AI-Driven Changeover Optimisation in Discrete Manufacturing: A Production Line-Based Analysis of Technology Readiness in Bearing

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AI-Driven Changeover Optimisation in Discrete Manufacturing: A Production Line-Based Analysis of Technology Readiness in Bearing Production

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Abstract. Discrete manufacturing is subject to challenges posed by changeovers due to diminishing batch sizes and the need for customisation. Concurrently retiring personnel deepens knowledge gaps. Despite the evident potential of AI demonstrated in various studies, the question of scalable implementation for changeovers remains largely unexplored. The present study examines the AI readiness for changeover optimisation at a global bearing manufacturer using pull-based production channel systems. The key challenges identified in this study include complex many-to-many relationships between operations and channels, products re-entering flows, and subcontracting arrangements that affect changeover efficiency. The investigation is guided by two research questions: (1) What AI capabilities provide the highest impact on changeover performance in discrete manufacturing? (2) What organisational readiness factors are necessary for successful AI solution lifecycle management? Using a literature review and case study methodology to examine model channels and changeover procedures, the study reveals significant discrepancies between AI's theoretical potential and practical realities. This work establishes a link between theoretical AI capabilities and practical implementation challenges, thus providing evidence-based guidance for firms evaluating AI opportunities. The key findings highlight that the success of the AI lifecycle depends on organisational readiness. We have also identified the operational AI capabilities required to optimise changeover performance. These offer a foundation for developing frameworks that enable manufacturers to navigate AI implementation while maintaining operational efficiency and leveraging lean manufacturing principles, based on the identified ML selection criteria and organisational readiness factors essential for successful AI adoption.

1. Introduction

The optimisation of discrete manufacturing has represented a persistent challenge since the advent of the industrial age. In the contemporary business environment, manufacturing companies encounter significant challenges in leveraging data-driven technologies for their benefit. The GBM model channel concept (MCC) was first defined in the 1980s [1]. It is organised around pull-based value streams with dedicated resources and bottleneck management. However, this production concept is being challenged today, as discrete manufacturing companies are facing increasing market demands for smaller batches, greater customisation and shorter lead times, resulting in increased complexity. Simultaneously, numerous industries face a loss of knowledge and experience due to workforce dynamics.

The utilisation of artificial intelligence (AI) is a potential solution to these challenges [2–4], there exists limited empirical guidance for the implementation of AI in traditional manufacturing contexts. In the context of European manufacturing companies, this issue frequently pertains to legacy equipment, which is characterised by limitations regarding connectivity and data availability. Consequently, this results in a suboptimal foundation for data-driven technologies [5]. Beyond these technical constraints, the influence of organisational support structures also contributes to AI adoption outcomes. Many companies have traditional support processes, such as human resources and budgeting. It is often challenging for these departments to achieve a balance between stable legacy processes and agile processes, which are necessary for the integration of data-driven technologies [6].

The application of AI in discrete manufacturing, and more specifically on the MCC, gives rise to numerous questions. In the light of prevailing industrial challenges, it is of considerable interest for a global bearing manufacturer (GBM) to understand how AI can facilitate the optimisation of the MCC changeover activities in legacy systems. Will MCC continue to be a strong production concept? Alternatively, will it be challenged by new concepts that leverage AI capabilities, such as real-time optimisation and predictions? The investigation focused on two research questions: (1) What AI capabilities provide the highest impact on changeover performance in discrete manufacturing? (2) What organisational readiness factors are necessary for successful adoption? In order to address the aforementioned research questions, the study combines a literature review regarding AI capabilities in a changeover context with an exploratory case study at GBM. The empirical analysis focuses on changeover practises within selected production channels at the channel level, with a specific focus on a UVA Lidköping SGP 320 grinding machine at the GBM. This serves as a deep-dive example at the machine level to complement the channel-level analysis.

2. Frame of reference

2.1 Digital transformation in manufacturing

Digital transformation is a complex process with many challenges, which can be described in terms of various dimensions like technology, people and processes [6, 7]. These challenges necessitate the implementation of structured methodologies to understand, improve and manage. The deployment of AI, real-time analytics, and other data-driven solutions has shown to reveal tensions within complex sociotechnical environments [8], between data centralisation and operational autonomy, between innovation and production efficiency goals and between short-term operational stability and long-term infrastructure adaptability.

Manufacturing companies encounter difficulties in leveraging AI to their advantage [3, 4]. European manufacturing companies have identified a correlation between legacy equipment and limitations in terms of connectivity and data availability, which are considered to be a weak foundation for data-driven technologies [5]. Legacy manufacturing systems have shown to be deficient in both the infrastructure and the practices necessary to accommodate the exponential growth in data volumes, and thus present significant challenges to support data-driven operations [9]. The restricted data processing capabilities intrinsic to legacy control systems constitute another substantial constraint. In addition to these challenges, the heterogeneous nature of the legacy manufacturing ecosystem introduces the potential of incompatible data, which requires substantial data-processing resources.

A typical transformation process is IT-OT convergence, where traditionally separate information technology (IT) systems, focusing on cost-efficient cloud architectures, need to integrate with operational technology (OT) systems, focusing on latency and robustness [10]. This facilitates integrated data flows, real-time decision-making, and coordinated control.

Digital transformation initiatives are not always people-centred, with technology being prioritised over the human aspect [2]. Human challenges are multifaceted in nature, necessitating a balance between highly optimised manufacturing operations and exploratory implementation efforts for data-driven technologies [8]. As is often mentioned in the context of IT-OT convergence [11], this transformation process is challenging at a human level. This is due to the fact that IT and OT traditionally exhibit substantial differences in values, priorities and expected behaviours. A critical challenge for manufacturing companies is the retirement of seasoned operators, which can result in difficulties in the transfer of tacit knowledge and the maintenance of operational reliability. These challenges, when considered collectively, span the entire lifecycle of data-driven solutions, encompassing design to implementation and operation.

The extant literature provides only a limited amount of empirical guidance for the implementation of AI in traditional manufacturing contexts. The present study is concerned with the guidance gap for AI-enabled changeover optimisation in traditional manufacturing.

2.2 AI capabilities in manufacturing

The utilisation of artificial intelligence (AI) in value stream mapping (VSM) can be enhanced through the identification of impediments to flow, the monitoring of parameters, and the evaluation of discrepancies in manufacturing processes [12]. While VSM provides a structured, static view of production flows and bottlenecks, it offers limited support for real-time coordination and adaptive decision-making in GBM's dynamic manufacturing context.

Synchroperation is a concept that can indicate how the GBM production system can be adjusted based on synchronisation of real-time data, organisational coordination and decision-making to achieve more resilient and agile manufacturing [13]. Synchroperation, therefore, extends the traditional VSM by incorporating a temporal perspective and cross-functional coordination. Guo et al. [13] propose a categorisation of synchroperation into three different dimensions, each addressing different, yet complementary coordination challenges in manufacturing (see Figure 1). The operationalisation of synchroperation in practice will require an underlying AI architecture capable of real-time analytics and coordinated decision-making across system levels. Soldatos [14] presents an AI-enabled architecture integrating numerous AI capabilities, including modular AI orchestration, which facilitates the development of both low-level and high-level AI models, as well as the evaluation of time-series models and the integration of large language models for document management. Additionally, the architecture facilitates multimodal AI inspection, integrating computer vision and acoustic analysis to detect quality deviations and identify equipment anomalies. Building upon these AI capabilities, the practical deployment of AI/ML solutions for specific use cases requires a more granular approach. The selection of appropriate Machine Learning (ML) techniques to facilitate the optimisation of production changeover in discrete manufacturing requires a multidimensional approach. The assessment encompasses not only the predictive accuracy of the model but also considers operational fitness, explainability, deployment feasibility, and robustness. It is vital to align the capabilities of the model with the temporal, multivariate, and real-time nature of changeover processes. In addition, it is essential to leverage edge-cloud infrastructure to deploy AI solutions that are both intelligent and industrially viable. The structured model selection guidelines ensure that AI-driven changeover optimisation is not only technically sound but also practically impactful.

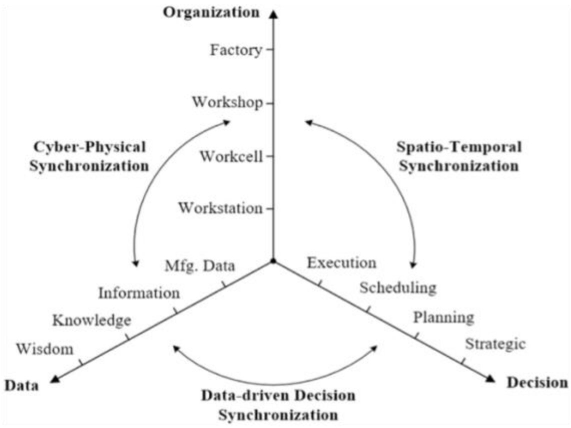

Figure 1. Dimensions of synchroperation (Taken from ([13]).

2.3 Technical and Organisational Challenges in Manufacturing AI Adoption

The advancement of manufacturing towards AI-driven, human-centred models faces various barriers, encompassing technical limitations, organisational resistance, and governance gaps that hinder implementation[15]. Extant literature reveals that organisational factors such as digital skills, company size, and R&D intensity have a greater impact on AI adoption than purely technical conditions. Furthermore, advanced cognitive and domain-related competencies are more significant than generic 'social skills' for achieving digital transformation success [16–18].

Technical barriers include the use of black-box recommendations, which may be based on an insufficient quantity of high-quality training data, causing reliability concerns and limiting the operator's trust in the models when they encounter real-world variability beyond controlled conditions [15]. As indicated by the relevant literature, concerns have been raised regarding the potential for security vulnerabilities to arise as a consequence of poor architecture and the absence of software updates for critical IT infrastructure [10]. Organisational resistance manifests as skills gaps, unwillingness to follow AI recommendations, and insufficient leadership support. Vollbehr [6] describes how senior management must balance stable execution with explorative innovation, which is needed for the implementation of data-driven technologies. Otherwise, short-term performance imperatives will predominate any digital implementation initiatives. Furthermore, SMEs encounter challenges that are disproportionate in comparison to those faced by large manufacturers. These challenges include a lack of financial resources, technical expertise, and sufficient data access, which are necessary for effective implementation [15]. Manufacturing systems must also secure lifecycle management, including secure deployment, management, and maintenance of AI solutions in a performance-driven shopfloor context. Modular system architectures, including edge-devices, are thus imperative to enable real-time performance, data security, and long-term maintainability of AI capabilities within legacy manufacturing environments[19, 20].

3. Method

3.1 Research design

The present study adopts an exploratory mixed-methods case study design to investigate the potential of AI to support changeover optimisation in discrete manufacturing environments. A systematic literature review is integrated with empirical field studies and interviews at the GBM, with the aim of bridging the theoretical frameworks of AI readiness with operational realities on the shop floor. The combination of methods enables a theory-informed, yet empirically grounded analysis. The research process is structured in three sequential phases:

1) Exploratory phase: In the initial phase, an integrative review of an emerging topic [21] is conducted to identify the state-of-the-art in AI-driven changeover optimisation, including barriers to adoption in legacy production contexts. The review focuses on publications addressing AI capabilities, digital transformation challenges and organisational readiness frameworks related to manufacturing.

2) Empirical phase: A case study is conducted within the GBM production network, focusing on selected model channels representing varying levels of automation, digital maturity, and operational complexity. The data collection process entailed numerous visits to the shop floor (four hours total). This was complemented by a meticulous documentation analysis, encompassing production key metrics reports, standard operating procedures, and resetting handbooks. The collection process was further augmented by seven semi-structured expert discussions, each spanning approximately one hour, involving key stakeholders such as two production managers, local and global resetting experts, operators, a lean expert and a digital transformation specialist. The objective of the expert discussions was to achieve insight triangulation. The discussions were guided by predefined thematic prompts related to changeover practices, data availability, decision-making processes, and perceived barriers to AI adoption, while allowing flexibility to explore context-specific issues emerging from each channel.

3) Analytical phase: In the third phase, qualitative insights from observations and interviews were analysed thematically alongside quantitative production metrics. The analysis examines the gap between AI's theoretical potential and its practical implementation.

3.2 Case selection and unit of analysis

The unit of analysis in this study is the production channel, which represents a complete and self-contained value stream within the GBM's MCC. Each channel incorporates all the primary operations (machining, assembly, inspection, and packaging), thus establishing an appropriate analytical boundary for evaluating the performance of AI-enabled changeover and the system's readiness. Two different channels were initially selected to provide comparative insight across maturity levels: DD01 – GBM World Class Channel while the a new DD11 is an Automatic Resetting Channel. The combination of these two enables cross-channel comparison of barriers to AI integration, data availability, and operator involvement. Each channel functions as an integrated sub-case within the overall GBM case, allowing both in-depth contextual analysis and pattern identification across organisational and technical configurations. Preliminary observations from these channels inform the discussion of organisational readiness factors and technical barriers, highlighting the need for channel-specific rather than standardised AI implementation approaches. This provides a robust empirical foundation for future in-depth cross-channel comparative studies examining AI-integration barriers, data availability requirements, and the role of operator expertise in successful AI adoption.

3.3 Case selection and unit of analysis

The two research questions guided both data collection and analysis. RQ1 (What AI capabilities provide the highest impact on changeover performance in discrete manufacturing?) was addressed through a comprehensive literature review and empirical analysis of both changeover decision practices and prevailing general AI practices at GBM. RQ2 (What organisational readiness factors are necessary for successful adoption?) was addressed through the exploratory case study, in which variations in channel maturity and digital infrastructure across the case organisation were examined.

4. Use case description

4.1 The production system framework

In this section, we will be examining the production system framework. The MCC is a concept that functions in conjunction with the GBM production system, of which the resetting methodology is an integrated part. "The GBM standard to reduce resetting times and improve flexibility was integrated from a stand-alone method into the GBM Production System as one of the core stability tools… The channel resetting time is a loss in production due to the set-up between two material families. It is a necessary but non-value-added activity…" *[22]*. The Master Production Schedule (MPS) is predicated on customer demand and bottleneck rate, with the output defined in this manner. The Material Requirements Planning (MRP) system is then utilised to determine the quantities of material and components to be procured (see Figure 2).

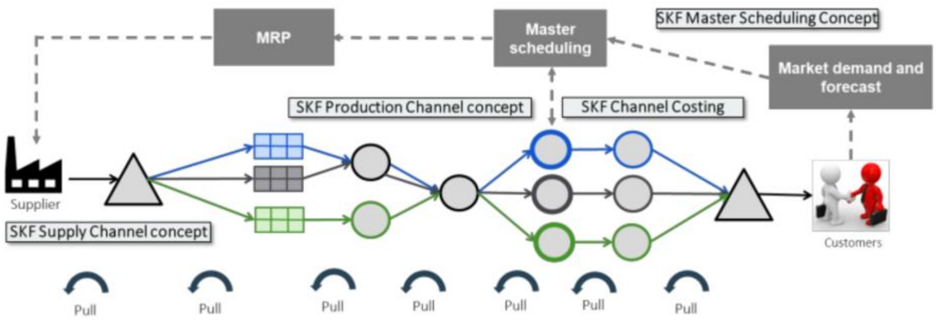

Figure 2. Overview of the GBM channel concepts, of which the production channel is an integrated part.

The GBM's structured approach, by integrating the resetting methodology into the Production System Framework, creates a foundation for AI enhancements. In this way, lean principles can be combined with new AI capabilities, such as predictability and anomaly detection. The combination of established concepts, such as the resetting methodology, with AI development can give rise to people-related challenges. These challenges, as described by Ahlskog et al.[7] may include a lack of knowledge and skills, cultural mindset, and resistance to change.

4.2 Prerequisites and competence development

It is imperative that a GBM factory prepare and consider several points prior to implementing resetting improvement activities. These points are based on experiences from best-in-class factories at GBM. These prerequisites include the identification of a subject matter expert (SME) candidate, the implementation of a structured follow-up process and the establishment of a pilot channel including change management practices. In order to become a resetting expert at GBM, a defined journey is followed, which comprises four stages. The first stage is that of a 'novice' with a basic understanding of the resetting topic, via a 'generalist' who has experience of deployment at one machine/area. Subsequent steps continue with the 'specialist' extending focus to encompass an entire production line/channel. In order to become an 'expert', it is necessary to demonstrate leadership across multiple production lines and factories.

4.3 Flow optimisation and flow-stoppers

To continuously optimise this flow, the GBM uses value stream mapping (VSM) to identify flow-stoppers, monitors flow-parameters and performs gap assessments. A flow-stopper is a condition that complicates the flow management. They can be categorised into three main groups: structural issues, operational instabilities, and scheduling misalignments.

4.3.1 Structural issues

Structural issues arise from fundamental design flaws, such as a mismatch between bottlenecks and product assortment. When the bottleneck machine is not dedicated to a specific product line, but instead used for a broad range of products, there is a risk that the machine will be occupied by lower-priority products. Many-to-many relationships, another type of structural issue where multiple channels share multiple operations, create a tangled web of dependencies that is nearly impossible to manage with a simple pull system. A third type of structural issue is when there is a mix of in-house and subcontracted operations. Imagine a part that leaves a production line, gets a special coating at a sub-contractor, and then re-enters the same line later—this is a classic flow-stopper.

4.3.2 Operational instabilities

Operational instability is another category of flow stoppers, related to the variability and reliability of the processes themselves. There are many sources of process instabilities, such as machine breakdowns, tool wear and breakage, variation in input material or parameter drift, causing grinding burn due to small changes in coolant flow or pressure or temperature rise leading to thermal expansion of parts/machines, affecting tolerances.

4.3.3 Scheduling misalignments

Scheduling misalignments, the third category of flow-stoppers includes issues related to the execution of the MPS, when there is a gap between the planned sequence of work and what happens on the shop floor. It can be a product that deviates from the planned flow by leaving the channel for a special operation and then re-entering, resulting in a disrupted flow. Another scheduling misalignment is when a component does not follow the sequence from first to last operation, as this might cause products and components to be out of sync.

4.4 Resetting methodology at the GBM

The resetting methodology is a three-step process starting with step 1 - organisational improvements/ challenges, through step 2 - SMED [18] implementation, to step 3 - technical automation. Experience inside GBM has shown that most of the lost time during resetting originates from inefficient organisation, up to 60%. Further, single machine improvements account for 25% of improvement potential, leaving 15% for the third step – technical improvements. The traditional set-up following a linear progression poses a risk that artificial boundaries are created between these steps. An AI-optimisation can, however, potentially address two or three steps simultaneously, through an integrated approach.

4.5 Current AI implementation challenges in production changeover

Mature production lines at GBM develop informal optimisation practices driven by operator experiences. This creates a gap between documented standardised operating procedures (SOPs) and actual practice. However, a conflict arises between maintaining high-performance stability and AI-driven improvements, which add complexity and therefore a risk for disruption of operational excellence. AI models are subject to a whole range of lifecycle risks [15], including reliability concerns, security vulnerabilities, model drift, data quality degradation, maintenance debt, and versioning. When trying to evolve from SMED to AI-optimisation, it is critical to understand these practical limitations. Retiring experienced operators with decades of knowledge regarding channel-specific optimisation pose a great risk for the GBM. This creates an urgent need for systems that capture and codify this tacit knowledge, so it can be transferred to junior operators. Some tacit knowledge exists as informal workarounds and operator-driven optimisations outside documented procedures.

5. Results

This section presents the empirical findings of the study, structured in relation to the two research questions. Section 5.1 addresses organisational and technical variations influencing AI readiness across production channels, contributing primarily to RQ2. Section 5.2 addresses RQ1 by synthesising critical selection criteria for the choice of AI capabilities for changeover optimisation based on observed decision-making complexity and operational constraints.

5.1 Channel maturity and performance variations

Addressing RQ2, this section presents empirical findings on channel maturity, performance, and digital readiness. Both organisational and technical factors influence AI adoption, and readiness varies significantly by machine. Highly automated channels have different challenges than manual-intensive ones, which require fundamental digital infrastructure. Performance metrics and lean assessment records reveal significant variation in resetting complexity. One 2014 time study found that a changeover on a UVA Lidköping SGP 320 grinding machine took ~37 minutes and involved 30 sequential steps versus 55 steps for another type of changeover on the same machine. Solutions need to be tailored to specific channels and machine characteristics. AI architectures need to be modular and adaptable [24]. Viewed through the decision dimension described by Guo et al. [13], variation in channel maturity and performance reflects increased decision complexity in AI adoption. Readiness depends on clearly defined decision authority and governance mechanisms which enable local adaptation while maintaining strategic coherence and effective AI model lifecycle management.

5.2 AI and ML techniques to support production resetting/changeover

In response to RQ1, this section describes empirical insights from observed changeover practices together with expert discussions at GBM and existing literature. It aims to identify AI capability requirements that have the highest potential impact on changeover performance in discrete manufacturing. Rather than identifying a single optimal algorithm, the findings emphasise critical AI-capability selection criteria that align with the temporal, multivariate, and context-dependent nature of changeover decision-making. These AI capabilities are operationalised through a structured set of model selection criteria that guide the development of AI solutions for changeover optimisation. Several practicalities need to be considered when selecting ML models. Models must be not only technically capable but also operationally aligned with the realities of the shop floor in discrete manufacturing. Drawing from the experience of a team of AI/ML experts at the GBM, with extensive backgrounds in developing optimisation solutions in various implementation contexts, we aim to support predictive changeover optimisation. This is done through scalable, interpretable, and resilient AI solutions that integrate effectively with existing production constraints. To achieve this goal, we have developed a structured set of criteria to guide the ML model selection. These support the development of the AI solution that fulfils the targeted capabilities. These criteria ensure that models are not only practical but also interpretable, deployable in real time, and robust enough to handle the challenges of industrial environments. The following table (Table 1) outlines the key factors for model selection, each based on the practical demands of changeover optimisation.

Table 1. Overview of ML models selection criteria related to changeover.

Criteria	Why it matters	Key approaches	Implementation notes & relevant literature
Temporal Awareness	Changeover processes are inherently time sensitive. ML models must understand the temporal dynamics of production transitions to minimise downtime and improve scheduling efficiency	Gated Recurrent Unit (GRUs), Temporal Convolutional Networks (TCNs), Long Short-Term Memory (LSTM)	Effective models can predict the sequence and duration of changeover steps, enabling proactive adjustments and smoother transitions. [27]
Multivariate Input Handling	Changeover optimisation involves multiple data sources such as sensor readings, operator actions, product specifications, and environmental conditions. Models must integrate these diverse inputs to form a holistic understanding of the process.	Autoencoders for feature fusion, Multimodal deep learning, Ensemble learning (e.g., Random Forests, Gradient Boosting)	High-dimensional data requires models capable of learning complex multivariate relationships. This is essential for generating accurate and actionable insights. [28]
Explainability	Operators and engineers must understand the rationale behind model recommendations to confidently act on them.	SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), Rule-based models (e.g., decision trees, symbolic regression)	Explainable models facilitate issue diagnosis, decision validation, and compliance with operational standards. [29]
Real-Time Inference Capability	Changeover decisions sometimes need to be made instantly, adapted to the changing dynamics of the shop floor to avoid production delays. ML models must deliver time-bound and reliable predictions.	Online learning algorithms (e.g., Online Gradient Descent), Lightweight neural networks (e.g., MobileNet, TinyML)	Lightweight algorithms are essential for deployment on constrained hardware, such as edge devices. [25]
Edge-Cloud Compatibility	Usually, the infrastructure spans both edge and cloud environments. AI models must operate seamlessly across these platforms to ensure flexibility and scalability.	Model partitioning and offloading, Containerised ML deployment (e.g., Docker + Kubernetes)	Edge deployment enables quick, local decision-making with minimal latency, crucial for time-sensitive operations. Cloud platforms support large-scale model training and analytics, enhancing

			performance and adaptability. [26]
Robustness to Noise and Missing Data	Manufacturing data is often imperfect due to sensor faults, human error, or environmental variability. Models must be resilient to such inconsistencies.	Ensemble learning, Robust loss functions (e.g., Huber loss), Data imputation techniques e.g., K-Nearest Neighbours (KNN) imputation, Multiple Imputation by Chained Equations (MICE), Adversarial training	Robust models maintain performance despite data quality issues, ensuring continuous operation and reliable changeover recommendations.[27]
Optimisation Capability	AI-driven changeover must ensure smooth production transitions and reduce downtime. Models must adapt to changing production conditions and learn optimal strategies over time.	Reinforcement Learning, e.g., Deep Q-Network (DQN), Deep Deterministic Proximal Policy Gradient (DDPG), Bayesian Optimisation	Reinforcement Learning models learn through interaction with the environment, refining policies that enhance efficiency and reduce operational costs. [30]
Transfer Learning Capability	In discrete manufacturing, data availability for specific changeover scenarios may be limited. Transfer learning allows models to leverage knowledge from related tasks or domains, reducing training time and improving performance in low-data environments.	Pretrained Networks, Domain Adaptation, and Few-shot learning	Transfer learning enables faster deployment and better generalisation, especially when historical changeover data is sparse or inconsistent. [31]
Human-in-the-Loop Integration	Changeover decisions often require human oversight. ML models should support interactive feedback and allow operators to guide or override predictions when necessary.	Active Learning, Interactive reinforcement learning, Mixed-initiative systems, Feedback Loops	Human-in-the-loop systems improve trust, adaptability, and safety by incorporating expert feedback during model inference or retraining. [28]
Lifecycle Maintainability	ML models in manufacturing must be maintainable over time, including retraining, monitoring, and updating as production conditions evolve.	MLOps frameworks, Model Monitoring, Drift Detection, Continuous learning systems	Maintainable models reduce technical debt and ensure long-term reliability and compliance with evolving operational standards.[23, 29]

6. Discussion

The integration of AI in manufacturing reveals a paradox between performance promises and operational realities. For AI to function efficiently, in this complex context, it needs human expertise. The GBM changeover use case demonstrates implementation challenges, where each resetting represents a vast area of possible configurations. Changeover duration of a grinding machine can range from minutes to several hours, because the operator must navigate a range of complex decisions about tools and configurations to achieve quality levels for the produced products as quickly as possible. The following questions guide this resetting process:

- **SMED-related tactics:** 'Can I perform offline set-up, or do I need to adjust the machine directly?' Access to a staging area and tools are key factors in the context description.

- **Tooling and sequence decision**: 'Which tools to change, and in what order, to minimise adjustments?' Key factors include tool wear and product specifications. Product mix complexity, like the number of product families and the parametric delta between variants, also impacts the context description.
- **Quality**: 'How to choose between aggressive adjustments (faster but riskier) and incremental changes (slower but safer)?'. 'How to decide when and how to measure which parameters to adjust after each test, based on material characteristics and historical data?'
- **Parameter optimisation:** 'Which parameters to prioritise for this specific changeover?' The aim is to balance multiple parameters, including wheel speed, feed rate, coolant flow, and dressing frequency. Is the historical recipe OK, or will it need adjustments?
- **Economic trade-off decision**: 'Should I prioritise speed, quality or tool life? Should a premium or standard grinding wheel be used? The decision depends on customer requirements, delivery schedules, and tool and product costs.

As batch sizes shrink and the demand for customisation increases, manufacturing organisations should, based on the ML selection criteria (Table 1) and the GBM case analysis, consider the following:

- **Data profiling**: Assess the quality, granularity, and availability of changeover-related data across any predefined set of standards, such as ISA-95 levels, before selecting models.
- **Use hybrid architectures**: Combine edge-based inference for real-time responsiveness with cloud-based training for scalability and continuous learning.
- **Prioritise explainability early**: Involve operators and process engineers in model validation using interpretable models to build trust and adoption.
- **Design for feedback loops**: Integrate model outputs into MES or SCADA systems to enable closed-loop optimisation and continuous improvement.
- **Simulate before deploying**: Use digital twins or simulation environments to test model behaviour under various changeover scenarios.
- **Monitor and retrain**: Establish pipelines and frameworks (MLOps) for model monitoring, drift detection, and retraining to maintain performance over time.

Current GBM applications for shopfloor analytics and ML models, validate these criteria (Table 1): **Temporal awareness** is essential for wheel dressing, gauge calibration and tool conditioning. **Multivariate input handling** is needed to jointly interpret CNC parameters, spindle-load curves, vibration signatures, MES instructions, and operator annotations. **Explainability** is vital for support operator trust and corrective action validation. **Real-time inference capability** and **edge–cloud compatibility** are used for vibration-based alerts and equipment condition monitoring. Finally, **robustness to noisy or missing data** and **transfer learning** has been effective for anomaly detection or visual quality prediction across machine variants. Finally, **human-in-the-loop integration** is consistent with established GBM practice, where operators provide feedback or overrides through parameter recommendation systems.

6.1 Future work

Dynamic capabilities (DCs) [30], provide a framework for understanding how AI adoption builds organisational resilience. Peretz et al. [2] identify three interdependent capabilities for SME AI readiness: acquiring fundamental resources (digital infrastructure and talent), establishing a learning organisation to create and spread AI competencies across functional roles. Thirdly, there is the operationalisation of AI through defined strategies and responsibilities. Additionally, organisations must implement a reliable AI lifecycle management system through the effective use of data quality management, structured decision-making processes, and clear accountability. Future research will examine how these capabilities and governance mechanisms jointly build resilient, AI-enabled manufacturing systems. By applying the resilience compass [31], we will map resilience practices to organisational resetting activities to visualise capability levels for effective AI implementation. The resilience dashboard [31] will also identify risks and assess capabilities to mitigate them. This systems-level view of organisational resilience levels offers critical insights into the readiness factors for successful AI adoption and utilisation.

7. Conclusions

This study explored AI capabilities in the context of optimisation of changeovers for a discrete manufacturing organisation, using GBM's model channel concept as the empirical context. Through a literature review and case analysis, we identified ten critical ML selection criteria (temporal awareness, multivariate input handling, explainability, real-time inference capability, edge-cloud compatibility, robustness to noise, optimisation capability, transfer learning capability, human-in-the-loop integration and lifecycle maintainability) that need consideration when trying to bridge technical feasibility with operational requirements.

The many diverse resetting decisions involve both quantifiable parameters and tacit assessments, where many decisions are also interdependent. Variability makes standardisation highly complex, imposing challenges in both how AI can support an operator with valuable recommendations and how such an ecosystem of AI models needs to be trained. One crucial AI capability is to identify the least common denominators between different types of resetting for building a scalable contextualisation. These findings were further validated through an informal survey, regarding AI implementation barriers gathered from Swedish industrial managers ($n \approx 150$) which revealed barriers clustered around three different dimensions, organisational challenges including leadership development, generational knowledge gaps and structural silos, technical challenges with OT integration complexity, data access limitations, and security concerns, and also governance dimensions concerning data integrity, organisational readiness and decision-making frameworks. While these answers represent practitioners' perspectives rather than systematic research findings, they align well with theoretical research pointing to multidimensional implementation barriers for data-driven technologies.

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