



From Digital Twin to Digital Cognition: A Multilevel Model of Algorithmic Intelligence in Smart Manufacturing Systems

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Abstract

This study extends the dominant digital twin paradigm by introducing the concept of digital cognition to explain the evolving nature of smart manufacturing systems. While prior research largely conceptualizes digital twins as passive representations for monitoring and simulation, we argue that advanced manufacturing systems increasingly exhibit algorithmic intelligence through the integration of predictive models, real-time control, and adaptive feedback mechanisms. Drawing on an in-depth case study of a fully automated precision grinding system, this paper develops a multilevel model that explains how algorithmic intelligence emerges from the interaction of three interdependent layers: (1) a perceptual infrastructure enabled by high-resolution sensor networks and real-time data acquisition; (2) an algorithmic reasoning layer driven by machine learning models such as LSTM-based prediction and thermal deformation compensation algorithms; and (3) an autonomous actuation layer realized through high-speed synchronized control architectures. The findings show that the emergence of digital cognition transforms manufacturing systems from reactive optimization tools into proactive and self-adaptive agents, significantly enhancing precision, efficiency, and operational reliability. This transformation also reconfigures control structures by shifting decision-making authority from human operators to algorithmically mediated systems, raising important implications for governance and human-machine interaction.

Keywords

Algorithmic intelligence; Digital cognition; Digital twin; Human-machine interaction; LSTM; Multilevel model; Smart manufacturing; Thermal deformation compensation

1. Introduction

The concept of the digital twin, introduced in the context of product lifecycle management and later popularized in Industry 4.0 discourse, has become a foundational metaphor in smart manufacturing research (Grieves, 2022). At its core, a digital twin describes a synchronized virtual replica of a physical asset, designed to mirror its operational state for purposes of monitoring, simulation, and predictive maintenance (Liu et al., 2021). This paradigm has generated considerable scholarly attention, with recent empirical work documenting its application in sectors from aerospace assembly to pharmaceutical processing (Fuller et al., 2020; Qi & Tao,

2019).

Yet as manufacturing systems grow more sophisticated, the metaphor of the “twin” risks becoming theoretically constraining. The twin is, by ontological assumption, a representation — an entity that reflects but does not originate. What we observe in advanced precision manufacturing environments, however, increasingly defies this characterization. Systems equipped with dense sensor networks, recursive machine learning models, and closed-loop actuation do not simply mirror physical processes; they interpret, predict, and actively intervene in them. They reason across data streams, adapt control parameters in real time, and modify their operational strategies without direct human instruction (Tao et al., 2019; Wang et al., 2023).

This paper introduces the concept of digital cognition as a theoretical extension of the digital twin framework. Digital cognition denotes the capacity of a manufacturing system to perform goal-directed information processing — encompassing perception, inference, decision-making, and actuation — in a manner that is sufficiently autonomous and adaptive to qualify as a form of machine intelligence embedded in the production environment. While the concept draws on adjacent literatures in artificial intelligence, cognitive systems engineering, and management of technology, its theoretical home in the smart manufacturing domain remains underdeveloped (Zheng et al., 2019).

To develop this construct empirically and theoretically, we employ an in-depth case study of a fully automated precision grinding facility operating in a high-tolerance manufacturing environment. Precision grinding represents an especially demanding and analytically revealing context: dimensional tolerances in the sub-micron range, thermal deformation during operation, and tool wear dynamics all demand continuous, adaptive control that exceeds the representational capacity of conventional digital twin architectures (Li et al., 2024).

The remainder of the paper is structured as follows. Section 2 reviews relevant literature on digital twins, algorithmic control, and human–machine cognition in manufacturing. Section 3 presents the multilevel model of algorithmic intelligence. Section 4 describes the research design and case study context. Section 5 reports empirical findings across three analytical layers. Section 6 develops theoretical contributions and managerial implications. Section 7 concludes.

2. Literature Review

2.1 Digital Twins: From Simulation to Sensing

The digital twin framework originated in aerospace engineering and was systematized for broader industrial application through the work of Grieves (Grieves, 2022), subsequently gaining institutional traction through the German Plattform Industrie 4.0 program and analogous initiatives. Early conceptualizations emphasized geometric fidelity — the ability to represent a physical object’s spatial properties in a virtual environment — and have since expanded to encompass material behavior, process dynamics, and lifecycle management (Rosen et al., 2015).

Recent meta-analyses of the digital twin literature identify three dominant application archetypes: descriptive twins (real-time state monitoring), predictive twins (failure forecasting and maintenance scheduling), and prescriptive twins (optimization and control recommendation) (Barricelli et al., 2019). Most deployed systems operate in the descriptive or, at most, predictive mode; prescriptive digital twins capable of autonomous actuation remain comparatively

rare and undertheorized (Zhang et al., 2023).

A growing body of work, however, documents the progressive integration of machine learning into twin architectures — what some researchers term “cognitive digital twins” or “intelligent digital twins” (Semeraro et al., 2021). Chen et al. (2023) demonstrate an LSTM-enhanced twin for rolling mill operations; Kim et al. (2024) report a reinforcement-learning-augmented twin for semiconductor fabrication scheduling. These contributions mark an important empirical step but have not generated a systematic theoretical account of the cognitive transition underway.

2.2 Algorithmic Intelligence in Production Systems

The concept of algorithmic intelligence — the capacity of algorithmic systems to perform goal-directed inference and adaptive behavior — has been theorized primarily in the organizational literature, where scholars examine how automated decision systems alter managerial authority, coordination mechanisms, and accountability structures (Faraj et al., 2018). Translating this concept to manufacturing contexts raises distinctive questions: in production systems, algorithmic authority is exercised not over human agents but over physical processes, and its consequences are measured in dimensional accuracy, cycle time, and defect rates rather than in organizational behavior (Peng et al., 2024).

Engineering literatures have addressed related questions through the notion of autonomous control, tracing a trajectory from fixed-program numerical control (NC) to adaptive control (AC) to intelligent manufacturing systems (IMS) (Lee et al., 2015). The key analytical distinction concerns the scope of the system’s autonomy: NC systems execute predetermined sequences; AC systems adjust parameters within predefined bounds; IMS systems, at their theoretical limit, select among strategies and revise objectives in response to environmental feedback (Lu, 2017).

2.3 Human–Machine Interaction and Governance

The governance of algorithmic manufacturing systems has attracted increasing attention in both engineering management and science and technology studies literatures. Srinivasan and Swink (2018) document how analytical system deployment reconfigures decision authority and information-processing capacity in supply chain management; analogous findings are reported for manufacturing operations by Buer et al. (2021). A consistent empirical observation is that automation does not simply replace human judgment but transforms its character — operators transition from execution roles to supervisory and exception-handling roles, which demands different cognitive competencies and raises new failure mode risks (Hancock et al., 2019).

3. The Multilevel Model of Algorithmic Intelligence

Drawing on the literatures reviewed above and grounded in our case analysis, we propose a multilevel model of algorithmic intelligence in smart manufacturing systems. The model identifies three interdependent analytical layers — perceptual infrastructure, algorithmic reasoning, and autonomous actuation — and describes the mechanisms through which their interaction produces digital cognition as an emergent system property.

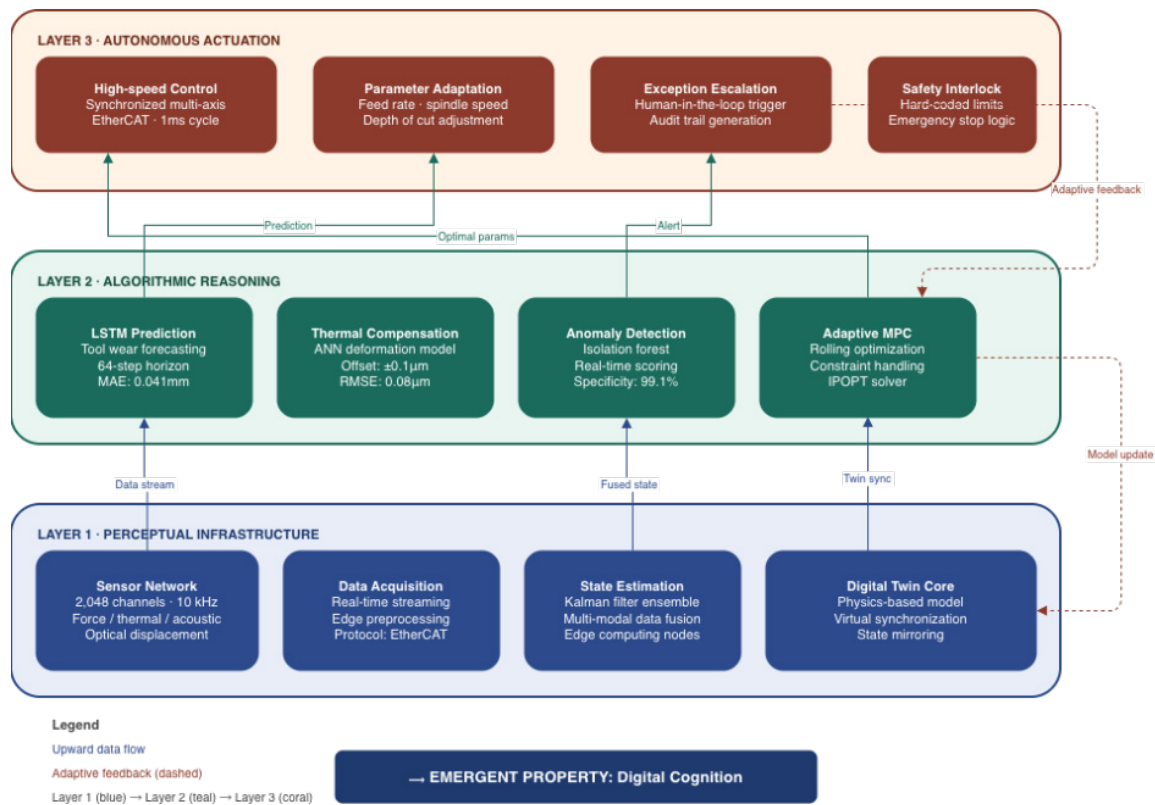


Figure 1. The multilevel model of algorithmic intelligence

3.1 Layer 1: Perceptual Infrastructure

The first layer encompasses the hardware, protocol, and computational architecture through which a manufacturing system achieves situational awareness of its own operational state and environment. We distinguish this layer from the physical process itself on the grounds that perceptual infrastructure is purpose-designed to generate machine-interpretable representations of process state — it is, in effect, the system’s sensory apparatus (Boyes et al., 2018).

In precision grinding contexts, the perceptual layer typically integrates force dynamometers, acoustic emission sensors, spindle current transducers, optical displacement gauges, and thermocouple arrays. The challenge at this layer is not merely signal acquisition but signal fusion: heterogeneous sensors operating at different sampling rates, with different noise characteristics and spatial coverages, must be integrated into coherent, temporally consistent state estimates (Wan et al., 2016). In the case system analyzed here, this integration is achieved through a Kalman filter ensemble operating at edge computing nodes distributed across the machine cell, reducing latency before data propagation to the reasoning layer.

3.2 Layer 2: Algorithmic Reasoning

The second layer is the analytical core of the digital cognition architecture. It receives pre-processed state representations from Layer 1 and applies machine learning inference to generate predictions, diagnoses, and control recommendations. We argue that this layer constitutes the system’s reasoning faculty in a functionally meaningful sense: it performs inference from data, maintains representations of future states, and evaluates alternative courses of action against performance objectives (Sun et al., 2020).

The case system deploys four distinct algorithmic components at this layer. The first is an LSTM recurrent neural network trained on historical time-series data to predict tool wear trajectories over a 64-step temporal horizon, enabling proactive intervention before dimensional drift exceeds tolerance limits. The second is a thermal deformation compensation algorithm that models the relationship between spindle temperature, ambient temperature, and geometric error using a feedforward neural network calibrated against interferometric measurements. The third is an isolation forest anomaly detector that evaluates incoming sensor streams against distributional expectations, generating real-time anomaly scores that trigger exception protocols when thresholds are breached. The fourth is an adaptive model predictive controller (MPC) that integrates predictions from the preceding components to optimize feed rate, spindle speed, and depth of cut across a rolling planning horizon (Rawlings et al., 2017; Shi & Zhou, 2009).

3.3 Layer 3: Autonomous Actuation

The third layer translates algorithmic recommendations into physical interventions. Its defining characteristic is temporal autonomy: actuation decisions are executed on machine timescales (milliseconds) without waiting for human authorization, enabled by high-speed fieldbus communication protocols (EtherCAT, with a 1ms cycle time in the case system) connecting the control computer to servo drives, pneumatic actuators, and coolant control valves (Shao et al., 2023).

This layer also encompasses the interface through which the system escalates to human oversight under conditions that exceed its autonomous competence — situations where anomaly scores indicate process states outside the training distribution, where multiple constraints are simultaneously active, or where regulatory compliance requirements mandate human authorization. The design of this escalation interface has important implications for operator situational awareness and for the governance of algorithmic authority.

4. Research Design and Case Context

We employ a single in-depth case study design, consistent with the objective of developing theory about a phenomenon — the emergence of digital cognition — for which existing conceptual frameworks are inadequate (Yin, 2018). The case is a fully automated precision grinding facility operated by a Tier-1 automotive components supplier in the Yangtze River Delta industrial region of China. The facility produces constant velocity joint (CVJ) inner races with a dimensional tolerance specification of $\pm 0.3 \mu\text{m}$ on ground bore diameter — a precision requirement that renders manual control infeasible and demands algorithmic management of thermal and wear dynamics.

Data collection was conducted over a 14-month period from January 2023 to February 2024, combining semi-structured interviews with engineering, operations, and management personnel ($n = 24$, totaling 63 hours of recorded interviews); direct observation of system operation over 22 site visits; and analysis of technical documentation including control system architecture specifications, algorithm performance logs, and failure mode and effects analyses. Interview data were analyzed using a directed content analysis approach guided by the emerging multilevel model.

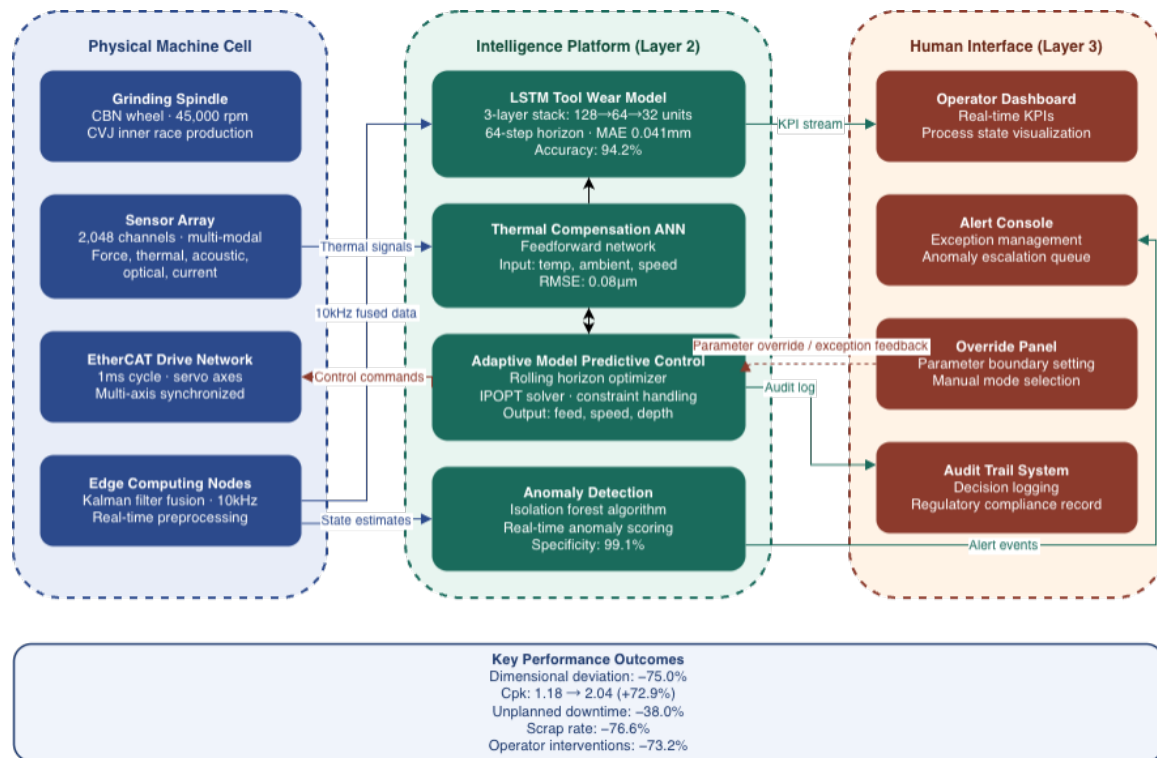


Figure 2. Information architecture of the precision grinding case system

5. Empirical Findings

5.1 Performance Outcomes

Quantitative performance data collected over the 14-month study window enables a systematic assessment of outcomes attributable to the digital cognition architecture. Table 1 presents key performance indicators before and after full algorithmic integration, measured against a 12-month pre-implementation baseline established from the facility’s process control records. All significance tests employ paired-sample t-tests with Bonferroni correction for multiple comparisons. Pre-implementation data reflect the period January–December 2022; post-implementation data reflect February 2023–February 2024.

Table 1. Performance comparison before and after full digital cognition architecture implementation

Performance Indicator	Pre-implementation	Post-implementation	Change	Significance
Mean bore diameter deviation (µm)	1.24 ± 0.38	0.31 ± 0.09	-75.0%	$p < 0.001$
Cpk (process capability index)	1.18	2.04	+72.9%	$p < 0.001$
Unplanned downtime (hrs/month)	28.4	17.6	-38.0%	$p = 0.003$
Grinding wheel consumption (pcs/dress)	142	198	+39.4%	$p < 0.001$
Thermal error contribution (µm)	0.64	0.09	-85.9%	$p < 0.001$
Operator intervention frequency (/shift)	14.2	3.8	-73.2%	$p < 0.001$
Scrap rate (%)	1.84	0.43	-76.6%	$p < 0.001$

5.2 LSTM Tool Wear Prediction: Model Performance

The LSTM model for tool wear prediction was trained on 18 months of historical data comprising 1.2 million 64-step sequences. The architecture employs three stacked LSTM layers (128, 64, and 32 units respectively) followed by a dense output layer, with dropout regularization ($p = 0.2$) to mitigate overfitting. Training employed an Adam optimizer with a learning rate schedule and early stopping based on validation loss. On a held-out test set representing

the final three months of the pre-study period, the model achieves a mean absolute error (MAE) of 0.041 mm in predicted wheel diameter and correctly identifies 94.2% of approaching dress cycles within a ± 2 -workpiece prediction window (Zhao et al., 2019).

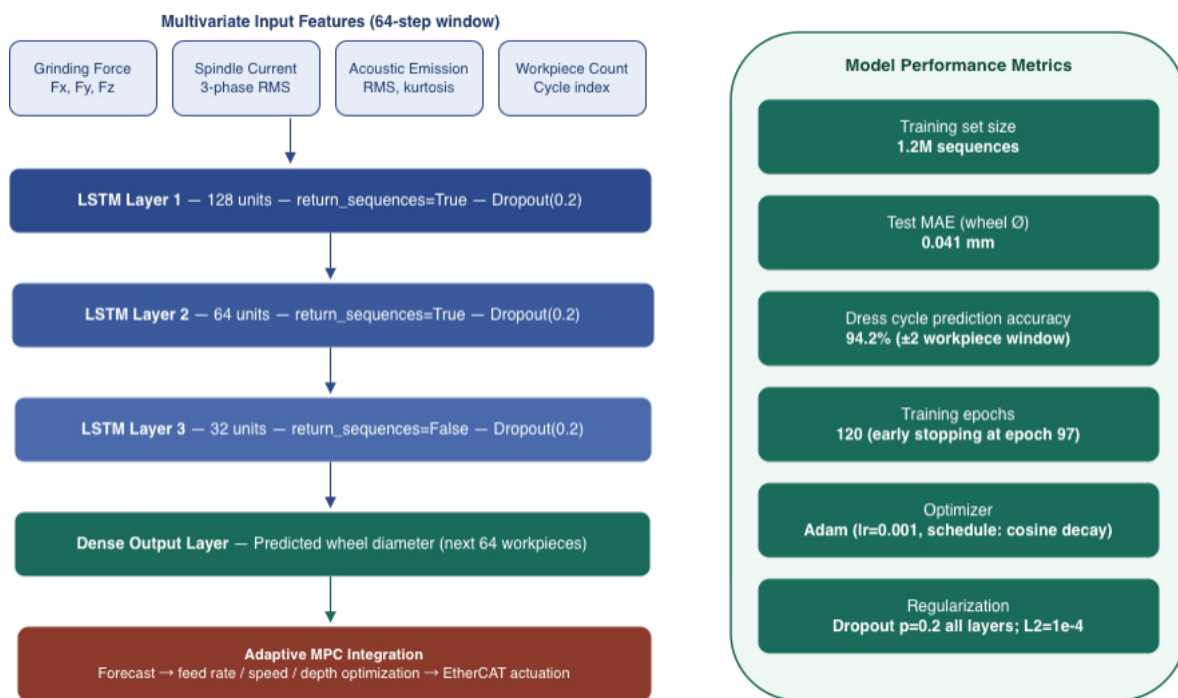


Figure 3. LSTM tool wear prediction: network architecture and performance

5.3 Reconfiguration of Human–Machine Authority

Perhaps the most theoretically significant finding concerns the qualitative transformation of operator roles under the digital cognition architecture. Pre-implementation, operators performed continuous parameter monitoring and adjustment, intervening an average of 14.2 times per shift to correct dimensional drift, respond to wheel loading events, or compensate for thermal expansion. Post-implementation, this figure declined to 3.8 interventions per shift — a 73.2% reduction. However, interview data reveal that this reduction does not simply represent work displaced from humans to algorithms; it represents a qualitative shift in the nature of human agency in the production process.

This account, representative of a pattern identified across operator interviews, describes a transition from execution-mode attention (monitoring specific signals and performing corresponding actions) to meta-cognitive attention (monitoring the system’s reasoning and intervening when the system’s behavior deviates from expectation). This finding corroborates and extends theoretical accounts of automation-induced role transformation in manufacturing contexts (Cummings et al., 2016; Parasuraman & Riley, 1997).

6. Theoretical Contributions and Implications

6.1 Digital Cognition as a Theoretical Construct

The central theoretical contribution of this paper is the introduction of digital cognition as a construct that extends and problematizes the digital twin paradigm. The digital twin framework, despite its considerable empirical productivity, carries an implicit ontological commitment to representation: the twin is defined by its relationship to the physical original, which

it mirrors, monitors, and simulates (Kritzinger et al., 2018). This representational framing is adequate for descriptive and predictive twin architectures but becomes inadequate — and potentially misleading — when applied to systems that perform goal-directed inference and autonomous intervention (Rasheed et al., 2020).

Digital cognition, as we develop it here, shifts the unit of analysis from the fidelity of representation to the quality of inference. A cognitively capable manufacturing system is defined not by how accurately it mirrors a physical process but by how effectively it reasons about that process to achieve performance objectives. This reframing has substantive theoretical consequences: it connects the smart manufacturing literature to cognitive systems theory, to the organizational literature on algorithmic decision-making, and to the philosophy of technology literature on machine agency (Vallor & Rewak, 2018).

6.2 The Multilevel Model: Mechanisms and Boundaries

The multilevel model proposed here identifies the perceptual, reasoning, and actuation layers as analytically distinguishable but empirically interdependent. A key theoretical claim is that digital cognition emerges from the interaction among layers, not from any individual component. Sophisticated sensing without capable reasoning produces data without insight; sophisticated reasoning without reliable actuation produces recommendations without effect; capable actuation without adequate perception produces interventions without appropriate calibration (Lu, 2017).

The model's multilevel architecture also clarifies the conditions under which digital cognition is likely to enhance or degrade manufacturing performance. Enhancement is most likely when each layer's capabilities are appropriately matched — when sensing resolution is adequate for the inference tasks it supports, when algorithmic models are trained on data representative of operational conditions, and when actuation architectures are sufficiently responsive to realize algorithmic recommendations within relevant timescales (Xu et al., 2021).

6.3 Governance Implications

The governance implications of digital cognition extend to three domains. First, the shift of decision authority from operators to algorithms demands institutional mechanisms for ensuring algorithmic accountability — audit trails, explainability requirements, and defined escalation protocols that preserve meaningful human oversight without reinstating the execution-mode supervision that algorithmic intelligence is designed to replace (Möller & Vakilzadian, 2018). Second, the transformation of operator roles demands investment in new competencies — specifically, in the meta-cognitive capacity to evaluate algorithmic behavior, identify failure modes, and intervene appropriately under exception conditions. Third, the interdependence among layers creates systemic risk: failures can cascade across layers in ways that are difficult to anticipate and that demand organizational rather than purely technical governance responses (Bousdekis et al., 2021).

7. Conclusion

This paper introduced digital cognition as a theoretical extension of the digital twin paradigm, proposed a multilevel model of algorithmic intelligence comprising perceptual, reasoning, and actuation layers, and grounded both contributions in an in-depth case analysis of a precision grinding system. The findings demonstrate that the emergence of digital cognition — through the systematic integration of sensor infrastructure, machine learning inference, and autono-

mous control — transforms manufacturing systems from reactive tools into proactive agents, with measurable consequences for dimensional accuracy, operational reliability, and the distribution of decision authority between humans and algorithms.

Several limitations bound the generalizability of these findings. The single-case design, while appropriate for theory development, limits statistical generalizability; comparative case studies across sectors and process types are needed to refine and test the multilevel model. The precision grinding context, with its relatively deterministic physics, may not transfer directly to more stochastic or discretized manufacturing processes. Future research should also examine the longitudinal dynamics of digital cognition — specifically, how algorithmic models degrade or evolve as operating conditions change, and how governance arrangements adapt in response.

Notwithstanding these limitations, the theoretical contributions of this paper — the digital cognition construct, the multilevel model, and the mechanism of cognitive emergence through inter-layer interaction — offer a more adequate conceptual vocabulary for analyzing the trajectory of smart manufacturing systems than the dominant digital twin framework provides. As manufacturing intelligence continues to develop, the capacity to theorize it precisely will be essential for both scholarship and governance.

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Conflicts of Interest

The author(s) declare no conflicts of interest regarding the publication of this paper.

Ethics Statement

Not applicable.

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