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Layer Model for the Design of Data-Driven Business Models – AI Integration and Industrial Data Fusion Across Hierarchical Levels

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ABSTRACT

This paper presents a structured framework for analyzing the role of intelligent sensor systems in enabling data-driven and potentially disruptive business models in manufacturing. Building on a five-level layer model - comprising sensor, machine, shopfloor, plant, and value chain - the study systematically examines each level along five analytical dimensions: data, processes, IT systems, interfaces, and standards. For each level, the current state and expected future developments are exemplarily assessed through literature analysis and industrial case examples. This multi-dimensional approach reveals digitalization potentials and integration barriers at each stage of the value creation process. The findings are then synthesized to explore cross-level fusion strategies, enabling new forms of vertical and horizontal integration. The methodology follows the Zachman framework logic, ensuring structured coverage of each layer and aspect. Real-world use cases–ranging from pay-per-part offerings to cross-company data spaces–illustrate how sensor-based integration supports novel business logics such as Equipment-as-a-Service, predictive quality management, or audit-ready digital twins. The paper contributes to Industry 4.0 discourse by linking sensor fusion architectures with value creation mechanisms, demonstrating how technical infrastructures and business models must co-evolve. The proposed model serves as both a diagnostic tool for digital maturity and a design template for future-ready industrial service models.

Keywords: Data fusion, Artificial intelligence, Industry 4.0, IIoT, Digital twin, Value chain integration, Industrial data spaces, Cloud-edge architectures, Production system architecture

INTRODUCTION AND RESEARCH QUESTIONS

This paper presents a current innovation initiative by a medium-sized manufacturer specializing in intelligent sensor solutions. The basis is a sensor system that can be quickly integrated into forming machines such as presses and measures elastic deformations in the T-slots of the press table and ram. This sensor technology, which is described in detail in Kurth et al. (2021), is used to make forming processes more transparent, detect anomalies, or identify changes in the forming machine.

As shown in Kurth et al. (2023), this sensor can capture a characteristic measurement curve for the specific forming process, which is directly proportional to the forming force and functions as a digital fingerprint of the respective pressing stroke. The continuous analysis of these curves enables the detection of subtle variations in machine and tool behavior, such as wear, misalignments, and changes resulting from material and process fluctuations, tool wear, or manual interventions. Data processing is structured in two stages:

- On-Device AI: A resource-efficient artificial intelligence system embedded within the sensor classifies press cycles, filters anomalies, and extracts relevant features as part of a sensor data pre-processing.
- Near-Edge AI: Advanced pattern recognition algorithms and predictive models–deployed on an industrial PC in close proximity to the machine–perform higher-level analyses, such as estimating remaining tool life, detecting tool wear, or assessing part quality.

The current application focus is on operational enhancements, including: Condition monitoring of presses and tools, reduction of unplanned downtimes, real-time quality assurance of press parts.

Beyond machine-level benefits, the collected sensor data demonstrate increasing potential for cross-functional value creation. These data can support activities in production planning, quality management, and supply chain optimization. This raises strategic questions regarding the economic utilization of sensor-derived data to drive innovation in adjacent business functions.

The aim of this work is to systematically examine the role of smart sensor systems as enablers of data-driven and potentially disruptive business models. Three key research questions guide this investigation:

- Which structural or digital transformation trends across corporate functions could be supported by sensor data from press machines within the following focus areas quality management, production control, maintenance strategy, product development, and supplier integration?
- How can these functional areas be integrated into a hierarchical model spanning from sensor, machine, shopfloor, plant to value chain level in order to follow the objective to contextualize sensor-enabled innovation along vertical and horizontal dimensions of enterprise integration?
- What types of data-driven business models can be derived from the sensor data, for examples pay-per-part schemes, predictive quality-as-a-service, tool-as-a-service offerings, and digital twin implementations for audit readiness?

This paper contributes to the broader discourse on Industry 4.0 by demonstrating how embedded sensor intelligence and multi-level AI processing can serve as foundational elements for operational excellence and novel value creation mechanisms in manufacturing ecosystems.

METHODOLOGY

This study employs a conceptual-analytical methodology based on a multi-level layer model for digital integration in manufacturing. The model comprises five hierarchical levels–sensor, machine, shopfloor, plant, and value chain – and analyzes each along five key dimensions: data, processes, IT systems, interfaces, and standards. For every level, both the current state and anticipated developments are systematically assessed through structured literature review and analysis of industry practices. This dual-perspective approach enables the identification of structural barriers and integration potentials. The results form the foundation for cross-level synthesis and the conceptualization of integrated, data-driven business models. The methodology is exploratory and interpretive, aiming to uncover systemic interdependencies between digital infrastructures and value creation mechanisms. The model is then applied to multiple industrial examples, following the Zachman framework logic (Zachman, 2004), in which each layer and dimension is systematically addressed.

LAYER MODEL FOR DISRUPTIVE BUSINESS MODEL DESIGN

The layer model is mainly derived from the automation pyramid, building on the ISA-95 standard (see Meudt et al. (2017) and complementary papers developed by this project), the evolving cloud–edge computing landscape (Gole et al., 2022; EUCloudEdgeIoT.eu, 2025), and the RAMI 4.0 architecture (Contreras et al., 2017).

Table 1: Five-layer-model for business model design in manufacturing (derived from ISA-95, RAMI4.0 and the CIS cloud-edge continuum and adapted by the authors).

Level	Data	Activities/ Processes	IT Systems	Interfaces/ Standards
Sensor	• Status quo: Sensors provide basic measurement data; contextual data rarely used. • Future: More sensor raw data (value + context) processed locally and transmitted to cloud for global use.	• Status quo: Sensor setup and calibration often manual, causing downtimes. • Future: Self-calibrating intelligent sensors reduce manual intervention.	• Status quo: Sensors directly linked to PLCs; no direct IT connectivity. • Future: Sensors send data directly to edge/cloud systems in parallel.	• Status quo: IO-Link established but proprietary formats prevail. • Future: OPC UA with semantic self-description enables open, interoperable sensor interfaces.
Machine	• Status quo: Machine data often used locally with proprietary protocols. • Future: OPC UA companion specs enable cross-vendor machine data interoperability.	• Status quo: Maintenance based on time or failure events. • Future: Predictive maintenance minimizes unplanned downtimes.	• Status quo: Proprietary PLCs; limited remote diagnostics. • Future: Digital twins accompany machines across the lifecycle.	• Status quo: Few common machine data standards. • Future: OPC UA and Plug & Work allow vendor-independent machine integration.

Continued

Table 1: Continued

Level	Data	Activities/ Processes	IT Systems	Interfaces/ Standards
Shopfloor	• Status quo: Production data analyzed post hoc; real-time transparency rare. • Future: Real-time analytics via AI reduces scrap and adjusts production in real-time.	• Status quo: Machine retooling requires manual reconfiguration. • Future: Plug & Produce enables flexible reconfiguration without long downtimes.	• Status quo: MES systems manage shopfloor with limited IT integration. • Future: Cyber-physical production systems (CPPS) with real-time orchestration.	• Status quo: Heterogeneous fieldbus protocols dominate. • Future: OPC UA over TSN enables real-time, adaptive shopfloor communication.
Plant	• Status quo: Data silos between shopfloor and IT, OEE optimization potential untapped. • Future: Smart factory with digital twin enables agile simulation-based production control.	• Status quo: Production plans fixed; customer involvement rare. • Future: Order-driven integration via platforms.	• Status quo: ERP isolated from real-time shopfloor data. • Future: Unified MOM systems integrate ERP and MES with AI decision support.	• Status quo: Site-specific standards dominate. • Future: Reference architectures (RAMI 4.0, AAS) enable cross-site interoperability.
Value Chain	• Status quo: B2B data exchange mostly bilateral (e.g., EDI); limited data sharing. • Future: Federated data spaces enable multilateral data exchange across the value chain.	• Status quo: Supply chain operations manually coordinated with media breaks. • Future: Intercompany collaboration via shared digital platforms improves responsiveness.	• Status quo: ERP-based EDI systems, lacks secure infrastructure for multi-party data exchange. • Future: International Data Spaces (IDS) provide secure, sovereign data exchange.	• Status quo: Few digital process standards across companies. • Future: Open industry standards and compatibility drive efficient value chain integration.

This layer model enables the identification of digitalization potentials and structural barriers within and across levels. The resulting insights form the basis for the subsequent analysis of inter-level integration requirements. Thus, the model provides a conceptual foundation for the development of innovative and potentially disruptive business models in the manufacturing domain.

TYPES OF DATA-DRIVEN BUSINESS MODELS ENABLED BY SENSOR-BASED INTEGRATION: A LAYERED APPROACH

This section of the paper examines the emergence of data-driven business models in manufacturing, driven by the progressive integration of sensor technology across multiple levels of production systems. This analysis is organized according to a four-layer framework, extending from individual machine-level integration to cross-organizational value chain coordination. At each level, the study identifies core characteristics of the associated business models and presents illustrative use cases to support conceptual insights. The investigation deliberately adopts a broad perspective. Although there are approaches for sensor data-based business models in the field of forming technology (e.g., Alaluss et al. (2025)), forming technology is not emphasized separately in this analysis. Instead, the examples have been selected to demonstrate foundational mechanisms of disruptive, data-oriented value generation in industrial contexts.

First Fusion Level: Sensor and Machine Layer

Characteristics: The initial integration level focuses on equipping individual machines with smart sensor systems, resulting in smart product systems and associated services. The business logic transitions from conventional product sales to service-centric models, typically based on usage or outcomes. A common manifestation is “Equipment-as-a-Service” (EaaS), where manufacturers offer data-driven services such as predictive maintenance and performance optimization. These offerings are typically monetized via pay-per-use or pay-per-outcome schemes and are enabled through continuous monitoring of machine data, often facilitated by industrial IoT platforms.

At this level, the primary data sources include machine-level operational parameters such as energy consumption, vibration patterns, temperature, cycle counts, and fault codes. These are fused with control data from PLCs or embedded systems to generate contextual insights. The fusion process typically involves local preprocessing (e.g., via edge devices), real-time transmission via MQTT or OPC UA protocols, and aggregation in cloud-hosted analytics environments.

Processes supported by this fusion include condition monitoring, failure prediction, and usage-based service planning. From an IT systems perspective, relevant components include edge gateways, cloud IoT platforms, digital twins, and rule-based event engines. Standards such as ISO 21902 (predictive maintenance) and Asset Administration Shell (AAS) architectures are increasingly used to structure and harmonize data interfaces for plug-and-play interoperability between heterogeneous industrial devices.

Use Cases: Mader with its subsidiary LOOXR’s Industrial Air exemplifies this model through its “Druckluft 4.0” service, wherein the company retains compressor ownership while customers are charged for actual compressed air consumption. Integrated sensors collect operational data, which is utilized for efficiency assessments and predictive maintenance (Martin Köppe, 2024; Mader GmbH & Co. KG, 2019). Similarly, TRUMPF’s “Pay-per-Part” model allows customers to pay per manufactured unit rather than owning the machine. TRUMPF manages programming, monitoring, and maintenance remotely via sensor and camera infrastructure (TRUMPF 14.10.2020; TRUMPF 21.09.2022; TRUMPF 20.09.2023).

Second Fusion Level: From Sensor to Shopfloor Layer (Integration Across Multiple Machines or Production Cells)

Characteristics: At this level, sensor data from multiple machines or production cells is consolidated and fused to enable systemic optimization of shopfloor operations. The fusion includes time-series data from machine sensors (e.g., vibration, torque, force, temperature), status signals from programmable logic controllers (PLCs), operational metadata from MES systems, and contextual production information (e.g., order ID, shift plan, production and quality protocols). Data is preprocessed at the edge and transmitted via standardized protocols like OPC UA, MQTT, or REST APIs.

Business models aim to enhance Overall Equipment Effectiveness (OEE), reduce downtime, and increase throughput by leveraging centralized data aggregation, advanced analytics, and machine learning models. Supported processes include predictive maintenance, anomaly detection, bottleneck identification, production sequencing, and quality prediction.

Key IT systems involved at this level include MES platforms, industrial IoT hubs, AI analytics engines, and edge computing infrastructure. Standardized integration relies on e.g., ISA-95, OPC UA Companion Specifications, and the Asset Administration Shell (AAS). Semantic interoperability is increasingly supported through ontologies like eCl@ss or AutomationML. Providers often act as analytics service vendors, offering subscription-based access (Software-as-a-Service, SaaS) to tools for real-time monitoring and actionable insights across entire production lines.

Use Cases: Bosch's Nexeed platform represents a commercialized internal solution, now offered externally by Bosch Connected Industry. It enables real-time KPI tracking and condition monitoring through modular software components. Over 100 global manufacturers utilize these services (Bosch Connected Industry, 2021). Additionally, startups like oee.ai provide AI-based OEE analytics platforms that consolidate multi-machine sensor data and deliver actionable insights to production teams. In the domain of forming technology, the Metris concept developed by Andritz Schuler is noteworthy (SCHULER PRESSEN GMBH, 2024), as it facilitates the cross-system collection, fusion, and analysis of data at the shop floor level. Comparable systems are also being industrially implemented by companies such as Elunic shopfloor.GPT (elunic, 2025) or IFM (IFM, 2025), demonstrating a trend towards integrating advanced data analytics from sensor to shopfloor level within manufacturing processes.

Third Fusion Level: From Sensor to Plant Layer (Integration at the Factory/Site Level)

Characteristics: Plant-level integration entails networking sensor systems across the entire facility and interfacing with higher-order IT systems such as MES and ERP. The fusion of data at this level includes not only operational sensor data (e.g., pressure, flow, temperature, power consumption) but also contextual information from production planning (ERP), maintenance logs, inventory systems, and energy monitoring platforms. This multi-source integration enables a holistic view of production, logistics, and energy flows.

Supported processes include plant-wide energy optimization, integrated production planning, coordinated maintenance strategies, and sustainability tracking (e.g., CO_2 footprint monitoring). These processes benefit from near real-time synchronization between shopfloor data and business systems, thereby facilitating agile and data-informed decision-making.

Relevant IT systems beyond MES and ERP include energy management systems (EMS), building management systems (BMS), digital twin platforms, and advanced process control (APC) environments. Data integration and governance are supported by middleware solutions, semantic data layers, and message brokers (e.g., Apache Kafka). Commonly used interfaces and standards include OPC UA over TSN for deterministic real-time communication, ISA-95 for vertical integration, B2MML for structured data exchange, and the Asset Administration Shell (AAS) for interoperable digital representations. These frameworks enable scalable and standardized integration across heterogeneous systems, allowing plant operators and service providers to implement outcome-based business models focused on continuous performance improvement.

Use Cases: Heidelberg Materials employs a company-wide platform for managing cement plant operations, leveraging AI to reduce energy intensity (Heidelberg Materials, 2024). Similarly, Siemens' Insights Hub platform enables site-wide machine connectivity and AI-powered analysis, supported by cloud infrastructure (Siemens, 2025b; Siemens, 2025a). These solutions are often deployed under service contracts with success-based remuneration. Energy efficiency contracting, where providers are paid based on realized savings, represents a further example of value-based monetization at the plant level.

Forth Fusion Level: From Sensor to Value Chain Layer (Cross-Organizational Integration)

Characteristics: The highest integration level involves the sharing and utilization of sensor and operational data across company boundaries throughout the value chain. Data fusion at this stage includes real-time operational sensor data (e.g., machine status, usage metrics, environmental conditions), logistics and supply chain data (e.g., inventory levels, transport status, delivery schedules), and business process data from ERP, PLM, and SCM systems. Additionally, sustainability-related data (e.g., carbon footprint, recyclability) is increasingly integrated to support regulatory compliance and circular economy models.

Supported processes include collaborative supply chain planning, cross-company quality management, demand forecasting, lifecycle monitoring, and sustainability reporting. These processes benefit from harmonized and sovereign data exchange, enabling agility and resilience across networked production and logistics systems.

Relevant IT systems include cross-company data spaces (e.g., Gaia-X-compliant infrastructures), trusted data connectors (e.g., IDS Connectors), blockchain or distributed ledger systems for traceability, and AI platforms for federated learning and multi-party optimization. Standards and interfaces such as EDC (Eclipse Data Connector), AS4/ebMS for secure B2B messaging, and semantic models like RAMI 4.0 and eCl@ss support interoperability. Frameworks like the International Data Spaces (IDS) architecture and the Asset Administration Shell (AAS) ensure data sovereignty, auditability, and trust across participants in the ecosystem.

This level gives rise to ecosystem-oriented business models, characterized by multi-actor collaboration via shared platforms or federated environments. Monetization occurs through platform subscriptions, transaction-based pricing, or performance-linked compensation, often with added value derived from shared insights and co-developed services.

Use Cases: Airbus's Skywise platform aggregates sensor data from over 8,500 aircraft and provides shared access to stakeholders in the aerospace ecosystem, including airlines, suppliers, and maintenance providers. The platform supports predictive maintenance and operational efficiency improvements while enabling a shift in Airbus's business model toward digital services (Bernard and Hoffmann, 2023). Similarly, the Catena-X initiative in the German automotive sector establishes a federated data infrastructure to support cross-company data exchange and the development of end-to-end digital business models (e.g., traceability, collaborative quality management, demand forecasting) (Catena-X Association, 2025).

CONCLUSION

This paper demonstrates that sensor-based integration in manufacturing is more than a technical upgrade – it is a strategic lever for rethinking value creation across all levels of industrial operations. By applying a structured five-layer model, we show how data fusion — from individual machines to entire value chains — can systematically enable new forms of monetization, service innovation, and cross-organizational collaboration.

At the heart of this transformation lies the interplay between sensor data, IT systems, standards, and business processes. Each level of integration unlocks specific potentials: machine-level intelligence supports usage-based services like Equipment-as-a-Service; shopfloor-level consolidation enables real-time production optimization; plant-level fusion drives outcome-based contracting; and value chain integration fosters ecosystem-based business models through shared data spaces. In all cases, sensor fusion is not only a technical enabler, but also a structural driver of new business logic.

What becomes clear is that future-ready industrial business models cannot be designed in isolation from their digital infrastructure. Data architecture, interoperability frameworks, and AI capabilities must co-evolve with business model components such as customer value, revenue logic, and delivery mechanisms. The proposed layer model serves as a diagnostic tool to assess digital maturity and as a design template to develop scalable, resilient, and data-driven service offerings. It bridges the often disconnected worlds of operational technology and strategic business innovation — making it a valuable asset for manufacturers navigating the shift from product-centric to data-enabled business paradigms.

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