity, master data quality, and speed of root cause analysis.

The findings address the gap in the literature concerning the practical integration of AI technologies with established lean methodologies, contributing both theoretical and practical insights to the Industry 4.0 discourse. As manufacturing environments continue to grow in complexity and variability, AI-assisted value stream analysis embedded within structured continuous improvement cycles emerges as a credible route to sustaining competitive advantage while accommodating broader sustainability and efficiency objectives. Ongoing work will extend the implementation to additional production areas and sites, deepen the learning capabilities of the AI-Assistant, and develop more comprehensive frameworks for evaluating human–AI collaboration in manufacturing contexts.

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