

Supplementary Materials

A powerful tool to bridge knowledge chasm in IIoT: industrial foundation model

Hao Ren¹, Haojie Ren^{2,3}, Ruotong Jia¹, Chunhua Yang⁴, Weihua Gui⁴

¹School of Information Science and Engineering, East China University of Science and Technology, Shanghai 200237, China.

²State Key Laboratory of Ocean Engineering, Shanghai Jiao Tong University, Shanghai 200240, China.

³Shanghai Changxing Ocean Laboratory, Shanghai 201913, China.

⁴School of Automation, Central South University, Changsha 410083, China.

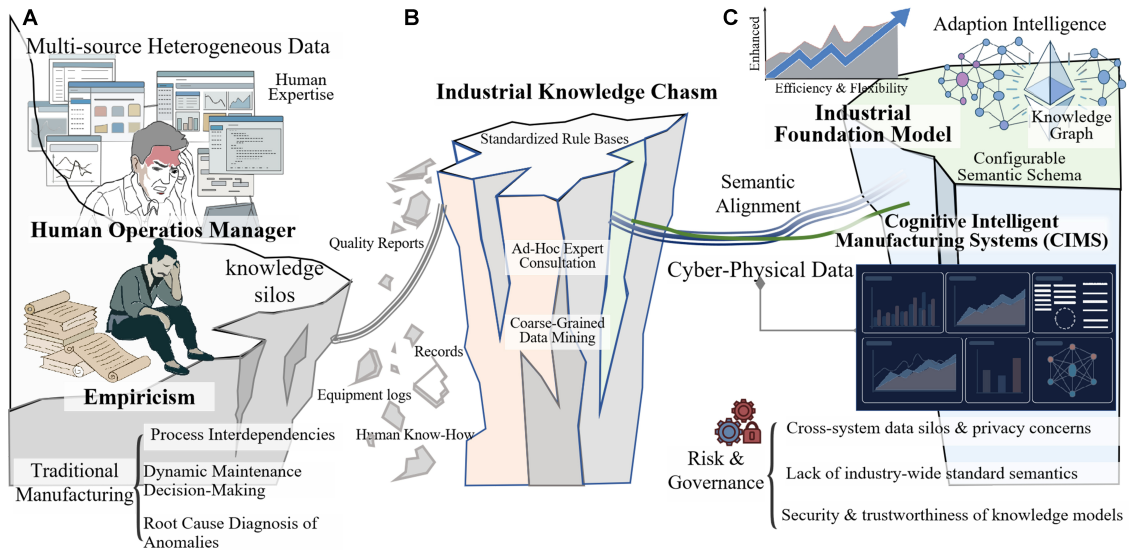
Correspondence to: Dr. Hao Ren, School of Information Science and Engineering, East China University of Science and Technology, Shanghai 200237, China. E-mail: renhao@ecust.edu.cn

1. Supplementary Table 1. Comparison between the proposed IFM and related frameworks

Framework	Primitives	Integration	Constraints	Deployment	Limitations	Distinction
General foundation models fine-tuned on industrial data	General representation learning	Weak or implicit	Usually not embedded	Cloud-centric	Limited process semantics and weak constraint guarantees	Embeds process semantics and physical constraints at the model and training layers
Knowledge-driven manufacturing frameworks	Knowledge representation and reasoning	Strong symbolic knowledge	Rule-based	Usually system-specific	Limited multimodal learning and scalability	Integrates knowledge graphs with multimodal pretraining and cross-process adaptation
Digital-twin-based frameworks	Simulation and state mirroring	Process models	Model-based	Often platform-dependent	High modeling cost and limited transferability	Uses digital twins as one validation environment rather than as the core model

Physics-informed machine learning	Physics-constrained learning	Partial	Strong	Model-level	Limited knowledge and multimodal integration	Combines physics-informed learning with knowledge graphs and industrial multimodal encoders
						Provides a transfer protocol with explicit sharing, and negative-transfer detection
Conventional transfer learning / hybrid modeling	Task adaptation or mechanism-data fusion	Task-specific	Partial	Process-specific	Negative transfer and limited semantic alignment	Four-gap diagnosis, gap-to-mechanism mapping, three-layer architecture, and transfer protocol
Proposed IFM	Bridging IIoT knowledge chasms	Multimodal + symbolic + causal	Embedded at multiple layers	System-level privacy and safety	Requires careful layer separation and validation	

2. Supplementary Industrial Knowledge Chasm: A Taxonomy



Supplementary Figure 1. An abstract conceptual illustration of the Industrial Knowledge Chasm: (A) the limitations of empirical manufacturing limitations under heterogeneous data overload; (B) the legacy methodologies that collectively constitute the knowledge chasm; and (C) advanced resolution approaches, which are empowered by Industrial Foundation Models and Cyber-Physical Data, alongside essential considerations regarding risk and governance.

In traditional manufacturing, various decision-makings rely on domain expertise and empirical heuristics, as illustrated in Supplementary Figure 1A. When confronted with multi-source and highly heterogeneous operational data, human operation managers are prone to cognitive overload. The dependence on fragmented knowledge silos impedes operational efficiency in resolving complex inter-process interdependencies, executing real-time dynamic maintenance decisions, and diagnosing root causes of anomalies ^[1]. Conventional attempts to bridge these domain barriers remain fragile and susceptible to failure due to their static and non-scalable nature.

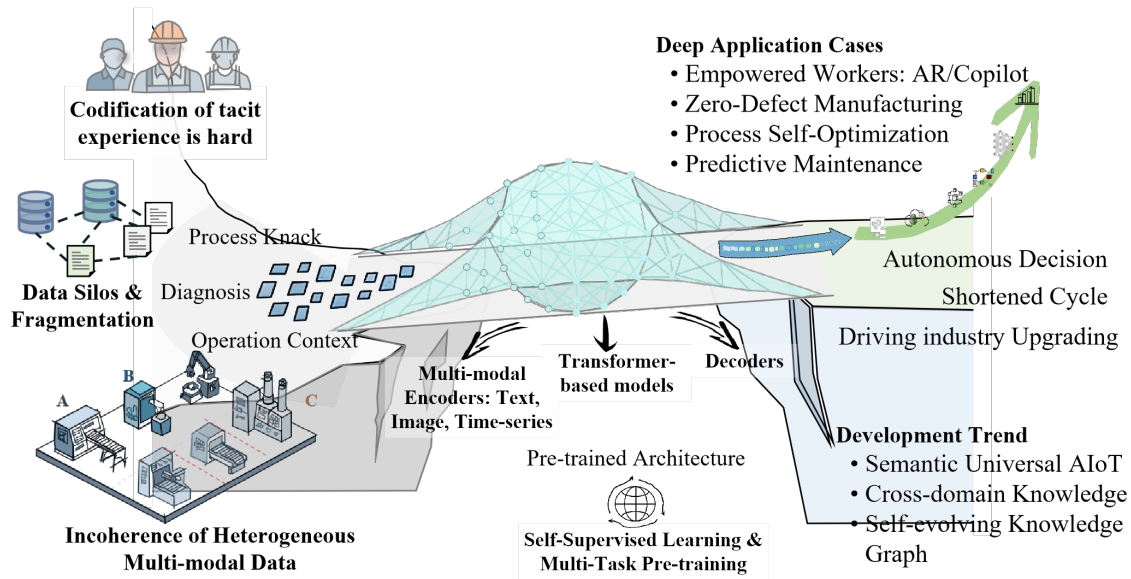
Supplementary Figure 1B shows the Industrial Knowledge Chasm, flanked by conventional resolution methods. Classical methodologies—such as rigid standardized rule bases, reactive ad-hoc expert consultations, and coarse-grained data mining—lack the semantic flexibility and contextual awareness ^[2]. Consequently, explicit physics-based models and implicit human intuition remain disjointed.

To span the substantial gap, Supplementary Figure 1C presents the cognition framework, which is driven by an Industrial Foundation Model integrated with Knowledge Graphs and configurable semantic schemas, continuously ingesting multi-modal cyber-physical data. By transforming disconnected data streams into structured and interpretable knowledge pipelines, it provides the cognitive flexibility necessary for cross-domain orchestration ^[3]. However, to fully realize this paradigm shift, critical risk and governance challenges must be addressed, including cross-system data silos and privacy risks, the absence of industry-wide semantic standardization, and the underlying security and trustworthiness issues of AI-driven knowledge models. Supplementary Table 2 summarizes the mapping from symptoms to dominant gaps, bridging mechanisms, and evaluation indicators.

Supplementary Table 2. Gap diagnosis, bridging mechanisms, and evaluation indicators

Gaps	Typical Symptoms	Bridging Mechanism	Evaluation Indicators
Data gap	Missing modalities, distribution shift, sparse labels, temporal unsynchronization	Multimodal pretraining, self-supervised learning, data augmentation	Coverage, robustness, generalization error
Knowledge gap	Semantic misalignment, missing causality, incomplete constraints, fragmented model knowledge	Knowledge graphs, causal reasoning, constraint embedding, semantic schemas	Causal consistency, semantic alignment, constraint completeness
Architecture gap	High latency, unstable deployment, weak integration, nondeterministic interfaces	Cloud–edge–device orchestration, deterministic interfaces, model–system separation	Latency, throughput, deployment stability
Trust gap	Low trust, unclear responsibility, security and privacy concerns	Safety shield, secure execution, verifiable explanation, auditability	Privacy leakage, violation rate, auditability, human trust

3. Supplementary Industrial Foundation Models for the Cognitive Brain.



Supplementary Figure 2. Schematic of the pre-trained industrial foundation model functioning as a unified cognitive bridge across the industrial knowledge chasm. The left panel identifies the structural bottleneck, wherein tacit operational experience and heterogeneous domain data are inherently difficult to formalize. The center panel presents the bridging topology, which leverages Transformer-based multi-modal encoders (accommodating text, image, and time-series inputs) and decoders refined via self-supervised multi-task pre-training. The right panel illustrates the resultant downstream autonomous orchestration capabilities, together with the prevailing trends in technological evolution.

To overcome the inherent difficulty of capturing non-codified operational knowledge, Supplementary Figure 2 illustrates how a pretrained industrial foundation model functions as a robust cognitive bridge across the industrial knowledge chasm. The architecture employs specialized multi-modal encoders designed to concurrently ingest text, visual inspection imagery, and sensor time-series data. Through self-supervised learning and multi-task pretraining, the model maps high-dimensional, unstructured raw signals into a shared latent space, without relying on labor-intensive manual labeling or rigid expert rules ^[4].

Supplementary Table 3. Capability-to-mechanism mapping

Capability	Mechanism	Input	Output	Verification Indicator
Multimodal perception	Industrial multimodal encoder	Sensor, image, text, time series	Unified representation	Perception accuracy
Causal question answering	Causal graph, intervention, counterfactual reasoning	Process variables, knowledge graph	Causal explanation	Causal consistency
Constraint-aware planning	Constraint satisfaction, scheduling	ERP/MES data, safety constraints	Feasible plan	Constraint-violation rate
Cross-process adaptation	Process-specific adapter	Target-process data	Adapted model	Target performance
Trustworthy execution	Safety shield, verifiable explanation	Plan, model explanation	Verified action	Auditability, human trust

Supplementary Table 4. Three-layer classification of IFM components

Component	Layer	Necessity	Main Interaction	Role
Industrial multimodal encoder	Model	Essential	Fuses sensor, image, text, and time-series data	Provides unified industrial representation
Shared latent space	Model	Essential	Aligns modalities and processes	Supports cross-domain integration
Process-semantic embedding	Model	Essential	Links representations to process semantics	Preserves process-specific meaning
Physics-constraint embedding	Model	Essential	Embeds physical laws and constraints	Improves consistency and safety

Knowledge-graph embedding	Model	Essential	Injects symbolic and relational knowledge	Supports reasoning and retrieval
Self-supervised pretraining	Training	Essential	Learns from unlabeled industrial data	Builds general industrial representations
Physics-informed learning	Training	Essential	Constrains learning with physical laws	Reduces physically inconsistent predictions
Knowledge-enhanced learning	Training	Important	Integrates knowledge graphs	Improves causal and semantic reasoning
Hybrid learning	Training	Important	Combines mechanism-based and data-driven models	Balances interpretability and flexibility
Cross-process adaptation	Training	Essential	Adapts to target processes	Enables transfer with limited data
Deterministic interfaces	System	Essential	Connects to controllers and execution systems	Ensures reliable actuation
Safety shield	System	Essential	Verifies actions before execution	Prevents unsafe actions
Secure execution environment	System	Important	Protects model and data	Supports privacy and security
Cloud–edge–device orchestration	System	Essential	Distributes computation	Meets latency and reliability requirements
ERP/MES/DCS integration	System	Essential	Connects to industrial software	Enables operational feasibility

Supplementary Table 5. Cross-process transfer protocol

Transfer Element	Shared Across Processes	Process-Specific	Required Adaptation Data	Negative Transfer Detection
Physical laws	Yes	Boundary conditions	Few-shot operating data	Physical inconsistency
Sensor modalities	Partially	Sensor placement and calibration	Calibration data	Distribution distance
Control semantics	Yes	Actuator constraints	Control logs	Constraint violation
Fault patterns	Partially	Process-specific fault modes	Fault cases	Target validation performance
Operating procedures	No	Yes	Expert rules	Expert review
Safety constraints	Partially	Process-specific thresholds	Safety records	Violation rate

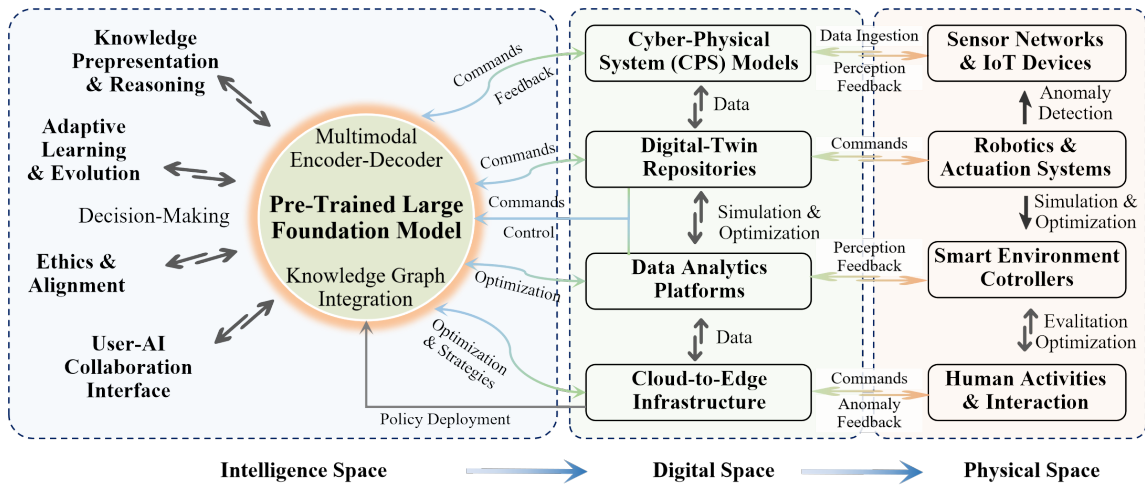
Supplementary Table 6. Comparison with conventional transfer learning and hybrid modeling

Method	Sharing Mechanism	Adaptation Data	Physical Constraints	Negative Transfer	Interpretability	Expected Advantage
Conventional transfer learning	Parameter or feature transfer	Moderate to large	Weak	High	Low to moderate	Limited process semantics
Hybrid modeling	Mechanism –data fusion	Process-specific	Strong	Moderate	Moderate to high	Strong physical consistency but limited

						transfer
	Shared					Balances
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Cross-process transfer protocol and negative transfer detection. We propose a process-invariant representation plus process-specific adapter architecture. The process-invariant representation captures shared physical laws, sensor modalities, control semantics, and common fault patterns. The process-specific adapter captures target-process dynamics, constraints, operating procedures, and parameter ranges. Table 5 specifies what is shared, what remains process-specific, what adaptation data are needed, and how negative transfer is detected. Table 6 compares the proposed IFM with conventional transfer learning and hybrid modeling.

4. Supplementary Large Models for Intelligent-Digital-Physical Spaces



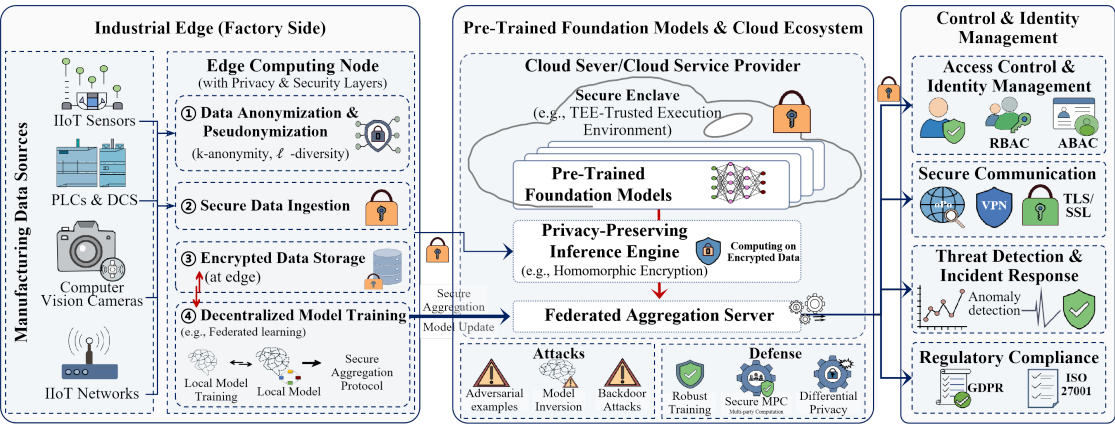
Supplementary Figure 3. Triadic architectural framework interconnecting Intelligence, Digital, and Physical spaces in the IIoT era, structured into three interrelated domains: Intelligence Space, anchored by a multimodal pre-trained foundation model integrated with knowledge graphs; Digital Space, comprising cyber-physical system (CPS) models, digital twins, and cloud-to-edge infrastructure; and Physical Space, encompassing sensor networks, robotic actuation, and human-in-the-loop.

Intelligent manufacturing refers to the integration of advanced technologies—such as IIoT, big data, and artificial intelligence—with traditional manufacturing processes. The core driving force of this evolution lies in the new generation of artificial intelligence, particularly large-general-purpose models [5]. They are expected to enable the construction of intelligent-digital-physical convergence spaces for multi-scenario ecosystems, with key focal areas including digital-physical fusion perception, internal and external connectivity, collaborative cognition and computation, and optimized decision-making and execution, as illustrated in Supplementary Figure 3.

Within this architecture, Intelligence Space serves as the high-level decision engine, anchored by a pretrained large foundation model with a multimodal encoder-decoder backbone enhanced by knowledge graph integration. The intelligence space coordinates five critical functional vectors: explicit knowledge representation and reasoning, adaptive learning and evolution, real-time decision-making, ethical alignment and safety guardrails, and intuitive user-AI collaboration interfaces. Cyber Space acts as an intermediate digital twin layer that bridges cognitive reasoning with physical execution,

integrating Cyber-Physical System (CPS), digital twin repositories, high-performance data analytics platforms, and cloud-to-edge infrastructure. It enables vertical data aggregation, predictive simulation, and runtime optimization over digital replicas. Physical Space captures concrete operational dynamics in real time through sensor networks, IoT devices, robotics, smart environment controllers, and human-in-the-loop.

5. Supplementary Industrial Privacy Protection and Edge Trust in the Era of Pretrained Large Models



Supplementary Figure 4. End-to-end privacy and security protection architecture for IIoT foundation model ecosystems, structured into three hierarchical layers: factory-side edge computing nodes implementing multi-tiered data anonymization, encrypted storage, and decentralized federated learning; the cloud ecosystem integrating secure enclaves (TEE), privacy-preserving inference via homomorphic encryption, federated aggregation, and robust defense mechanisms; and enterprise-level frameworks encompassing access control, secure communication, threat detection, and regulatory compliance.

As the deepening integration of academia and industry, a collaborative, open, and multi-scenario ecosystem is emerging as the prevailing trend in the development of intelligent manufacturing. This trend inevitably entails large-scale flows of industrial information and data [6,7], while simultaneously introducing diverse cybersecurity threats and data leakage risks. To address these security challenges, Supplementary Figure 4 presents an end-to-end privacy-preserving and security-enforced architecture spanning the industrial edge, cloud ecosystem, and enterprise control tiers.

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