Prototyping Industry 4.0: Tracing Infrastructural Resonance in a Smart Factory Demo

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With the advent of Industry 4.0, Internet-of-things, and data-centric technologies, the concept of the smart factory (automation of the factory) has gained traction to make machines more than mechanical artifacts. It creates an ecosystem of technologies providing infrastructure to embed technological advancements with the emerging needs of the system. However, with the increasing demand for automation, several socio-technical challenges pertain due to the infusion of several infrastructural layers in the smart factory settings. We present "Demo Smart Factory", which automates a logistic pipeline, including dummy manufacturing, quality assurance, and sorting, and provides control mechanisms on the real-time sensor data based on components and units of the factory to different stakeholders via a digital twin. Through this exemplary use-case of a logistics smart factory demo, we aim to illustrate the resonance between different infrastructural layers and highlight key socio-technical factors that shape the design and implementation of smart factory systems. We also identify key pitfalls that need to be avoided or balanced in realizing large-scale and multi-layered interventions like a smart factory.

Additional Key Words and Phrases: Smart Factory, Automation, Digital Twin, Industry 4.0, Internet of Things

1 Introduction to Related Work

In recent years, Industry 4.0 has gained rapid momentum, bringing transformative changes to the way industries operate. This revolution is driven by the rise of cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI), data analytics, and robotics [9]. These innovations are transforming the manufacturing landscape by replacing traditional manual processes with automated systems that are connected, intelligent, and self-optimizing [3]. The concept of the smart factory lies at the heart of this revolution, where automation goes beyond replacing human labor to create an interconnected ecosystem often termed automation via digital twin [12]. In these factories, several infrastructures, including machines, sensors, systems, and work practices, communicate with each other in real time to optimize workflows throughout the supply chain, from raw material handling to the delivery of finished products [4, 5]. However, as automation and advanced technologies are incorporated into these factory settings, they bring about a set of socio-technical challenges that need careful consideration [5].

Star and her coauthors conceptualized infrastructure as the "entirety of devices, tools, technologies, standards, conventions, and protocols on which the individual worker or the collective rely to carry out the tasks and achieve the goals assigned" [10]. In the context of smart factories, infrastructures manifest as layered socio-technical systems comprising physical/sensor, data, communication, and application/work layers. These infrastructures are each situated

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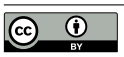


Hussain Abid Syed, Mehrbod Manavi, Syed Muhammad Salar Zaidi, Syed Basit Ali Rizvi, Marc Gerbracht, Thomas Ludwig, Volker Wulf (2025). Prototyping Industry 4.0: Tracing Infrastructural Resonance in a Smart Factory Demo. In *Proceedings of the 12th International Conference on Communities & Technologies* (C&T 2025), July 21–23, Siegen, Germany. EUSSET. https://doi.org/10.48340/ct2025-1008

within a broader organizational infrastructure that supports collaborative and cooperative work practices. The physical layer encompasses machines, sensors, and IoT devices embedded in production environments; the data/communication layers manages the acquisition, storage, and transfer of operational and contextual data, often to and through cloud-based infrastructures; and the application layer facilitates process control, decision support, and visualization aligned with situated work practices.

Building on Pipek and Wulf [8] notion of infrastructuring, these layers are not static, but rather dynamic accomplishments that evolve through ongoing use, breakdown, and innovation, referred to as Points of Infrastructuring (PoI). Ludwig et al. [6] expanded this vocabulary through the concept of infrastructural resonance, which captures how transformations at a PoI in one layer can trigger ripple effects across other layers, mobilizing repairs and actions, and reshaping adjacent infrastructures. Such resonance processes form a network of practice-based cooperation that spans local infrastructural contexts, allowing innovations and interventions to diffuse across local infrastructural boundaries and settle into new, stable configurations.

Resonance activities can be understood as not only initiating local repair but also creating visibility for broader practice-based adaptations, accessible to others engaged in similar work, to the designers of the hardware-software ensembles, or to those who developed the underlying technological substrate. These processes illustrate how the evolution of infrastructure is a socio-material intervention, emerging from entangled practices rather than top-down design. In smart factory contexts, this layered interdependence is particularly complex, given the tight coupling between hardware, software, and work layers, but also because “smartness” often obfuscates infrastructural fragilities under the guise of efficiency.

The introduction of multi-layered infrastructures, such as our Smart Factory use case with invisible layers of infrastructure / implicit technological substrates like data, communication, and work layers, and non-hidden layers like the physical and application layers, can create complexities that are difficult to navigate under the lens of resonating infrastructures. Further complexities are added when different layers are managed by teams with multi-disciplinary backgrounds, often localizing the infrastructural repairs and reform rather than considering the resonance effects of repairs. As these global infrastructures present a compelling case as sociable technologies, innovation-led PoI can be challenging, especially when workers implicate these resonating infrastructures and repairs leading to job displacement [4], feeling inadequate in skills [11], and chances to practice workarounds [7]. Through the creation of a demo Smart Factory and its different stages, we employ infrastructural resonance as a critical analytical lens for diagnosing breakdowns, surfacing latent interdependencies, and enabling participatory adaptation across multi-disciplinary team settings.

The Demo Smart Factory was developed under the initiative of the Data Lab at the University of Siegen as a demonstrator for the automation of key logistical functions within a factory environment, including dummy manufacturing, quality assurance, and sorting. The system enables real-time monitoring and control of operations via a Digital Twin application, which creates a virtual replica of the physical factory. Conceived as a "test-before-invest" space, the smart factory initiative supports small and medium-sized enterprises (SMEs) in the region by allowing them to explore IoT- and data-centric infrastructures and apply these insights to their industrial contexts.

The development process was highly interdisciplinary, involving researchers and students in mechatronics, electronics, robotics, human-computer interaction, and computer science. Coordination was managed through multiple communication channels, including regular meetings for formal decision-making, asynchronous communication via email to update sub-teams, and informal synchronous and asynchronous exchanges via Miro and Telegram. The demo was designed and developed in iterative stages, not only aligned with infrastructural layering, beginning with the

physical layer and expanding upward, but also shaped by emergent innovations, feedback from industrial partners, mandates from funding agencies, and alignment with other sub-projects within the overarching **"Mittelstand-Digital Zentrum"** Project [1]. The demo aims to enable stakeholders in SMEs, such as shop floor workers, managers, and administrators, to access real-time operational data and control mechanisms, empowering them to prototype and contextualize their smart factory use cases.

Infrastructuring served as the central conceptual lens throughout this multi-technology endeavor. During the development, multiple socio-technical tensions, points of infrastructuring (PoIs), infrastructural inversions, and resonance phenomena emerged, which are explored and reflected upon in this demo paper. This paper will follow the following sections: starting with the Demo architecture, leading to operational workflow, and finally the findings.

2 Demo Design, Functional Units and Workflow

During the ideation phase of the demo, four primary functional units were defined to model the workflow of the smart factory: the manufacturing unit, quality control unit, sorting unit, and warehouse. Figure 1 shows the overall workflow on the ground.

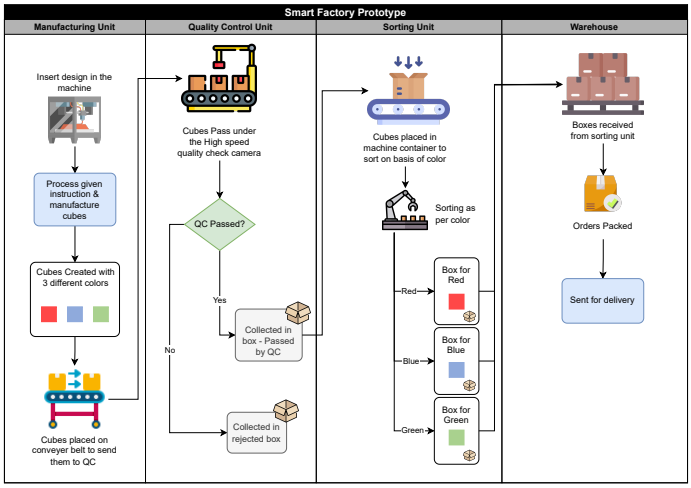


Fig. 1. Smart Factory Demo Workflow

The manufacturing unit includes 3D printers intended to produce colored cubes. Initially, the plan was to install three printers; however, we later opted for using pre-printed cubes to avoid delays caused by real-time printing and to bring the demo closer to real-world practices. In typical factory settings, manufactured items are often stored temporarily before undergoing quality assurance, sorting, and distribution. The pre-printed cubes are transported via a conveyor belt to the quality control unit, where a robotic arm and a vision system identify and remove defective cubes based on predefined criteria such as color, size, and shape. Specifically, a camera detects invalid cubes (such as white or undersized ones), which are then removed through a gate mechanism, while valid cubes proceed to the next stage, i.e., sorting. In the sorting unit, color sensors classify the cubes and direct them into designated bins. A central robotic arm subsequently collects the sorted cubes and loads them onto a transport train. The final step involves transporting these

[1] https://digitalzentrum-lr.de/

boxes to the warehouse, thereby completing the demonstration cycle of the smart factory workflow. Figure 2 illustrates the paper-based design and concept of the demo smart factory.

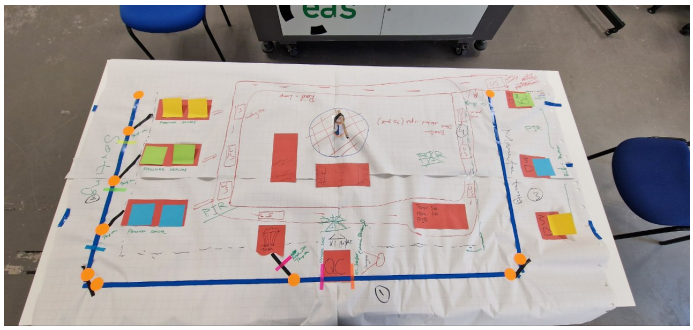


Fig. 2. Smart factory collaborative ideation prototype

After the demo was organized around a horizontal logistical pipeline including manufacturing, quality assurance, sorting, and warehousing, reflecting the task-based segmentation of the overall workflow, the demo was extended vertically towards the infrastructure stack that is needed to support the execution of intended 'smart' in the smart factory. The infrastructure stack represent a layered architecture, beginning with the physical and sensor layer (e.g., motors, gates, conveyor belts, sensors, camera), and extending upward through circuit, communication, and data layers, toward the application and work practice layers where human interactions, decision-making, and control are situated. Once the idea of a physical layer was established, other infrastructural layers evolved in alignment, enabling cross-layer coordination.

3 From Physical to Sensor and Communication Layer

After finalizing the overall structure of the demo, the mechanical structure was constructed using **Mindstorm LEGO** kit[2] (Figure 3). This included conveyor belts representing the individual shop floor segments, along with servo motors, rotators, and gate actuators for manufacturing, quality control, and sorting units. During the first iteration of mechanical structure development, it became evident that other infrastructural layers (sensors and circuits) were required to support automation, before we integrate the robotic arm and the train responsible for transporting sorted bins. Consequently, a decision was made to initially limit the mechanical structure to the core shop floor units to automate the core functionality of the smart factory, with plans to extend it iteratively over time. This means that in the first iteration, pre-printed cubes will be manually placed on the conveyor belt to initiate the pipeline in the manufacturing unit, and later manually transferred to the warehouse without the use of the robotic arm or the transport train.

[2]https://shorturl.at/Qquf1

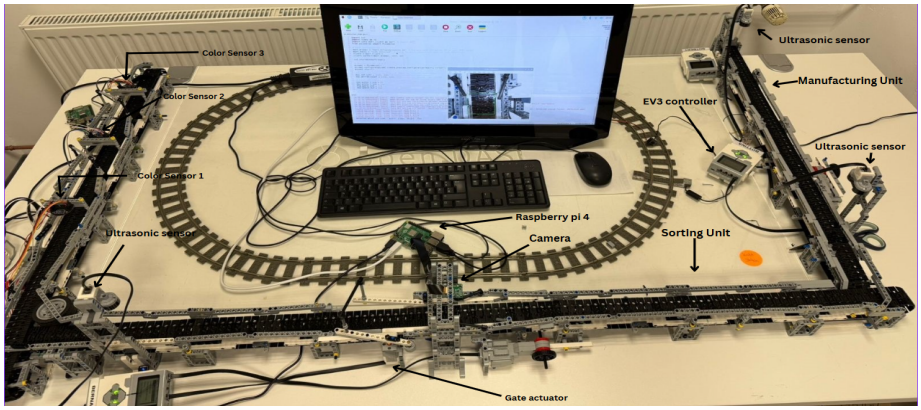


Fig. 3. Prototype Model

Following the development of the mechanical layer, the sensor and communication infrastructures were implemented to enable first-level automation. The operational sequence of the physical layer, now enhanced by the sensor and communication layers, is as follows:

(1) **Object Detection and Manufacturing Conveyor Start:** The first stage includes cube detection via ultrasonic sensors [3] integrated into the manufacturing unit's conveyor. This step includes the detection of the placed cube on the belt (later will be done by the robotic arm). When the entry ultrasonic sensor detects the presence of a cube, the control unit starts the conveyor in the quality control to move the cube to the next stage.

(2) **Transfer to QA Conveyor:** At the end of the manufacturing conveyor, there is an exit ultrasonic sensor that detects the incoming cube. When a cube is detected, it automatically starts the next conveyor to move the object to the quality control conveyor.

(3) **Conveyor Synchronization Checks:** Ultrasonic sensors are also used to count the cubes, and this count must be synchronized within each shop floor unit to ensure that the conveyor belt starts and stops precisely as cubes pass through, thereby optimizing energy and resource utilization.
- If the counts are equal, the manufacturing Conveyor is stopped to prevent overflow.
- If the counts are unmatched, the manufacturing Conveyor continues to run.

(4) **Quality Control:** Next, we have our quality assurance check through a camera, specifically the IMX477 Arducam camera [4]. It is installed as a structural addendum on the top of the quality assurance unit's conveyor. An algorithm was written to check both the dimensions, shape and the color of the incoming cubes. The camera was interfaced with the controller [5] for this purpose and programmed for the quality check:
- If the product meets the required standards, it is forwarded to the sorting unit.
- If the product fails the validation checks, it is rejected and pushed into the waste bin by pushing it out of the conveyor belt using the gate pushers.

(5) **Sorting Process:** When a cube is successfully validated and passed from the quality check, it moves to the end of the quality control conveyor, where there is another ultrasonic sensor. This sensor detects the validated

[3] https://shorturl.at/0BCPq
[4] https://www.arducam.com/b0242-arducam-imx477-hq-camera.html
[5] https://www.raspberrypi.com/products/raspberry-pi-4-model-b/

cube and starts the sorting unit's conveyor. In the sorting unit, the cubes are sorted into colors with two checks pushing the cubes into their sorted bins to be transported to the warehouse (which will, in later smart factory iterations, be operated by the robotic arm and transport train).

4 From Communication to Data Infrastructure

The communication layer transmits the timeseries and context-specific data from the sensors mounted in the physical layer to the Kafka server. Figure 4 shows the data flow with the communication components. The circuit and communication layer of the system begins close to where the data is generated, commonly referred to as the edge. Here, hardware such as the LEGO EV3 controller [6] and the Raspberry Pi 4 serve as local units responsible for capturing sensor data and controlling actuators. The EV3 collects real-time data from sensors (e.g., detecting objects or motor rotation) and sends it to the Raspberry Pi 4, which acts as a local processing node. The Raspberry Pi, running a lightweight Linux-based OS, handles the data and publishes it using the MQTT protocol [7].

MQTT is a lightweight, low-overhead protocol specifically designed for low-bandwidth, high-latency, or unreliable networks, making it well-suited for connecting IoT devices. It follows a publish-subscribe messaging pattern in which client devices (e.g., sensors or Raspberry Pi) publish messages to a central message broker (Kafka server in our case). Other clients can subscribe to specific topics (different data streams like data from different sensors or other processings units in the demo) and receive updates when new messages are published, enabling efficient and decoupled communication among distributed components. The data collected from the physical layer is transmitted via MQTT to a centralized Kafka server [8], with a Kafka producer running on the Raspberry Pi capturing and forwarding these messages in real time for scalable stream processing.

Subsequently, the messages are consumed by a Node.js Express server [9], which performs two core functions: persisting data to a MongoDB database [10] for query and analysis, and committing real-time updates to clients using socket-based communication. The Node.js socket layer [11] allows seamless interaction with a React Native mobile application [12], ensuring users receive live factory data streams and status updates.

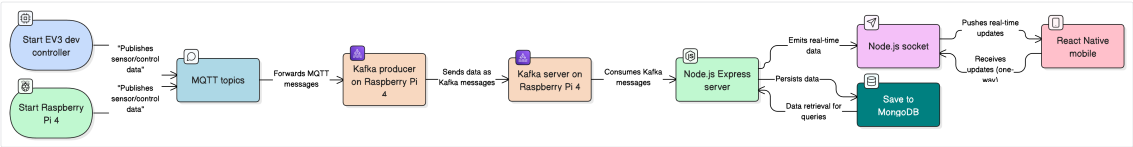


Fig. 4. Data Flow

5 From Data to Application/Work Layers

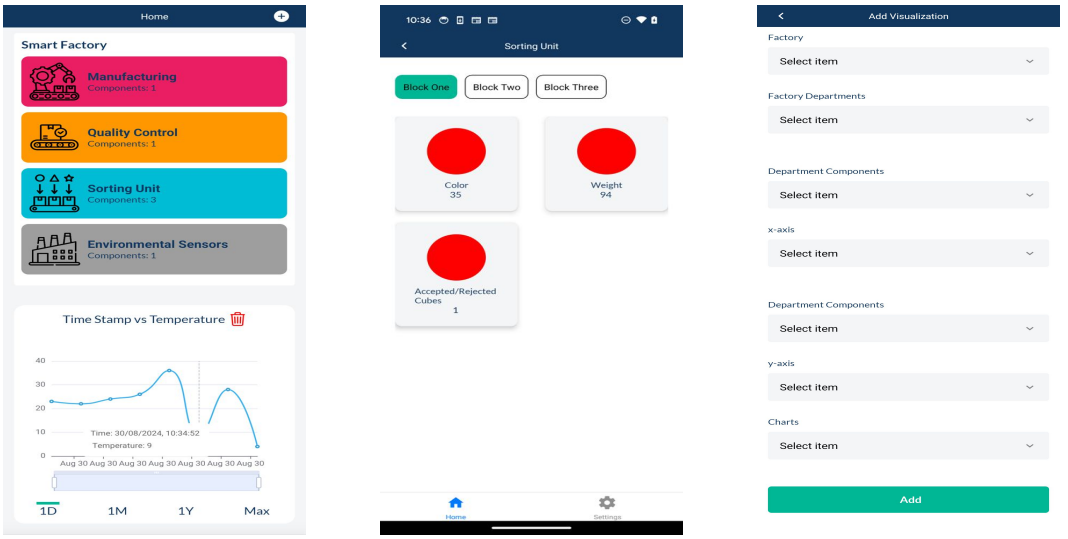
The backend system of the smart factory application is developed using Node.js, and at the core of this system lies the Kafka service, which communicates with the Kafka server to manage topic creation, deletion, and message handling. This service supports the production and consumption of messages and manages multiple consumers to facilitate

[6] https://education.lego.com/de-de/product-resources/mindstorms-ev3/downloads/developer-kits/
[7] https://mqtt.org/
[8] https://kafka.apache.org/
[9] https://expressjs.com/
[10] https://www.mongodb.com/
[11] https://socket.io/
[12] https://reactnative.dev/

seamless, real-time data flow across various system components. Additionally, MongoDB serves as the backend database for historical data, storing digital twin representations of factory components, user data, and other relevant information. The system also provides a RESTful API, divided into two primary categories: Kafka interaction endpoints, which enable real-time topic and stream control, and user/application management endpoints that support user authentication, digital twin operations, access control, and visualization management.

The digital twin application mirrors the physical smart factory through a hierarchical model, i.e., components, departments, and the factory (Figure 5a). At the base level, components represent individual sensors or devices that monitor key operational aspects such as the number of cubes produced, quality control stats, sorting status, actuator and gate conditions, and conveyor belt activity (Figure 5b). These components are grouped into departments, corresponding to physical units such as manufacturing or quality control. Departments facilitate the monitoring of aggregated unit-specific performance and operations. At the top level, the factory entity aggregates data from all departments, providing a comprehensive operational overview enriched with metadata such as factory location and current status. This layered structure enables multi-level data analysis and hierarchical access control, supporting both localized insights and system-wide decision-making. The application is also scalable, allowing users to create and link multiple factories. Within each factory, multiple departments can be added, and each department can include a collection of all relevant operational components.

A key feature of the system is user visualization management, which allows users to create and interact with customized visualizations based on real-time and historical data. These visualizations are stored in the database and associated with specific users and workplaces to ensure contextual accuracy. The flexible schema accommodates various visualization types and metric attributes, allowing dashboards to be tailored to specific roles and needs (Figure 5c). This extensible design ensures that insights are effectively delivered to relevant stakeholders, facilitating collaborative work practices such as shared planning, collective decision-making, and process optimization within the smart factory environment.



(a) Home Screen (b) Sorting Unit Screen (c) Add Visualization Screen

Fig. 5. Application Screens

6 Findings: Infrastructural Resonance

6.1 Innovation in Work Practices led Point of Infrastructuring for Sustainability Goals

As the design and development progressed during the first iteration, accompanied by continuous evaluation with SMEs, funding agencies, and experts, including project colleagues and collaborators from other SME-related projects, we encountered additional implications, particularly related to sustainability objectives. These considerations became increasingly central to most funded projects during the period from 2021 to 2023, aligning with the sustainability goals set by the Federal Ministry for Economic Affairs and Energy of Germany (called Federal Ministry for Economic Affairs and Climate Action at that time). This vision emphasizes that Industrie 4.0 is predominantly driven by the potential of new technologies and processes in industrial manufacturing. Companies leveraging digital technologies and data can achieve significant synergies, particularly in their performance toward sustainability goals such as climate change mitigation, resource efficiency, decarbonization, energy optimization, and the transformation of work structures [2]. These objectives were critically reviewed and discussed within our multidisciplinary team. Given that researchers from various disciplines interpret sustainability in diverse ways, the integration of these objectives created a Point of Infrastructure (PoI) concerning the intersection of technological and work innovation within the smart factory demonstrator. To respond, we initiated ideation and brainstorming sessions focused on the question: What does it mean to develop a sustainable smart factory, and how must the existing demo be adapted to achieve this vision? Based on prevailing definitions, a sustainable smart factory is one that actively considers environmental factors such as CO_2 emissions, energy consumption, and resource-efficient operations to support sustainable optimization.

To address this, the first step involved expanding the system's capability to capture relevant environmental data. We integrated additional physical-layer sensors, including temperature, humidity, pressure, and CO_2 sensors, enabling visibility into environmental conditions tied to sustainability goals.

This PoI further resonated across the communication and data infrastructure layers, prompting the need to configure data acquisition at the Raspberry Pi and storage in Kafka. The new environmental data streams triggered cascading PoIs in the application and work layers as well, necessitating mechanisms for real-time data visualization, interpretation, and control. Figure 6 shows the cascading resonance and PoI among different infrastructural layers of the smart factory. These renew and repair activities in different layers were not only technical but also organizational, requiring the adaptation of work practices to support collaborative decision-making and process optimization. Ultimately, they aimed to enable data-driven strategies for reducing energy consumption and CO_2 emissions by leveraging trends and actionable insights, necessitating new ways of working and optimizing processes.

6.2 Innovation in Technology-led Point of Infrastructuring for Artificial Intelligence

As the infrastructural layers stabilized, we encountered a new turning point where technological innovation once again led to a Point of Infrastructuring (PoI). Over time, as the MongoDB system accumulated sufficient data, we were able to leverage it for training AI algorithms. This PoI initiated a cascading effect across the existing infrastructural layers, and in the process of localized repair and adaptation, two new infrastructural layers emerged to support AI integration and as an implication of this integration.

Figure 6 illustrates both the resonance and emergence phenomena triggered by AI incorporation. The first PoI occurred in the data layer, necessitating the development of mechanisms for structured time-series data collection, storage, and pruning. As the AI layer was being established, it required entirely new conventions of practice, including

data evaluation, enrichment for insight generation, modeling, and algorithm training. Algorithm selection also became a central concern.

Our team responded by benchmarking and comparing various AI models for time-series and structured data, evaluating their potential applications within the Smart Factory context. This evolution led to further PoIs in the application layer, which now needed to support not only data visualization but also event-triggering mechanisms based on AI-driven predictive analysis.

These triggers could be applied to real-time data streams to enable active monitoring without human intervention. Previously, real-time dashboards allowed human users to visually identify insights and opportunities. Now, historical data could be analyzed collaboratively to define predictive triggers that automatically detect and act upon such opportunities, alerting users to action for processes such as starting and stopping machines for optimal energy consumption, using temperature triggers for balancing the heating and cooling conditions in the factory, etc. This shift required significant changes in work practices, including redefining the scope and interpretation of AI-generated insights within the factory. A critical challenge became how to appropriately contextualize and respond to predictions, especially given their impact on operational decisions.

Finally, the resonance across infrastructural layers culminated in the emergence of an additional or a well-formed ethical, legal, and social implications (ELSI) layer, which introduced its own distinct work breakdown PoI. As a result, new conventions of practice had to be developed to ensure transparency, accountability, and trust in AI-generated decisions and event triggers.

While ELSI concerns have traditionally been addressed as background governance issues (like user roles, permissions, agency, and control) in digital transformation and Industry 4.0 initiatives, the integration of artificial intelligence renders them far more central. This transformation arises from fundamental differences between traditional rule-based automation and AI-based systems. Traditional automation is typically deterministic and transparent; its decision-making can be traced via logic trees or process flows, making it auditable and explainable.

In contrast, AI systems (with deep learning) introduce non-transparent, probabilistic decision-making, often functioning as black boxes whose outputs cannot be directly traced to a sequence of clearly defined rules. In the context of the smart factory, sensor data used for anomaly detection or predictive maintenance activates AI-driven autonomous decision-making, such as generating event suggestions that serve as real-time triggers in data monitoring. This means that decisions made by AI algorithms are adopted by users as operational decisions, effectively delegating agency from humans to machines. This delegation triggers a redistribution of moral and legal responsibility. Questions emerge regarding who—or what—is accountable for specific outcomes: the algorithm, the data, the developer, or the system operator. These ambiguities shift ELSI concerns from peripheral compliance considerations like in rule-based smart factory automation to core elements of system and application design, thus demanding heightened and structured attention to key ELSI principles: accountability, fairness, and interpretability. This infrastructural resonance and invoked PoIs force the ELSI concerns to crystallize amid AI as a cross-cutting meta-layer, embedded within and informing every phase of AI system development and deployment, rather than being invisible and passive as in rule-based automation.

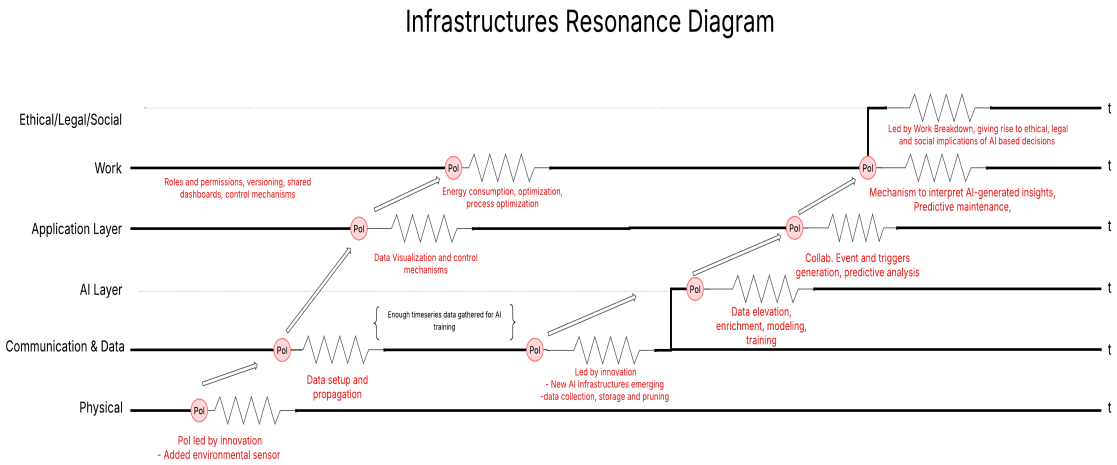


Fig. 6. Infrastructural Resonance and Cascading PoIs

7 Discussion: Socio-Technical Challenges and Open Questions

Our prototyping journey uncovered several critical findings that highlight several socio-technical challenges inherent in developing smart factory automation systems. These insights are essential for informing future efforts in Industry 4.0 prototyping and deployment.

7.1 Balancing Development Goals vs Emergence Scenarios

A project of this scale is not without its biases and assumptions. For example, we initially assumed that real-time 3D printing was viable—but it was not. This constraint forced us to pivot and simulate cube creation instead. Another common assumption, typical in iterative system development, is that incremental and iterative development is inherently beneficial. While this is often true, our experience highlighted that the tight coupling of different infrastructures demands heightened vigilance and careful planning. It is essential to leave space for the emergence of new processes, artifacts, and even infrastructural layers throughout the development lifecycle.

An important observation during the creation of this demo was that many projects tend to focus on normalcy, i.e., designing for standard, functioning states. However, non-normal or failure scenarios are often overlooked. We recommend integrating fallback control mechanisms, such as visual indicators for error states and higher-level supervisory controls, particularly when incorporating AI, to enhance system resilience.

Our development was also significantly delayed by challenges in sourcing appropriate hardware components and reliable sensors. The iterative nature of prototyping and interdependent infrastructures means that hardware availability directly influences progress. Procuring, testing, and calibrating devices such as ultrasonic detectors and color sensors introduced unexpected delays. This highlights a common bottleneck in automation prototyping: hardware supply chain issues can severely extend development timelines. To mitigate such risks, we emphasize the value of simulation and emulation tools that enable virtual testing of mechanical and sensor functions in parallel with hardware development. These tools support continued progress even while waiting for physical components.

In the data and communication infrastructure, our initial system design used Apache Kafka as the central communication/data backbone for transmitting sensor data. However, the EV3 controllers, used for managing motors and sensors, exhibited limited processing capabilities. As a result, Kafka-based messaging significantly impaired system performance. To address this, we transitioned to MQTT, a lightweight publish-subscribe protocol more suitable for resource-constrained embedded devices. This shift illustrates the importance of aligning communication architecture with hardware capabilities, and highlights the value of decoupling data processing from control logic to balance performance, reliability, and adaptability.

This change also revealed resonance effects in infrastructural layers, where adjustments in one layer (communication) had downstream impacts on others (application behavior and control logic). Such interdependencies emphasize the need for holistic system design in complex automation environments.

7.2 Communication and Coordination Challenges in Multi-disciplinary Teams

A notable challenge emerged from asynchronous and inconsistent communication across team subgroups. Varied working hours and unclear task ownership led to duplicated efforts and rework, undermining efficiency. This lack of synchronized collaboration impeded progress toward small, iterative goals within the planned timelines. Insufficient coupling between teams and loosely coordinated workflows resulted in fragmentation and inefficiency. Establishing shared communication protocols, regular synchronization points, and clearly defined roles is essential for improving coordination and accelerating prototyping.

While the team included members from diverse roles and disciplines, miscommunication and asynchronous involvement contributed to delays. The absence of shared documentation further complicated onboarding processes. These challenges were compounded by ongoing Points of Infrastructure (PoIs) and cascading infrastructural resonance, which made it increasingly difficult to maintain a consistent, version-controlled design archive.

Throughout the project, various documents were created as boundary objects (diagrams, flowcharts) to facilitate understanding among team members from different disciplines. However, we observed that establishing shared understanding through clear documentation proved more effective than relying solely on alignment in meetings. We discovered that several system functions, although represented in architecture diagrams, lacked precise definitions and clearly scoped responsibilities. This led to misinterpretations and conflicts in understanding. For example, control nodes were referenced in the system architecture, but their operational roles, such as whether they should start/stop conveyors, manage rejection thresholds, or regulate sorting bin capacities—were not concretely specified. This gap highlights a fundamental issue in problem formulation and requirements clarity, which is crucial when translating a sociotechnical phenomenon into technical design [1]. Ambiguous definitions not only reduce shared understanding among team members but also pose a significant risk for misaligned infrastructuring efforts.

8 Future Work

The next development stage includes integration of the robotic arm, which will automate product placement and sorting. After integration, the arm will be tested for better efficiency and handling of the products. The train delivery system will be developed and tested after the robotic arm is fully operational. The focus will be on ensuring that the system is efficient and fast when transporting sorted products to the docking station.

9 Conclusion

This paper has detailed the prototyping journey of a smart factory demo, highlighting the risks and nuances in Industry 4.0 automation that require not only technical innovation but also effective management, including team coordination, clear problem definition, and hardware-software integration. A multi-layered intervention, such as the smart factory, offers an ideal opportunity to observe infrastructural resonance and Points of Infrastructure (PoIs) triggered by diverse stimuli. Through the course of this demo development, we also revealed the challenges and subtleties of multidisciplinary collaboration, which, while essential, are not without roadblocks. These include misaligned expectations, terminological ambiguities, and the need for ongoing articulation work to maintain shared understanding across disciplinary boundaries. Ultimately, our findings underscore the importance of adopting a sociotechnical lens in Industry 4.0 projects, one that recognizes infrastructure as emergent and evolving, shaped by both human practices and technological design. Future work should continue to explore how infrastructuring and collaborative practices co-evolve to support sustainable, adaptive, and ethically grounded automation systems.

10 Acknowledgment

The Smart Factory demonstrator was developed as part of an initiative within the Data Lab, supported under the Mittelstand-Digital Zentrum Ländliche Regionen project. This demonstrator aims to offer a hands-on and exploratory Smart Factory environment that illustrates various infrastructural layers, helping small and mid-sized companies conceptualize and design use cases for automation and digital-AI transformation in their business contexts. This initiative is funded by the Federal Ministry for Economic Affairs and Climate Action (BMWK).

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