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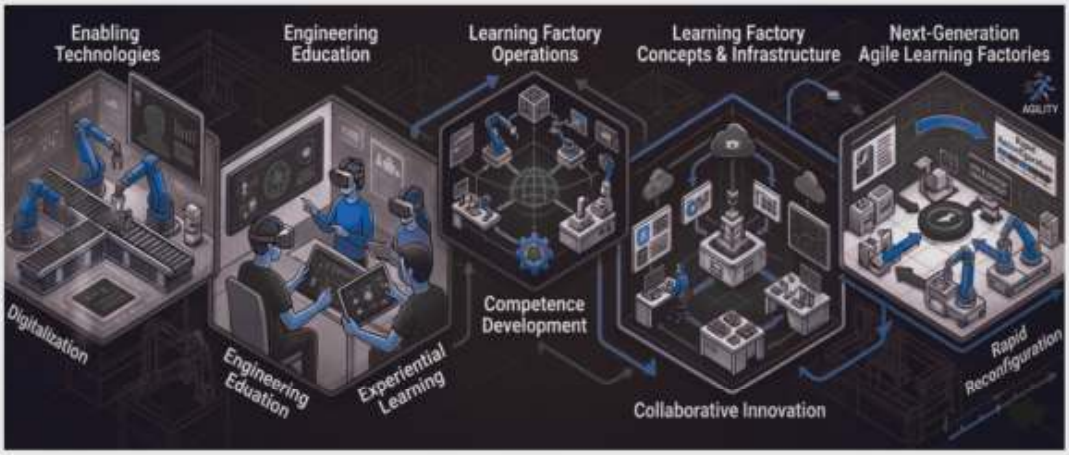


# Next Gen Learning Factories

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***Editors***

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# Preface

This book provides comprehensive and practical insights into the latest developments and innovations in learning factories, with a particular focus on next-generation approaches in engineering education and manufacturing systems. It brings together cutting-edge research contributions and real-world applications that support the advancement of teaching, learning, and industrial practice, combining theoretical perspectives with applied case studies to reflect the evolving role of learning factories as environments for experiential and competence-based learning. The book adopts a practice-oriented and research-driven approach that integrates scientific contributions with application-focused insights, highlighting innovative methodologies, emerging digital technologies, and experiential learning concepts that enhance competence development. It addresses current developments and challenges such as digitalization, adaptive learning environments, and collaborative innovation, offering new perspectives on the future of learning factories. The volume compiles selected contributions from the 16th Conference on Learning Factories (CLF 2026), held from 5–7 May 2026 at the Free University of Bozen-Bolzano, Italy, and covers five fundamental areas, including enabling technologies, engineering education, learning factory operations, learning factory concepts and infrastructure, and next-generation agile learning factories. These areas represent key dimensions of current research and practice, addressing both technological and pedagogical aspects. This book is designed for a diverse audience, including researchers working on learning factory-related topics, practitioners seeking insights into real-world applications, and doctoral students and lecturers interested in modern teaching methodologies and experiential learning environments. The book serves as a valuable resource for advancing learning factory concepts, supporting collaboration between academia and industry, and contributing to excellence in education and research in manufacturing engineering and production management.

The Editors

# Developing a Web-Based Digital Twin for an Agile Production Simulation System as a Learning Factory Platform

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**Abstract.** Industrial digital transformation requires educational paradigms that overcome the physical constraints of traditional learning factories. This paper presents a web-based Digital Twin (DT) for a fischertechnik Agile Production Simulation (APS) system. Using WebGL, the application provides an interactive 3D environment accessible via standard browsers without plugins. The system supports real-time data streaming for monitoring the physical line and an offline simulation sandbox for safe what-if experimentation. The DT was applied in an international project-based course to enable remote observation and joint scenario work. The approach lowers deployment barriers and provides a reusable blueprint for web-native Digital Twins in engineering education.

**Keywords:** Digital Twin (DT), Learning Factory, Agile Production Simulation (APS), WebGL.

## 1 Introduction

Learning factories connect theoretical instruction with industrial practice by enabling hands-on work in realistic production environments. Modular, miniaturized production lines - such as fischertechnik-based systems - offer affordable, and reconfigurable platforms for teaching automation, material flow, and manufacturing planning. However, their educational impact is often constrained by limited physical availability, restricted observability of internal states, and supporting software that is difficult to deploy across heterogeneous student devices and partner institutions.

Digital Twins can address these constraints by providing a synchronized virtual representation of physical assets and processes. They make hidden states observable, support what-if analyses, and enable remote participation. Many learning-factory twins rely on desktop applications, plugins, or tightly coupled frameworks, which increases deployment effort and limits cross-site collaboration. This work investigates a WebGL-based Digital Twin as an accessibility-first alternative: delivered in the browser, coupled through lightweight events, and complemented by an offline sandbox.

## 2 Agile Production Simulation System (APS)

The fischertechnik Agile Production Simulation (APS) is a modular smart-factory training system with automated stations linked by track-guided AGVs (Fig. 1). A compact controller stack coordinates sensors, actuators, and station logic to realize end-to-end material flow (logistics, buffering, machining, and quality checks). Workpieces are NFC-identified and moved along printed tracks, producing signals such as occupancy and cycle status. Vendor tools visualize layouts and basic motions, but usually lack web-based remote access, extensible streaming, and a reusable simulation sandbox - gaps addressed by the presented Digital Twin approach.

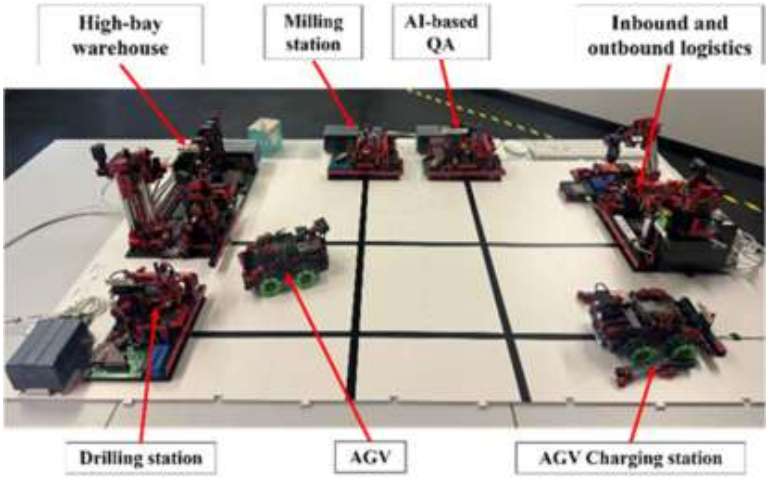


**Fig. 1.** Agile Production Simulation System (APS).

## 3 Related Works

Learning factory research emphasizes competency development through realistic tasks and knowledge transfer. Miniaturized factories based on LEGO or fischertechnik support systems-integration learning and gamified scenarios [1, 2, 3]. Digital Twin work spans scheduling, human-centered twins, and interaction-focused approaches [4, 5, 6], and game engines (e.g., Unity) are used for educational 3D twins [7, 2]. Many solutions remain desktop-bound or proprietary, limiting scalability in bring-your-own-device and international settings. WebGL-based Digital Twins emphasize accessibility (URL-based, no installers) and fast sharing of interactive scenarios, often prioritizing event-driven visualization over high-fidelity physics or closed-loop control. This work couples such a browser-native 3D front end to a tangible APS and adds an offline sandbox for repeatable experimentation.

## 4 Requirements for a Web-Based APS Digital Twin as Learning Factory

To support competency-based learning and remote collaboration, the digital twin should provide interactive 3D visualization on typical student devices, browser access without plugins, and safety-constrained connectivity to the physical APS. It should offer an intuitive UI for monitoring states and navigating the scene, and include an offline simulation mode for testing scenarios before supervised trials. Open technologies are preferred to avoid vendor lock-in and support extensibility.

## 5 Implementation of the Web-Based APS Digital Twin

Implementation of the web-based APS Digital Twin followed an agile Scrum methodology across several stages:

### 5.1 Overall Architecture

The system uses an edge-to-web architecture (Fig. 2). Shop-floor signals from APS controllers are mapped at an edge gateway and forwarded to the web client via WebSockets. The client renders state from publish-on-change events to minimize resource consumption. Whitelisted commands can be routed back through the gateway for supervised interaction. Responsiveness depends on network conditions and gateway throttling; the client uses a last-value-wins strategy with light interpolation. The channel is not intended for hard real-time actuation.

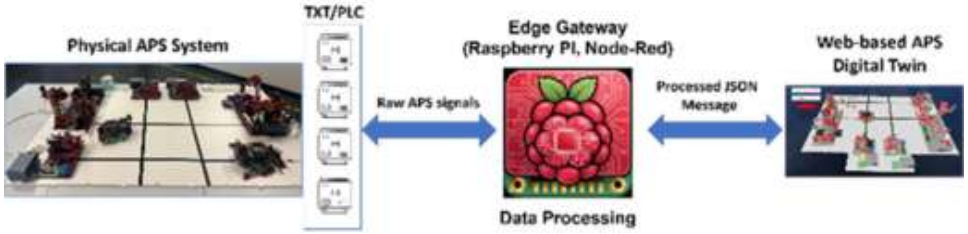


**Fig. 2.** Overall architecture of the web-based APS Digital Twin.

### 5.2 3D Model Preparation and WebGL Client

The APS CAD model (STEP) was converted to FBX after mesh optimization in Blender (removal of non-functional geometry, merging repeated parts, and controlled decimation). Moving components were assigned correct pivots for plausible kinematics. The client was implemented in Unity and deployed as a WebGL build. Browser-oriented optimizations (level-of-detail and batching) were applied, and incoming signal tags are bound to scene objects via a deterministic naming convention (Fig. 3).

**Fig. 3.** APS 3D-Moel in Unity 3D.

### 5.3 Functional Implementation of the Digital Twin

The digital twin logic is implemented in Unity as an event-driven runtime mirror of the APS. Node-RED forwards live signals to the Web client via WebSocket, and the twin updates its scene directly from these events. To keep the WebGL client lightweight, behavior is simplified: station logic is represented through state variables and scripted sequences, while collision-accurate physics, PLC cycle timing, and adaptive optimization are out of

scope. This supports learning outcomes centered on process understanding and state interpretation, but it limits conclusions about production performance.

- WebSocket ingest: a Unity C# "WebSocketHandler" connects to the gateway and dispatches normalized messages to "OnVariableDataReceived". Tags are bound deterministically using a module–component–axis naming convention.
- Kinematics and process control: parameterized controllers map variable updates to motions and states (robot, AGV, drill/mill, handover, color/state cues) using reusable primitives (e.g., "Rotation", "Variable-DrivenMovement_Child").
- Script architecture: about 35 scripts are split into reaction scripts (parse/validate, update variables, raise events) and action scripts (execute motions and inter-station coordination).

### 5.4 Data Communication Interface and Middleware

A Raspberry Pi runs Node-RED as middleware to translate station-level signals into web protocols. Node-RED applies filtering, debouncing, and rate limiting, and emits compact JSON messages. Reliability is supported by heartbeats and automatic reconnection. Safety is addressed through input validation and a restricted set of write commands.

### 5.5 User Interface of the Web-Based APS Digital Twin

The UI provides 3D navigation, connection status feedback, and dashboards for key station states (Fig. 4). A debug view exposes signal events and system messages for teaching and troubleshooting. Besides live coupling, an offline simulation mode is provided: Node-RED drives the same event interface as the physical APS. In this prototype, the sandbox uses deterministic sequencing with simplified timing; failures and stochastic disturbances are not fully modeled, improving repeatability but reducing realism for performance prediction.

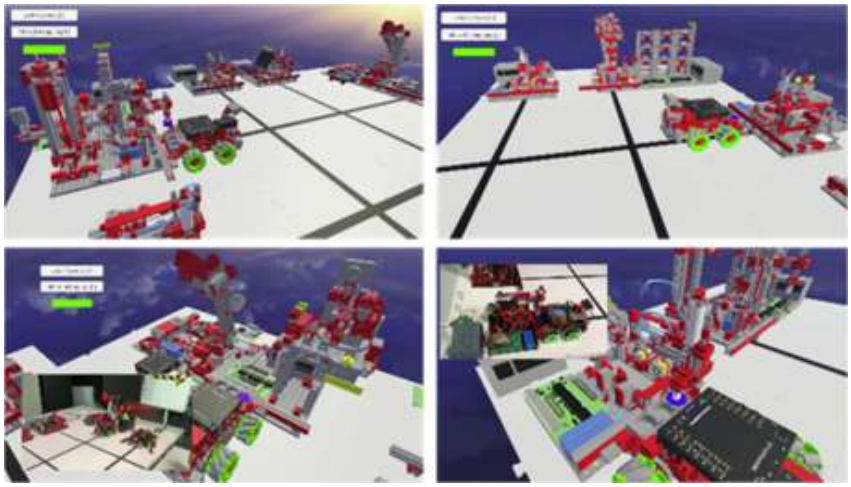

**Fig. 4.** APS Digital Twin as WebGel Application.

### 5.6 Server Deployment

The WebGL build is delivered as static content via a reverse proxy (e.g., Nginx). Containerization supports reproducible deployment and encrypted tunneling can expose the application securely for classes and remote partners without opening inbound firewall ports. The WebGL build is delivered as static content via a reverse proxy (e.g., Nginx). Containerization supports reproducible deployment and encrypted tunneling can expose the application securely for classes and remote partners without opening inbound firewall ports.

## 6 Conclusion and Experiences

A web-based Digital Twin of the fischertechnik APS was implemented to extend learning-factory education beyond physical presence and proprietary software. The WebGL client provides browser-native 3D visualization and an edge gateway streams real-time signals via lightweight events. The offline simulation mode offers a safe sandbox for experimenting with production/logistics strategies and thus supports agility at the learning and reconfiguration level (agile learning). Evaluation is exploratory: the system was used in an international project course (12 students) with instructor observations and student reflections. No controlled comparison or standardized instruments (e.g., SUS, pre/post tests) were applied, so results demonstrate feasibility. Future work will add mixed-method evaluation and extend the sandbox model (timing/failures).

## 7 Discussion and Limitations

While WebGL delivery lowers installation barriers and enables fast dissemination across institutions, it also introduces practical constraints. Browser-based rendering and memory limits can reduce frame rate for large or highly detailed learning-factory models, requiring mesh simplification, texture compression, and selective level-of-detail loading. Moreover, the architecture is not designed for hard real-time behavior: network jitter and varying client performance can cause delayed or uneven state updates. In our prototype, Node-RED publishes state changes at a configurable update rate and the client applies throttling/interpolation to maintain smooth interaction; therefore, the system is best suited for monitoring, guided experimentation, and supervised scenario testing rather than closed-loop control. Finally, the offline simulation mode prioritizes repeatability over physical fidelity. Timing granularity, fault injection, and stochastic disturbances are simplified, which supports structured exercises but limits the validity of quantitative throughput or energy-optimization conclusions drawn purely from the sandbox.

**Acknowledgment**. This work was funded by the Baden-Württemberg Stiftung (Baden-Württemberg-STIPENDIUM, IC DT-P). We thank fischertechnik for its support.

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# Immersive Virtual Commissioning with Digital Twins: Implementation of a Robot-Based Automated Storage System in a Project-Based Course

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**Abstract.** Virtual commissioning (VC) tests automation and robotics systems against a virtual plant before physical commissioning, reducing risk, time, and cost. Combined with digital twins (DT) and virtual reality (VR), VC enables immersive exploration of control logic and system behavior. This paper presents a project-based master's course that integrates VC, DT, and VR. Students implement a VR-enabled digital twin of a robot-based automated storage and retrieval system (AS/RS) using Unity3D, realvirtual.io, and URSim. We outline the architecture (slot management, robot control, PLC-like logic, and VR interaction) and report a formative evaluation with two cohorts showing improved systems thinking, toolchain proficiency, and teamwork. The results indicate that VR-based digital twins are an effective teaching approach and transferable to other learning-factory and industrial scenarios.

**Keywords:** Virtual Commissioning, Virtual Reality (VR), Digital Twin (DT).

## 1 Introduction

Rising automation and robotics increase the complexity of production and intralogistics systems, making physical commissioning risky and costly. Late-discovered errors can lead to delays, rework, and safety issues. Virtual commissioning (VC) reduces these risks by validating automation programs on a virtual plant before installation. Digital twins (DT) provide executable system models, and virtual reality (VR) enables immersive interaction with them. In education, combining VC, DT, and VR supports realistic, project-based learning across the automation lifecycle—from 3D modelling and control design to virtual testing. This paper presents a master-level project course using a VR-enabled digital twin of a robot-based AS/RS as the central learning object. It (1) describes the course integration of VC, DT, and VR, (2) presents the use case and implementation, and (3) reports formative results from two student cohorts.

## 2 Introduction into Virtual Commissioning, Digital Twin and Virtual Reality and Project-Based Course Subsection Sample

### 2.1 Virtual Commissioning

Virtual commissioning links PLC/robot programs to a virtual plant to test logic, sequences, and safety before physical commissioning. Executing code on a realistic model reveals errors early, shortens ramp-up, and enables safe testing of critical scenarios, supporting students' system-level understanding [1, 2].

### 2.2 Digital Twin

The digital twin is an executable 3D model of the system (robot, conveyors, rack, totes, sensors/actuators). In the AS/RS case it also includes slot and inventory data, enabling a virtual plant where students can test control strategies and layouts without hardware.

### 2.3 Virtual Reality

Virtual reality immerses users in the digital twin via a head-mounted display and tracked controllers. They move through the 3D plant, inspect components at real scale and operate virtual panels, gaining an intuitive understanding of layout, reachability and ergonomics. In the course, VR serves as the primary interaction platform, where storage and retrieval tasks are defined directly inside the virtual environment.

### 2.4 Project-Based Course Design

The course "Virtual Reality for Industrial Applications" uses project-based learning with small teams working on industrially inspired use cases such as the robot-based automated storage system. Over one semester, each team designs a VR-enabled digital twin, integrates virtual commissioning and develops VR interfaces for operation and monitoring. Short lectures, weekly supervision and milestones support iterative development, and the course concludes with a final demonstration and reflection on technical and organizational aspects.

## 3 Related Works

Research on virtual commissioning and digital twins has led to numerous frameworks that validate automation systems before physical commissioning, often by linking PLC hardware and MES layers to 3D plant models [3]. These platforms reduce industrial commissioning time and create authentic learning environments in higher education. Increasingly, game engines such as Unity are used to build interactive digital twins connected to industrial PLCs (e.g. Game4Automation) [4], enabling students to design virtual plants and test PLC logic before working on real hardware. Commercial tools like FACTORY I/O [5] support this with predefined 3D plants for PLC training. The integration of VR into VC is more recent but growing [6], with studies showing that immersive visualization improves spatial understanding, ergonomics assessment and communication of design decisions. Mixed-reality labs that combine virtual plants with real hardware further raise motivation and allow safe experimentation with faults and controller tuning [7, 8]. However, fully integrated educational concepts that bring together VC, digital twins and VR in one coherent, project-based course remain rare. The approach in this paper addresses this gap by having students develop an industrially realistic VR-based digital twin of a robot-based AS/RS and use it for virtual commissioning.

## 4 Implementation of the Use Case "Robot-based Automated Storage"

The robot-based automated storage and retrieval system handles small totes between an inbound conveyor, a storage rack and an outbound conveyor. A UR30 robot performs all transfers. The implementation models this system as a digital twin in Unity, controls storage and retrieval with PLC-like logic, operates it via VR interfaces and keeps a consistent digital inventory of all slots.

### 4.1 Case Study Characteristics and Practical Problems Addressed

The AS/RS case study includes (i) one UR30 robot, (ii) inbound/outbound conveyors, and (iii) a rack with 400 slots defined via a CSV slot library (Fig. 1). Beyond didactic goals, it supports typical commissioning tasks: detecting I/O mapping mismatches, validating sequences and interlocks (e.g., tote presence, slot availability), checking robot reachability/waypoints before on-site trials, and improving stakeholder communication through immersive visualization of system state and inventory.

**Fig. 1.** Detailed 3D Model of the storage system.

### 4.2 Toolchain

The Unity3D provides real-time 3D/VR and C# scripting. realvirtual.io supplies sensors, actuators, drives, I/O, and PLC-like control. URSim is used to program and test the UR30. Industrial CAD models are imported into Unity and equipped with colliders, kinematics, and realvirtual.io components.

### 4.3 Virtual Commissioning Workflow and Data Requirements

VC uses three inputs: CAD/3D assets, the CSV slot library, and an I/O list mapping virtual signals to URSim. Unity runs the Digital Twin and VR UI, URSim executes robot programs, and both are coupled via realvirtual.io I/O. Scenarios are executed in VR to verify sequences/state transitions and test border cases (invalid slot IDs, reachability limits, I/O timeouts), enabling early integration checks before physical deployment.

### 4.4 Digital Twin Modeling and Slot Library

The rack's 400 locations are defined in a CSV (side/row/column/target coordinates). Unity loads this file at startup; the same structure maintains the digital inventory (occupied/free) and updates after each store/retrieve. Layout changes require only CSV edits.

### 4.5 Robot Control and I/O

URSim programs cover pick, store, retrieve, and place, parameterized by slot IDs and waypoints from the slot library (Fig. 2). Unity–URSim communication uses realvirtual.io digital I/O with compact command/status encoding: Unity issues requests (e.g., "store slot X"), URSim returns progress/completion. PLC-like logic in realvirtual.io coordinates conveyors, robot actions, and inventory updates via sensors and state machines.

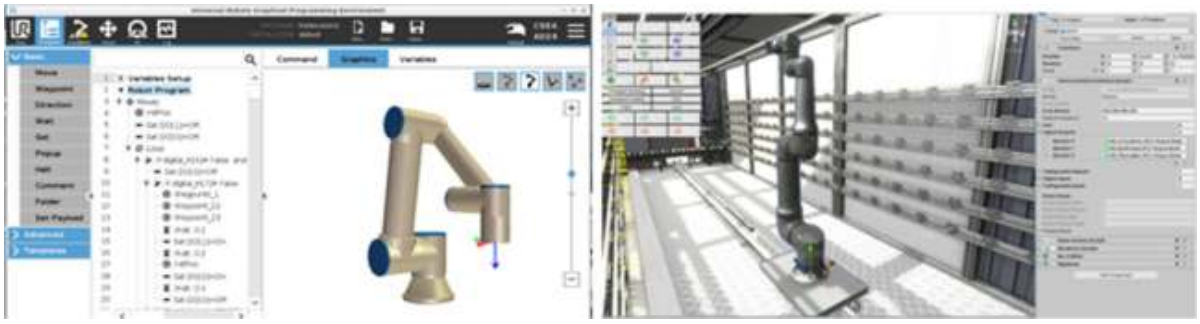

**Fig. 2.** Robot Control in URSim (left), UR30 Robot in the storage system (right).

### 4.6 VR User Interaction

The operation is via three VR panels: storage (enter slot ID with validity/availability checks), retrieval (analogous), and an inventory view showing all slots as free/occupied indicators (Fig. 3). Users interact with XR ray selection and trigger; teleportation enables quick movement between key viewpoints (conveyors, robot, rack).

**Fig. 3.** VR User Interface: Availability Panel (left), Storage Panel (right).

## 5 Evaluation of the Implementation of the Use Case "Robot-Based Automated Storage"

The VR-based digital twin was formatively evaluated in two cohorts of a master's course (≈45 students) using project reports, reflections, and instructor observations. Students reported improved understanding of the interaction between mechanics, sensors, PLC-like logic, and robot motion, and gained practical experience building and connecting a digital twin (CAD import, colliders, I/O mapping, state machines). They also improved VR interface design for presenting system states and creating usable interactions. Technically, the toolchain enabled meaningful virtual commissioning of the AS/RS: storage and retrieval sequences ran reliably via realvirtual.io logic, and URSim integration provided realistic robot behavior and helped reveal configuration issues relevant to real deployments. The project-based format supported modular development, role distribution, and communication similar to industrial teamwork. No standardized quantitative usability data (e.g., SUS) or pre/post learning tests were collected; future course runs will include short surveys and rubric-based pre/post comparisons.

## 6 Scalability, Transferability, and Limitations

Educational scalability can be achieved by replicating the software stack (Unity + URSim + realvirtual.io) across multiple workstations and by separating development from VR use: students can work in desktop mode and use VR for milestones and reviews. Remote delivery is possible using a preconfigured project image and recorded demonstrations; multi-user VR is a promising extension but requires networking, shared-state management, and synchronization. Transferability involves setup effort (industrial CAD preparation, colliders/kinematics, I/O mapping, URSim programs, slot libraries) and VR-capable hardware. Fidelity is limited by URSim and Unity abstractions (e.g., simplified timing and failures), which constrains performance prediction but is acceptable for learning system behavior and interfaces.

## 7 Conclusion

This paper presented a project-based master course integrating virtual commissioning, digital twins, and VR. Using a robot-based automated storage case, students built a VR-enabled digital twin with Unity, realvirtual.io, and URSim, gaining hands-on experience in 3D modelling, control logic, VR interaction, systems thinking, and teamwork. Future work includes fault handling, multi-robot coordination, learning evaluation, and remote multi-user VR.

**Acknowledgment.** The authors thank the 2024–2025 master's students of "Virtual Reality for Industrial Applications" (HKA) and realvirtual.io GmbH. This course was part of SMART-XR (MASTER Program), co-funded by the European Union.

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# Designing Learning Factories for Vocational and Higher Education: Fostering Interdisciplinary Learning Groups with Authentic Business Processes

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**Abstract.** A learning factory provides an innovative environment for both vocational training and higher education. In many cases, however, training activities in a vocational context are implemented as isolated modules in learning factories rather than being embedded into a coherent educational framework that connects different learning locations. To overcome this limitation, concepts are introduced that enable the linking of vocational training modules with academic course con- tent, thereby fostering cross-level, interdisciplinary and cross-institutional learning opportunities. Within the project LernGo, these approaches are applied through the use of a robotic arm, which serves as the fictitious customer order, illustrating how theoretical knowledge and practical skills can be combined across different learning sites. This integrated approach not only strengthens knowledge transfer but also creates dynamic, collaborative learning environments that bridge educational contexts and promotes sustainable competence development.

**Keywords:** Vocational Education and Training, Higher Education, Collaborative Learning, Learning Site Cooperation.

## 1 Introduction

The ongoing digital, demographic, and ecological transformations are profoundly reshaping the requirements of vocational education and training systems. The dual education system in Germany faces increasing pressure to integrate emerging technological competencies, such as digital process management, artificial intelligence, and sustainable production technologies while simultaneously addressing demographic shifts that demand new strategies for attracting and retaining diverse groups of apprentices.

In this context, *überbetriebliche Berufsbildungsstätten* (ÜBS, inter-company vocational training centers) play a crucial role in stabilizing and modernizing the German dual education system. ÜBS serve as complementary learning venues designed to sup- port training companies that are unable to cover the full scope of required vocational competencies due to limited production portfolios, specialization, or resource constraints. By offering standardized, practice-oriented training modules, ÜBS ensure that all apprentices, regardless of their company's size or technological capabilities, acquire the essential skills defined in national training regulations. [1, 2].

At the same time, universities face the challenge of preparing students for increasingly complex professional environments [3]. Higher education institutions must develop graduates who possess both theoretical knowledge and the ability to apply concepts in real-world engineering and production settings. Learning factories have become an important instrument for bridging this gap, as they provide realistic environments in which learners can engage with manufacturing systems, digital tools, and interdisciplinary problem-solving [4].

Extending this concept to ÜBS may offer additional opportunities, as apprentices could similarly benefit from hands-on learning in structured, technology-rich environments. Such an expansion could potentially strengthen the alignment between vocational and academic learning processes, particularly in areas where emerging technol-

ogies increasingly blur traditional boundaries between occupational profiles.

Creating a shared learning space in which apprentices and university students work together on common tasks may also offer pedagogical benefits. Joint learning scenarios provide opportunities for learners to engage in cross-level collaboration, exchange perspectives, and negotiate problem-solving strategies. These interactions could support the development of social and communicative competences, such as teamwork, coordination, and professional communication, skills that are essential for future work in interdisciplinary industrial contexts. Moreover, mixed learning groups may help establish a shared language between vocational and academic learners, facilitating smoother collaboration in professional environments where teams often consist of workers with diverse educational backgrounds.

Against this background, the present paper introduces an approach to integrating learning factory concepts into a structured cooperation between ÜBS and university. It outlines how a shared learning object, in this case, a robotic arm representing a fictitious customer order can serve as the foundation for collaborative learning scenarios that link vocational and academic education. Building on existing research on vocational education and training, learning factories and cross-institutional learning, the paper outlines competence-oriented learning scenarios and reflects on how such an integrated model could support sustainable competence development across educational levels.

## 2 State of the Art

Within the German dual system, inter-company vocational training centers (ÜBS) already provide a broad and standardized training portfolio that supplements company- based learning and ensures the acquisition of nationally required vocational competencies [5]. In recent years, the concept of Learning Factories has increasingly expanded into vocational education, and several pilot implementations have been introduced at vocational schools to strengthen process understanding, digital competences, and problem-solving skills in authentic production environments [6].

In the university context, Learning Factories are now firmly established. Numerous higher education institutions operate Learning Factories for research, engineering education, and industry-oriented training, often focusing on multidisciplinary teamwork, hands-on engagement with cyber-physical systems, and realistic simulation of manufacturing processes [4, 7]. Although most Learning Factories serve heterogeneous user groups including apprentices, trainees, students, and industry practitioners [4, 6], the intentional design of shared learning scenarios for apprentices and university students has not yet been widely documented. Expanding learning factories towards cross-level learning may therefore represent a promising avenue for educational innovation and future research.

General research on collaborative learning between apprentices and university students remains limited. Empirical evidence from other domains suggests, however, that mixed-level learning formats can foster communication skills, mutual understanding, and teamwork. For instance, interprofessional training wards in healthcare demonstrate that nursing trainees and medical students can successfully learn together, engage in shared responsibilities, and develop social and communicative competences through structured collaboration [8]. Additional evidence from vocational schools with study-integrated bachelor programs shows that apprentices and students can benefit from joint learning settings when pedagogically structured, thereby supporting the development of shared professional understanding and collaborative skills [9].

Despite these insights, there is currently no systematic research examining integrated learning settings in which vocational apprentices and university students work together within a Learning Factory environment. This highlights a clear research gap regarding cross-level learning in engineering and manufacturing education and underscores the potential of Learning Factories as shared learning spaces for fostering joint competence development across educational levels.

## 3 Concepts

The aim of the learning-factory environment is to use a shared order-fulfilment process for a robotic arm as a foundation for designing learning scenarios that promote exchange and collaboration between vocational apprentices and university students. The robotic arm as shown in Fig. 1 was chosen as the central product because it integrates key engineering disciplines such as mechanics, control systems, and electrical engineering, while simultaneously representing technological innovation and industrial progress. In addition, the robotic arm can be used to automate selected process steps.

To develop possible learning scenarios, it is necessary to analyze the competencies that each learning venue is expected to develop both within university engineering education and within inter-company vocational training. This comparison helps to define the specific emphasis areas of each learning site.

Table 1 illustrates overlaps and differences in competency development. A substantial intersection becomes visible, while the main differences concern the complexity and scope of the problem settings. Vocational apprentices typically require applied,
activity-oriented skills tailored to concrete operational tasks, whereas university pro- grams focus on cross-disciplinary, complex and innovation-oriented problem solving.

**Table 1.** Required Competence Framework of vocational and higher education. Based on [10, 11].

| **Vocational education and training** | **Both** | **Higher education** |
|---|---|---|
| Professional Competence | | |
| General and theoretical knowledge in the professional field | Knowledge of practical application | Broad and integrated knowledge of scientific fundamentals, understanding of theories and methods of a scientific discipline |
| Methodical Competence | | |
| Practical skills, dealing with application-related problems and tasks | Structuring the work process, goal-oriented and independent work, problem-solving strategies | Ability to innovate, broad range of scientific methods for solving complex problems |
| Social Competence | | |
| | Teamwork, conflict resolution, communicating facts | |
| Personal Competence | | |
| | Set, reflect on, realize, organize, and take responsibility for learning process and work objec- tives | |

Based on this distinction, we propose the following allocation of focal areas within the joint learning environment:

In the ÜBS learning factory, the primary task is the execution of the production process of the robotic arm. The university setting, by contrast, represents an innovation-oriented partner company that analyses, optimizes, and further develops both the process and the product based on the needs of the ÜBS. To support the development of professional action competence, it is crucial that the pro- duction process in the learning factory is modelled as realistically as possible. For this reason, the learning environment simulates authentic customer–supplier relationships.

The central learning task is defined through a customer order submitted to the ÜBS as the production site, shown in Fig. 1. Any identified development needs arising during
production are subsequently transferred from the ÜBS to the university as an additional customer order. Students and apprentices jointly work toward fulfilling the order. Continuous communication and coordination between both groups are essential for achieving the shared goal and for fostering collaborative competence development.

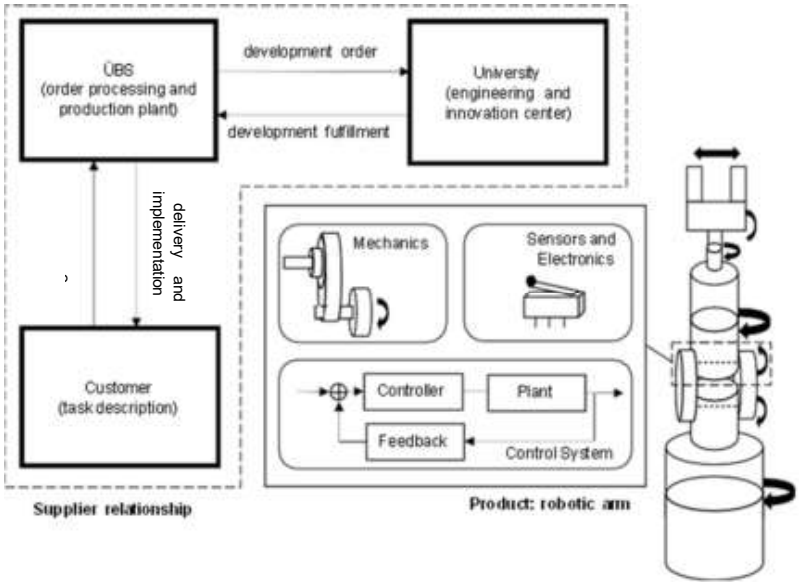


**Fig. 1.** Supplier-Relationship and Product of the Learning Factory.

## 4 Conclusion and Outlook

This paper has presented an integrated approach to connecting vocational and aca- demic learning through a shared Learning Factory environment. By using a joint order- fulfilment process for a robotic arm, a learning scenario was designed to foster collaboration, exchange, and competence development between university students and vocational apprentices. The concept highlights how realistic production processes, combined with structured communication, can support both technical and social skill acquisition.

Looking forward, the presented approach could be expanded into a Learning Factory Network, in which multiple Learning Factories operate in a coordinated manner. Within such a network, each facility could act as both a production and a development site, exchanging intermediate products and process insights with partner Learning Factories. This would allow learners to engage with extended supply chains, experience multi-site coordination, and

tackle more complex, distributed tasks that mirror real-world industrial environments. Such an interconnected structure would further enhance the potential for competence development, particularly in terms of collaboration, problem-solving, and innovation across educational levels. By systematically connecting Learning Factories, educational institutions may create dynamic, collaborative, and realistic learning environments that prepare students and apprentices for increasingly complex professional settings while fostering sustainable, transferable competencies.

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# Student-Driven Innovation Loops: Integration of Next-Gen Technologies into an Existing Lean Learning Factory

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**Abstract.** Learning Factories (LF) are continuously evolving environments that aim to align educational practice with emerging industrial requirements. Recent technological developments, here referred to as next-generation technologies, encompassing digital twin, collaborative robots and augmented reality (AR), have significantly shaped industrial production and, consequently, the skill sets expected from engineering graduates. Updating LF infrastructures to integrate these technologies is therefore essential, not only to maintain technical relevance but also to provide authentic and meaningful learning experiences. This short paper presents the top three infrastructure updates of the last two years at University of Applied Sciences and Arts Dortmund (FHDO) Lean LF, implemented through student-driven innovation loops. In this approach, student projects originating from courses and thesis work contribute directly to the evolution of the LF infrastructure. By integrating new technologies into the physical and digital learning environment, the LF becomes a co-creation space where students actively shape the learning platform while developing competencies in state-of-the-art industrial technologies. The contribution of this work lies in showcasing key technological advancements that have been integrated into the Lean LF infrastructure. The implementation of digital twins, collaborative robots and AR illustrates how next-generation industrial technologies can be systematically embedded into an existing LF environment. These updates strengthen the LF's role as a state-of-the-art testbed for modern production concepts and provide students with direct exposure to advanced industrial technologies in a realistic learning environment.

**Keywords:** Next-Gen Technologies, Student-driven Innovation Loops, LF Infrastructure Update

## 1 Introduction

Learning Factories (LFs) have become essential educational environments for preparing engineering students for modern industrial practices. As industrial production increasingly adopts next-generation technologies, such as digital twins, collaborative robots and augmented reality (AR), the expectations placed on graduates evolve accordingly [1]. To remain relevant, LFs must continuously update their infrastructures and integrate these technologies into their teaching and experimentation environments [2, 3]. Recent studies highlight that modernizing LFs is not only a technological challenge, but also a pedagogical opportunity. It enables the development of authentic competencies and exposure to state-of-the-art production systems [4, 5].

This short paper presents three major infrastructure updates implemented at the University of Applied Sciences and Arts Dortmund (FHDO) Lean LF over the past two years. All updates were initiated and developed through student-driven innovation loops. In the following first the method is introduced, including its theoretical background, related approaches, and the step-by-step procedure for its implementation. Subsequently, the further development of the FHDO Lean LF is presented using this method, starting with a brief description of the current state and followed by the three major infrastructure updates implemented over the last two years. Finally, the

effectiveness of the method is discussed, limitations are addressed, and directions for future development of the approach and its evaluation are proposed.

## 2 Student-Driven Innovation Loops

### 2.1 Theoretical Background and Related Educational Approaches

Student-driven innovation loops represent a structured approach in which students contribute directly to the development of LF infrastructures through project work, coursework or theses. This concept aligns with established educational models, such as project-based and experiential learning, which emphasize active knowledge creation through authentic engineering tasks [5, 6]. Similar principles are also reflected in the Conceive-Design-Implement-Operate (CDIO) framework that promotes design-oriented and implementation-oriented learning in real-world engineering contexts [7].

Recent studies show that involving students in the co-creation of learning environments enhances motivation, deepens domain understanding and results in sustainable improvements of these educational environments [8]. In the context of LFs, such student-driven mechanisms have the potential to expedite the adoption of emerging technologies, concurrently cultivating innovation competencies and reflective learning [9]. The integration of student work into the LF's continuous improvement cycle has been demonstrated to effect a transformation of the environment into a didactic platform and a dynamic development space [10].

### 2.2 Implementation Framework

The implementation of student-driven innovation loops follows a structured process that systematically links educational activities with the continuous development of the LF. At the beginning of each cycle, technological requirements are identified (*stage 1*) through periodic reviews of the existing infrastructure and alignment with emerging industrial trends. These needs are translated into defined project scopes that are integrated into courses or thesis frameworks and assigned to student teams (*stage 2*). Throughout the project period (*stage 3*), students work within a supervised environment in which staff provide methodological guidance and validate intermediate results. Iterative feedback sessions support the refinement of concepts and prototypes, while formal evaluation criteria guarantee that outcomes meet the requirements for potential integration into the operational LF environment. Upon completion of a project, the results are subject to a structured process of handover (*stage 4*). This process includes documentation of the results, as well as their technical verification and incorporation into the physical or digital infrastructure.

This four-stage implementation model is intended to ensure the continuous improvement of the LF, whilst maintaining academic requirements and technological reliability. Student-driven innovation loops are distinguished by their formal coupling of student projects with validated integration into the operational LF infrastructure. Unlike conventional project-based or CDIO-oriented approaches, the method establishes a closed-loop process that ensures continuous, reliable infrastructure development while extending student work beyond purely educational outcomes. To gain practical insight into the application the following chapter presents three next-generation technologies that have been integrated into the FHDO Lean LF over the past two years through student-driven innovation loops.

# 3 Top `Three Infrastructure Updates at FHDO Lean LF

## 3.1 Previous Setup of FHDO Lean LF

The FHDO Lean LF focuses on manual assembly processes and the integration of digitalization to support student learning and innovation. Its flexible assembly system consists of six workstations, storage shelves, conveyors, and transport carts, all designed for modularity and transformability, with additional digital tools including digital value stream mapping, operator assistance systems and sensors. The LF uses a robot kit as a demonstration product to teach lean principles, enabling students to apply lean methods, optimize processes, and design production layouts in a practical, project-oriented environment.

## 3.2 Update 1: Digital Twin

The FHDO Lean LF was expanded to include a simulation-based perspective through the development of a digital twin of the material flow. Utilizing discrete-event simulation software, students developed a model of the assembly process, encompassing workers, workstations, storage, and conveyors. The objective of this study was to methodically compare various personnel and logistics concepts in terms of throughput, utilization, and costs.

In multiple iterations, the layout, process times, and replenishment logic were calibrated so that the simulation model would reflect the real structure of the FHDO Lean LF as accurately as possible. Subsequent to this, the students analyzed scenarios with varying numbers of workers and additional logistics personnel over different observation periods. The model enables the modification of parameters such as the shift model, material replenishment logic, or personnel deployment in real time. Consequently, new simulations are initiated to assess the impact of these modifications without disrupting ongoing operations.

This implementation through a student-driven innovation loop demonstrates how a digital twin strengthens LFs in technological as well as didactical aspects. On the technological side the digital twin serves as an analysis tool to optimize the material flow in the LF. On the didactic side it functions as a teaching medium for simulation, lean management, and data-driven decisions.

## 3.3 Update 2: Collaborative Robot

At the FHDO Lean LF, a collaborative robot (cobot) that had not previously been integrated into the assembly process was gradually incorporated through a student-driven innovation loop. The goal was to automate the screwing of a control unit to the demonstration product, making the process faster and more reproducible than the manual method.

A low-cost screwdriving application was developed based on a pressure-activated cordless screwdriver and through the utilization of 3D printing technologies. This includes the design of a precisely fitting screwdriver holder and a magazine for the assembly parts. Additionally, a fully automated screw conveyor that reliably supplies the cobot with screws was developed by the student. To increase process reliability and transparency an Andon light with an integrated start button was incorporated into the control circuit.

The cobot's process flow is as follows: first, a part is taken from the magazine with the gripper and placed on the assembly product. The cobot then grasps the screwdriver, to which the developed screwdriver holder is attached. Using magnetism, a screw can now be picked up from the screw conveyor and brought to the assembly location. The screw is screwed in by applying pressure. This sub-process is repeated three times until all four screws are screwed in. The screwdriver is then returned to its designated holder and the process starts again from the beginning.

Through this iterative implementation, the student learned to design and realize cost-efficient automation solutions using 3D printing technologies, tool-holder development, and process-reliability enhancements, while the LF benefits from a scalable, low-cost demonstrator that enriches hands-on training in industrial automation.

### 3.4 Update 3: Augmented Reality

An augmented reality (AR) application was developed with the help of a student-driven innovation loop as part of a bachelor's thesis at the FHDO Lean LF to support manual assembly processes. The technical implementation was realized using a head-mounted AR device in combination with a commercial AR authoring and guidance platform. These tools were utilized to construct an interactive, visually supported assistance system that supplants paper-based work instructions.

The application references and highlights assembly objects in designated areas using two-dimensional and three-dimensional elements. It uses visual markers, superimposed contours, and context-sensitive hints for grasping, joining, and positioning, supporting assembly and handling processes. Integrating these visual elements increases transparency and reduces errors. Spatially anchored instructions with media content are clearer and more effective than traditional paper-based instructions.

This project demonstrates how AR can enhance traditional assistance systems by enabling more flexible, paperless, and efficient operational workflows. Furthermore, it emphasizes the potential of AR as a key enabling technology for advancing human-centered production concepts within the Industry 5.0 framework, while providing the FHDO Lean LF with an innovative demonstrator that enriches experiential learning and supports research on future-oriented assistance technologies.

## 4 Discussion

The student-driven innovation loops at the FHDO Lean LF have proven successful, as new technologies were effectively integrated and are now being used sustainably within the LF. The students' strong academic performance, as demonstrated by their high grades, reflects the learning outcomes. Feedback on the method and the projects was gathered both through formal course evaluations and informal discussions related to the projects. Students acquired substantial technical skills in areas such as material flow simulation, 3D printing, design, electronics and sensor technology and coding, while also developing essential soft skills including teamwork, project management, problem-solving, and project documentation.

Limitations of the current approach are the absence of a standardized framework for quantitatively measuring learning outcomes and the technological impact on the LF. These limitations will be addressed in future research. The initiative's main focus was on the technological advancement of the LF and developing a practical didactic framework for student projects. This approach can be transferred to other LFs, provided that similar teaching formats and the necessary technological infrastructure, such as hardware and digital tools, are in place.

## 5 Conclusion and Outlook

This short paper demonstrated how student-driven innovation loops can serve as an effective mechanism for continuously modernizing LF infrastructures while simultaneously enriching engineering education. The three presented updates, a digital twin of the material flow, a cost-efficient cobot application, and an AR-based assembly assistance system, showcase how student projects can generate tangible technological advancements. These implementations highlight that involving students in the co-creation of LF environments not only accelerates the

adoption of next-generation production technologies but also deepens practical competencies in simulation, automation, and human-centered assistance systems. The method of student-driven innovation loops has proven to be particularly effective in this case because it mirrors industrial projects, allowing students to implement real-world technologies in an industry-like, hands-on environment, thereby fostering both practical and soft skills.

From a methodological perspective, future work focuses on developing a systematic evaluation framework for student-driven innovation loops. Such a framework enables the structured assessment of learning outcomes, project quality, and the long-term contribution of student work to the continuous improvement of the LF infrastructure. In addition, it provides a basis for comparing different implementation cycles and for refining the underlying didactic and organizational processes.

From a technological perspective, the innovation loop approach offers substantial potential for integrating further next-generation technologies into the FHDO Lean LF, particularly in the field of artificial intelligence. Possible applications include AI-supported assistance systems that respond to user behavior or process conditions in real time. Extending the existing innovation loops to these technologies would strengthen the LF as a future-oriented testbed and expand its role as a platform for hands-on, technology-driven engineering education.

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# Implementation of a Manufacturing Execution System in Connected Learning Factories

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**Abstract.** This paper presents the implementation of an industrial Manufacturing Execution System (MES) in the connected learning factory "Zukunftsfabrik Bodensee", where two sites form a networked, circular production system. The MES is introduced student-driven using an iterative process-prototyping approach, enabling early feedback and alignment with didactic objectives. The case highlights how university-specific constraints - campus IT, semester rhythms, student turnover - differ from industrial rollouts, and shows that an agile implementation can match didactic flexibility with industrial-grade robustness.

**Keywords:** Manufacturing Execution System (MES), Production Network, Interactive Process Prototyping Playbook, Learning Factory

## 1 Introduction and Background

Learning factories play a central role in developing competencies by combining education, research, and applied industrial practice [1]. This also applies to the Manufacturing Execution System (MES) implementation process which is the focus of this paper. The connected learning factory "Zukunftsfabrik Bodensee" (ZFB) consists of two sites and organizations: DHBW and IWT. ZFB assembles and disassembles microcontroller covers in different variants and follows the concept of circular economy (see Fig. 1) [2]. As in modern network-based architectures, MES standardizes communication and data models, supporting distributed decision-making and scalability [3]. Acting as an operational backbone, MES integrates heterogeneous assets and enables advanced optimization methods, such as data-driven or semantic modeling. In relation to the learning factory ZFB, MES is required to enable both interoperability of all assets and sites as well as make (circular) production processes possible.

This paper addresses the following research question: How can an industrial MES be implemented in a connected, multi-site learning factory while accommodating didactic requirements, organizational constraints, and heterogeneous technical assets?

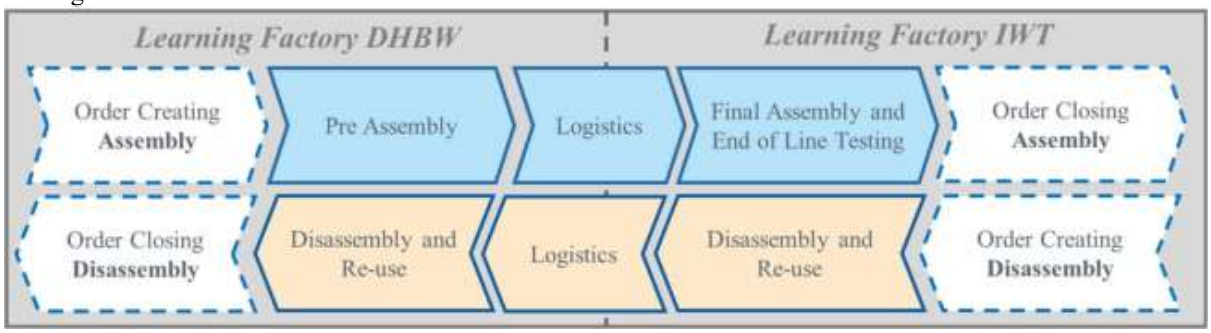

**Fig. 1.** Connected learning factories forming the concept of a circular economy at ZFB

## 2 Implementation Process

While MES are well established in large industrial enterprises, their implementation in small and medium-sized enterprises (SMEs) remains inconsistent due to cost, complexity, and limited internal resources. Therefore, recent studies focus on MES adoption strategies tailored to SME environments [4, 5]. A specific MES implementation framework and structured rollout model were published by Kletti [7], which proceeds through preparation, infrastructure setup, piloting and user training. More recent work, such as Peinl et al. [8], describes a two-cycle model combining strategic planning with iterative Scrum-based customization. In practice, many MES providers offer hybrid variants of these models to balance standardization and flexibility during implementation, such as the agile framework published by Keller et al. [9] for SAP-related systems. However, for MES implementation at learning factories, literature provides only limited insight into the implementation process itself. Even though many learning factories use MES, e.g., Process Learning Factory CiP (TU Darmstadt), Learning Factory for Cyber-Physical Production Systems (RWTH Aachen) [6], or Smart Mini Factory (Free University of Bozen-Bolzano), the specific challenges of academic environments and student-driven development are rarely addressed.

At the learning factory ZFB, MES implementation followed the Interactive Process Prototyping Playbook (IPP®) provided by the MES vendor Forcam Enisco GmbH, reflecting realistic implementation conditions resulting from a long-term industry partnership. Although both learning factory sites need to be operated independently for didactic and organizational reasons, they share concepts, data models, product and teaching scenarios. This motivates a common MES (provider), a coordinated initialization and implementation across both locations. While IPP® originates from a vendor-specific context, its core principles - iterative prototyping, continuous stakeholder feedback, and stepwise system integration (see Fig. 2) - align with established iterative MES implementation approaches. Consequently, the implementation presented in this paper is transferable beyond the specific vendor solution and learning factory setup.

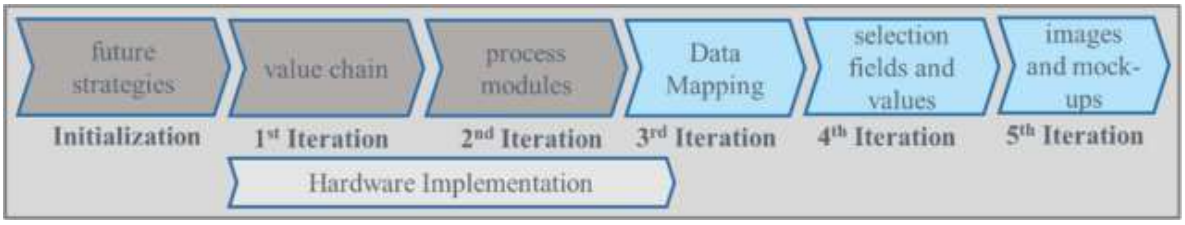


**Fig. 2.** IPP® [9] and hardware implementation

In principle, any MES implementation in learning factories can be done faster than in industry because scope and risk are lower. However, semester rhythms, student turnover, didactic goals and specific security requirements in university networks tend to slow down hardware-based MES implementation, especially in a network of connected learning factories. In the following, initialization of MES implementation at ZFB is described first, then hardware implementation and finally data mapping and configuration.

### 2.1 Initialization, Value Chain and Process Modules

In the initial workshop concept and current status of ZFB was outlined, and the requirements were defined with stakeholders of both factories. This includes visualizing the ZFB value chain and mapping the individual assets

and their interaction in more detail. This was done for all relevant operation modes, such as assembly and disassembly and product variants. Both joint and independent operation led to further operating modes and scenarios. After key-user training, students started to create process modules and to refine these operating modes.

### 2.2 Hardware Implementation

Based on the workshop results, system and architecture was defined by university staff. A three-tier architecture is chosen, consisting of an application server, a database server, and dedicated data acquisition servers (see Fig. 3). The system is dimensioned according to the expected number of workstations, machines and events per shift. For the ZFB learning factory, one MES instance and two data acquisition servers are defined. The architecture defines logical zones to separate MES, data acquisition and local IT. The physical host server is located at DHBW Ravensburg data centre and accessed via VPN. Therefore, a Proxmox virtualization environment enables the strict separation of roles and services, which is essential for security in the university network and for protecting other campus systems from experimental MES setups.

The database server runs Windows Server 2025 and Microsoft SQL Server. The application server, also on Windows Server, hosts the MES application from Forcam Enisco GmbH, which is connected to the database and configured (language, time zone, formats). For data acquisition, a Ubuntu-based server for each learning factory is virtualised. The industrial IoT gateway "Forcam Edge Connect" solution is installed and configured on these servers to collect signals from the assets and securely communicate with database and application server.

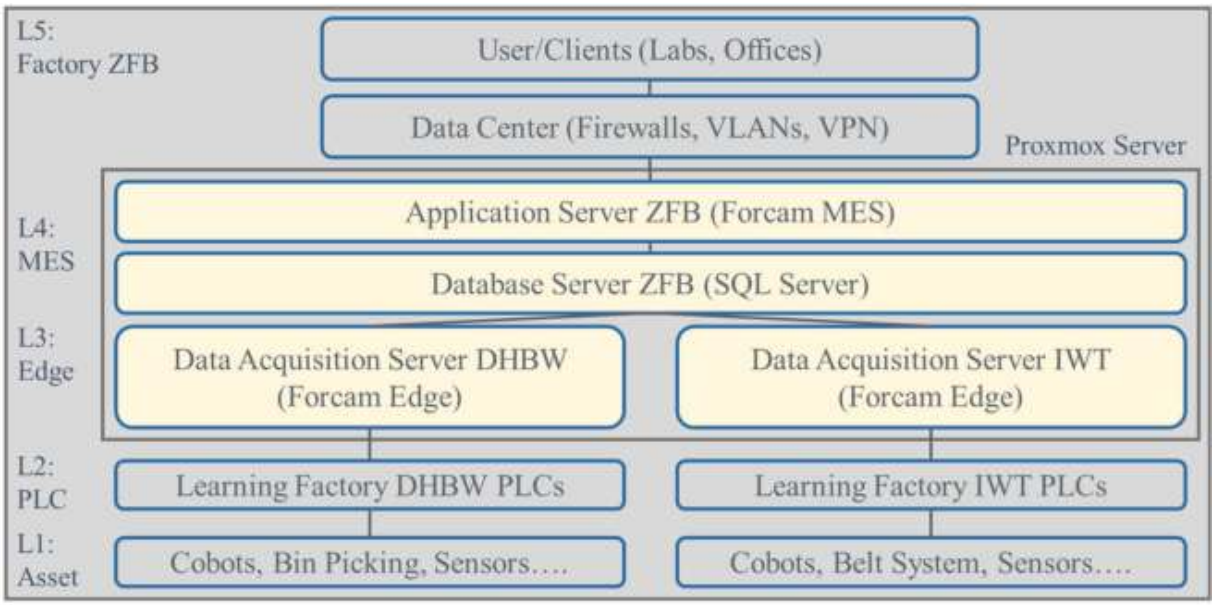


**Fig. 3.** IT architecture implemented using Proxmox virtualization at ZFB

### 2.3 Data Mapping, Field Selection and Configuration

With the infrastructure in place, the configuration of the data acquisition via Edge Connect was started by students. For each asset, suitable northbound communication protocols (e.g. OPC UA, MQTT) are selected. Based on the didactic, process and reporting requirements, the relevant signals are then defined and mapped, such as operating

states, downtimes and piece counters. For every signal from every asset a composition script is created to configure the entry specifying IP address, protocol, ports and the mapping of control variables to MES fields. One specific challenge is that the two learning factories operate on different IP ranges and are physically separated. Edge Connect reaches all machines via a routed link with IP address translation, while the production networks remain separated.

After the connection, the MES is functionally configured. A hierarchical resource structure is created that maps plants and assets to the real factory layout, following standards such as ISA-95. Shift models are defined, including regular shifts, planned downtimes and holidays. For downtime and quality analysis an individual catalogue of categories and reasons is configured. In parallel, user roles and an authorisation concept are set up to distinguish, for example, between student and administrator rights and to restrict access to critical functions. This separation is particularly important in a university setting, where many users work in the same system and experimentation must not jeopardize stability or security.

There is currently no direct integration with an ERP system. Instead, both learning factories use an XML-based ERP substitute provided by Forcam Enisco GmbH, which communicates with the MES via a bridge Application Programming Interface (API). Data exchange is bidirectional via a secured REST API: master and order data are transferred to the MES, while event logs, quantities and timestamps are reported back. For teaching and running ZFB, this “lightweight ERP twin” is sufficient and avoids the complexity of integrating a full enterprise ERP into the university environment.

### 2.4 Results

After a year of successful initialization and hardware implementation, data mapping could begin. Here, the students were able to connect four assets in just three months. Over 65 signals - covering essential asset parameters (machine states, cycle metrics, production quantities) - were connected, representing over 50% of initially scoped signals. This architecture enables transmission with a latency of <1s, supporting real-time monitoring dashboards and operator decision-making. Further, a shift model tailored to teaching and operation is now available, together with basic order management and master data for one product variant. From a didactic perspective, students gain

hands-on experience in distributed systems configuration and network architecture spanning two geographically separated sites.

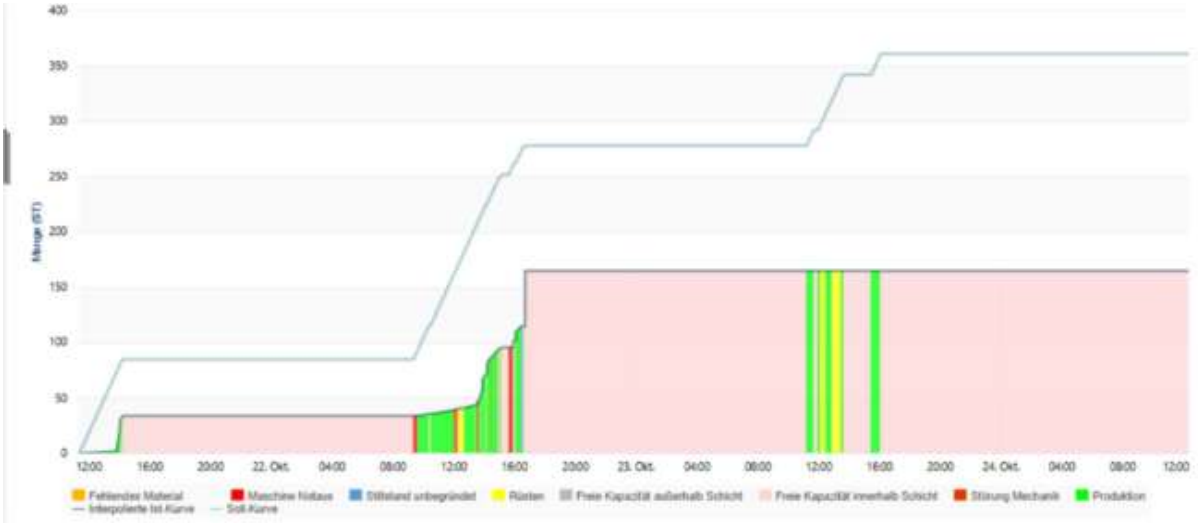


**Fig. 4.** Example of MES report for KPI operating states and piece counters at ZFB

Overall, the interactive implementation process was successful and the first results proved that the approach worked well for staff and students in the context of connected learning factories. Basic system, connections, and implementation prove robust and ready for further expansion. Current implementation prioritizes assembly/disassembly data visualized in Fig. 4. Additional KPIs - including lifecycle phase (remanufacturing), component recovery status (new, recovered, reused, recycled), and component recovery rate - will be introduced in the next semester.

## 3 Conclusion and outlook

The implementation at the connected learning factory ZFB shows that industrial MES concepts and implementation models can be transferred to learning factories, but not without adaptation. On one hand, the Interactive Process Prototyping Playbook (IPP®) proved suitable as a guiding framework: the iterative structure, early mock-ups and feedback cycles fit well with student projects and semester-based teaching. Results were available quickly, and students were exposed to hands-on MES configuration tasks. On the other hand, several characteristics clearly distinguish the learning-factory context from typical industrial MES projects. First, hardware-related activities progressed more slowly than software configuration. Semester rhythms, student turnover and varying prior knowledge led to repeating ramp-up phases. The lesson to be learned from this is that in learning factories, MES implementation requires particular attention to hardware infrastructure stability and human resource continuity, rather than focusing primarily on software configuration. Second, the distributed architecture (separate sites, different IT policies, routed network connectivity) introduced infrastructure complexity typically absent in single-site learning factories. Security integration with university IT, VPN access control, and multi-site data consistency required more oversight than anticipated. From a didactic perspective, this complexity becomes an asset: students experience realistic distributed systems challenges (network latency, security segmentation, inter-organizational

IT governance) that pure single-site facilities cannot replicate. Future work includes: (1) stabilizing data quality and extending Tier 2 signal integration for circular production scenarios; (2) measuring student learning outcomes via structured rubrics (Semester 2, planned for Spring 2026); (3) evaluating whether multi-site implementation provides didactic advantages over single-site learning factories.

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# Engineering Learning Factory - Transforming Engineering Education through an Interdisciplinary Experiential Learning Environment

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**Abstract.** Traditional frontal lecture-based approaches alone are no longer sufficient to prepare graduates for complex, interdisciplinary, and practice-oriented challenges in industry. To address this need, the Free University of Bozen-Bolzano is establishing a new Engineering Learning Factory as a cornerstone of its Faculty of Engineering. This new Engineering Learning Factory should be an interdisciplinary, experiential learning environment that integrates real-world processes, advanced technologies, and collaborative project-based education. By simulating authentic industrial contexts, students engage in hands-on experiences that combine mechanical, electrical/electronic and computer engineering with management, sustainability, and creative design perspectives. This approach not only fosters to increase technical proficiency of methods learned in theory, but also problem-solving, teamwork, and entrepreneurial skills of engineering students. The concept builds upon the global Learning Factory movement and community, while tailoring it to specific territorial needs and a close cooperation with regional industry. This facility will provide students with a unique platform to develop competencies that extend beyond disciplinary boundaries, preparing them to become reflective, responsible, and future-oriented engineers. This short paper provides insights about the future plans of the Free University of Bozen-Bolzano to expand the learning factory concept from single industrial engineering courses to the whole faculty of engineering highlighting didactical challenges.

**Keywords:** Learning Factory, Engineering Education, Problem-based Learning, Project-based Learning, Experience-based Learning.

## 1 Introduction

Engineering education is undergoing a fundamental transformation driven by increasing system complexity, rapid technological change, and the growing demand for interdisciplinary collaboration in industrial practice. Engineers are increasingly required to design, operate, and optimize complex socio-technical systems that span products, factories, companies, and supply chains. While traditional lecture-based teaching remains essential for conveying theoretical foundations, it often falls short in preparing students for the complexity, uncertainty, and integrative nature of real-world engineering challenges. In response, experiential learning approaches such as project-based learning, problem-based learning, and Learning Factories have gained prominence in engineering education. However, many existing Learning Factories remain focused on single disciplines or isolated courses, limiting their potential to support holistic engineering education across entire faculties to address this gap, the Free University of Bozen-Bolzano is developing an Engineering Learning Factory (ELF) as a faculty-wide experiential learning ecosystem. Building on an existing industrial engineering Learning Factory, the ELF extends the concept toward an interdisciplinary environment that integrates product development, industrialization, and operational processes, while embedding transversal themes such as sustainability, digitalization, and human-centric design.

# 2 State of the Art

## 2.1 Learning Factories in Engineering Education

A Learning Factory is commonly defined as a realistic representation of a factory system that integrates products, processes, resources, and organizational structures within an experience-oriented, participative, and often digital learning environment, allowing learners to apply acquired knowledge at an interactive level to increase competence [1,2]. Pittich et al. show that Learning Factories are particularly well suited for complex competence acquisition, as they combine action-based and comprehension-based learning within authentic production contexts [1]. Learners typically cycle through planning, execution, and reflection phases, enabling theoretical knowledge to be contextualized and transferred to new situations.

Empirical studies further demonstrate that action-oriented learning in Learning Factories enhances student motivation, learning retention, and professional development compared to conventional classroom instruction [3]. In addition to technical competencies, Learning Factories naturally foster communication, teamwork, and decision-making skills through collaborative problem-solving in realistic settings—competencies that are consistently identified as essential for modern engineers but difficult to develop through traditional teaching formats [4].

Learning Factories exist in a wide variety of forms and configurations. Comprehensive frameworks and morphologies distinguish between Learning Factories in the narrow sense - physical, on-site environments with real value creation—and broader concepts that include virtual, remote, and hybrid implementations [2]. From a didactical perspective, Learning Factories are grounded in experiential learning theories as well as problem-based and project-based learning approaches (PBL). Students actively engage in open-ended tasks, often working in multidisciplinary teams to analyze, design, operate, and optimize systems.

## 2.2 Future Trend Towards Project- and Problem-Based Learning

Recent developments in PBL and experiential learning indicate a clear shift toward technology-enhanced, interdisciplinary, and authentic learning environments that better prepare students for contemporary engineering challenges [5]. At the same time, PBL and experiential learning are increasingly embedded in broader organizational and societal contexts. Industry-enriched learning formats integrate external partners into curricula, enabling students to work on authentic challenges and bridge the gap between academic education and professional practice. Similarly, international and cross-cultural collaboration is expanding through digitally supported formats that allow students from different institutions and countries to jointly participate in PBL activities. Such global learning experiences contribute to the development of teamwork, communication, and problem-solving competencies in culturally diverse settings [6,7]. Pedagogical approaches like PBL provide contextualized understanding of engineering knowledge and design processes, support the integration of sustainability and societal considerations, and contribute to the development of competencies required for professional practice in dynamic and uncertain environments [8–9].

# 3 Future Engineering Learning Factory

## 3.1 Current Status

The Smart Mini Factory at the Free University of Bozen-Bolzano is designed as a Learning Factory for Industry 4.0, combining education, research, and industrial collaboration within a realistic manufacturing and assembly environment. Its primary goal is to enable experiential, hands-on learning that mirrors the complexity of modern and smart production systems while remaining flexible and modular for teaching and experimentation. As a

Learning Factory, the Smart Mini Factory allows students from industrial engineering and practitioners to actively engage with Industry 4.0 technologies rather than studying them in isolation. The facility integrates cyber-physical systems, industrial IoT, digital twins, collaborative robotics, and manufacturing execution systems to support learning in industrial assembly. Participants can design, operate, monitor, and optimize assembly systems, gaining practical insight into smart manufacturing and human–machine interaction. Manufacturing, production logistics, and robotics perspectives are combined to address real industrial challenges similar to those of real factories. In addition to academic education, the Smart Mini Factory functions as a training and demonstration platform for industry.

### 3.2 From an Industrial Engineering LF Towards an Engineering Learning Factory Serving the whole Faculty of Engineering

The scope of the current Learning Factory for Industry 4.0 is largely centered on industrial engineering perspectives. As product development and manufacturing systems increasingly require the close integration of mechanical design, electronics, software, and data-driven methods, this discipline-specific focus limits the potential for holistic engineering education across the full product lifecycle. To address these limitations, the Free University of Bozen-Bolzano is developing a faculty-wide Engineering Learning Factory (ELF) that extends the existing Learning Factory concept beyond industrial engineering toward an interdisciplinary engineering education environment. The ELF is designed to integrate mechanical engineering, electronics, computer science, and industrial engineering along the full product lifecycle—from idea generation and product design to industrialisation and operational processes (see Fig. 1).

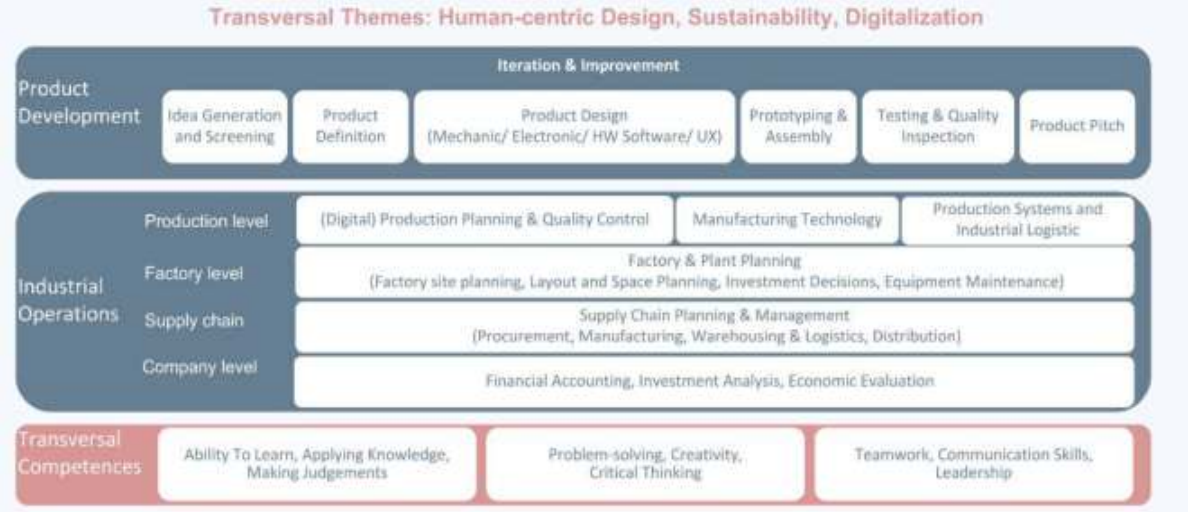


**Fig. 1.** Interdisciplinary and transversal themes in the ELF lifecycle

The conceptual foundation of the ELF follows a systems-oriented perspective that explicitly links product, factory, and supply chain levels. Learning activities are structured to allow students to experience how decisions made during early product development phases influence manufacturing processes, logistics performance, sustainability outcomes, and economic viability. This integrated view supports systems thinking and enables learners to understand engineering decisions within broader organizational and societal contexts. A key design principle

of the ELF is its alignment with project- and problem-based learning and experiential learning approaches. Students work in interdisciplinary teams that require the integration of multiple engineering domains. Rather than following rigid, predefined workflows, learning scenarios are intentionally designed to allow degrees of freedom, uncertainty, and iterative development, reflecting real engineering practice.

### 3.3 Innovation-Oriented and Start-up–Like Learning Scenarios

In addition to its educational objectives, the ELF provides an environment resembling early-stage innovation and start-up contexts. Students from different engineering disciplines collaborate across mechanical, electronic, software, and management domains without rigid organizational structures. Through interdisciplinary projects covering the full product lifecycle—from concept development to prototyping and testing—students experience realistic coordination, system integration, and design trade-offs under constraints of time, resources, and performance. This loosely structured, project-driven setting encourages rapid experimentation, iterative development, and informal collaboration, reflecting innovation processes commonly found in start-ups. As a result, the ELF not only supports interdisciplinary engineering education and preparation for industrial roles but also fosters an entrepreneurial mindset and enables innovation-oriented outcomes such as prototypes, product concepts, and potential start-up ideas.

### 3.4 Pilot Scenario: Interdisciplinary Drone Development Project

To operate the ELF concept, a drone development project is used as a representative interdisciplinary pilot scenario representing a highly integrative product that requires the interaction of mechanical design and manufacturing, electronics, control and software. Within the ELF, student teams work on the drone project from idea generation and requirement definition through design, prototyping, testing, and industrialization-oriented considerations. Students from the mechanical and industrial engineering program focus on structural design and manufacturing feasibility, including additive manufacturing and assembly concepts. Digital tools such as CAD/CAE are combined with physical prototyping and testing within the ELF infrastructure. Production planning, cost estimation, logistics, quality assurance, integration of AR/VR and sustainability assessment will be addressed in future courses. While the current implementation primarily involves industrial engineering perspectives, the integration of electronics and computer engineering is planned as a next development phase of the Engineering Learning Factory. The drone project serves as a demonstrator illustrating how the ELF enables faculty-wide, lifecycle-oriented, and interdisciplinary experiential learning. The scenario is scalable and transferable to other product types.

### 3.5 Challenges

The successful implementation and long-term sustainability of the ELF face several significant challenges. A primary difficulty lies in integrating interdisciplinary, project-based activities into existing curricula, which often lack the flexibility required for coordinated learning across multiple courses and disciplines. The transition from traditional lecture-based teaching to facilitation- and coaching-oriented roles requires substantial pedagogical adaptation, training, and institutional support from teaching staff. Additionally, assessing learning outcomes in innovation-oriented and start-up–like settings remains complex. Conventional assessment methods are often inadequate for capturing interdisciplinary collaboration, iterative learning processes, and entrepreneurial competencies.

### 3.6 Evaluation Concept

Student performance within the drone-based pilot project is currently assessed using a structured rubric-based evaluation framework aligned with the intended learning outcomes. Assessment consists of three components: (1) an oral project presentation evaluating communication quality, (2) a written technical report assessing methodological rigor and system-level thinking, and (3) the drone design and prototype, evaluated in terms of functionality and feasibility. This initial evaluation results primarily serve formative purposes, supporting iterative refinement of learning scenarios, assessment methods, and curricular integration. Summative evaluation and comparative studies are planned as the ELF matures.

## 4 Conclusion and Outlook

This paper introduces the Engineering Learning Factory (ELF) as a faculty-wide experiential learning ecosystem that extends traditional Learning Factory models toward interdisciplinary, project-based, and innovation-oriented engineering education. By integrating product development, industrialization, and operations across the engineering lifecycle, the ELF addresses the growing complexity of modern engineering systems. It supports holistic competence development through authentic, open-ended projects that combine technical, social, and entrepreneurial learning outcomes. Start-up–like collaboration fosters systems thinking, interdisciplinary coordination, and innovation-oriented mindsets, while increasing student engagement and program attractiveness. Future work will report empirical results from the drone-based pilot scenario and longitudinal competence development analysis.

**Disclosure of Interests.** The authors have no competing interests to declare that are relevant to the content of this article.

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# Who Doesn't Make a Learning Factory for Sustainability? The Domain Difference That Impeed Interdisciplinarity

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**Abstract.** Industry improvements encompass multiple domains in the pursuit of manufacturing innovation. Consequently, preparing tomorrow's workforce depends on interdisciplinarity and digitalisation, with learning factories emerging as a viable means of promoting such competencies. However, when sustainability learning goals are introduced, disciplinary differences can become a hindrance. Based on a document analysis and interviews conducted across ten education programmes at four providers of European Qualifications Framework levels 5 and 6 in Denmark, this study demonstrates how field-specific perceptions of sustainability, more so than those of digitalisation, embedded in regulation and on-the-ground educational practice create barriers to cross-domain learning factories. Educators, researchers, and institutions should consider these barriers when developing future multi-domain learning factories. The study yields two key findings. First, the interviews revealed that educators across the various programmes recognised the need for learning factories to generate data that informs sustainability calculations. Second, while the document analysis revealed an interest in sustainability issues, it also showed that this interest is not consistently supported by a common terminology on sustainability. The study identifies two ways in which educational institutions can ease barriers to interdisciplinary learning factories: through governance measures that mainstream sustainability vocabulary and priorities, and by encouraging educators to develop a common language within the learning factory environment.

**Keywords:** Barriers, Interdiciplinarity, Sustainability, Digitalisation

## 1 Introduction

Knowledge that spans disciplinary domains is difficult to develop yet crucial, as much innovation potential lies at the intersection between fields [1, 2]. This is also evident in manufacturing innovation, where the coherence between digitalisation, automation, and related technologies has been driving the manufacturing agenda [3]. Addressing this convergence requires both technical adjustments and knowledge management. Learning factories have proven to be a viable approach to crossdisciplinary learning, enabling students, industrial employees, and researchers alike to understand the interconnectedness of the industrial landscape [4]. These multi-dimensional learning factory activities – consisting of a learning purpose, didactical concepts, an operational model, a setting, a product, and industrial processes [5] – mimic the actual industrial environment in several dimensions and have proven effective in transferring technical knowledge within disciplines, and in translating knowledge across disciplinary boundaries [6].

One area where this approach is particularly relevant is the intersection of sustainability and digitalisation, which highlights the need to consider eco-innovation [7]. Learning factories have also been proposed as a way to foster students' innovative mindset, while sustainability-oriented learning factories are increasingly described in the literature as inherently interdisciplinary [8]. Addressing sustainability challenges requires learners not only to understand sustainability options within their own field, but also to recognise that improvements from one disciplinary perspective may create challenges for others. For example, energy savings achieved through improvements in production processes may far exceed reductions related to programming efficiency, illustrating how sustainability impacts vary across domains. Hence, sustainability-oriented learning factories provide a versatile space for trade-offs between disciplines [9]. Such needs may arise from legislation, national or local study plans, or from perceived knowledge gaps between learners and educators. Moreover, these gaps often involve both explicit and tacit knowledge, which further complicates knowledge transfer.

This study examines the variations in perceptions of digitalisation and sustainability within learning factories among institutions. It does so through document analysis and interviews with educational professionals across four Danish providers of higher technical education

## 2 Methods

To investigate this, a dual-method approach was employed, consisting of document analysis and a series of semi-structured interviews with educational professionals [10]. The targeted education programmes were selected across four higher education institutions using theoretical sampling based on their familiarity with the concept of learning factories or other simulation activities at their institutions, as well as the inclusion of learning goals related to digitalisation and sustainability. The selected programmes represent different technical domains, primarily production, automation, IT, and process technology. The analysis therefore relies on documents and interviews from four higher education providers, eight programme types, ten individuals, and six educational sites, all collected over a two-month period.

The analysis of the governing documents was conducted at multiple levels, including the governing law, legislative appendices, national study plans, and local study plans, with a focus on how digitalisation and sustainability are described.

The interviews were conducted to investigate how digitalisation and sustainability are understood across different educational institutions and faculties, with a particular emphasis on how learning goals are translated into learning activities and assessment criteria. The interviews also explored participants' experiences with learning factories [10]. They were guided by topics related to learning factories: familiarity, use of simulations, potential conversion of activities, current use practices, need for digitalisation elements, and need for sustainability elements.

The four institutions exhibit varying degrees of readiness for learning factories. All had previously participated in learning factory-related projects prior to the study and had also conducted research in the area. However, the degree of anchoring across the different institutions differed both in terms of manpower and capital investment. A learning factory readiness model is shown in Figure 1, in which the enrolled institutions are positioned at different stages of readiness.

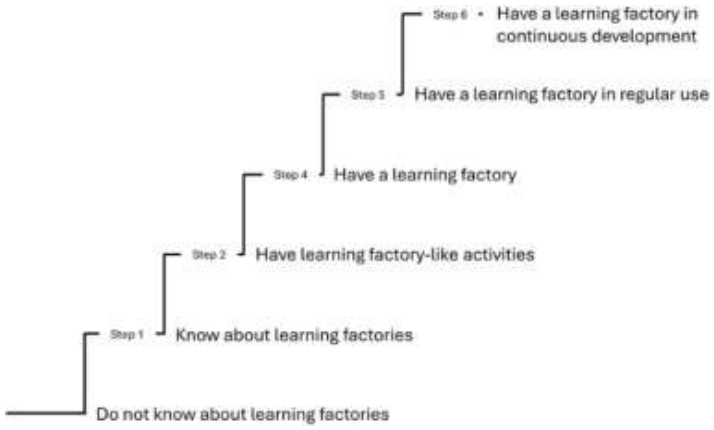


**Fig. 1.** Learning factory readiness. Own production.

## 3 Results

The document analysis reveals the potential for implementing learning factories, while the interviews highlight both the barriers to and opportunities for their adoption. The analysis shows that both digitalisation and sustainability are incorporated into national legislation, study plans, and local appendices, thereby enabling students in the selected programmes to engage with these topics.

Digitalisation was often mentioned explicitly, extending to the technology level (programming languages, design tools, and manufacturing processes). Although implementation varies across educational settings, digital skills generally dominate learning objectives, reflecting the role of digitalisation in strengthening overall competencies. In contrast, digitalisation, understood as the broader process of transforming analogue processes into digital ones, was mentioned less.

Meanwhile, sustainability was typically referenced in broader and less operational terms, often framed as an area students should be aware of rather than master. It was described in general terms, with limited definitional precision and few explicit connections to technologies or specific industrial processes.

Educators were positive about using learning factories to demonstrate complex yet controllable effects that are often otherwise only treated theoretically, as in the planning and control of factory production. Many interviewed educators found it particularly appealing to use the learning factory as a vehicle for connecting this theory to physical, tangible activities. Overall, most educators reported that they were ready to adopt a learning factory approach in their education to illustrate complexity and connect learning activities to students' prior knowledge. However, two primary concerns emerged: the need for appropriate equipment and the organisational challenges associated with interdisciplinarity.

Whereas the document analysis uncovered non-specific definitions of sustainability – ranging from broad sustainability definitions such as the UN 17 Sustainable Development Goals to narrower definitions based on minimising resource consumption – the interviews with educators indicated that these governing objectives are typically translated into a more limited operational definition in practice, often centred on reducing CO2 emissions. The consensus found in this narrow definition of sustainability facilitates the operationalisation of sustainability within learning factory activities, but it may also oversimplify the complexity of sustainability challenges in real production environments. A second key finding from the interviews was educators' desire to introduce measurement equipment into learning factory setups. Such equipment would enable data collection during production

runs, allowing learners to use real operational data in sustainability simulations. Interviewees emphasised that working with data generated within the learning factory itself – for example in life cycle assessments (LCAs) – is far more meaningful than relying on standardised reference data, as it enhances realism and learner engagement. A third key takeaway is that perceptions of digitalisation and sustainability differ across domains. IT professionals tend to focus on the energy consumption and hardware requirements associated with software solutions, whereas production specialists primarily consider material consumption and waste streams. These differences highlight the importance of aligning sustainability and digitalisation concepts through task-centred learning design to support interdisciplinary collaboration.

As shown in the model above (1), the enrolled institutions span steps 1, 2, 4, and 6. The first institution is at step 1: they are familiar with learning factories from a previous project but have not yet started working on them, nor have they formed the interdisciplinary bonds between educators that can aid the internal development of the learning factory. Individual educators recognise potential benefits but lack firsthand experience. Nevertheless, they readily connect learning factory dimensions to their sustainability activities. The second institution is at step 2: it has implemented activities resembling learning factories, having experimented with extending course domains beyond traditional disciplinary boundaries. However, these efforts have not yet been supported by educator upskilling or investment in software and hardware infrastructure. The institution nevertheless intends to pursue further development in the near future. The third institution (at step 4) operates an in-house learning factory, purchased off the shelf. However, the system has not been significantly adapted to local educational needs and therefore continues to rely largely on the preprogrammed modes installed at purchase. Despite this limited customisation, the setup helps students and educators view production processes from a continuous improvement perspective. These modes have served their intended purposes well and have therefore remained largely unchanged for several years. The fourth institution (at step 6) has a learning factory in continuous development. There is strong employee interest, but major hardware investment has not been made. Both students and educators improve the setups each semester.

It should be noted that although case four demonstrates higher readiness, its learning factory may not necessarily be more technologically mature than that of case three. Off-the-shelf solutions can offer substantial advantages, while developing in-house solutions typically requires significant time and resources.

## 4 Discussion and Conclusion

Learning factories can provide a shared task for different professions, as learning must build upon prior knowledge. Many learning factories excel in demonstrating new knowledge, but collaboration across domain boundaries can be challenging. Learning factory practitioners must consider this when creating organisational readiness, particularly concerning sustainability and digitalisation.

Figure 2 shows three modes of interdisciplinary collaboration. In the first, the educators work together and develop interdisciplinary knowledge with their own students. This could be a joint development of cases. In the second mode, educators work together in both development and teaching. Here, the educator from the neighbouring domain can illuminate students' prior knowledge and facilitate discussion and validation. In the third mode, the students work together in the learning factory, developing a shared understanding and language.

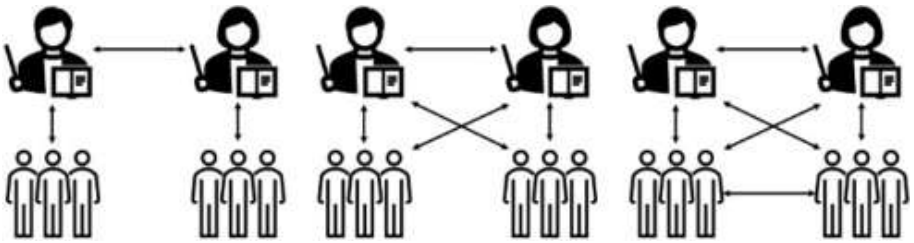

**Fig. 2.** Modes of interdisciplinarity: (A) the educators work together, but apply alone; (B) they also teach together; and (C) the students meet across disciplinary boundaries.

Even in learning factories undergoing continuous development, interdisciplinary differences can be a hurdle, as shared prior knowledge may not be established, making interdisciplinarity difficult to achieve. This is evident for digitalisation, which carries different meanings across production, process, automation, and IT professionals. Likewise, sustainability is interpreted differently across the educational domains. Furthermore, organisational readiness does not necessarily imply maturity, and it remains unclear how long maturity takes to develop or to what extent it can be acquired through investment rather than built through iterative use. While equipment investment is often crucial for demonstrating authenticity and linking learning to prior knowledge, authentic collaboration and learning outcomes cannot be fully purchased; they emerge through repeated, structured engagement within the learning factory environment.

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# An IoT-Enabled LMS Framework for Learning Factories: IkasMES

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**Abstract.** Learning Factories (LFs) are key infrastructures for bridging the gap between theoretical education and industrial practice in vocational education. In Basque VET centres, LFs and Learning Management Systems (LMS) have operated as entirely separate systems, with instructors manually transferring shop-floor data into the LMS a fragmented approach that limits self-directed learning and data-informed formative assessment. This short paper presents IkasMES, an IoT-enabled LMS framework developed at Tknika that acts as an "educational MES" connecting pedagogical planning with real production activities for the first time. The architecture combines an IoT sensing layer, a data integration and KPI derivation layer, and LMS services for managing learning workflows and visual dashboards for students and instructors. Built on open-source technologies and designed for replication across the Basque VET network, IkasMES is deployed as a laboratory-scaled pilot with instrumented workstations, secure OT/IT separation, and role-based access to learning data. A design science methodology guides the development, including needs assessment with Basque VET stakeholders and a planned quasi-experimental evaluation. Preliminary insights indicate strong stakeholder interest and the feasibility of using real-time operational data to support self-directed learning, challenge-based learning, and more objective feedback processes. Future work includes AI-driven adaptive learning paths for learners with special needs, developed in connection with the European project SkillAIbility and aligned with the human-centric vision of Industry 5.0.

**Keywords:** Learning Factory, IoT, Manufacturing Execution System, Challenge-Based Learning, Vocational Education, Self-Directed Learning.

## 1 Introduction

Learning Factories (LFs) provide authentic production environments in which vocational learners can apply theoretical knowledge in realistic industrial contexts. In the Basque Vocational Education and Training (VET) system, Tknika's Learning Factory plays a central role as a testbed for Industry 4.0 technologies and innovative didactic approaches such as challenge-based learning [1, 2]. Despite this infrastructure, a persistent gap remains between what happens on the shop floor and what is captured in digital learning environments.

In Basque VET centers, Learning Factories and Learning Management Systems have coexisted as entirely separate systems. Instructors used the LMS for content delivery, assignment management and assessment, while the LF operated as a standalone physical environment. Any connection between the two relied on manual effort: instructors collected data from the shop floor and entered it into the LMS by hand. This fragmented approach offers limited visibility of learners' actual activity [3, 4], creates significant administrative overhead, and delays the feedback that is essential for self-directed and challenge-based learning.

To bridge this gap, Tknika has initiated the IkasMES project: the development of a purpose-built, IoT-enabled LMS framework that integrates the Learning Factory directly into the digital learning ecosystem. IkasMES is conceived as an educational equivalent of a Manufacturing Execution System (MES) [5] it links learning modules and challenges defined in the LMS with the execution of tasks at instrumented workstations, capturing machine and process data and translating it into pedagogically meaningful indicators. Built entirely on open-source technologies, IkasMES is designed from the outset to be replicable and transferable across the network of Learning

Factories in the Basque VET system. The framework aims to support self-directed learning, challenge-based learning, and data-informed formative assessment.

This short paper has two goals: (1) to present the core architecture and deployment of IkasMES in Tknika's LF, and (2) to outline the methodological approach and planned evaluation that will compare IkasMES against a traditional LMS in a real VET setting. The focus is on the integration of infrastructure and pedagogy rather than on final learning outcomes, which will be reported in future work.

## 2 IkasMES Framework and Architecture

### 2.1 Conceptual Model

IkasMES is structured around four layers that link physical operations in Tknika's Learning Factory with learning processes:

- **Layer 1 – Sensing and activity capture:** Machines, tools and workstations in the LF are equipped with sensors and PLCs that capture machine states, cycle start/stop events, and operator identification. These data streams create a continuous trace of students' physical activity.
- **Layer 2 – Data integration and pedagogical KPIs:** An IoT data pipeline aggregates and stores time-series telemetry and learning-related events. Processing services transform raw signals into pedagogically relevant indicators such as time-on-task, task completion, error frequency, or machine utilization during specific learning challenges.
- **Layer 3 – Learning execution management (IkasMES LMS core):** LMS services manage roles (students, instructors), challenges, tasks, and assessment records. Each task instance in a challenge is linked to its corresponding operational data, allowing learning artifacts and physical performance metrics to be viewed together.
- **Layer 4 – Visualization and interaction:** Dashboards integrated into the LMS provide students with real-time feedback on their performance in the LF and allow instructors to monitor the progress of teams and identify bottlenecks or support needs.

This layered structure ensures that technical components directly serve educational workflows while maintaining modularity for future extensions (Fig. 1).

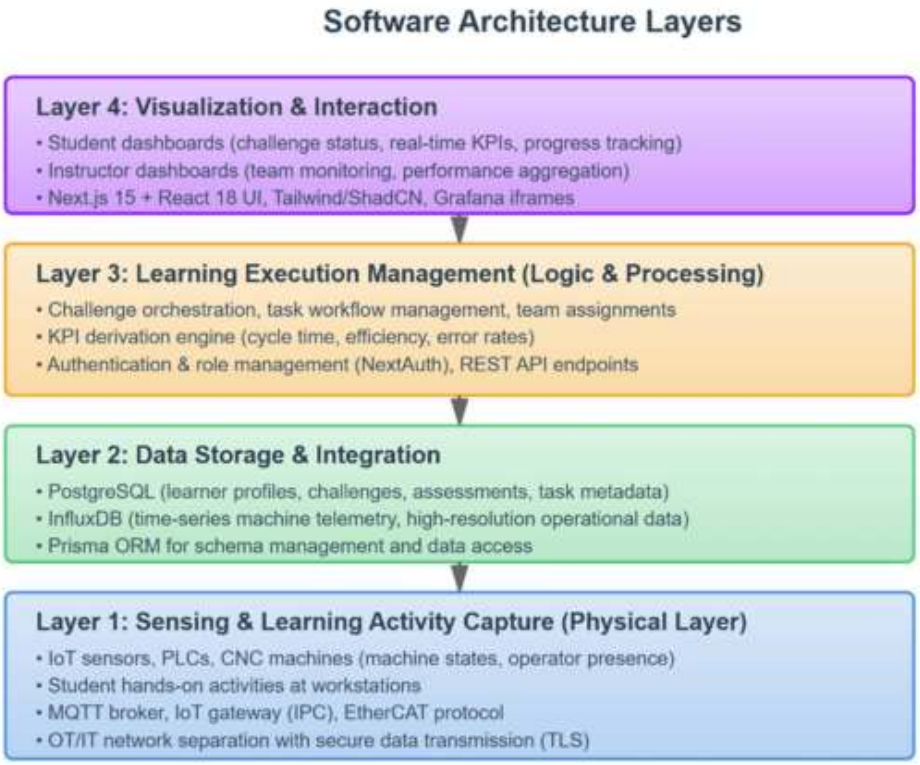


**Fig. 1.** Software architecture layers of IkasMES showing vertical integration from physical operations to user interaction.

### 2.2 Physical and Logical Deployment at Tknika

The pilot implementation of IkasMES is deployed in Tknika's Learning Factory as a laboratory-scaled cell composed of several instrumented workstations. Each station combines configurable benches, industrial equipment, and sensing infrastructure to monitor machine status and operational events. Students interact with these stations as part of challenge-based learning scenarios.

Operational technology (OT) devices in the LF are isolated from the broader information technology (IT) infrastructure but connected through secure gateways. An industrial PC acts as an IoT gateway, translating shop-floor protocols into secure telemetry streams for the educational environment. Time-series data and learning records are stored in dedicated databases within Tknika's infrastructure, with network segmentation and role-based access to preserve security and privacy.

On the logical side, IkasMES constitutes Tknika's first integrated LMS for the Learning Factory environment. Prior to this project, no LMS was connected to the LF: learning management and shop-floor operations were handled through entirely separate systems. IkasMES closes this gap by providing authentication and role management for students, instructors and administrators; challenge and task definition tied to competencies and modules; and automatic linking of each task execution to sensor-derived KPIs. Students access dashboards showing challenge status, performance trends and comparisons between planned and actual execution, supporting self-reflection and planning (Fig. 2).

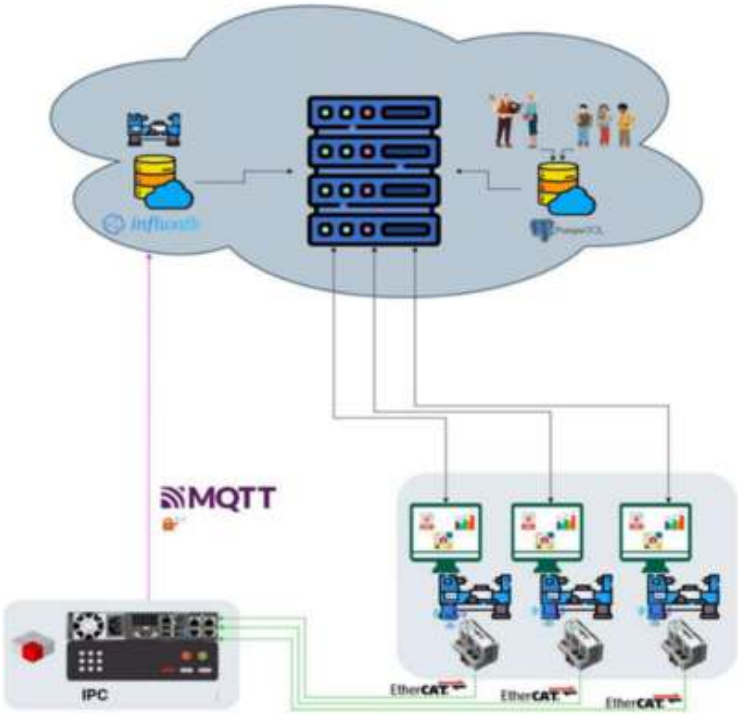


**Fig. 2.** Physical and logical architecture of IkasMES at Tknika's Learning Factory.

# 3 Methodology and Evaluation Plan

## 3.1 Design Science Approach and Needs Assessment

The development of IkasMES follows a design science methodology with iterative cycles of design, implementation and evaluation. An initial needs assessment was conducted with stakeholders from Basque VET centers, including instructors, coordinators and pedagogical directors. These consultations highlighted several challenges: limited visibility of what students actually do in Learning Factories, dependence on self-reported activity, delayed feedback on performance, and a lack of tools to support self-directed learning in challenge-based environments [6].

These findings informed the design priorities of IkasMES: automatic capture of activity in Tknika's LF, transformation of operational data into educational KPIs, dual dashboards for students and instructors, and privacy-by-design mechanisms aligned with institutional and regulatory requirements. The first design cycle resulted in the current pilot implementation of IkasMES in Tknika's Learning Factory.

### 3.2 Planned Deployment and Quasi-Experimental Evaluation

The next phase consists of deployment of IkasMES in one of Basque Vet center's mini-factories, which are used by small student groups for intensive, project-based learning. The evaluation will adopt a quasi-experimental design that compares:

- An **experimental group** using IkasMES, with full integration between the LF and the LMS.
- One or more **control groups** use a traditional LMS without automated data captured from the shop floor.

The study will span at least one academic cycle in which students carry out challenge-based projects in the Learning Factory. Quantitative data will include indicators of self-directed learning (e.g. autonomous task initiation, planning and re-planning), engagement (e.g. time-on-task, dashboard consultation), and performance (e.g. completion of challenges, quality assessments). Qualitative data will be gathered through interviews, instructor feedback and classroom observations to understand how IkasMES shapes teaching practices and learners' perceptions [7,8].

The main research questions focus on whether IkasMES increases the transparency of learning processes in the LF, supports self-directed and challenge-based learning, and reduces the monitoring workload for instructors while maintaining or improving learning outcomes. Statistical analysis of quantitative data will be complemented by thematic analysis of qualitative evidence.

## 4 Preliminary Insights and Future Work

Early use of IkasMES in Tknika's Learning Factory suggests that the integration of IoT data into the LMS is technically feasible and pedagogically promising. Instructors report that access to objective indicators of student activity in the LF helps them to move from continuous "monitoring" towards more targeted coaching and feedback. Students show interest in dashboards that visualize their performance and progress, although some require support to interpret the data effectively [9,10].

Future work will focus on the full deployment of IkasMES across one of Basque Vet center's mini-factories and the completion of the quasi-experimental study. A central priority of open-source architecture is replicability: the same stack is designed to be adopted by any Learning Factory in the Basque VET network with minimal adaptation, progressively eliminating the manual data-transfer burden that currently persists across the system. The results will be used to refine the framework and adjust the design of dashboards and KPIs. Looking further ahead, Tknika is exploring the integration of AI-driven adaptive learning paths, with particular attention to learners with special needs or different learning rhythms ensuring that the system supports inclusive and personalized vocational education. This line of work is being developed in connection with the European project SkillAIbility, in which Tknika participates, and is framed within the human-centric vision of Industry 5.0 [8]: a framework that emphasizes the empowerment and augmentation of people through technology, and the symbiosis between human capabilities and digital tools in manufacturing and vocational training.

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# Design and Implementation of the Reconfigurable Cobot Workstation into the Learning Factory Environment

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**Abstract.** One of the key features of Industry 4.0 automation is the development of collaborative robots (cobots) designed to work alongside humans. Their importance is further highlighted in Industry 5.0, which, in addition to promoting resilience and sustainability, places people at the center of industrial processes. Cobots are generally easy to operate. However, most cobots lack a machine vision system, which makes reconfiguration of the cobot workstation more challenging. With the growing trend toward product personalization, it is essential to reduce product changeover time to lower the costs. In the learning factory environment, the reduction of the product changeover enables using the same cobot in many different projects and applications. It enhances flexibility and increases the usage of the cobot that usually has low OEE (Overall Equipment Effectiveness) in the learning factory environment. A concept of reconfigurable cobot workstation has been developed in the Learning Factory at FESB, University of Split. This research presents its successful implementation for Franka cobot. The proof of concept is presented through different application examples that are used for education of students and life-long learning activities.

**Keywords:** Cobot, Reconfigurable Workstation, Learning Factory.

## 1 Introduction

The evolution of manufacturing under Industry 4.0 is characterized by the integration of digital technologies – such as the Internet of Things, artificial intelligence, and real-time data exchange – to create connected, smart factories [1]. With Industry 5.0 as its update [2], a shift in this transformation is its human-centric focus, moving beyond the automation-for-replacement paradigm of Industry 3.0. The goal is to synergize human creativity with machine precision, creating systems that are both automated and flexible enough to collaborate with human operators [3]. This approach has positioned collaborative robots (cobots) as one of the key enabling technologies in Industry 4.0/5.0.

Modern cobots are defined by their ability to operate safely alongside humans in shared workspaces, utilizing environmental sensing, compliant mechanics, and autonomous decision-making to perform joint tasks [4]. To function within a collaborative environment, cobots incorporate advanced safety features like force limiters and velocity/acceleration monitoring. They are commonly deployed for repetitive, physically demanding tasks such as part handling and positioning, screwing bolts, and similar. This deployment reduces worker injury risk, improves workflow efficiency, and allows human operators to focus on higher-value activities, thereby contributing directly to the core Industry 4.0/5.0 objectives of productivity, adaptability, and optimized human skills. However, to fully unlock this collaborative potential, careful attention must be paid to the design of the cobot workstation.

The ongoing evolution of cobots necessitates parallel progress in workstation design. A well-designed workstation is essential for safe, efficient, and uninterrupted human-robot collaboration. Furthermore, it represents a necessary step toward the human-centricity – a goal of Industry 5.0. Unfortunately, many existing collaborative

workstations rely on simple, improvised surfaces like flat tables or T-slot plates, which lack the precision required for tasks setup (Fig. 1).

**Fig. 1.** Common cobot workstations with T-slot plates [5, 6].

If the cobot is not guided by vision system, it needs to be spatially adjustment for the task that has been set up. This can lead to misalignment errors, failed operations, and production inefficiencies. To address this gap, this research proposes the construction of a reconfigurable workstation based on a tooling plate instead of T-slot plate. The tooling plate design, similar to the conventional welding workstations, enables precise, repeatable component placement, thereby enhancing workflow reliability for both the cobot and the human operator, or in to put it short: it enables reconfigurability.

Reconfigurability is especially important in the learning factory environment, where reduction of the product changeover and setup times enables using the same cobot in many different projects and applications. It is a common thing in LF that the cobot is used as an industrial demonstrator in LF's assembly line, then students use it for their different projects, and it becomes time consuming moving the cobot around LF and setting up its worktable for different projects or demonstrations. Of course, the solution can be to purchase more cobots. However, this paper presents different solution: cobot's worktable design that enables easy reconfiguration of the workplace thus allowing usage of the cobot in many different projects in a single day.

## 2 Methodology

The selection of a collaborative robot (cobot) workstation constitutes a multi-criteria problem. This is due to the wide range of possible designs, which are contingent upon the final application. Key requirement for the workstation in this case is reconfigurability, which includes: adaptability, easy configuration, a plug-and-play capability that minimizes setup time used for cobot's spatial adjustment, as well as low cost and assembly complexity. Such a problem necessitates a structured evaluation using multi-criteria decision-making methods [7].

A benchmarking process identified three fundamental design variants [8] and multi-criteria decision-making was applied to evaluate cobot workstation designs. The analysis resulted in the selection of a workstation with the cobot installed onto it, which was consequently chosen for detailed design [9], manufacturing and assembly as a reconfigurable workstation for a Franka collaborative robot (Fig. 2a).

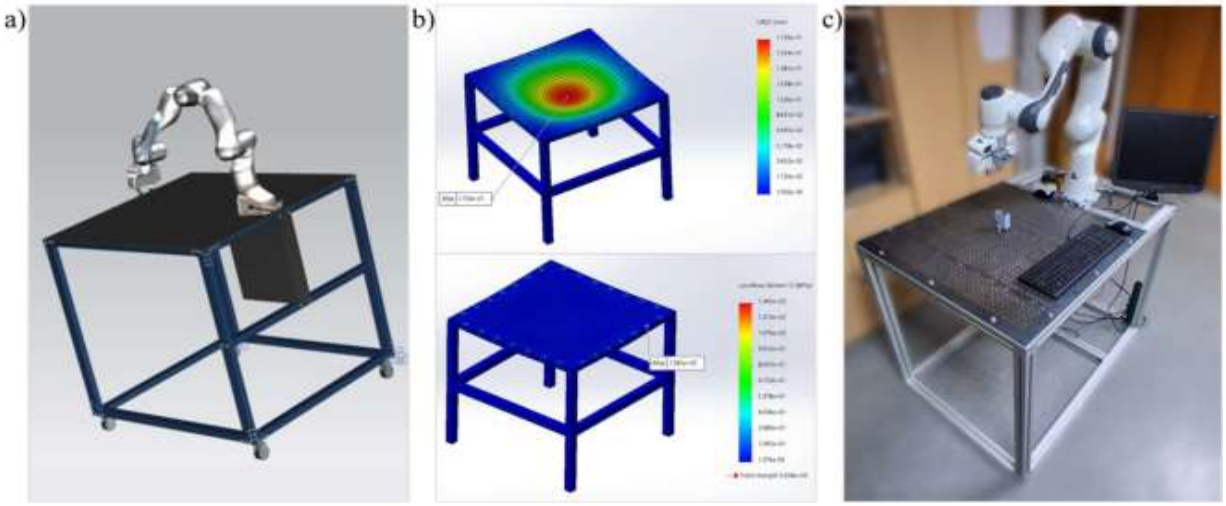


**Fig. 2.** Reconfigurable cobot workstation design process: a) Selected design of the cobot workstation; b) Cobot workstation FEM analysis (stress and displacement analysis); c) Final product with cobot Franka Panda.

The detailed design process included a stress and displacement analysis of the workstation's tooling plate which was selected to be 5 mm thick steel plate (DIN EN 10111). This part is critical part of workstation, since the tooling plate consists of more than 1200 holes and the goal was that it can sustain a product weight up to 50 kg. CAD and FEM models of the tooling plate were created for the FEM analysis of stress and displacement (Fig. 2b). The results of the FEM analysis confirmed the design's structural integrity with a maximum stress of 134.5 MPa and a maximum displacement of 0.172 mm under the 50 kg load. It is a low stress comparing it to the steel's yield strength of 620.4 MPa. Franka cobot has 3 kg payload and it weighs approx. 20 kg, so it could be mounted on the tooling plate without issues. Nevertheless, cobot wasn't mounted on the tooling plate in a final design, which allows using cobots weighing 30+ kg with 10+ kg payloads, and the design remains over-dimensioned.

Following the approval of the workstation design through FEM analysis, physical construction, i.e. manufacturing and assembly commenced. The primary components included the steel tooling plate, responsible for product placement, and a structural frame made from aluminum profiles with a rectangular T-slot cross-section. A slight modification was made to the original design variant: the tooling plate is used only for upholding the parts and product, and the collaborative robot (Franka Panda weighting approx. 20 kg) was mounted separately onto the frame (Fig. 2c).

## 3 Results

Reconfigurable cobot workstation allowed easy workplace configuration with minimal setup times (several minutes), and, more important, it allowed easy reconfiguration from one cobot task to another cobot task, i.e. from one workplace configuration to another. At first, it seems that reconfigurable cobot workstation enabled SMED (Single-Minute Exchange of Die) approach, which minimizes setup times in manufacturing processes, especially in cases of product changeover.

However, in the learning factories the OEE of cobot is low, therefore a need for SMED is usually not needed. But, reconfigurable cobot workstation actually enabled the reconfigurability itself. As mentioned before, switching from one cobot task to another can be quite demanding and time consuming, because a cobot needs to be

positioned in a precises position that task demands. It usually requires cobot's spatial adjustment, or trial and error method until the task is working.

For learning factory implementation purposes, a documentation template was made for presenting the workplace configuration that can be easily transferred into reality. A simple task of RAM assembly and disassembly is made together with its workplace configuration documentation. With a workplace configuration scheme (Fig. 3a), a cobot task can be set up within several minutes (Fig. 3b).

Nevertheless, removing products and parts belonging to RAM assembly/disassembly task takes several minutes, as well. After that, cobot workplace can be configured for another task.

In this case, second cobot task is 3D scanning by using Photoneo Phoxi 3D scanner [10]. Using a similar workplace configuration document, the workplace has been set up in no time (Fig. 4).

These two simple examples clearly demonstrated that using a reconfigurable cobot workstation in learning factory environment enabled that cobot can be easily used for different tasks, different students' projects, different demonstrations, etc. Every other approach will usually end up with purchasing more cobots. Because, it is hard to avoid complex workplace reconfigurations, if single cobot is used.

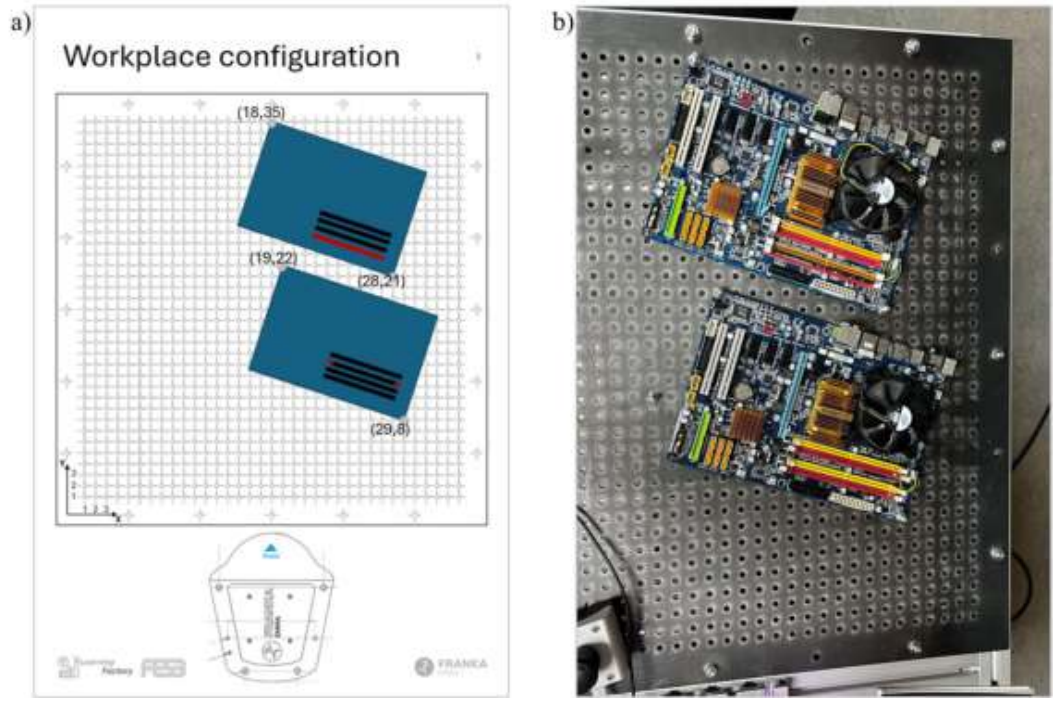


**Fig. 3.** Workplace configuration for computer RAM assembly/disassembly: a) Workplace configuration template; b) Workplace setup.

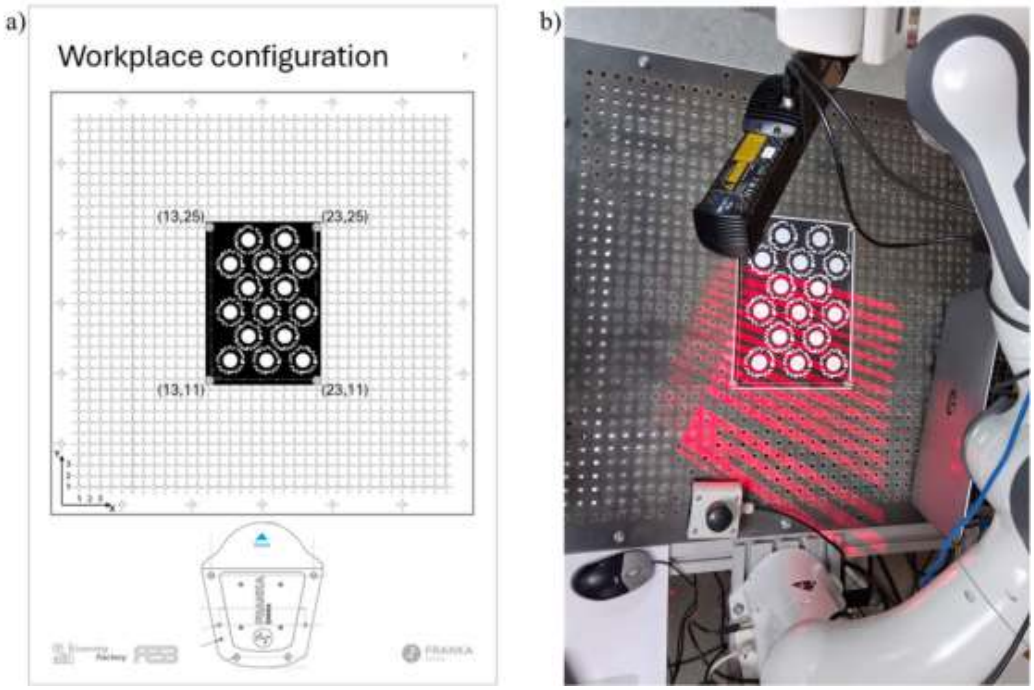


**Fig. 4.** Workplace configuration for Photoneo Phoxi 3D scanner: a) Workplace configuration template; b) Workplace setup.

## 4 Conclusions

This research presented an approach in which reconfigurable cobot workstation is made for application of cobot in the learning factory environment. As already mentioned, using a cobot in learning factory usually ends up with low OEE of cobot, but enormous setup (changeover) times when moving a cobot from one task to another.

The presented reconfigurable cobot workstation successfully addresses this issue by enabling the reconfigurability with low setup (changeover) times: from few minutes to dozen of minutes, depending of the setup complexity. The workplace configuration documentation has been developed to further enhance the process. In this paper two significantly different workplace configurations are presented: RAM assembly/disassembly example and Photoneo Phoxi 3D scanner example. It takes only several minutes to reconfigure the workplace from one task to another.

The future research will consist of testing the reconfigurability of the workstation on more complex workplace setups for more precise cobot tasks. The limitation of the designed workplace is that specialized jigs should be made to position some products or parts on the tooling plate, and it is something that also requires future research.

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# An Exemplary Morphology to Conceptualize an Industrial Metaverse-Enabled Net-Zero Smart Learning Factory

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**Abstract.** This short paper presents an exemplary morphology to conceptualize an industrial metaverse-enabled net-zero smart learning factory, starting the learning journey from traditional industrial setups towards industrial metaverse-managed factories targeting practitioners, full-time, and part-time students. Therefore, we adapt existing morphologies to our conceptual design for the innovative learning factory at TTZ Leipheim, integrating industrial metaverse technologies with manufacturing processes for indoor drone production. The smart factory includes, e.g., a novel Control Tower concept in which students, visitors, and operators use smart glasses and spatial computing to monitor, interact with, and control production processes. We exemplify our proposed morphology, map attributes, and objectives in production areas. Therefore, we demonstrate how physical assembly stations, AGV-powered logistics, or immersive digital interfaces provide our stakeholders with smart factory knowledge. Thus, the paper outlines a structured morphology for designing the next-generation learning factory and its alignment with learning objectives.

**Keywords:** Smart Learning Factory, Industrial Metaverse, Morphology

## 1 Introduction

The manufacturing sector currently faces the dual challenge of developing human-centric and resilient production systems while advancing toward ambitious sustainability targets [1]. Small and medium-sized enterprises (SMEs), in particular, face significant barriers in navigating the parallel transitions from their current industrial setup toward Industry 5.0 and net-zero emissions [2]. Limited resources for experimentation and a shortage of in-house expertise often hinder their ability to adopt and implement emerging technologies effectively [3]. At the same time, conventional manufacturing education, combined with technologies such as AI, RFID, and IoT sensors, continues to separate theoretical knowledge from hands-on practice, leaving students and practitioners underprepared for increasingly integrated digital-physical production environments [4, 5]. As technological innovation progresses faster than educational frameworks can evolve, the gap between academic research and industrial application continues to widen.

To bridge this gap, the TTZ in Leipheim plan to build a 500 m² learning factory aiming to help our stakeholders experience the journey from the current industrial setup towards an industrial metaverse-driven smart factory. Lovich defines the term metaverse as “a combination of the virtual reality and the mixed reality worlds accessed through a browser or headset, which allows people to have real-time interactions and experiences across distance“ [6]. Leaders in the field of digital technology, such as Nvidia with Omniverse and Facebook with Meta, are investing heavily in metaverse solutions [7]. Beyond data-driven monitoring and optimization, the industrial metaverse layer provides additional value through immersive co-presence [3], embodied interaction, and persistent virtual environments [4]. In this work, the industrial metaverse is understood as an extension of conventional Industry 4.0 systems [8, 9], in which digital twins act as core building blocks of a persistent, networked virtual environment.

While individual digital twins are commonly used to represent machines or factories, the industrial metaverse integrates multiple interconnected digital twins, for example, at factory and supply-chain levels, thereby enabling a holistic representation of internal operations and inter-organizational networks. In our learning factory, this enables novel use cases such as virtual learning and training spaces, where learners can interact with production systems independent of physical location, reducing travel requirements and supporting flipped-classroom and self-directed learning concepts. Thus, the industrial metaverse does not replace existing smart factory technologies but augments them by providing an immersive, interactive, and scalable environment that connects physical and digital manufacturing systems across organizational boundaries.

The core of our learning factory is a "Control Tower" — an octagonal platform inspired by the Manufacturing Control Tower concept, as a digital backbone that enables real-time visibility and coordinated decision making [10], from which learners, equipped with smart glasses, can observe various production areas while interacting with real-time digital overlays, process simulations, and predictive analytics. This immersive setting integrates drone manufacturing with modular training units covering logistics, production, assembly, and sustainability. We describe the (learning) objectives for each learning station by using our proposed morphology, ensuring the transfer and development of knowledge and expertise.

The Digital Control Tower serves as an integrative layer that connects heterogeneous data sources, digital twins, and spatial computing interfaces [11]. Machine and station-level data are acquired via sensors, PLCs, and industrial IoT gateways and integrated through MES and ERP systems, forming the basis for continuously updated digital twins [8]. Depending on the technical maturity of individual stations, update cycles range from near-real-time synchronization for highly instrumented equipment to periodic updates for retrofitted or legacy machines. Spatial computing devices, such as smart glasses and tablets, access these digital twins via the industrial metaverse platform, visualizing contextual information including KPIs, predictive maintenance indicators, and sustainability metrics [12]. System boundaries are defined at the station, factory, and network levels, allowing modular extension while ensuring consistency with the morphology-guided design of the learning factory.

In our case, the idea is that the Control Tower operationalizes, e.g., simulation or control of existing cyber-physical systems through metaverse-enhanced interfaces. For example, learners can simulate emission reductions at stations, optimize AGV routing using digital twins, or adjust injection molding parameters through gesture control, all in the virtual layer without disrupting the production process. Thus, the Control Tower supports Industry 5.0 transitions towards net-zero manufacturing and learning outcomes aligned with Dimension 1 of our proposed morphological framework.

## 2 Learning Factory Areas

The journey from traditional setups to an industrial metaverse-driven smart factory offers several advantages. First, it enables stakeholders to experience a pathway in small steps towards a competitive manufacturing network. Second, it provides evidence of the industrial metaverse's effectiveness by enabling safe, cost-effective experimentation with traditional and advanced technologies. Third, it accelerates learning through immersive visualization of value creation at the factory and network levels, such as Scope 1, 2, and 3 emissions. Thus, the integrated metaverse concept enables learners to experience the complexity of modern manufacturing systems, whereas conventional learning factories tend to treat the digital and physical environments as separate domains. Our physical smart learning factory consists of interconnected zones that represent specific manufacturing needs and the coverage of the supply chain network. Figure 1 visualizes the material flow and numbered stations. The following factory description serves as an illustrative example of how the morphology guides the design of a planned learning factory, rather than a validated implementation; the ongoing (internal) project plans construction and empirical evaluation through 2028.

**The Digital Control Tower and Event Area (Station 1)**: The control tower manages and connects the supply chain with production planning and steering. As it is the starting point for any order processed, it integrates with IT infrastructure, e.g., the ERP system or an industrial metaverse platform, to run augmented and virtual reality (AR/VR) applications. We base the Digital Control Tower on an octagonal platform equipped with smart glasses, monitors, and tablets. Learners step onto the platform using any "smart" equipment and physically turn toward different production areas, allowing them to access contextual information, e.g., real-time KPIs or predictive maintenance alerts. Hand gestures thereby enable interaction with virtual controls, allowing parameter adjustments and scenario testing without disrupting production. The surrounding event area facilitates demonstrations, group discussions, and collaborative learning activities, creating an immersive environment where digital twins and physical processes converge.

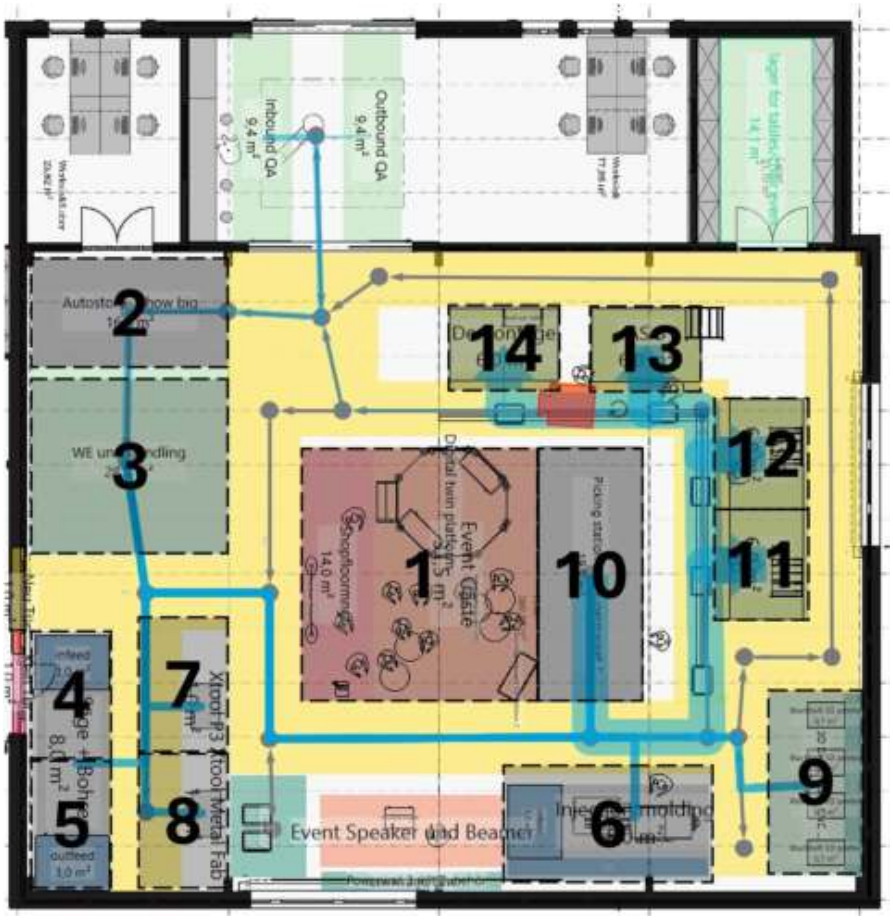


**Fig. 1.** Layout of the smart learning factory with numbered stations

**Inbound and Warehouse Area (Stations 2-3)**: We use forklifts for unloading and quality checks, while AGVs transport goods to either the conventional RFID-tracked shelving system (Station 2) or the AutoStore automated

warehouse (Station 3). This dual approach allows learners to directly compare traditional and Industry 4.0 warehouse operations, observing how AutoStore provides real-time inventory visibility and demonstrates automation efficiency gains.

**CNC Machining and Material Processing (Stations 4-6)**: These stations feature integrated CNC machining, drilling, and injection molding integrated within our industrial IoT infrastructure. Sensor networks monitor machine status, tool wear, and energy consumption, feeding real-time data into the digital twin environment. Learners observe predictive maintenance algorithms, optimize machining parameters, and analyze carbon footprints while experiencing how we retrofit traditional equipment with Industry 4.0 capabilities.

**Manufacturing Hub (Station 7-9)**: Four Blackbelt 3D printers enable continuous belt printing and rapid prototyping, while Xtool P3 and Metal Fab laser cutters provide precision cutting for non-metallic and metallic materials. Connected to our PLM system, this station demonstrates design freedom, material efficiency, and hybrid manufacturing approaches to respond to demand fluctuations.

**AI-Powered Picking Station (Station 10)**: At the AI-picking station, workers pick and place raw materials onto automated guided vehicles, which serve as carriers for subsequent manufacturing steps. The station uses AI technology for object recognition and error prevention logic, currently connected to the ERP system and planned for integration into the industrial metaverse. This integration will enable monitoring of the picking process, training of workers in virtual environments, and simulation of human-humanoid collaboration scenarios. The system provides real-time feedback on picking accuracy and visualizes remaining quantities for automatic ordering.

**Assembly Stations (Stations 11-13)**: Slow-moving AGVs equipped with fixtures transport work-in-progress between three assembly stations connected to our MES. Digital work instructions delivered through tablets or AR glasses guide assembly tasks and enable real-time quality documentation. This mobile assembly concept demonstrates flexible manufacturing where workpieces move to operators, allowing dynamic workload resequencing based on real-time demand.

**Disassembly and Circular Economy Station (Station 14)**: The disassembly station addresses end-of-life product management and circular economy principles. Here, learners disassemble used drones, assess component condition, and decide whether to reuse, remanufacture, or recycle. Connected to the ERP and sustainability tracking systems, this station enables the calculation of Scope 3 emissions, material recovery rates, and circular economy KPIs.

## 3 Industrial Metaverse Learning Factory Morphology

To ensure that each station delivers clear learning outcomes and maintains educational rigor, we developed a comprehensive morphology for industrial metaverse-enabled learning factories (Tables 1-5). Since our factory comprises multiple interconnected zones, each with distinct learning approaches and objectives, this structured framework helps instructors systematically design, document, and communicate their educational setup. Beyond serving as a planning tool for individual facilities, the morphology establishes a common language that enables learning factories across different universities to compare approaches, share best practices, and collaborate on research.

**Table 1.** Dimension 1: Strategic Framework

| # | Design element | Characteristics |
|---|---|---|
| 1.1 | Target group | Bachelor \| Master \| Part-time/MBA \| Practitioners \| VPN |
| 1.2 | Industrial status | Industry 3.0 \| Industry 4.0 \| Industrial Metaverse |
| 1.3 | Learning goals: Cognitive | Remember \| Understand \| Apply \| Analyze \| Evaluate \| Create |

| | | |
|---|---|---|
| 1.4 | Learning goals: Affective | Receive \| Respond \| Value \| Organize \| Characterize |
| 1.5 | Learning Goals: Psychomotor | Observe \| Imitate \| Practice \| Adapt |

**Table 2.** Dimension 2: Educational Design and Setup

| # | Design element | Characteristics |
|---|---|---|
| 2.1 | Learning Environment | Traditional classroom \| Sandwich method/blended learning \| AR/VR @ learning factory \| Virtual learning |
| 2.2 | Core Topics | Lean creation process \| Circular economy \| Sustainability/social impact \| Artificial intelligence \| Smart information logistics \| Factory planning \| Additive manufacturing \| Worker participation \| Object recognition engineering \| Digital twin/service twin/human twin |
| 2.3 | Feedback for Learners | Right/wrong \| Corrective \| Assisting \| Constant support in AI |
| 2.4 | Didactic Context | Stand-alone \| Integrated |
| 2.5 | Tangibility | Completely virtual \| Predominantly virtual \| Predominantly physical \| Completely physical |
| 2.6 | Mobility | Immobile \| Limited mobility \| Mobile |
| 2.7 | Participation Capability | In person \| Hybrid \| Remote |
| 2.8 | Degree of Personalization | Participant personalization \| Group personalization \| None |
| 2.9 | Trainer | Professor \| Researcher \| Student assistant \| Technical expert |

**Table 3.** Dimension 3: Physical Infrastructure

| # | Design element | Characteristics |
|---|---|---|
| 3.1 | Process Type | Workshop production \| Small series \| Serial \| Mass |
| 3.2 | Value Stream Level | Station/machine \| Cell \| Cost-center \| Factory/network |
| 3.3 | Status of Application | Research/development \| Demonstrator \| Prototype \| Industrial solution |
| 3.4 | Factory Areas | Lean Management \| Energy & resource efficiency \| Industrial resource engineering \| Global Industrial production \| Business engineering \| Industry 3.0 \| Industry 4.0 |
| 3.5 | Energy source | Grid (conventional) \| Grid (green tariff) \| On-site renewables \| Hybrid \| Off-grid |
| 3.6 | Emissions monitoring scope | Scope 1 (direct) \| Scope 2 (energy) \| Scope 1+2 \| Scope 1+2+3 |

**Table 4.** Dimension 4: Technical Infrastructure

| # | Design element | Characteristics |
|---|---|---|
| 4.1 | Automation Pyramid | Sensors & actuators \| PLC \| SCADA \| MES \| ERP \| IOS |
| 4.2 | ICT Protocol | Physical \| Data \| Network \| Transport \| Session \| Presentation \| Application \| More than application |
| 4.3 | Assistance System | Digital assistance \| Physical assistance \| Industrial robots \| Light robots \| Heavy robots (>1000) \| Wearable robots |

| | | |
|---|---|---|
| 4.4 | Traceability | Radio based technology \| Optical technology |

**Table 5.** Dimension 5: Operational Metrics & Research

| # | Design element | Characteristics |
|---|---|---|
| 5.1 | Learning Environment | Case study \| Role play \| Simulation \| None |
| 5.2 | Feedback for Learners | Participant \| Group personalization \| None |
| 5.3 | Didactic Context | Stand-alone \| Integrated |
| 5.4 | Tangibility | Completely virtual \| Predominantly virtual \| Predominantly physical \| Completely physical |
| 5.5 | Mobility | Immobile \| Limited mobility \| Mobile |
| 5.6 | Participation Capability | In-person \| Hybrid \| Remote |
| 5.7 | Degree of Personalization | Participant personalization \| Group personalization \| none |
| 5.8 | Operational Costs per Year (€) | < 10000 \| 10000 - 100000 \| 100000 - 1 million \| > 1 million |
| 5.9 | Peer-Reviewed Publications Related to LF per Year | < 5 \| 5-15 \| 15-25 \| >25 |
| 5.10 | Third Party Funds | < 10000 \| 10000 - 1 million \| 1 million - 20 million \| > 20 million |
| 5.11 | Research Object | New technology \| New processes \| New methods \| New management tools \| New materials \| New didactical methods \| New fundamental discoveries |
| 5.12 | Involved Persons in Research Process | Top grade researcher (e.g., full professor, director of research) \| Senior researcher (e.g., associate professor) \| Recognized researcher (e.g., assistant professor, post-doc) \| First stage researcher (e.g., PhD student) |

## 4 Discussion, Limitations, and Future Research

This paper introduces a five-dimensional morphology for industrial metaverse-enabled smart learning factories, extending existing frameworks by integrating spatial computing and digital twin technologies. The morphology provides both a theoretical contribution—a structured design space for next-generation learning factories—and practical value as a blueprint that professors, practitioners, and firms can use to build or upgrade their facilities. In practice, the morphology is applied iteratively: instructors first define the target group and learning goals (Dimension 1), which constrain the relevant educational design attributes (Dimension 2). For each physical station, the instructor then works through Dimensions 3–4 row by row, selecting the applicable characteristics and documenting the rationale. Not all dimensions carry equal weight in every setup — for instance, a learning factory focused on logistics will emphasize different elements within Dimension 3 than one focused on CNC machining. The morphology thus serves as a comprehensive checklist rather than a prescriptive template and allows scalability depending on, e.g., firm size. For example, a single-station learning factory may require only a fraction of the physical and technical infrastructure dimensions, while the strategic and educational dimensions remain fully applicable. Key limitations include the lack of empirical validation across multiple implementations and the absence of quantitative metrics linking morphology dimensions to learning outcomes.

Additionally, rapid technological evolution may require updates to the periodic framework. Future research should prioritize systematic evaluation through expert validation and case studies, development of assessment

metrics for learning effectiveness that link morphology dimensions to measurable learning outcomes, and ROI. Further, establishing standardized assessment protocols across learning factories will enable comparison of learning effectiveness and support student mobility between facilities.

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# Learning Factory from the First Year of Engineering: Experiences in a University of Applied Sciences

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**Abstract.** Many engineering programs emphasize practice-oriented education, yet students often encounter real industrial systems only in later years. In our new Robotics degree program, learning factory principles are introduced from the first semester through a project-based introductory robotics course. The course combines lectures with weekly hands-on activities, in which students work with industrial robotic arms in a factory-like setting. They begin by analyzing a manual assembly task, then design a simple robotic cell, develop and test programs in an offline simulation environment, and finally deploy their solutions on physical robots. This exposes them to a complete workflow from task analysis to implementation. The course is embedded in a broader curricular strategy that extends the learning factory concept to later modules. Informal student feedback suggests that early exposure to real robots increases motivation and supports the integration of theoretical and practical competences.

**Keywords:** Learning Factories, Didactic Processes, Robotics Education, Project-Based Learning.

## 1 Introduction

A large body of research has demonstrated the educational benefits of learning factories in engineering education [1]. In the narrow sense, a learning factory is characterized by authentic industrial processes, multiple stations, a changeable setting that resembles a real value chain, and the manufacture of a physical product [2]. Such environments allow students to experience realistic production scenarios while still in a controlled, didactically structured context.

In many engineering programs, however, students encounter real industrial systems only in later years, after several semesters of predominantly theoretical courses. This delays the integration of abstract concepts with practical experience and may limit motivation and engagement, particularly in application-oriented programs such as those at Universities of Applied Sciences.

In our new Robotics degree program at H¨ame University of Applied Sciences, we adopt a learning factory approach from the first year onward. The learning factory is envisioned to support three pillars [3]:

- Education: providing a safe, hands-on environment with authentic industrial equipment;
- Industrial interaction: engaging with regional companies to understand needs and co-develop activities;
- Research: enabling students to address topics such as machine learning and advanced robotics in later stages of their studies.

This paper focuses on the first pillar and, in particular, on the first-year intro-ductory robotics course that serves as the entry point to the learning factory. We describe the course design, the laboratory infrastructure, and a practical project in which students implement an assembly task with industrial robotic arms. We also outline how this course is embedded in a broader curricular strategy, form-ing a longitudinal learning factory integrated across the program. Finally, we discuss initial observations based on informal student feedback and reflect on planned extensions of the learning factory concept.

## 2 Program Context and Learning Factory Concept

The Robotics degree program is offered at H¨ame University of Applied Sciences and is explicitly designed to be practice-oriented. From the beginning, students are expected not only to learn theoretical foundations in mathematics, programming, and control, but also to apply these concepts to solve real problems.

Building on the characteristics and pillars of learning factories discussed in the Introduction, our approach is to distribute learning factory activities across several modules rather than concentrating them in a single laboratory. The same physical and digital resources are revisited in different courses, with increasing levels of complexity and autonomy expected from the students.

## 3 First-Year Robotics Course

In the first module of the degree program, students take an Introduction to Robotics course. This is their first systematic contact with industrial robots. The course combines lectures on fundamental concepts with weekly laboratory sessions, in which students work directly with robotic arms in a factory-like environment.

The main objectives of the course are that students:

- Understand basic principles of robot operation, workspaces, and motion types;
- Become familiar with industrial safety concepts and standards related to robotics;
- Develop introductory skills in robot programming and task planning;
- Experience the full workflow from analyzing a manual task to implementing a simple automated solution.

### 3.1 Laboratory Infrastructure and Equipment

To support these objectives, we have set up a dedicated robotics area within a network laboratory. A key advantage of this location, as also noted by other authors [3], is that it operates on an isolated local area network (LAN), where we have full control over the computers and network configuration. This facilitates the use of vendor-specific software, custom tools, and external simulation environments.

For every robot, a vacuum gripper and a finger gripper are available. For most of the introductory tasks, the vacuum gripper is used. We complement the standard tooling with 3D-printed fixtures and holders, for example a holder for a glue stick.

In the initial laboratory sessions, students work in small teams on separate robots to become familiar with basic operations and safety procedures. In later sessions, two teams are asked to collaborate and integrate two robots into a shared task (Fig.1), moving closer to a small-cell or mini-line configuration.

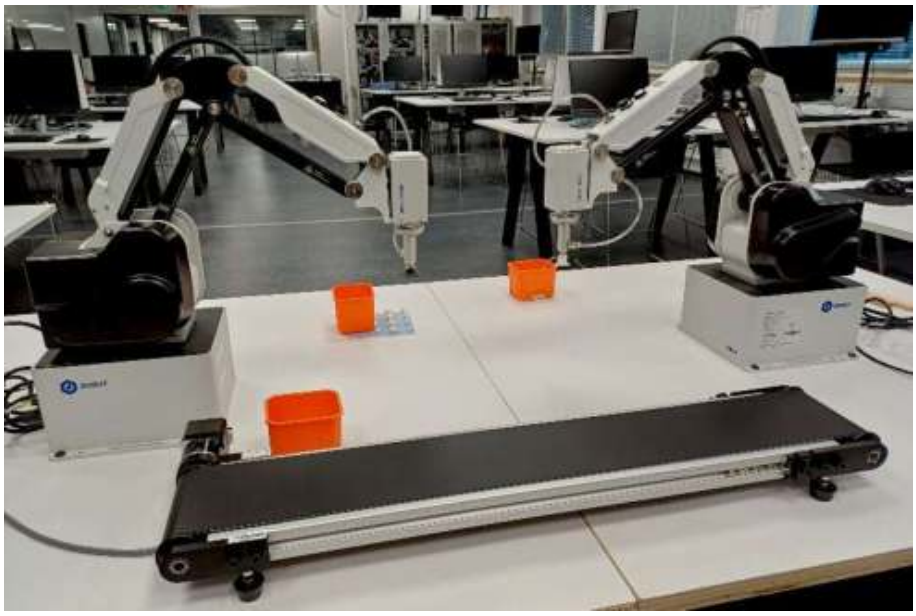

**Fig. 1.** Two Dobot MG400 robots configured for collaborative tasks.

### 3.2 Software Workflow

The MG400 can be programmed using the manufacturer's DobotStudio software, which offers a visual block-based language and support for Lua scripting. While DobotStudio is well suited for direct interaction with the robot, it does not support offline programming (OLP): users need to be connected to the robot to develop and test programs. This is impractical in an educational setting, and to address this limitation, we use educational licenses of RoboDK [5] as the main offline programming and simulation environment. RoboDK provides a 3D simulation of the workcell, supports import of CAD models, and allows programming of the MG400 using visual blocks or a Python Application Programming Interface (API).

The typical workflow for students in the course is as follows:

1. Analyze a simple manual task and define the desired automated operation (e.g., a pick-and-place sequence).
2. Model or adjust the workcell in RoboDK, including robots, fixtures, and workpieces.
3. Program and test the robot motions offline using RoboDK, ensuring reachability and collision avoidance.
4. Use a post-processor to generate Lua code from the RoboDK program.
5. Upload and execute the Lua program on the physical MG400 robot using DobotStudio.

This workflow exposes students to an industrially relevant development process, where most programming and testing is done in a virtual environment and it also allows more efficient use of laboratory time.

### 3.3 Project Work: Assembly Task with Two Robots

The central project in the course is an assembly task in which students program two robots to collaborate on producing a small physical product. The chosen product is a 3D card composed of four paper layers (see Fig. 2a). This task is simple enough to be feasible for first-year students, yet rich enough to illustrate key aspects of industrial robotics.

The target process involves alternating pick-and-place operations and glue application. In a typical configuration, one MG400 robot is responsible for picking individual layers from a stack and placing them in position, while the second robot applies glue between layers. The final assembled card is shown in Fig. 2b.

The project is introduced in the very first laboratory session, where students are tasked with designing the cards and assembling them manually. During this initial phase, they measure the time required to complete the manual operations, providing a baseline for cycle time analysis.

For the glue application, we initially used a glue stick attached to one of the robot arms with a 3D-printed holder. This low-cost solution allowed students to experiment quickly with process parameters.

## 4 Extension of the Learning Factory Across the Curriculum

Beyond the first-year robotics course, several other courses in the degree program are being aligned with the learning factory concept. The goal is that students repeatedly

**Fig. 2.** (a) The four layers of the 3D card used in the assembly task. (b) The assembled 3D card

encounter coherent factory-related scenarios, gradually adding new technologies and perspectives as they progress through their studies.

In the *Robotic Process Automation course*, the focus shifts from physical robots to software robots and business process automation. We designed a final project that connects legacy engineering tools with an enterprise resource planning (ERP) system, thereby linking technical design activities to manufacturing and logistics.

Students automate the simulation of an electronic circuit using LTspice. The software robot runs the simulation, verifies selected parameters, and, if the results meet predefined limits, exports a bill of materials (BOM). In the Odoo platform [6], we configured a small manufacturing company using the inventory and manufacturing modules. The BOM generated by the software robot is entered into the inventory module, and students create a manufacturing order while checking material availability in current stock. This setup allows students to see how design data flows into manufacturing planning and inventory management, and how software robots can bridge between legacy tools and modern ERP systems.

The *Machine* Vision course is being structured around applications in the learning factory. Its main objective is to develop competence in using cameras and image processing to provide information to robots and other automation components.

The *Control Systems* course will emphasize practical aspects of automation and control. We plan to use industrial PCs (IPCs) to control conveyor belts and robots, integrate sensor signals, and coordinate multiple devices.

In addition to on-site activities, we have a robotic arm that can be remotely controlled through a web interface [7]. The robot model is the same as those used in the learning factory, and we plan to extend the remote-access concept to other robots in the factory. This will support flexible access for students.

It is also in our plans to create a digital twin of (parts of) the learning factory. The digital twin would combine simulation models, live data from sensors and controllers, and a visualization of the current system state.

## 5 Conclusions

In this paper, we have presented the design and initial implementation of a learning factory within the first year of a new Robotics degree program. By introducing industrial robotic arms and authentic automation workflows from the very first semester, we aim to bridge the gap between theoretical foundations and practical engineering application.

The core of this approach is a project-based introductory course where students transition from manual task analysis to automated cell design and implementation. The use of industrial-grade equipment (Dobot MG400) and professional offline programming tools (RoboDK) ensures that students develop skills that are directly relevant to the manufacturing industry. Furthermore, the integration of this environment with other courses creates a longitudinal learning experience that reflects the complexity of modern production systems.

While a formal evaluation is still pending, informal discussions with students have been highly positive. Students report that early exposure to real robots significantly increases their motivation and helps them better understand the relevance of theoretical concepts introduced in other courses. They particularly value the learning-by-doing aspect and the opportunity to work on a complete, albeit simplified, value chain from the first weeks of their studies.

Future work will focus on expanding the physical infrastructure to support more complex assembly scenarios. We also plan to further develop the digital layer of the learning factory by strengthening the integration with other systems.

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# AI for Problem Solving in Quality Management: An Experiential Learning Approach in the I-FAB Learning Factory

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**Abstract.** Learning Factories (LFs) have become increasingly important in engineering education, offering environments where students can engage in experiential learning and connect theoretical knowledge with industrial practice. In 2016, LIUC University established the i-FAB LF, a foosball assembly line where students experience real factory scenarios, as part of educational formats designed to develop skills in lean manufacturing and Industry 4.0. In this context, a variety of activities devoted to industrial engineering students has been developed. Among these, a learning activity centered on the integration of Artificial Intelligence (AI) into quality management stands out as a representative example, fostering the development of the skills required by the new workforce in the context of Industry 5.0 (I5.0). This activity offers a hands-on, team-based learning experience, with its pedagogical foundation rooted in the A3 problem-solving framework, which guides students in systematically identifying quality issues, collecting relevant data, and analyzing root causes in the production process. Following this structured analysis, students apply their insights to develop an AI tool leveraging convolutional neural networks to automatically detect and classify assembly defects. In this way, the A3 process provides both the diagnostic foundation and the data-driven roadmap for AI implementation, connecting structured problem solving with innovative technological countermeasures. Taken together, these elements foster skills in creative and innovative thinking, collaboration, data analytics and problem solving – considered as key competencies in the I5.0 paradigm. The contribution of this study is to present the LF-based educational activity and to report students' perceptions collected through a structured questionnaire on three dimensions: learning experience and pedagogical design, collaboration and motivation, and quality of the learning environment.

**Keywords:** Industry 5.0, Engineering Education, Experiential Learning, Problem Solving, Artificial Intelligence.

## 1 Introduction

The manufacturing landscape is undergoing a major transformation under the influence of the Industry 5.0 (I5.0) paradigm, which focuses on the synergy between Industry 4.0 (I4.0) technologies and a renewed emphasis on sustainability, resilience, and human centricity. As a result, engineering education must likewise change and equip students to handle the new challenges that arise in this evolving context [1].

In this regard, experiential learning has proven to be an increasingly effective approach for bridging the gap between theoretical knowledge and practical application, and Learning Factories (LFs) represent one of the most effective environments to implement this kind of learning in education [2]. These environments provide realistic and hands-on settings in which students can experiment, make mistakes, and observe the consequences of their decisions in simulated and controlled production contexts. The i-FAB LF, founded at LIUC University in 2016,

is one such environment. Designed around a foosball assembly line, it integrates the application of lean manufacturing principles with the use of digital technologies to reproduce realistic industrial conditions within an academic context [3].

Within this framework, LIUC University has developed a set of experiential learning modules aligned with the I5.0 objectives. Among these, the activity discussed in this paper focuses on having students first apply lean problem-solving techniques for defect analysis on the assembly line and then develop an Artificial Intelligence (AI) tool for quality management, based on a simple Convolutional Neural Network (CNN) and capable of automatically detecting assembly defects.

This paper aims to present this educational activity in detail and to discuss students' perceptions of the learning experience.

## 2 Background

While I4.0 focused on automation, connectivity, and digitalization, I5.0 re-centers attention on the human dimension. Educational models must therefore integrate not only technological competencies but also human-centric skills such as creative and innovative thinking, collaboration, data analytics and problem solving [4]. In order to balance technology training with experiential, reflective, and interactive learning approaches, this transition necessitates a review of educational strategies.

Within this evolving context, Kolb's experiential learning model [5] remains a reference framework for designing practice-based engineering curricula. LFs are particularly suited to this paradigm because they allow the iterative combination of doing, observing, conceptualizing, and experimenting. Moreover, experiential approaches enable educators to evaluate learning not only in terms of the knowledge acquired but also in terms of students' ability to reflect on their experiences and apply the practical skills they have developed [6].

Among the pedagogical methodologies adopted in the field of experiential learning [7], the A3 methodology – derived from Toyota's lean philosophy – is a structured approach to problem solving that promotes systematic reasoning, visualization, and communication. It consists of several stages – problem identification and analysis including setting objectives (Plan), implementation of countermeasures (Do), evaluation of results (Check), and improvement or standardization (Act) – that closely align with Kolb's experiential cycle. When integrated into educational contexts, the A3 methodology becomes a powerful learning tool, guiding students through reflection and evidence-based problem solving.

Complementing these approaches, the increasing diffusion of AI, and particularly computer vision, is transforming quality management processes in manufacturing [8]. CNNs enable the automatic recognition of defects, improving speed and reliability. Integrating AI into educational projects allows students to understand both the opportunities and the limitations of these systems, fostering literacy in algorithmic reasoning and ethics. When AI is introduced within an experiential context – such as a LF – it supports a practical and direct engagement with technology, rather than abstract coding exercises.

## 3 Methodology

The educational activity was designed and implemented within the i-FAB LF at LIUC University in 2025. This section outlines the methodological framework adopted for the study, including the learning objectives, structure and pedagogical design, tools and technologies, case description, and evaluation approach.

### 3.1 Learning Objectives

The activity aimed to enable students to: (i) understand and apply the A3 problem solving methodology in a manufacturing context; (ii) collect, organize, and analyze process data related to product quality; (iii) design and train a CNN model to detect defects in assembly operations; (iv) integrate AI outcomes into a lean problem solving loop, proposing preventive actions; finally, (v) reflect on the implications of AI for human decision making in quality management.

### 3.2 Structure and Pedagogical Design

The activity followed a typical experiential learning cycle, consisting of four stages:

1. Concrete experience: students were introduced to a simulated production process in the i-FAB foosball assembly line. They performed assembly operations and recorded process data, including images of assembled parts.
2. Reflective observation: teams analyzed defect occurrences, discussing potential causes and data reliability.
3. Abstract conceptualization: after learning the theoretical foundations of problem solving and the A3 methodology, students applied these concepts by using the A3 template to formalize a problem statement, identify root causes, and propose countermeasures.
4. Active experimentation: based on the data collected, students developed a CNN prototype capable of classifying assembly defects. They then assessed the tool's potential for integration into quality monitoring systems.

### 3.3 Tools and Technologies

The CNN was developed by leveraging Microsoft Azure services. Indeed, Microsoft Azure Machine Learning Studio was exploited as a web-based platform for building an image-classification CNN. Students uploaded images to Azure Blob Storage through the Studio interface, labelled them with the built-in data-labelling tool, and trained the CNN in hosted Jupyter notebooks (PyTorch) on managed GPU compute. Experiments and metrics (e.g., accuracy, loss, and confusion matrix) were tracked in the workspace, while datasets and models were versioned for easy repeatability. Multiple models were tested in the hosted environment. The final model was tested on a held-out set using Azure ML's built-in evaluation tools.

### 3.4 Case Description

The activity was implemented during a laboratory session involving master's degree students in Management Engineering. Each team of four to five students acted as a cross-functional problem-solving unit, mirroring industrial team structures.

Initially, the students conducted a short production run in i-FAB, during which they intentionally introduced controlled process variations to generate data on assembly defects on the foosball scoreboard (e.g., wrong block unit color, incomplete tightening, missing parts). Using the A3 framework, they mapped the process flow, recorded defect types, and analyzed causes through tools such as the fishbone diagram and Pareto chart.

Finally, the teams used the labelled images to train and test a simple CNN for defect identification and classification. While the AI model was intentionally simple, focusing on supervised learning and basic image processing, it gave students hands-on experience in developing practical AI solutions.

### 3.5 Evaluation Approach

The evaluation of the educational activity was designed to measure its impact not in terms of knowledge acquisition but in terms of students' perceptions regarding learning experience and pedagogical design, collaboration and

motivation, and quality of the learning environment. To this end, a structured questionnaire [9] was developed and administered at the end of the laboratory session.

The questionnaire comprised 20 items, each rated on a 1–4 Likert scale, where 1 indicated strong disagreement or low satisfaction and 4 indicated a high level of agreement or satisfaction. The items were grouped into three categories: (i) learning experience and pedagogical design, aimed at assessing the adequacy of prior knowledge, clarity of objectives, methodological effectiveness, challenge level, and topic relevance; (ii) collaboration and motivation, focused on evaluating students' engagement, teamwork dynamics, and perceived balance between individual and group work; (iii) learning environment, intended to analyze the quality of the physical space considering safety, layout, acoustics, lighting, and temperature conditions.

The questionnaire was completed by 12 students who participated in the experiential learning activity within the i-FAB LF, providing a comprehensive overview of their perceptions and forming the basis for the analysis presented in the following section.

## 4 Results and Discussion

The questionnaire results reported in Table 1 indicate an overall positive perception of the learning experience, suggesting that students valued the experiential approach implemented within the i-FAB LF. This positive perception can plausibly be attributed to the activity's experiential design, aligned with Kolb's learning cycle [5], which links hands-on practice with theory, thereby supporting engagement and deeper understanding. Students particularly appreciated the clarity of objectives (Mean = 3.75) and the relevance of the topics (Mean = 3.67), indicating that they perceived a meaningful combination of problem solving and AI applications. Collaboration and motivation also received high ratings (Mean = 3.5), reflecting the strong engagement generated by the team-based approach.

Lower scores, however, highlight some improvement areas. The perceived adequacy of prior knowledge (Mean = 3.00) and the challenge level (Mean = 2.83) suggest that the AI component was demanding for students with limited technical background. A short preparatory module or more guided support on AI tools could make future sessions more accessible, even though these reported scores – while lower relative to other dimensions – remain fairly satisfactory in absolute terms.

Regarding the physical environment, evaluations were consistently high, with only temperature conditions (Mean = 2.83) scoring slightly below average. Overall, the laboratory proved to be a safe, comfortable, and collaborative learning space.

Overall, the activity was well received; however, minor adjustments in preparation and environment could further enhance its inclusiveness and impact.

**Table 1.** Six highest mean scores from the student questionnaire

| Item | Mean |
|---|---|
| Clarity of objectives | 3.75 |
| Relevance of the topics | 3.67 |
| Collaboration and motivation | 3.50 |
| Adequacy of prior knowledge | 3.00 |
| Challenge level | 2.83 |
| Temperature conditions | 2.83 |

## 5 Conclusion

As previously discussed, the proposed activity is specifically designed to foster creative and innovative thinking, collaboration, data analytics and problem solving – key skills for the future workforce in the I5.0 era. By integrating the A3 problem-solving methodology with AI applications, the educational activity enabled students to experience a complete cycle of experiential learning, connecting structured analytical reasoning with innovative technological solutions for quality management.

The results from the questionnaire indicated that students perceived the pedagogical design as effective, particularly in fostering their collaboration and engagement within a safe and well-designed learning environment. At the same time, some challenges emerged, mainly related to students' heterogeneous technical backgrounds and the perceived complexity of AI tools. Future iterations of the module could address these limitations, while also expanding dataset variability and introducing more advanced AI functionalities. These enhancements would further strengthen learning outcomes and offer students an even richer and more realistic problem-solving experience.

In conclusion, this study highlights how educational initiatives inspired by the I5.0 paradigm can be implemented and perceived within LFs, offering a basis for further reflection on human-centric engineering education.

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# Die Lernfabrik – Learning Factory for Sustainable, Circular, and Digital Production

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**Abstract.** Pilot production lines have proven to be an excellent infrastructure for teaching and learning in a practical context. Therefore, we restructured "Die Lernfabrik" into a learning factory for sustainable, circular, and digital production. Two shop-floor labs and a NerveCenter, serving as a digital control room, cover the primary value-creation processes. Learners are involved in producing two products: a cylindrical battery cell and a miniature electric car. The processes on the shop floor cover forward (manufacturing and assembly) and backward (recycling and remanufacturing) value-creation based on principles for sustainable and circular production. As enablers, a range of digital technologies and fields of expertise is covered – from methods and tools in life cycle engineering to production technologies and business decision-making. Each trainer contributes modular course units that address the specific needs of students, industry experts, or decision-makers. A digital learning platform enables individual learning paths. As a result, the new learning factory provides the infrastructure for theoretical and practical education required by production and life-cycle engineers.

**Keywords:** Cyber-Physical Production System, Life Cycle Engineering, Battery Production.

## 1 Introduction

Engineers apply science and mathematics to develop innovative solutions that meet defined product requirements. The resulting products and artifacts have implications for the environment, society, and the economy. On the one hand, this reflects gains in prosperity; on the other hand, it reflects adverse social and environmental impacts, accelerating climate change and environmental contamination [1]. Therefore, frameworks for environmental thresholds and planetary boundaries have been established to outline the scope of action for target-driven Life Cycle Engineering (LCE) [2]. Furthermore, these frameworks are operationalized [3] and provide a basis for educating all engineers as life-cycle engineers with a focus on absolute sustainability and a just transition [4]. Pilot production lines embedded in a Learning Factory (LF) environment have proven suitable for supporting education and training [5]. Although skills and competencies for LCE are vital for sustainable development in the production context [4], present learning factories lack an educational operationalization of life cycle engineering.

Therefore, the vision of "Die Lernfabrik" is an LF that enables people to shape the production of the future in a sustainable, circular, and digital way, visualized in **Fig.** .

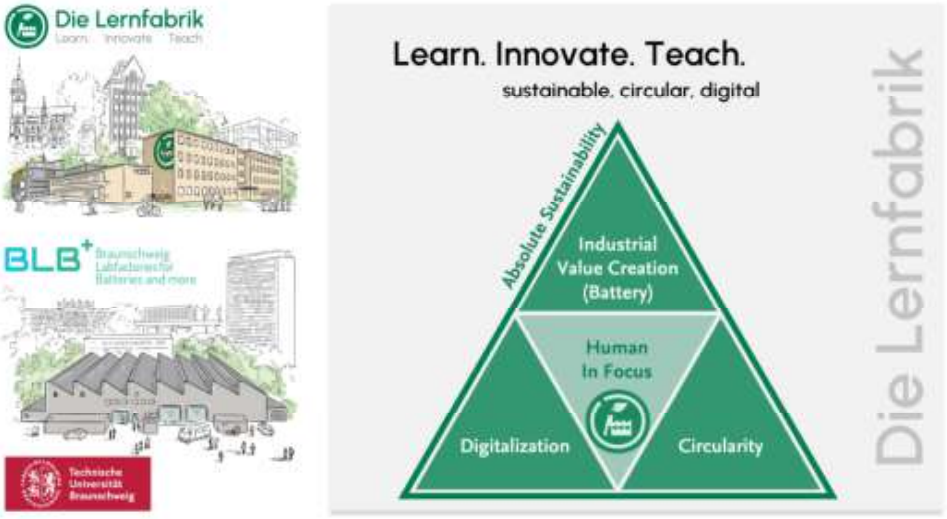


**Fig. 1.** Core topics for the education of life cycle engineers in "Die Lernfabrik"

The LF takes a human-centered approach (human in focus). The core topic is industrial value creation within the boundaries of absolute sustainability. The application use cases are the production of lithium-ion batteries, comprising batch, continuous, and discrete production steps, and the manufacture of a scaled-down electric vehicle. Circularity and digitalization are essential enablers.

The setup incentivizes engineers to reflect on principles and standards for responsible manufacturing in the context of absolute sustainability. Circularity addresses challenges associated with material-related impacts and strategies to improve the effectiveness and resilience of material flows in circular production. Digitalization provides methods and tools to achieve excellence in quality and performance within sustainable production systems. Within the learning factory, engineers tackle life cycle engineering challenges at the normative, strategic, and operational levels (cf. [6]).

## 2 Concept

The mission of "Die Lernfabrik" is to impart knowledge and skills for Circular Production (CP) based on life cycle thinking and a holistic understanding of factories. Digital methods and technologies, as well as the requirements for an absolute understanding of sustainability, are thus integral. Battery cell production is used to mimic real-world situations. Batteries are a key technology and a component of many modern products. They are indispensable for electromobility. Products and the batteries installed in them must be convincing from a technical, economic, and environmental perspective. The production of battery cells and their integration into products, right through to dismantling and recycling, can be experienced in a practical, interdisciplinary environment. Attractive training and continuing education opportunities are realized in the LF through innovative teaching and learning formats.

"Die Lernfabrik" builds upon a Cyber-Physical Production System (CPPS) approach [7] embedded within four main operating principles, as shown in **Fig.** .

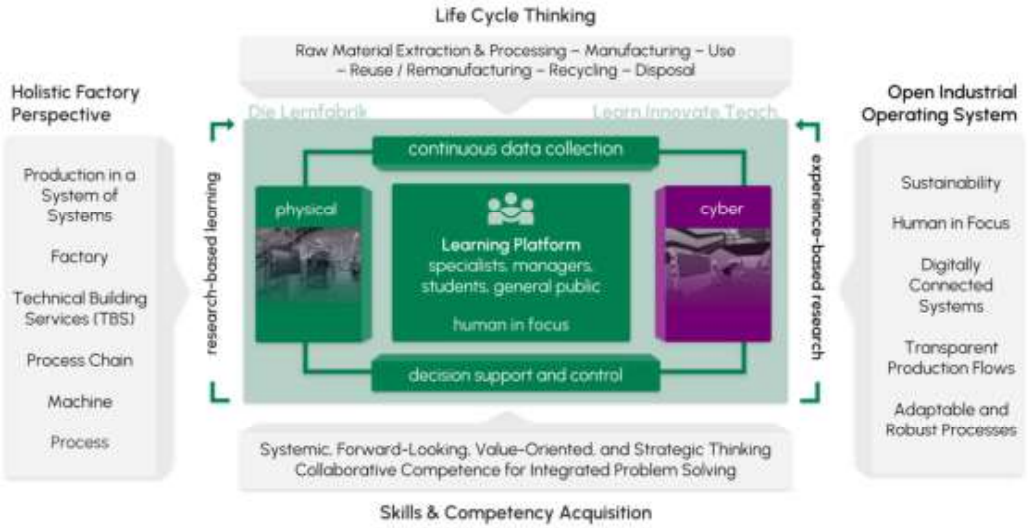


**Fig. 2.** Conceptual framework for "Die Lernfabrik"

The four main operating principles form the fundamental building blocks of the structural LF concept. Derived from our mission, *Life Cycle Thinking* and a *Holistic Factory Perspective* define the main viewpoints on the CPPS. We investigate production within the scope, from single processes to process chains, and at the factory level, up to its embedding in a system-of-systems environment. Furthermore, the "pure act or process […] of actually physically making a product from its material constituents" [8] has significant implications on the life cycle. Therefore, *Life Cycle Thinking* considers the whole product life cycle from the origin of material constituents to product (re)use, remanufacturing, end-of-use, and disposal. With an *Open Industrial Operating System* compatible with global industrial initiatives (cf. [9]), the LF ensures *Skills and Competency Acquisition*, empowering engineers to recognize and reflect on their responsibilities to society and the environment (cf. [4]).

The CPPS of the LF provides an infrastructure for research-based learning and experience-based research. It comprises all relevant components for a control loop between the physical and cyber worlds. The physical world represents the LF's CP System. It includes all machines and physical assets within the LF, the technical building services, the factory building, and operators, trainers, and learners. Furthermore, the materials and products that are ingoing, outgoing, or recovered within the CP are part of the physical world. Three main elements connect the physical and the cyber world. Firstly, continuous data collection enables the provision of raw operational data and analytics data for all activities in the cyber world, such as data analytics, modeling, and simulation. Secondly, the results of these activities are transferred back to impact the activities in the physical world through decision support and control. Thirdly, the Learning Platform (LP) acts as the primary interface and educational hub for trainers, specialists, managers, students, and the general public. It consists of a Learning Management System (LMS) and a Mixed Reality Platform (MRP). The LMS provides capabilities for creating and managing educational content. At the same time, the MRP transfers relevant physical-world teaching scenarios into a virtual environment for risk-free experimentation and simulation. Further activities in the cyber world drive these virtual environments. Advanced data analytics, modeling, and simulation are applied to energy management, material tracking and tracing, production and factory planning, production control, and digital life cycle engineering.

## 3 Implementation

The concept is implemented as part of the Technische Universität Braunschweig's infrastructure. The available physical area is split into three core labs: Battery Production (BP) lab, Component Integration (CI) lab, and Nerve-Center (NC). Further innovation activities closely associated with the LF are conducted in the Technology Exploration (TE) labs. They are located in other areas of the technical center and in off-site research centers. Furthermore, the LF collaborates with a university teaching and learning facility for technical and vocational training.

The BP lab operates a pilot line for the CP of cylindrical 21700 lithium-iron phosphate (LFP) battery cells, with real and virtual processes. Most of the activities for electrode production, cell assembly, formation, ageing, and mechanical recycling are performed on-site. To ensure a safe, low-risk learning environment, few processes, such as mixing, electrolyte filling, and some recycling steps, are performed at a nearby battery research center and on virtualized machines in the cyber world.

In the CI lab, the battery cells are used to realize a circular product, as demonstrated by a miniature electric vehicle. The base version consists of three pre-assembled components, namely the *Drive Platform*, the *Control Unit*, and the *Power Unit*. Thus, actors in the integrated assembly and disassembly system combine the modular components semi-automatically on manual workstations or in a small collaborative robot cell. The system provides remanufacturing capabilities.

The NC provides an intelligent and interactive environment for digital LCE, supporting planning, decision-making, and control in CP systems. On the frontend, users can immerse themselves in visualizations displayed in parallel across up to three front touch monitors and two lateral projector screens. A Digital Life Cycle Engineering Toolbox is provided to enable advanced methods for life cycle assessments towards absolute sustainability and a holistic life cycle management for the learning factory. The backend is powered from the technical node room, providing network, server, and computing infrastructure for data acquisition, modeling, and simulation. Impressions from the three labs are shown in **Fig.** .

Throughout the LF shop floor, several assets link the physical and the cyber world. At the intersection of NC tools and the LP, we developed a shop-floor assistance and decision-support system. It provides the necessary interface for interacting with virtual machines and educational content to deliver decision support for roles such as operators, energy managers, or environmental managers. Energy managers benefit from xEnergy [10], an asset that supports education and training for energy industrial symbiosis, battery storage management, and energy-based production planning and control.

**Fig. 3.** Impressions from the three core labs located on a schematic floor plan.

Raw operational data is acquired from machines via OPC UA, from energy meters in the electrical distribution cabinets, and from additional industrial sensors. The collected data is a substantial basis for most cyber activities in the LF. This provides scientifically relevant results for research-based learning and experience-based research.

The implemented LMS [11] is based on the open-source software ILIAS 9 [12] and is used for digitally supported knowledge transfer, monitoring of learning progress, self-assessment, and formal knowledge assessment. An integrated learning map allows for the visual representation of the course structure, adaptive, individualized learning paths, and highlights relations between individual courses. The LMS thereby functions as a central platform linking the physical world with the MRP. The MRP [13] is a web-based, multi-device, cross-platform solution that provides a LF environment in virtual reality and operating instructions in extended reality. The backend powers a no-code content creation and management system to support trainers and learners. Furthermore, the MRP is a building block of the Learning Factory Industrial Metaverse (LFIM). There, different modeling and simulation tools for factory, layout, and ergonomics planning are integrated into a single digital representation of the learning factory.

## 4 Summary and Outlook

“Die Lernfabrik” for sustainable, circular, and digital production provides students, researchers, and professionals with a unique environment for holistic life cycle management education in a production context. It operates from a holistic factory and life-cycle perspective towards an open operating system for skills and competency acquisition. A CPPS for the LF was implemented for a pilot battery production line and a miniature electric vehicle assembly line. Its positioning within the learning factory morphology (cf. [5]) is detailed in the supplementary material. After successful implementation and machine ramp-up, the next step is to further integrate industry and general public partners on topics such as LCE, CP, and LFIM. In the coming months, several university courses

and industry seminars will be held at the learning factory. Research activities on CP in LFs will continue to provide insights from experience-based research.

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# 5 Supplementary Material

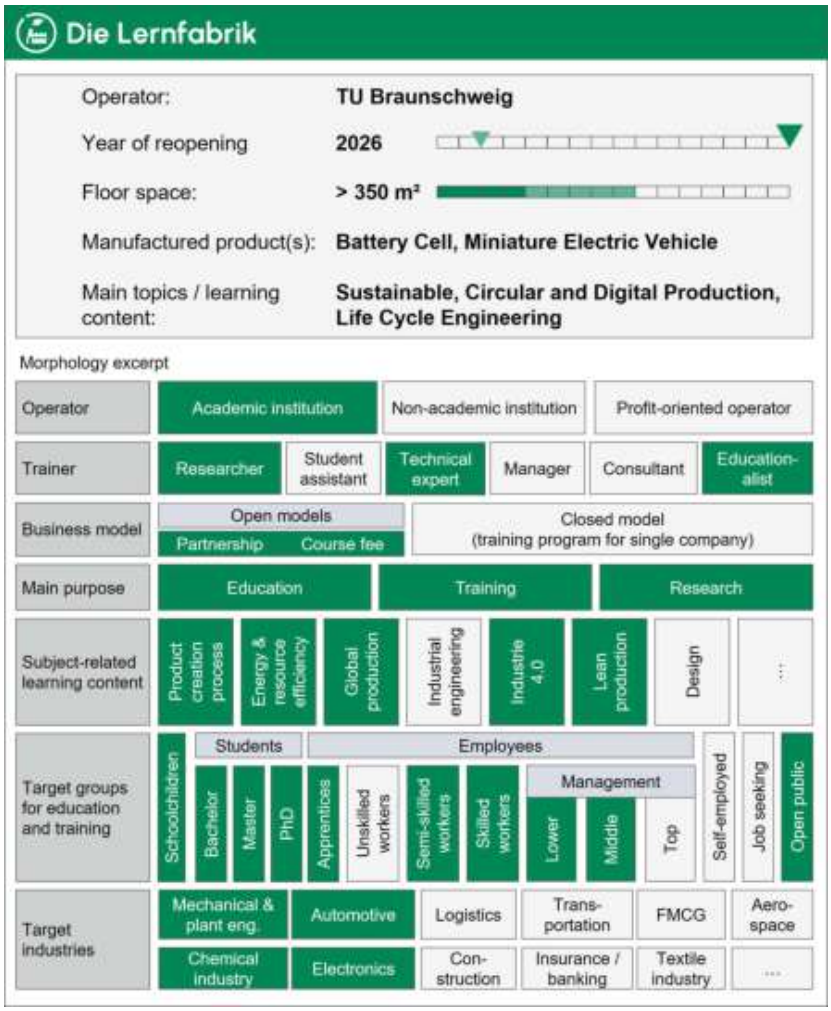


**Fig. 4.** Positioning within the LF morphology (cf. [5])

# Design Implementations in a Learning Factory Focused on IoT and Industry 4.0 Technologies

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**Abstract.** The paper focuses on the design of a Learning Factory (LF) and describes the approaches taken to adopt advanced technologies and their application in modern manufacturing and assembling processes. The framework adopted in redesigning or building a new LF is presented, and the LF operations on a LF focused on IoT and Industry 4.0 are described. Several learning opportunities related to Internet of Things (IoT) and Industry 4.0 technologies are shown, and some of the challenges associated with implementing in the learning process the experiential learning experiments developed in the LF are described.

**Keywords:** Learning Factory, Learning Opportunities, Learning Models

## 1 Introduction

The concept of Industry 4.0 for implementing intelligent, self-optimizing digital manufacturing and maintenance processes allows companies to take easier decisions related to improving productivity and maintenance, increasing uptime, and reducing costs. Although the concept provides advantages for modern manufacturing, the implementation of Industry 4.0 in production has been slow as it can put manufacturers, and particularly small and medium enterprises (SMEs), at risk of losing out on contracts where they are outbid by smaller, more agile startups who are focused on bringing in technologies like Industrial Internet of things (IIoT) or hyper automation to their talent of specialty. The key enablers of adopting digital technology are skills, leadership, and governance.

A key element in adopting Industry 4.0 concepts towards digital manufacturing is the existence of experts and expertise in the field. University graduates cannot be experts in Industry 4.0 – at least for a while – as there are no engineering programs highly specialized in digital manufacturing. Therefore, providing interdisciplinary knowledge and experiential learning skills related to digital technologies to undergraduate students, and developing research projects in Industry 4.0 for graduate students can offer future graduates a proficient level of skills and expertise in several elements that define the Industry 4.0 concepts. These elements include Internet of Things (IoT); IIoT; digital sensors and actuators; real-time big data; cloud computing; data mining and advanced analytics; artificial intelligence (AI); machine learning (ML); cyber physical systems and digital twins; portable and wearable devices; robotics; vision systems; autonomous vehicles; additive manufacturing; and augmented, virtual, and mixed reality (AR/VR/MR).

A possible academic approach to provide Industry 4.0 expertise and skills to students is to combine the theoretical knowledge taught in courses or developed in projects with the development of experiential learning skills gained in modern hands-on facilities that focus on digital manufacturing technologies such as a Learning Factory (LF). Although there are many LF in the world, each LF has been established with a different objective. Abele et al. [1] have classified the types of learning factories to include: (1) learning factories for production

process improvement; (2) teaching and learning factory concepts; (3) learning factories for re-configurability, production, and layout planning; and (4) learning factories for Industry 4.0. Several LF allow learning and training of the key aspects of Industry 4.0 [2-5].

The purpose of the paper is to present a LF that has been developed from scratch with a focus on IoT and Industry 4.0 technologies. The challenges of designing, establishing, and operating a LF are presented in Section 2, and several learning models provided by the LF are described in Section 3.

## 2 Design Implementations

Designing a LF is a complex task, and the published literature [6-9] provides some guidelines and best practices that could be useful to universities interested in building a new LF. There are many challenges in designing, establishing and operating a LF, and the high investment requires a good plan. Although starting with reading the published literature is good practice, it is recommended to find answers to a series of basic questions related to the designing the LF concept; establishing learning opportunities; designing the infrastructure; and identifying the operational requirements.

A modern LF has been developed in Canada at McMaster University in the W Booth School of Engineering Practice and Technology (SEPT). The SEPT LF has been founded as an alternative to traditional research engineering programs with the purpose of emphasizing a hands-on practice-based flexible curricula embedded with experiential learning strategies. This LF replicates a fully integrated factory of the future and focuses on the core ingredients of Industry 4.0 that are fully supplemented by IoT technologies. This LF addresses three major learning approaches, namely teaching, training, and research, and it is used for the innovation and the development of current ideas. The teaching components focus on undergraduate studies; the training component focuses on demonstrating the Industry 4.0 concepts to industry; the research component is addressed through graduate studies, summer research internships, student mobility programs, and special campus-wide projects.

The undergraduate learning approaches that take place in the LF include the development of capstone projects, development of the LF facilities, and undergraduate research internships. The advantage of using a LF in the development of capstone projects resides in the use of the modern digital approaches in manufacturing, assembly and testing of the designed device. The graduate students use the LF's AM resources to study their thesis questions. The SEPT LF has two metal AM machines and several 3D printers for plastic and carbon fibre reinforced parts used by students to design, build and test components for specific application such in fields that include automotive, tooling, aerospace, and orthopedic implants, or to perform non-destructive tests such surface characterization using a Coordinate Measuring Machines (CMM) and surface flatness measuring equipment, and compare the results with the simulation studies conducted prior to these builds.

One of the future purposes of the SEPT LF is training industrial employees by demonstrating the Industry 4.0 concepts. The LF is expected to be a hands-on training facility that will allow small, medium and large companies to use modern manufacturing approaches that implement various levels of digitization and cyber-physical systems. Furthermore, the LF offers a gateway for industry, government and non-profit partners to access SEPT's diverse assets, from faculty members with specialized expertise to industrial-tailor training and state-of-the-art facilities. The SEPT LF supports regional development, growth and sustainability by helping community partners discover and adopt new and emerging practices and technologies.

Lab space is always a premium feature in academic environments. The laboratory area allocated to a LF the learning factory is a key factor in designing its infrastructure. The SEPT LF has been built from scratch on a room with a relatively small surface area, this challenge limiting the number of technologies that can be selected to implement the educational goals of the facility.

To address the surface challenge, the LF has been connected with several specialized labs, the LF acting as a hub to all the other lab facilities available to students. Undergraduate and graduate students and industry partners use the facility to learn about Industry 4.0 within a hands-on environment using production and assembly line modules and specialized stations for quality testing, stamping and packaging. The LF provides its users an implementation of IoT technologies to demonstrate the main characteristics of Industry 4.0 that include vertical networking of production systems; horizontal integration of global value chain networks; end-to-end engineering of overall value chain; using high-impact disruptive technologies; and web based-access for all operations from any device and from anywhere.

The technology approaches implemented in the SEPT LF are the use of cyber-physical systems, the digitization of the production line using Industry 4.0 concepts, and the development and use of IoT applications. The specialized laboratory facilities connected to the LF hub are related to the Department's fields of study. The Automation labs include devices related to process and manufacturing automation. The Power and Energy lab demonstrate modern approaches like the smart grid. The Design, Prototyping and Simulation lab includes a Product Lifecycle Management (PLM) software, major CAD/CAM/CAE software packages, hardware machines for prototyping, and cluster of computers that run various simulation software packages for different fields of specialization. The Robotics lab complements the classical pick and place application with collaborative robots and Automated Guided Vehicles (AGV) that carry robots and create automated transfer of parts between machining, assembly and storage stations. The Smart Systems lab allows the design, manufacture, assembly and testing of smart devices, as well as the demonstration and development of various smart systems applications. The Automotive lab allows the development and testing of electrical and hybrid electrical vehicles with different autonomous levels. The Controls and Mechatronics lab provides a place for the implementation and testing of the electrical, electronic and control components such as microcontrollers and PLCs used in the applications developed in the other labs. The Additive Manufacturing lab includes several 3D printing devices for metal and plastic used to manufacture components for many types of applications and for conducting research activities in additive manufacturing (AM).

The focus of the SEPT LF being educating students and training employees in implementing Industry 4.0 elements in production and using IoT/IIoT technologies, the facility needs a solid networking infrastructure. This infrastructure includes access to the standard university-wide wired network and to two wireless networks - one local and one campus–wide. There are two Local Area Networks (LAN) specifically set up for the LF access. The data center is in the LF and is also used as the control centre for initiating manufacturing processes using the Manufacturing Execution System (MES) software. Blade servers mounted on a server rack are used for creating 64 virtual machines (VM). Two 24-port managed switches are installed inside LF and inside server room. Two types of hypervisors are available in the LF to create, manage, and monitor virtual machines: These hypervisors run directly on the blade servers and hosts to control the hardware and to manage guest operating systems such as Windows and Linux. Examples of such hypervisors can be provided upon request to the readers of this paper.

## 3 Learning Opportunities

The goal of the LF is to replicate a fully integrated factory of the future and feature the core ingredients of Industry 4.0 fully supplemented by IoT technologies that impact various sectors of society such as automation, transportation, health care, environment, and other sectors operations. To prepare graduates for these interconnected sectors, the educational system requires a multidisciplinary and multifaceted approach that gives students the opportunity to develop modern technological skills.

### 3.1 Designing the LF IoT Infrastructure

The IoT Interface includes a server room, IoT devices, and manufacturing stations. The server room includes a pfSense network separator, a 24-port managed switch, a VMmanager Server, an Unisphere NAS (Network Attached Storage), a production WMware, a development WMware, and an access point. The IoT devices include wireless access points, IoT tablet devices, IoT gateways, and mobile IoT gateways. The manufacturing stations used in the LF include a Design and System Management station, a CNC (Computer Numerical Control) station, a Metal Additive Manufacturing station, an Assembly station, a Joining station, a Quality Control station, an Electronic station, a Marking station, a Post Processing station, and an AGV (Automated Guided Vehicle). Several messaging platforms are included in the infrastructure. The SEPT LF uses UniSphere I, UniSphere II, and UniSphere III platforms used to publish, subscribe, store and process streams of data/records as they occur.

### 3.2 IoT Learning Models

The SEPT LF has developed IoT learning models to allow participants to quickly grasp the concept and principles of IoT. The hardware system connects several sensors, such as ultrasonic; IR distance; temperature; humidity; wind speed and direction; carbon dioxide; and a light sensor to a microcontroller. Various microcontrollers are available for testing this system. The data generated by this system is read by a single board computer and pushed out via a wireless router to one of the local UniSphere platforms or to the remote cloud servers. After developing apps for real-time data visualization and data storage, participants can develop apps based on the tools available on their platform.

The LF provides learners several IoT learning models and subsystems such as sensors & actuators; LoRa weather module; RFID & web server integration; RFID based smart parking system; IoT & aerospace; IoT home lighting; smart motor control; power monitoring; air quality monitoring and Power over Ethernet (PoE). Each of these models have a different microcontroller/single board computer along with the appropriate sensor/actuator and support interfacing circuit boards. They have ethernet ports connected to a wireless router that is connected to the LF infrastructure. The authors of this paper can provide information about any of these IoT learning systems.

#### LoRa Long Range Weather Learning Model

This learning module, whose schematic is shown in Fig. 1, demonstrates long-range, low-power environmental monitoring using Arduino microcontrollers, LoRa SX1278/RFM95 transceivers, and sensors such as DHT22 and BMP180 to collect real-time weather data across distances of 5–10 km without relying on cellular or internet connectivity, making it suitable for agricultural and remote deployments. The students have option of using LoRaWAN network servers.

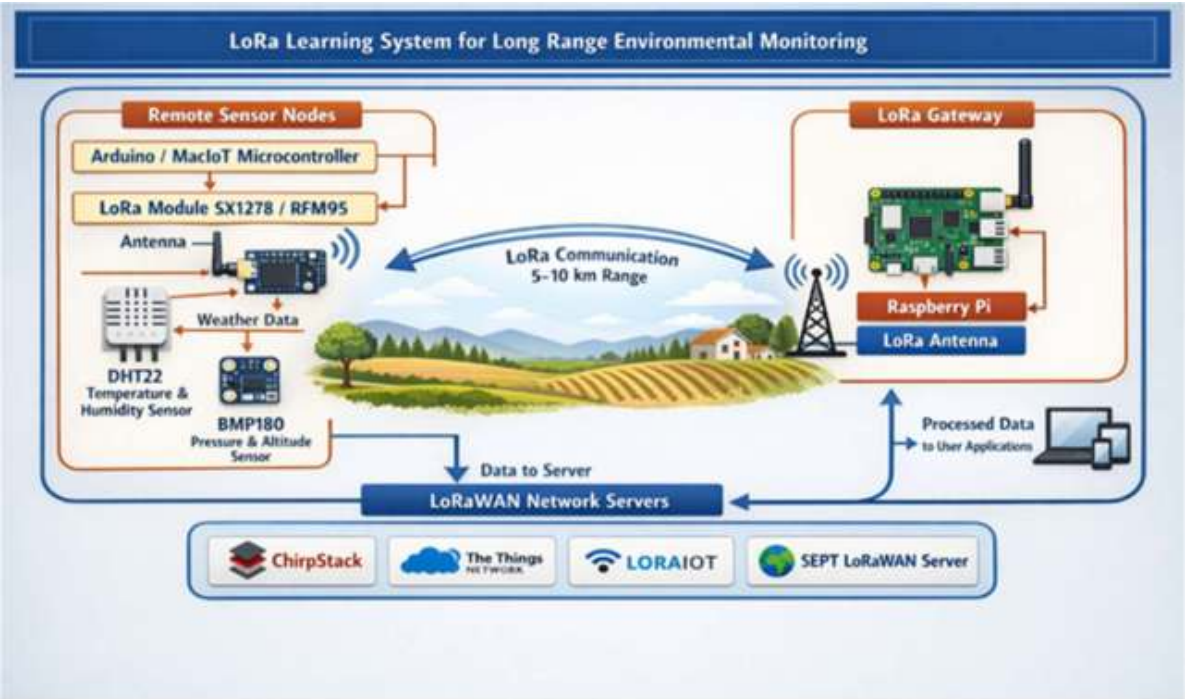


**Fig. 1.** LoRa Long Range Weather Learning Model

### RFID Smart Parking Learning Model

This learning module, whose schematic is shown in Fig. 2, showcases automated parking management by integrating RC522 RFID readers for vehicle authentication, IR or ultrasonic sensors for slot occupancy detection, servo-based barrier gates, and LCD displays to provide a functional miniature parking solution that teaches students about access control, embedded systems, and IoT-enabled resource monitoring.

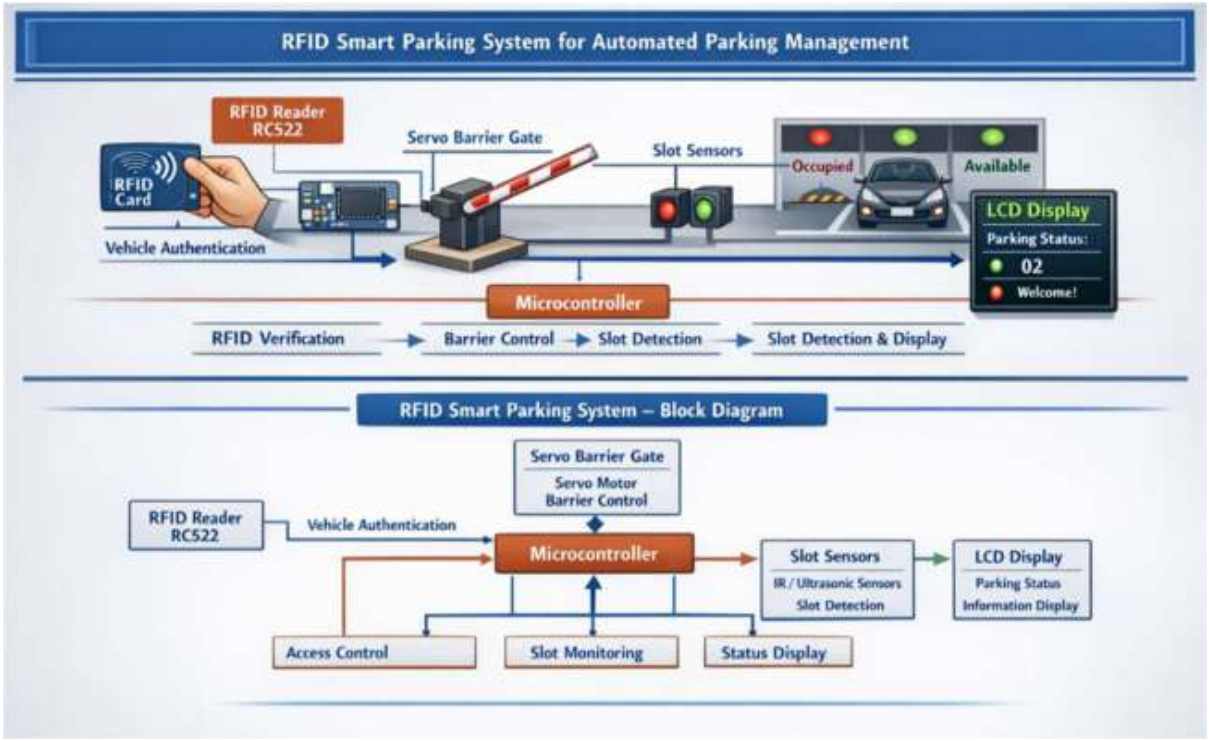


**Fig. 2.** RFID Smart Parking System Learning Model

### IoT and Aerospace Learning Model

The purpose of this learning module, shown in Fig. 3, demonstrates an aerospace-inspired IoT control system that measures vibration on a small airplane model, stabilizes its attitude using a PID controller, and streams data to the cloud for trend analysis, showcasing the trade-off between real-time edge control and cloud analytics.

The airplane sits on a tilt stand that can tilt on demand (manually for disturbances or with an optional high-torque servo at the hinge for automated tests). A stepper motor is mounted on the nose to introduce controlled vibration/imbalance or to act as an active vibration actuator. A vibration sensor (accelerometer) is mounted on top of the fuselage. A microcontroller reads acceleration, runs a PID controller at the edge to meet a desired tilt/vibration target, drives the stand servo and/or the nose stepper, and then uploads processed data to the cloud for long-term analysis.

Processing latency is reduced since the data does not have to wait until reaching a database to be processed. The plane self stabilizes in response to changes in the acceleration. This data is then sent to the cloud database where further analysis can conclude long term more complex trends.

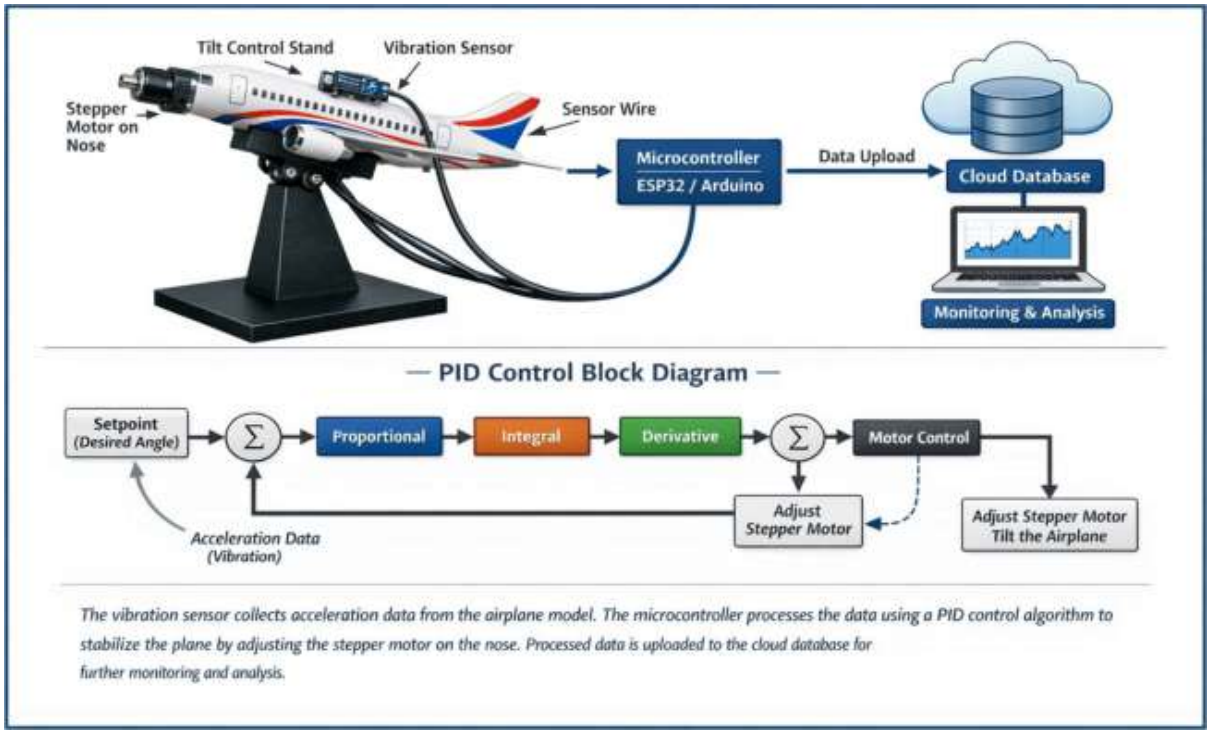


**Fig. 3.** IoT and Aerospace Learning Model

### Industry 4.0 Smart Motor Control Learning Model

This learning module, shown in Fig. 4, simulates automated hole-punching on a rotating platform using an ESP32 or Arduino controller, stepper motors for precise rotational positioning, solenoid-based punching mechanisms, and IoT dashboards (i.e. SEPT Cloud Platforms, Blynk, ThingsBoard, Google Cloud IoT, Node-Red) for real-time monitoring of production parameters, illustrating the core principles of cyber-physical automation, synchronization, and remote industrial process supervision. This model offers accessible yet powerful demonstrations of modern IoT automation.

**Fig. 4.** Industry 4.0 Smart Motor Control Learning Model

## 4 Summary

The SEPT LF provides students the educational opportunities to develop multidisciplinary skills related to mechanical, electronic, computer, communication, and automation engineering and engage them in applied research and allow them to develop significant skills required for employment in the current and future industry.

The paper presents some challenges related to the design, development, and operation of a LF and describes the approaches taken at McMaster University to address some of these challenges. The goal of the paper is to provide help to various academic institutions who intend to develop a new LF or add modern educational opportunities related to implementing Industry 4.0 concepts through projects that involve IoT. The paper also lists a series off major campus-wide projects developed by students enrolled in different Departments that have improved in the LF their multidisciplinary skills.

The learning models described in the paper inspire students to explore further applications of IoT based solutions to many other problems. These learning models showcase the power of IoT as well as its trade of between depth of processing. Meanwhile, learners also understand that, since computations are performed in real time, complex trends and feature extraction are generally limited.

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# Using Spatial Computing to Program a Programmable Logic Controller for Didactic Approaches in a Learning Factory Context

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**Abstract:** The manufacturers of Programmable Logic Controller (PLC) hardware typically offer an Integrated Development Environment (IDE) for developing on their hardware platform. These IDEs can be highly complicated for novices to use due to their lack of training or education. Therefore, it is a major challenge for companies to acquire skilled automation engineers, and it takes them a long time to educate or upskill personnel to meet future requirements in automation plants. We propose a training system that can reduce the amount of required training by using a spatial computing concept platform combined with an AI software platform to solve programming tasks and related activities such as error handling, implemented as a Proof of Concept (PoC). The training system is implemented using C# and Python on a PC and uses Epson Smart Glasses as the user interaction device, based on a human–computer interface that presents an icon-based view of the PLC programming language. The system has been tested for usability by associate lecturers and is currently being researched for improved user interaction within the icon-based human–computer interface and the hand-based human interaction. Our contribution advances spatial computing research as an effective learning method.

**Keywords:** Spatial Computing, Programmable Logic Controller, Human Interface, Industry 5.0, Learning Factory.

## 1 Motivation and Introduction

The training or education on PLCs today is based mainly on enterprise applications running on normal computers connected to a mouse and keyboard. The manufacturers of PLC hardware typically offer an IDE for development on their hardware platform. These IDEs can be highly complicated to use for novices due to their lack of training or education on those systems. Experienced developers can also have difficulties when using a new specific IDE to develop for a new hardware PLC. Therefore, it can be a major challenge for companies to get skilled automation engineers for solving programming tasks, and it takes a long time to educate or upskill people to solve the requirements that automation plants will have in the future. Our approach is to remove the mouse and keyboard by using machine learning [1] and not moving focus from the interaction indicators on mouse and keyboards [2] our method will completely remove those devices from the learning system. We are aiming for a training system that can reduce the degree of training required using spatial computing with the technology of an augmented reality (AR) based platform used for solving programming tasks, simulation and the other connected tasks.

## 2 State of the Art Didactic Practice

The normal didactic practice in technical education today without the learning factory approach is typically based on classroom lectures with practical exercises [3].

A lecturer presents the topic as a PowerPoint/Impress presentation with a combination of theory and examples from real life. The student will then typically have PLC-software installed on their computer for small exercises

during the course, where they try to follow the instructions from the lecturer, and understand the theory as well as the very complex PLC-software. At the end of the course, most of the students will not have learned the basics, because of the overload of information during the lectures. This approach demands many hours of work on the PLC-software in simulation/test platforms.

## 3 Methodology

Some work has been done on programming with AR as in [4, 5, 6] and [7] where it is used for robot programming which is notoriously difficult to learn and maintain for the operator unless it is done daily. The same problem is present for PLC programmers, where it requires high learning qualifications. The system is built up around the Epson Moverio BT-45CS AR Smart Glasses[1], Siemens Tia Platform, and a s7-1500 PLC as showed in Fig. 2, which shows a rich image describing the system architecture. The platform aims to work on any manufacturers development platforms and is based on Ladder Programming languages [8] which is the most common language for programming a PLC today. We have selected the Epson Smart Glasses because they give an easy software interface for extraction from camera view; with 60 Hz framerate and the presentation layer working as an extra desktop where the object can be shown for the operator. The computation flow is a closed-loop control loop [11] where the Epson camera is sending frames to a central computer, then calculates each frame for objects, hand movements, etc. The computer system calculates the behavior and presents it back to the Epson Smart Glasses as seen on Fig. 1. To get a correctly calibrated AR scene, we use the standard equation as described in [4] with the use of homography mapping Equation 1. or hand gesture and interaction with physical PLC equipment during test and simulation of programming.

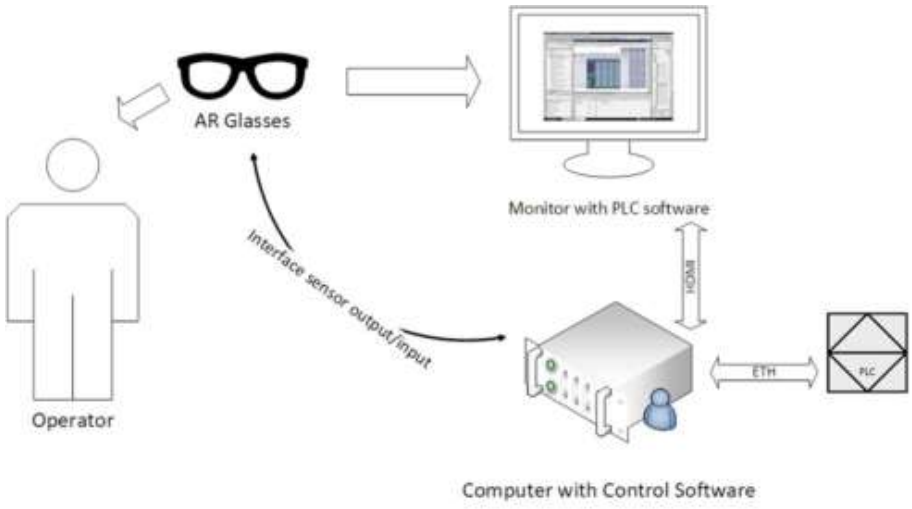


**Fig. 1.** Rich image for the system architecture where the operator uses AR glasses and hand gestures for programming the PLC

[1] https://tech.moverio.epson.com/en/basic_function_sdk/developers_guide/

This matrix procedure is necessary to capture perspective, rotation, and scale changes and allowing the system to place virtual objects realistically onto real scenes.

The homography equation have the $(X, Y, Z)$ as parameters in 3D space and camera focal length $f_x, f_y$ as the pixel coordinates for the optically center $C_x, C_y$.

$$\begin{bmatrix} x \\ y \\ w \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \quad (1)$$

The system uses Model-view-controller (MVC) as its design pattern using different implementations for frontend and backend. The backend processes use a core microservices structure with a common Application Programming Interface (API) for intercommunication between the steps as defined in Fig. 2.

The main hand gesture processes use the Python version of MediaPipe Gesture Recognizer [9] for applying the accuracy and efficiency advantages from deep pattern recognition and the built-in version of OpenCV for image handling. We are also using the Emgu CV [10] framework to be able to develop the system in C# to get a faster and easier implementation of the frontend in the system. The first version of the operator view can be seen in Fig. 3, where the three subsequent steps show two areas on the sides for input and output components. The middle areas are the collection of Ladder networks where the operator can place a component from the input or output by dragging them with a hand gesture movement. In the same way, the operator can connect two components using hand movements. The black arrows in Fig. 3 present the hand gesture movements. The bottom area is used for event buttons such as settings, movement between user screen elements, etc. The frontend is implemented with Microsoft Windows Presentation (WPF) for the graphical view.

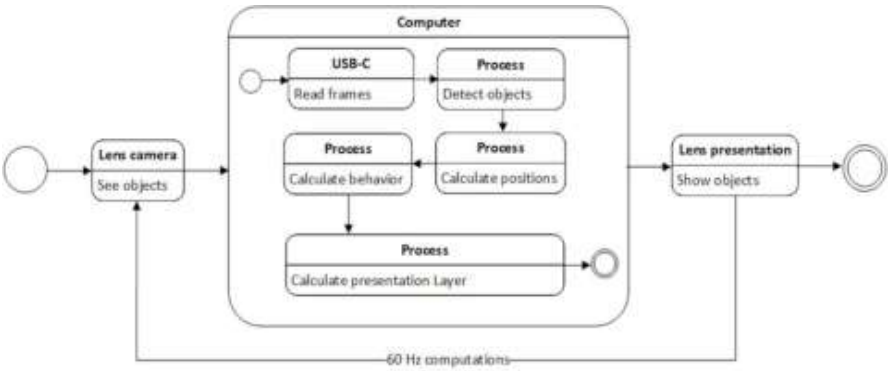


**Fig. 2.** Closed-loop control loop for acquiring data, calculating a solution and presenting it for the user.

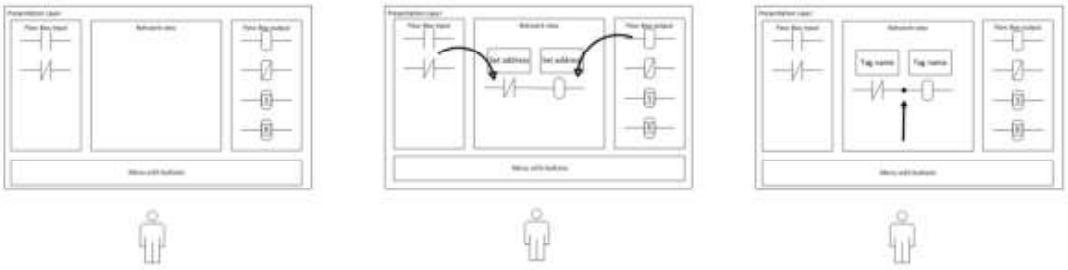

**Fig. 3.** The operator view for the programming steps displays two side panels for input and output components, with a central area for sequencing them into events. The black arrows represent hand gesture movements.

The Microsoft Windows Presentation application can be seen in Fig. 4 which shows the input and output components in blue color with text for better operator understanding. The white background in Fig. 4 would normally be black but for clarity, it has been replaced. The black color will be removed by the presentation layer software in the Epson Smart Glasses.

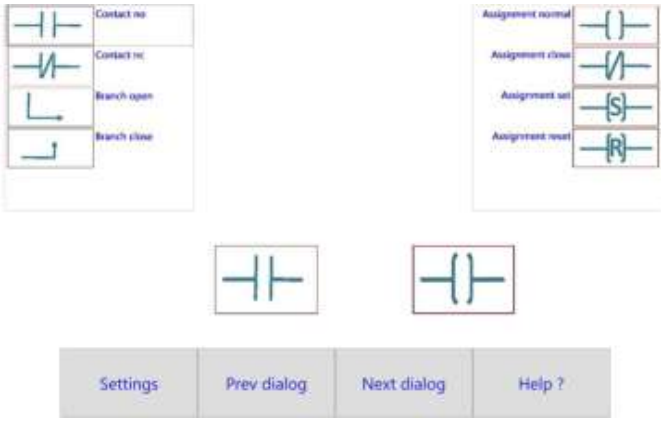


**Fig.** 4. MS WPF Desktop screen dump of the presentation layer for system application.

The system control engine calculates the operator input in an Extensible Markup Language (XML) Siemens Tia file located on the computer. The XML file is used for automatic programming of Siemens PLCs based on import/export of programs, settings etc. The TIA Portal interface is an Application Programming Interface (API) that supports the xml file structure for import and export of programs. Siemens has a framework based on C# programming language that implements these functionalities in a Windows Enterprise application.

## 4 Discussion

The work is a part of a longer ongoing project, and the first preliminary results are ready. The main elements are working and have been tested on several senior teachers with automation backgrounds as PLC programming

educators. The actual implementation is a complex task, and we initially started with a more common software platform for implementing the PoC but rejected it because of limitations in the software. We need to be able to control all levels of the software, so we can add AI where it suits the technology. The user outcome based on this didactic approach seems to appeal to students with a technical background. This might be because they have extensive experience with gaming where they use advanced control devices. Generative AI is also becoming increasingly integrated into professional programming workflows in the PLC world as no code programming. The use of a virtual mouse and keyboard for computer interaction [2] can be used for applications within the automation as the plant simulation with data from digital twins [12] where operators can select vital parameters for monitoring the processes in the plant. Our future research projects will aim to investigate in which context and applications.

## 5 Conclusion and Outlook

This contribution has described a new approach in a Learning Factory context for learning PLC programming with spatial computing. The approach has been implemented with the use of a PoC software framework based on machine learning for hand gesture detection and classification. The PoC has been verified and tested by lecturers to determine the behavior of the system. The system is still in an early state, and more work is needed to determine if it is an improvement on the standard way of working. Our PoC currently only supports Ladder Programming languages [8] in order to focus on the didactic approach and our system architecture and not the other languages within PLC programming as defined in IEC 61131-3 [13]. It will be some of the next steps to investigate strategies for implementing these languages into our platform.

Our further research will be extending the spatial computing technology against automatic generation of code based on process information from the operator and the use of a digital twin of real processes. We will do this using the emerging technologies such as generative AI, machine learning, or speech recognition with the goal of autonomous process implementation in the future automation world.

Our research will also try to encapsulate the three human senses: sight, hearing, and touch in the virtual world as the foundation of spatial computing. It is possible to add more operator behavior from sensor fusion that combines data from multiple sensors to create a more accurate and comprehensive understanding of the environment. Epson Moverio is equipped with various types of sensors such as an accelerometer, geomagnetic sensor, gyroscope, etc. Sensor fusion will also be part of the upcoming research.

**Disclosure of Interests.** The author has no competing interests to declare that are relevant to the content of this article.

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# Learning Factories as a Catalyst for Innovation in Southern African Engineering Education

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**Abstract.** Engineering education in Southern Africa faces significant challenges in preparing undergraduate students for the demands of the modern industry. Innovative educational environments, such as learning factories, offer a promising solution to bridging the gap between academia and industry. The study explored the potential of learning factories in catalysing skills development and innovation in Southern African engineering education. The research focused on questions such as: "What is the current status of Learning Factories in Southern African engineering education and what are the key benefits and challenges of implementing Learning Factories in the region?" Learning factories provide students with the opportunity to design, develop, and test systems, processes, and products in an ideal yet effective learning environment. The study investigated the current state of learning factories in Southern African engineering education, identified best practices, and proposed a framework for their enhanced implementation. The findings suggested that learning factories can greatly enhance the quality of engineering, increase graduate employability and drive innovation in the region. The study's findings informed the development of innovative engineering education models, providing insights for educators, industry stakeholders, and policymakers, thereby promoting economic growth and innovation. Results have implications on curriculum design, industry/academia partnerships and teaching methods.

**Keywords:** Learning Factories, Skills Development, Capacity Building.

## 1 Introduction

The rapid pace of technological advancements, particularly in fields such as automation, artificial intelligence (AI), and robotics, has fundamentally reshaped the engineering landscape globally. Southern Africa's engineering education faces a critical challenge in meeting the demand for skilled engineers as traditional theoretical instruction fails to equip students with hands-on, industry-relevant skills, hindering the region's ability to navigate technological advances and drive economic growth [1]. Graduates are a liability to businesses during their initial years of employment. The employer goes above and beyond to help engineering graduates find lucrative employment after graduating from college. This bridges the gap between theoretical knowledge gained in universities and industry's hands-on requirements [2]. This mismatch results in low employability, limited problem-solving capabilities, and a lack of innovation. Learning factories offer hands-on, industry-relevant training that bridges the gap between theory and practice, equipping the students with practical skills and problem-solving capabilities. Despite their success in developed countries, Learning factories have been underexplored and underutilised in the Southern African context.

The study explores learning factories' potential to drive innovation in Southern African engineering education, proposing a framework integrating Industry 4.0 technologies to enhance skills development and foster innovation in key sectors and addressing the gap between theory and practice [3]

The paper examines the evolution of global learning factories and their impact on engineering education, highlighting their potential to help address Southern Africa's engineering education challenges. A proposed implementation framework is outlined, emphasizing industry academia partnerships, curriculum reform and capacity building or sustainable growth and innovation in the region's engineering education.

### 1.1 Overview of Engineering Education in Southern Africa

Southern African universities struggle to equip students with practical skills, leaving graduates unprepared for the manufacturing sector's demands. Traditional teaching approaches, outdated facilities and limited industrial alignment create a theory-practice gap. Making it hard for students to apply knowledge in real-world scenarios and hindering their productivity and employability [1].

Limited Industry alignment

Traditional curricula can be slow to adapt to the rapidly changing demands of the labour market, resulting in a mismatch between graduates' skills and employers' expectations. Failure to update and align curricula leads to the teaching of content that may not reflect current practices, technologies, and skill requirements [4]. The results are graduates with a mismatch of skills and proficiencies. For these graduates to be employable, they must undergo rigorous training and development to be effective in the industry. For the curriculum to be relevant, all stakeholders should provide input to its development, with industry leaders contributing with a louder voice, since they are the eventual employers [5].

### 1.2 Southern African Industrialisation Strategy

According to the Southern African Development Community. (2015), the region urgently needs to take advantage of its rich and varied resources, particularly in mining and agriculture, to boost industrialisation through value addition and beneficiation. The strategy focuses on the significance of the Southern African Development Community (SADC) region's technical and economic transformation through industrialisation, modernisation, skills development, science and technology, and deeper regional integration. The three pillars of the strategy are: competitiveness as an active process of transitioning from comparative advantage to competitive advantage; industrialisation as a catalyst for economic and technological transformation; and regional integration and geography as the setting for industrial development and economic prosperity.

## 2 Literature Survey

Learning factories originated in the 1990s at Penn State University. Initially focusing on mechanical engineering and manufacturing, they have evolved to incorporate Industry 4.0. Key characteristics include authentic processes, hands-on learning, and industry collaboration [6].

### 2.1 Global Best Practices in Learning Factories

Global best practices in creative education are on display at the learning factories at TU Darmstadt (Germany), TU Wien (Austria), the University of Split (Croatia), Asia University, Pahang (Malaysia), the University of Windsor (Canada), and Penn State University (USA). These factories provide opportunities for industry collaboration and practical learning experiences, with an emphasis on Industry 4.0, lean production, smart manufacturing, and

digital technologies. These institutional learning factories demonstrate a global perspective on innovative education, emphasising hands-on learning, industry collaboration, and technological innovation [7].

### 2.2 Impact of Learning Factories in Developed Countries

Learning factories have impacted post-secondary education in industrialised nations by serving as a strategic initiative to bridge the gap between academic institutions and industry needs, promoting technical innovation, practical skills, and a workforce better equipped to meet contemporary industrial demands [8]. This includes developing processes and systems that confer competitive advantages in manufacturing and production. In industrialised nations, learning factories greatly improved education and industry cooperation. They provide realistic industrial settings that help bridge the knowledge gap between theory and practice [9].

### 2.3 State of Engineering Education in Africa

Southern African engineering education faces challenges such as traditional teaching methods, limited resources, and standardised curricula, which lead to skills gaps in digital literacy, innovation, and problem-solving. This results in unemployable graduates hindering economic growth, innovation and competitiveness in the region's industries. South Africa is the only country in the Southern Africa region with learning factories. The remaining countries have either innovation hubs, research institutes and training centres, or traditional laboratories and workshops [7, 10].

### 2.4 Learning Factories in South Africa

The Council for Scientific and Industrial Research (CSIR)'s learning factories develop skills for the Fourth Industrial Revolution (4IR), fostering creativity and innovation in South African industries. This aligns with the goals of innovation skills renewal and re-industrialisation [10]. Stellenbosch University's Learning Factory simulates real production environments, equipping students with practical Industry 4.0 skills, bridging theory and practice and fostering innovation in smart manufacturing and problem-solving [2]. The Department of Industrial Engineering at Stellenbosch University held the 15th Conference on Learning Factories (CLF 2025) from 25 to 28 March 2025. The conference emphasised improvements in production management and manufacturing engineering, particularly in relation to Industry 4.0 technologies and human-centred applications [11].

Learning factories, through industry-linked initiatives such as Technological Higher Education Network South Africa (THENSA) partnerships, are significantly enhancing South African tertiary education and producing work-ready graduates who contribute more quickly to the economy. The expectation is to bridge the skills gap, improve graduate employability through practical skills, encourage innovation in Science, Technology, Engineering, and Mathematics (STEM), and make learning more relevant to Industry 4.0 needs [12]. These methods, which extend beyond traditional theory to cultivate flexible, entrepreneurial talent essential to South Africa's economic growth, better prepare students for complex workplace demands by emphasising practical, real-world problem-solving, such as in robotics, artificial intelligence, and advanced manufacturing. Learning factories are acting as platforms for research in advanced smart manufacturing and Industry 4.0 [13].

### 2.5 Key Skills Gaps in the Region

There are limited proficiencies in emerging technologies such as the Internet of Things, automation, Artificial Intelligence, Big Data, and Cybersecurity, as well as gaps in innovation capacity, including insufficient creativity, critical thinking, and problem-solving skills. In problem-solving, graduates lack practical experience and the ability to apply theoretical knowledge in practice. Contributory factors to the persistence of gaps include outdated curricula, limited collaboration between industry and academia, a lack of developmental programs, and inadequate funding [14].

### 2.6 Addressing the Skills Gaps

Learning factories can more effectively address skills gaps than innovation hubs by providing practical, hands-on training that bridges the gap between theory and practice, as shown in Figure 1. They offer continuous professional development environments enabling working professionals to upskill or reskill in emerging technologies, thereby enhancing industry relevance and workforce readiness [2].

**Table 1.** Learning factories and Innovation Hubs relationships [15]

| Feature | Learning Factory | Innovation Hub |
|---|---|---|
| Primary goal | Concerned with skills development and education with emphasis on hands-on training in a production environment | Create business opportunities and support entrepreneurship |
| Focus | It's mainly the practical application of knowledge, process testing, and enhancement of skills | Focuses on idea development, networking, and business development |
| Environment | It is a realistic production and industrial setup | It is typical of a collaborative workspace |

### 2.7 Considerations for Setting up the Framework

Establishing a learning factory requires strategic alignment with industry needs, curriculum development, and pedagogical design that focus on experimental learning with modern technologies. The framework should be flexible, adaptable to changing industrial settings, and informed by regional and global best practices [16].

## 3 Materials and Methods

The research adopted an action-learning approach (constructivism), combined with a quantitative survey of engineering education in the region, with a focus on South Africa, which already has Learning factories at some of its institutions. South Africa has the highest-ranked universities in Africa and is home to some of the top 500 universities in the world. Other Southern African countries had two or fewer universities in the 1500+ band worldwide. Most Southern African countries could not be ranked; they had only reporter status (akin to a participation certificate). The framework was developed and hinged on that, as well as on what is also happening in the global world. The study also aligned with the guidelines set by the SADC document on the SADC Strategy and Roadmap 2015-2063 [17].

A review of the literature was conducted using published articles from 2022 to 2025. To enhance reliability, the literature was sourced from databases such as Scopus, Google Scholar, ScienceDirect, and research institutions' and organisational reports aligned with the study. The key terms used in the search were learning factories, innovation, problem-solving, the skills gap in engineering education, designing learning factories, and fourth industrial revolution technologies. The insights gained were then used to develop an ideal framework, as shown in Figure 2.

The research utilised preparation, capacity building, monitoring, sustainability, and implementation as phases to develop the framework, as shown in Figure 1. During the preparation phase, regional members will seek guidance and share ideas with South African members who already have experience establishing learning factories. The regional task force is expected to oversee all phases up to implementation.

## 4 Results and Discussion

Tertiary institutions and Universities to develop teaching strategies for experiential learning, addressing skills gaps in Southern Africa's mining, agriculture and manufacturing sectors through industry partnerships and digital literacy initiatives [Ref 9]

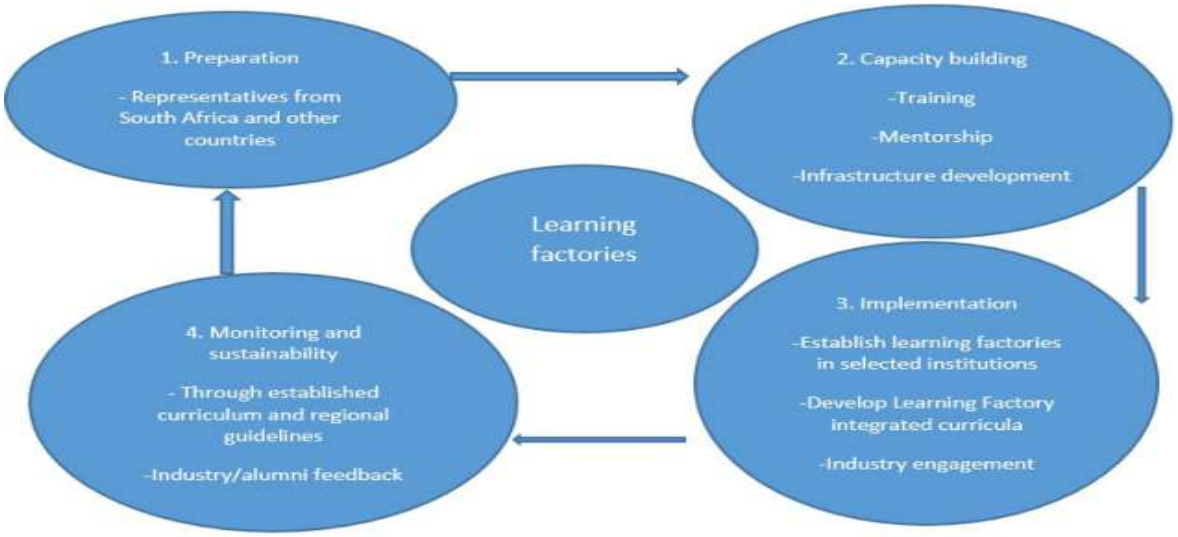


**Fig.1.** Potential pilot implementation framework

Using South Africa's four current Learning Factories as regional hubs benchmarks, the operational framework seeks to create a network of Learning Factories throughout Southern Africa. Preparation, Capacity Building, Implementation, and Monitoring and Sustainability comprise the four phases of the proposed implementation framework, as indicated in Figure 2. A regional task force can be formed to oversee the development and implementation. Strong alliances, transparent governance, consistent finance, and industry relevance are all highlighted in the framework. With an emphasis on addressing regional disparities, encouraging knowledge sharing among Learning Factories, and creating a regional community of practice for Learning Factory professionals, the anticipated results include increased innovation and entrepreneurship, improved skills development, and enhanced regional collaboration, ultimately fostering economic growth and development in Southern Africa. Economic growth in the region can contribute to economic stability and poverty reduction.

In Southern Africa, the operational structure offers numerous advantages. The framework promotes innovation, entrepreneurship, and skill development by facilitating regional cooperation, information exchange, and capacity building through the use of South Africa's current Learning Factories. A focus on strong relationships, transparent governance, and industry relevance ensures Learning Factories' continued effectiveness in addressing local economic challenges. Learning Factories can grow owing to the framework's emphasis on replication and scalability, which maximises impact and fosters economies of scale. This can lead to even better international rankings for the institutions, as they will be effectively equipped, thereby contributing significantly to research and innovation in the region and their respective countries. Countries in the region can enter into a memorandum of understanding on resource sharing, as it may not be feasible for all countries to establish learning factories in different areas of specialisation. Total factor productivity is expected to rise as graduates acquire the skills required for

manufacturing, mining, and processing operations. The framework provides for regional development in education and research and in the economy.

### 4.1 Discussion

The implementation of Learning Factories in Southern Africa has the potential to significantly address the region's engineering education challenges, bridging the theory-practice gap and enhancing employability by equipping students with hands-on, industry-relevant skills. However, the success of the proposed framework depends on overcoming several challenges. Resource constraints, particularly in infrastructure and funding, may limit the initial setup and sustainability of Learning Factories, particularly in under-resourced areas. The digital and resource divides pose significant barriers to the widespread adoption of these initiatives. While industry-academia collaboration is crucial for ensuring that the curriculum aligns with real-world demands, some industries may be reluctant or unprepared to engage meaningfully with educational institutions. Targeted investments in infrastructure, industry engagement, and human capital development are needed, with future work focusing on validation funding and digital divide solutions. Longitudinal studies evaluating the impact of Learning Factories on student outcomes, industry innovation, and regional economic growth will be essential to refining the model.

## 5 Conclusion

Learning factories serve as a dynamic and functional teaching-learning environment [18]. Learning factories network in Southern Africa can boost skills, innovation and entrepreneurship. Leveraging on South Africa’s existing infrastructure, the staged framework can enhance competitiveness and address regional challenges. Success hinges on strong relationships, governance and funding. Learning from the best global practices and addressing regional needs guide the establishment. Main hurdles include securing funding, developing infrastructure, establishing industry partnerships, modernising curricula, and training faculty. Addressing these hurdles will be crucial for effective implementation.

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# Competency and Cognitive Engineering in Learning Factories: A Quasi-Experimental Evaluation of Tinkercad Simulator for Digital Electronics and Embedded Manufacturing Systems

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**Abstract.** The integration of simulation-driven learning environments into engineering education supports competency development aligned with modern manufacturing and automation systems. This study evaluates the Tinkercad Simulator within a virtual Learning Factory framework as a cognitive engineering intervention for digital electronics and embedded systems education. The objective is to determine whether simulation-based environments improve conceptual understanding, procedural accuracy, and design-oriented problem-solving while supporting cognitive engagement consistent with iterative manufacturing workflows such as design validation and testing. A mixed-methods case evaluation using a quasi-experimental two-group design was conducted over a 12-week semester with sixty undergraduate students. The simulation group used a virtual Arduino-based development environment, while the control group operated in an equivalent physical laboratory under identical instructional conditions. Quantitative performance metrics, including iteration counts, programming and wiring errors, pass rates, and summative assessment scores, were analyzed alongside qualitative reflective portfolios using Miles and Huberman's interactive model. Results show statistically significant improvements for the simulation group, including reduced iteration counts, fewer procedural errors, higher task completion rates (92% vs. 78%), and improved post-test performance (85.2% vs. 79.5%, $p < 0.001$), demonstrating improved design iteration and system-level reasoning transferable to manufacturing and embedded system implementation contexts.

**Keywords:** Cognitive Engineering; Competency-Based Learning; Digital Electronics; Simulation-Based Pedagogy; Tinkercad Simulation.

## 1 Introduction

The increasing complexity of manufacturing and automation systems requires engineering graduates to possess not only theoretical knowledge but also strong practical competencies in digital electronics and embedded systems [1]. Traditional laboratory-based instruction remains essential for hands-on learning but is constrained by high equipment costs, limited scalability, and restricted opportunities for individualized practice [2]. The Learning Factory concept addresses this gap by providing practice-oriented environments that connect academic learning with industrial and manufacturing operations [3]. However, physical Learning Factory implementations remain resource-intensive and difficult to scale.

Simulation-based learning tools provide an alternative by enabling iterative design, testing, and error correction within a controlled environment. The Tinkercad Circuits Simulator allows learners to design and program embedded systems using Arduino-based workflows while replicating key stages of manufacturing-oriented development, including validation and troubleshooting [4]. Despite increasing adoption, empirical evaluation of simulation when integrated into structured Learning Factory workflows remains limited.

This study is grounded in Cognitive Engineering and competency development principles. By reducing extraneous cognitive load through immediate feedback, simulation environments support abstraction, problem-solving, and system-level reasoning in embedded system design [5, 6]. The study therefore evaluates the extent to which

Tinkercad enhances conceptual, procedural, and design-thinking competencies within a virtual Learning Factory context, supporting competency development relevant to manufacturing and automation applications.

### 1.1 Research Aim and Questions

The primary aim of this study is to conduct a case evaluation of the Tinkercad Simulator as an educational tool in a virtual learning factory environment, utilizing the principles of cognitive engineering to strengthen competence development.

This aim is addressed through the following research questions:

- **RQ1:** To what extent does the Tinkercad Simulator improve learner performance and competency development in digital electronics and embedded systems tasks, measured by iteration counts, error reduction, pass rates, and summative assessment outcomes?
- **RQ2:** What qualitative evidence indicates that simulation-based learning promotes abstraction, system-level reasoning, creativity, and design problem-solving within a virtual Learning Factory environment?

## 2 Methodology

The study employed a mixed-methods case evaluation approach, combining a quasi-experimental design for quantitative performance analysis with a qualitative framework informed by Miles and Huberman's interactive model [8]. This integrated approach was selected to provide a robust evaluation, capturing both the measurable outcomes of the intervention and the underlying cognitive processes of the learners [9].

### 2.1 Research Design and Participants

A quasi-experimental, two-group design was implemented over one academic semester (12 weeks). The study population consisted of 60 undergraduate students (N=60) enrolled in a mandatory second-year course on Digital Electronics and Embedded Systems. Participants were randomly assigned to one of two groups:

1. Simulation Group (SG, n=30): Used the Tinkercad Simulator for all circuit design, programming, and testing activities.
2. Control Group (CG, n=30): Used a traditional physical laboratory setting with equivalent hardware for all activities.

Both groups received identical instructions, objectives, and tasks, with the practical environment (virtual vs physical) as the only variable.

### 2.2 Intervention and Instruments

The intervention involved scaffolded activities progressing from basic digital logic to advanced embedded systems projects using the Arduino Uno R3, with C++ programming conducted within a simulated IDE workflow comparable to CodeBlocks.

Four primary instruments were used for data collection and evaluation:

1. Pre- and Post-Intervention Summative Assessments
   Standardized tests measuring conceptual understanding, technical accuracy, and applied reasoning in troubleshooting and design tasks.

2. Performance Analytics Logs
   Automated data captured key quantitative metrics from Tinkercad, including:
   • Iteration Counts – number of attempts before task completion.
   • Pass Rates – percentage of tasks completed within time limits.
   • Time-on-Task – active engagement time per project.
3. Reflective Portfolios
   Weekly journals documenting design choices, challenges, error-correction strategies, and cognitive engagement.
4. Project Outcomes
   Final circuit designs and C++ submissions evaluated using a standardized rubric assessing functionality, efficiency, and design compliance.

### 2.3 Data Analysis

The study employed a rigorous, two-pronged data analysis strategy:

Quantitative Analysis: Descriptive statistics (mean, standard deviation) were used to summarize the performance metrics. Inferential statistics were applied to test the research hypotheses:

- A paired-samples t-test was used to assess the improvement in Summative Assessment scores (pre-test vs. post-test) within each group.
- An Independent Samples t-test compared post-test scores and performance metrics (iteration counts and pass rates) between the SG and CG.

Qualitative Analysis: Reflective Portfolios and Project Outcomes were analyzed using Miles and Huberman's interactive model [8], involving:

1. Data Reduction: Coding qualitative data to identify themes related to cognitive engagement, error patterns, and design strategies.
2. Data Display: Use of matrices to visualize links between the simulation environment and competency development.
3. Conclusion Drawing/Verification: Triangulating qualitative themes with quantitative results to ensure consistent and robust findings.

## 3 Results

Analysis of quantitative metrics and reflective portfolios confirmed the benefits of integrating the Tinkercad Simulator in physical learning environment (Figure 1).

- **Breadboard Setup:** Place an Arduino and a breadboard, connecting 5V to the positive bus and GND to the negative bus.
- **Digital Output (LED):** Connect an LED to a digital pin (e.g., Pin 13) and a resistor (220Ω−1kΩ220 cap omega minus 1 k cap omega 220Ω−1$k\Omega$) to ground to demonstrate binary output (High/Low).
- **Digital Input (Push Button):** Utilize a push button with a pull-down resistor (10kΩ10 k cap omega 10$k\Omega$) to feed a digital input pin (e.g., Pin 2) to demonstrate reading binary states.
- **Logic Gates & ICs:** Use 74HC series ICs (e.g., 74HC08 AND gate, 74HC32 OR gate) to build combinational logic circuits.

- **Simulation:** Click "Start Simulation" to run code or interact with buttons, seeing the results instantly without risk of damaging real components.

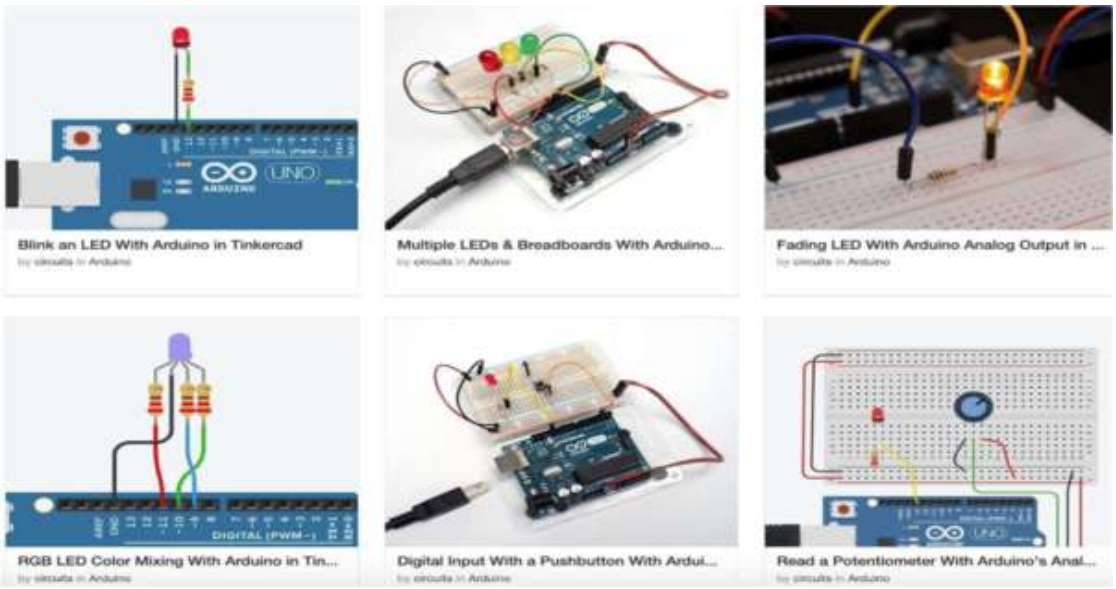


**Fig. 1a.**Physical electronics demonstration.

Tinkercad enables users to visualize electricity flow, learn wiring, and debug logic circuits in a safe virtual environment. Figure 1b presents the key digital electronics demonstrations in Tinkercad.

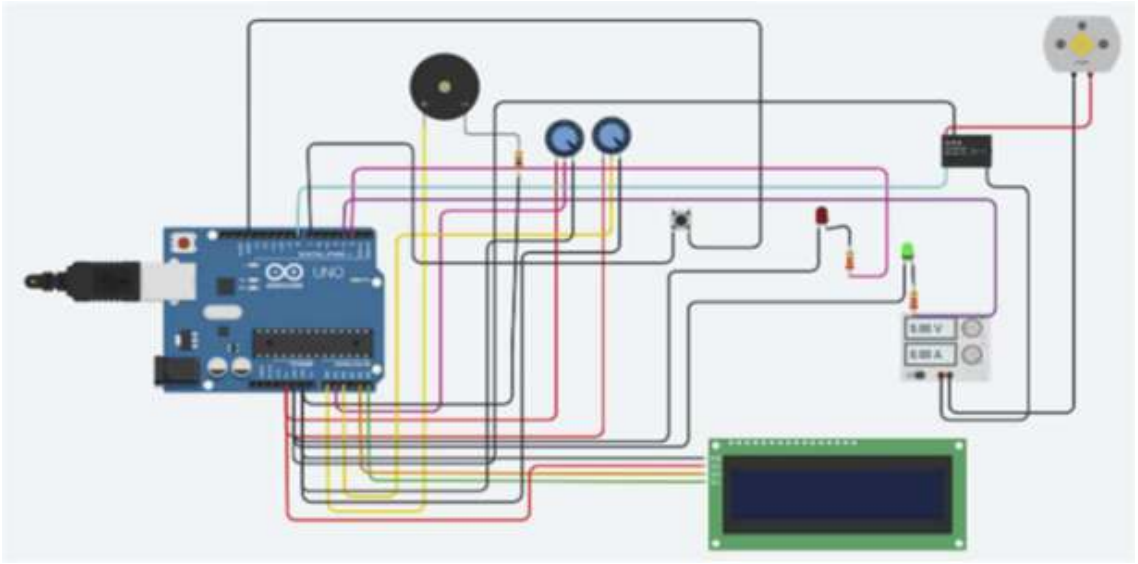

**Fig. 1b.** Implementation of Digital electronics demonstration in Tinkercad.

### 3.1 Quantitative Performance Analytics

The quantitative analysis focused on comparing the performance of the Simulation Group (SG) and the Control Group (CG) across key metrics derived from the Performance Analytics Logs and Summative Assessments.

**Performance Metrics (RQ1 and RQ2).** Analysis of the task completion logs revealed significant differences in the efficiency and accuracy of the two groups. As summarized in Table 1, the SG demonstrated superior performance in all measured metrics.

**Table 1.** Simulation and Control Group across key metrics Analytics

| Metric | Simulation Group (SG, n=30) Mean (SD) | Control Group (CG, n=30) Mean (SD) | Statistical Significance (p-value) | Supporting Finding |
|---|---|---|---|---|
| Iteration Counts (per task) | 2.8 (0.9) | 5.1 (1.5) | $p < 0.001$ | SG required significantly fewer attempts to achieve successful task completion. |
| Programming/Wiring Errors (per task) | 0.6 (0.4) | 1.9 (0.8) | $p < 0.001$ | SG exhibited a 68% reduction in documented errors compared to CG. |
| Pass Rates (Overall Task Completion) | 92% | 78% | $p < 0.01$ | SG successfully completed a higher percentage of the assigned tasks. |

The significant reduction in iteration counts (RQ1) indicates that scaffolded simulation accelerates design iteration. The decrease in programming and wiring errors (RQ2) further shows that the virtual environment reduces procedural mistakes, enabling learners to focus on logical design rather than physical constraints.

**Summative Assessment Scores (RQ4).** The Summative Assessments, designed to measure technical accuracy and applied reasoning, showed a measurable improvement in the SG. A paired-samples t-test confirmed that both groups showed significant improvement from pre-test to post-test ($p < 0.05$). However, an Independent Samples t-test on the post-test scores revealed a significant difference between the groups:

- SG Post-Test Score: Mean = 85.2% (SD = 4.1)
- CG Post-Test Score: Mean = 79.5% (SD = 5.5)
- Statistical Significance: $p < 0.001$

This result directly addresses RQ4, demonstrating that the simulation-based approach led to a measurable and statistically significant improvement in technical accuracy and applied reasoning in summative assessments.

### 3.2 Qualitative and Cognitive Engagement Findings

Thematic analysis of Reflective Portfolios (RQ3), guided by the Miles and Huberman model, identified cognitive benefits associated with the Tinkercad environment. Learners reported increased willingness to experiment due

to immediate and reversible feedback, supporting rapid design iteration and alternative problem-solving approaches.

*"In the physical lab, I would spend ten minutes triple-checking my wiring before plugging it in. In Tinkercad, I just try it. If it fails, I know instantly, and I can fix it in two seconds." (SG Participant 14, Portfolio Week 6)*

Learners also demonstrated improved abstraction and system-level reasoning, focusing on code logic and component interaction before physical implementation.

*"The simulation forced me to think about the logic first… It made the whole system feel more like a single program." (SG Participant 22, Portfolio Week 9)*

These findings align with quantitative results, indicating reduced cognitive load and greater focus on abstraction and system-level design.

**Improved Creativity and Design Problem-Solving.** Analysis of final projects and portfolio reflections showed that the SG explored more creative solutions, with higher project complexity and originality. The simulation environment enabled rapid testing without physical constraints, supporting stronger design problem-solving and enhanced creativity.

# 4 Discussion

The findings support the integration of the Tinkercad Simulator within a virtual Learning Factory environment for digital electronics and embedded systems education, demonstrating improved competency development and cognitive benefits through enhanced design accuracy, iteration efficiency, and system-level reasoning.

## 4.1 Interpretation of Findings and Theoretical Linkages

The statistically significant improvements observed in the Simulation Group confirm the study's hypothesis. Reduced iteration counts and programming/wiring errors (RQ1 and RQ2) indicate improved procedural competency, as immediate visual feedback reduces cognitive load and supports focus on system logic, consistent with Cognitive Engineering principles [4], [6]. Higher summative assessment performance (RQ4) demonstrates improved conceptual understanding and applied reasoning. Qualitative findings (RQ3) show that the simulation environment promotes abstraction, system-level reasoning, and iterative experimentation, strengthening design-thinking competency and contributing to improved technical accuracy and more robust embedded system design outcomes.

## 4.2 Bridging the Transfer of Virtual-to-Physical Competencies

Simulation-based learning serves as an effective preparatory stage for physical implementation within a Learning Factory workflow and reflects manufacturing training conditions. The simulation group showed lower iteration counts (2.8 vs. 5.1, $p < 0.001$), a 68% reduction in programming and wiring errors (0.6 vs. 1.9), and higher task completion rates (92% vs. 78%), indicating earlier stabilization of control logic. Reflective findings showed increased experimentation and faster error correction, supporting abstraction and system-level reasoning. Establishing logical correctness virtually reduces cognitive load during physical implementation, enabling focus on hardware integration, fault isolation, and system validation aligned with manufacturing commissioning and troubleshooting.

## 5 Conclusion

This study confirms the effectiveness of the Tinkercad Simulator as a cognitive engineering tool for developing digital electronics and embedded systems competencies within a Learning Factory framework. The simulation group showed reduced iteration counts, fewer programming and wiring errors, and higher task completion rates, indicating earlier stabilization of control logic and improved system-level reasoning before physical implementation. The findings support simulation as a preparatory phase aligned with iterative testing and validation practices in manufacturing operations. The study provides a scalable framework for integrating simulation into Learning Factory workflows, with future work focusing on long-term competency transfer and comparative evaluation across simulation platforms.

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# Enriching a Collaborative Assembly Cell with Visual Perception in a Learning Factory Environment

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**Abstract.** The Productive and "liveable" inclusion of human workforce is nowadays seen as a key enabler for unfolding the potential of digitalisation in industrial production—this is also reflected by several learning factories incorporating collaborative production settings into their program. In line with these efforts, the collaborative workstation built for education and research at HUN-REN SZTAKI has recently been upgraded with worker instruction, human–machine communication and complex perception subsystems. While currently serving as a demonstration testbed, further development of the workstation for use in a learning factory program is already on the agenda. The contribution of the paper is twofold: (1) it summarises the implemented architecture of advanced perception technologies and human–machine interface extensions added to the workstation, and (2) it presents initial considerations of a learning factory program utilising the upgraded infrastructure. The proposed learning portfolio is planned to widen existing design and development decision spaces, while lifting burdens of substantial—but less insightful—system development.

**Keywords:** Human–Robot Collaboration; Human-Centred Design; Visual Perception.

## 1 Introduction

Backed by experience of past years, it is often claimed that digitalisation will only unfold its full potential if humans can work in cyber-physical production systems in an efficient way, and under conditions that are consistently safe, healthy and "liveable". This recognition is reflected in the concept of "sociocyber-physical production systems", or in the "Industry 5.0" paradigm. Working towards these long-term goals, human-centred design explicitly addresses human strengths and needs [1]. Design approaches of collaborative workplaces now extend (mostly physical) ergonomics by cognitive and affective aspects, allowing the human to not only be safe but also feel to retain safety, overview, and control [2]. Herein, two areas receive particular attention: adaptive (possibly multi-modal) human–machine communication, and establishment of mutual awareness relying on advanced sensing and modelling techniques [3]. Preparing
future engineers for mastering these advances in production system design is becoming part of the areas to be addressed by education, which also applies to learning factories that feature human–machine collaborative workstations [4].

Aligned with this context, one of the collaborative workstations built for education and research at HUN-REN SZTAKI [5] has recently been upgraded with worker instruction, human–machine communication and complex perception subsystems, improving inclusion of humans in assembly processes. Giving an in-progress overview, the paper presents two contributions: (1) Section 2 gives a summary of the system architecture, as implemented in an individual, demonstration-oriented project. (2) Section 3 outlines how a multi-stage roadmap, already proven in earlier project-to-course development [5], will be followed to transform a one-off asset into reusable equipment and evolvable content—specifically targeting hands-on experience with designing and prototyping collaborative assembly environments—integrated into a larger-scale a learning factory program. Given that the transformation

of the system towards learning factory applicability is at its beginnings, the contributions of the paper are limited to presenting a specific implemented and tested prototype, as well as a roadmap proposed under working assumptions regarding relevance and feasibility of its use in a learning factory program.

## 2 System Overview

In order to provide an integrated research, development and demonstration platform, one of the collaborative workstations for small-scale assembly built up at HUN-REN SZTAKI has received additional sensing and workflow control architecture [6]. In its current configuration, the workstation comprises a UR5 cobot, an assembly surface with variable fixtures, as well as parts storage and delivery options. Cameras allow image acquisition and processing, yielding 3D information and relevant states of the entire human–machine assembly system. The architecture uses ROS2 (Robot Operating System [7]) as an integrating platform. As shown in Fig.1, the architecture integrates three computers, each serving a distinct group of functionalities: (1) user and process identification, (2) operator and workflow monitoring, and (3) action and communication. The major part of novelties are in groups (1)–(2), as presented below in detail.

### 2.1 User and Process Identification

Detection and identification of entities, most importantly people, form the starting point of scene interpretation. The detection pipeline relies on a YOLO-based architecture [8] achieving robust accuracy in real time. For the tracking stage, an implementation of ByteTrack [9] was found to perform best, especially in terms of continuity in the presence of intermittent occlusion.

Skeleton detection is a further step, in preparation for gesture and pose recognition. The solution uses VitPose [10], a transformer-based approach specifically developed for body keypoint detection, trained on the COCO WholeBody Dataset [11]. The algorithm can robustly estimate occluded joint positions as well, and was augmented with geometrical cell information to exclude estimations inconsistent with known constraints of the environment. Based on the extracted skeleton data, gestures are recognised to obtain feedback from the operator, and hand motions are tracked to verify process execution.

Face recognition is also performed in this section of the architecture. This is carried out to determine the unique identity of the operator, enabling authentication without adding further visual markings (e.g., optical identifier codes). Utilising FaceNet [12], a deep learning architecture pre-trained on the VGGFace2 dataset, facial features are processed to generate biometric signatures of known individuals. Continuity tracking mechanisms ensure elimination of unnecessary—and computationally demanding—face recognition passes.

### 2.2 Operator and Workflow Monitoring

The second major unit is responsible for monitoring whether the physical workflow and operator alertness remain within a reliable and safe operating area.

In the implemented solution, facial landmarks of the operator are extracted with PIPNet68 [13]. Upon compensating head tilt variation, a Percentage of Eye Closure (PERCLOS) [14] is estimated. An Average Eye Closure Speed (AECS) [15] is also determined, and 30s time-window averages of both PERCLOS and AECS are used for fatigue assessment. In addition, gaze detection is applied to estimate cognitive engagement (gaze orientation alignment with the work area), using the L2CS-Net model [16]. A further phenomenon is yawning—its indicators are relatively easy to extract from geometrical operations performed on facial landmarks. Time-window averaging prevents misinterpretation of transient mouth movement, e.g., while speaking.

Assembly flow monitoring, also a key functionality of the unit, is computationally far less demanding, due to the geometrical (and visual) characteristics of workpieces being easier to model, with more certainty and determinism. Moreover, today's digital product design practice readily delivers nominal models. This makes it easier to pre-determine key features of nominal process flow and common process errors, which can be identified in the images of the assembly scene. Assembly flow control can then enter the appropriate branch of process execution, and trigger communication to the operator as needed.

## 3 Learning Factory Application Roadmap

As described in earlier publications, education has been among focal application fields for the collaborative workstations at HUN-REN SZTAKI, from the beginning of their design and operation [5]. New additions to the infrastructure are also assessed for adaptation to use in education, either as enablers, or as learning objects. The knowledge enrichment potential of new technologies or operation approaches makes them good candidates for learning objects when two working assumptions appear realistic: (1) knowledge and skills related to the novelty are of current or anticipated relevance to the

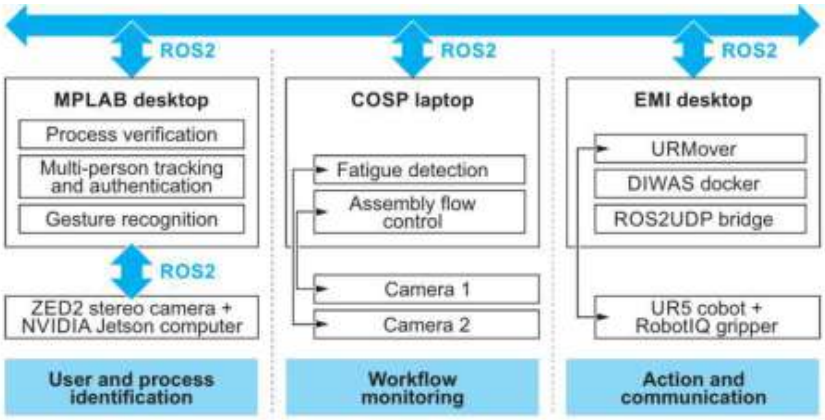


**Fig. 1.** System architecture of the demonstration prototype

industry (and thereby of importance for future engineers to acquire), and (2) integration of the novelty into learning factory activities is feasible regarding breadth and relevance of engineering choices open to students, and regarding estimated success rate in problem com prehension, solution and consolidation of experience. The workstation extensions presented in this paper relate to these working assumptions as follows:

**Relevance**—The growing impact of human–machine interrelations on production characteristics is widely recognised in literature [1–3]. Moreover, we see a departure from today's routine in the higher abstraction level of interfaces, and simultaneous higher inner complexity and versatility of components addressing these challenges. The growing penetration of such novelties in industrial production will demand up-to-date background knowledge and problem solving approaches. Therefore, introducing new technologies supporting human–machine interrelations is deemed relevant in curricula of future engineers.

**Feasibility**—A system with integration of such complex and simultaneously abstract components can leave a wide range of engineering choices open. Many of the decision chains culminating on a high abstraction level make it difficult to gauge how much effort it takes for a student to elaborate a working solution, prevent or mitigate

setbacks, and build lasting experience. This is also supported by anecdotal evidence of past individual student projects associated with research programs—expert assistance and additional work needed to advance past difficulties was on many occasions well beyond initial estimations. On the other hand, adaptability of components and automated design approaches do have the potential of making an adaptation feasible.

At the outset of the learning factory adaptation of the extensions presented here, feasibility remains a critical point, to be finally confirmed by completing the course development process applied in HUN-REN SZTAKI learning factories [5]. In the current case, infrastructure adaptation and course development will revolve around product changeover and process reconfiguration problems as an overall application narrative, wherein advanced components and techniques will support the involvement of humans as assets of flexibility and ingenuity. In accordance with the proven roadmap, the following steps will be taken:

1. Students are invited to individual research and development projects under close mentoring by one or more experts of the fields involved. Student feedback and further findings of didactic relevance are collected and carefully assessed by all groups involved.
2. System and problem configuration choices are suggested in collaboration with domain experts and former students who have participated in individual projects. Particular learning targets will be selected at this stage, depending on what is deemed to be in demand and what is realistically achievable.
3. Based on the suggestions, courses are developed or course options extended.
4. Students attending the courses deliver feedback, optimally as in-course or post-course consultations with domain experts and former students having conducted earlier individual projects.

## 4 Conclusion

The paper presented the extension of a collaborative workstation built for education and research at HUN-REN SZTAKI with advanced perception and communication capabilities, and proposed the application of a tried-and-proven roadmap for the transformation of an individual project outcome into a reusable learning factory environment and evolvable didactic content. The aim of the development is to enable hands-on experience with designing and prototyping collaborative assembly environments, specifically targeting the integration of system components and functionalities on a high abstraction level. While the initial project has already met its targets with a working demonstration environment, its transformation into learning factory assets was only presented as a plan, based on two main working assumptions: (1) high-level system integration skills will be relevant in future industrial production, and (2) learning factory adaptation will be feasible through appropriate tailoring of design decision spaces and development workload, to match capacities, motivation and learning approaches of learning factory students. Currently, findings are limited to anecdotal reports of past individual projects and a single research-oriented prototype, while the roadmap is supported by success achieved on other, more conventional, levels of abstraction. Follow-up publications are planned to present findings and advances of the transformation plan.

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# Integration of Digital Twins and Data Analytics in the BO Smart Factory Using XR

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**Abstract.** The ongoing digitalization of industrial processes is opening new opportunities for flexible, efficient, and transparent production. As part of the BO (Bochum) Smart Factory Lab, a digital twin is being developed that virtually maps the entire production environment and is linked to physical production in real time. The BO Smart Factory consists of several collaborative robots and a modular rail system that allows production processes to be flexibly adapted. In this environment, the drive and RC unit of a remote-controlled RC car is manufactured. During production, extensive process and control data is collected from the PLC systems and linked to the digital twin. The production parameters will be continuously monitored and allow processes to be optimized, and potential malfunctions to be detected at an early stage. The production of the complete RC car takes place in two stages: In the first stage, the drive and RC unit are assembled within the BO Smart Factory. In the second stage, final assembly takes place in an ergonomically designed assembly system with four assembly stations and one pre-assembly station. The second production stage is also mapped in a digital twin. This creates a complete virtual representation of the production chain. In addition to the two-stage production process, mixed reality is used to enable interaction with the digital twin and visualize work content to support the worker. This interaction creates an innovative learning and research environment that makes the transition to Industry 4.0 a practical experience. The BO Smart Factory delivers a demonstrator for adaptive production, in which data, models, and people work together in a digital environment.

**Keywords:** Digital twin, Smart factory, Data Analytics, XR.

## 1 Introduction

This article presents the learning and teaching concept of the BO Smart Factory at the Westphalian University of Applied Sciences and the Bochum University of Applied Sciences, which integrates the use of digital twins and data analytics methods.

The individual elements are summarized in a three-level hierarchical architecture model (Figure 1). The layer model comprises the macro level, which includes the BO (Bochum) Smart Factory with its core elements such as CPS and IOT. The meso level includes the assembly line and the digital twins. The micro level includes the RC car and the XR as well as the interactions and feedback of the students. The didactic approach at all three levels is not only to impart knowledge but also to encourage students to actively apply it, so that they always learn by doing.

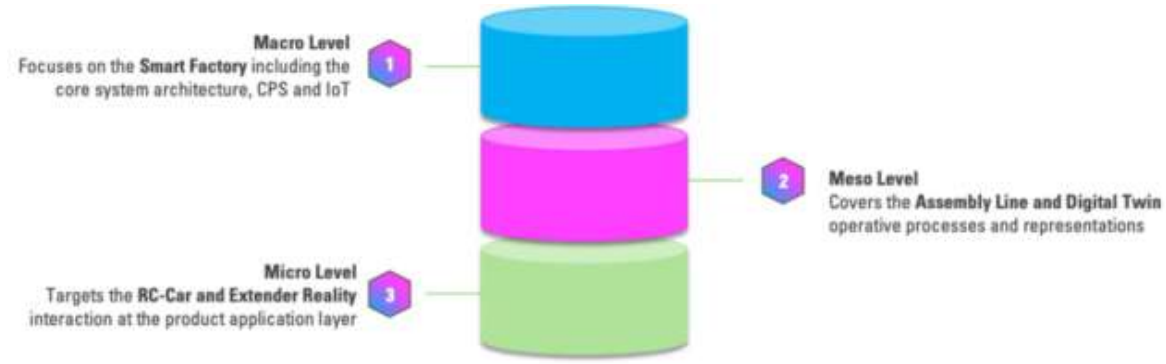


**Fig. 1.** Three-level hierarchical architecture model.

A digital twin is described as "a digital model that reflects physical objects, processes, or systems and, through data integration and real-time synchronization, enables the behavior and condition of its real-world counterpart to be analyzed and optimized"[1]. Digital twins are used in robotics and cyber-physical systems (CPS) primarily for monitoring, simulating, and optimizing complex systems. They enable the outsourcing of computationally intensive processes and support fault tolerance mechanisms, thereby reducing downtime. In robotics, they are used to control and connect manipulators in real time by continuously synchronizing virtual models with sensor data. In addition, the digital twin is used to safely operate autonomous robotic systems in remote or dynamic environments. In CPS in general, it improves predictive maintenance, adaptive control, and decision-making by precisely mapping and optimizing physical processes through virtual images. In collaborative robot scenarios, it also supports the testing, validation, and integration of complex multi-robot setups in virtual environments. Furthermore [2, 3], as well as production planning according to REFA [4] and factory planning and simulation. This allows the areas of digitalization and data analysis to be mapped for the design of efficient, modern production systems in the context of Industry 4.0. These areas provide the methodological and technological basis for the development and use of digital twins, in which physical systems are closely linked to their virtual representations, with a focus on the optimization of industrial production processes. With the help of the BO Smart Factory and the assembly line, a wide range of industry-oriented learning and teaching scenarios can be realized. First, the structure of the BO Smart Factory and the existing infrastructure are described. This is followed by a detailed description of the assembly line. A conventional RC car serves as a teaching and demonstration object. Both the BO Smart Factory and the assembly line are used in the learning factory to address a variety of issues. In addition to the use of digital twins, data analysis methods and extended reality (XR) technologies are also employed.

## 2 BO Smart Factory

The BO Smart Factory is in Building D3 at Bochum University of Applied Sciences and part of the macro level as mentioned before. Figure 2 shows the arrangement of the individual components within the Siemens NX CAD system. This representation was the first digital CAD drawing of the BO Smart Factory and was used to check the extent to which the planned system could be integrated into the spatial conditions.

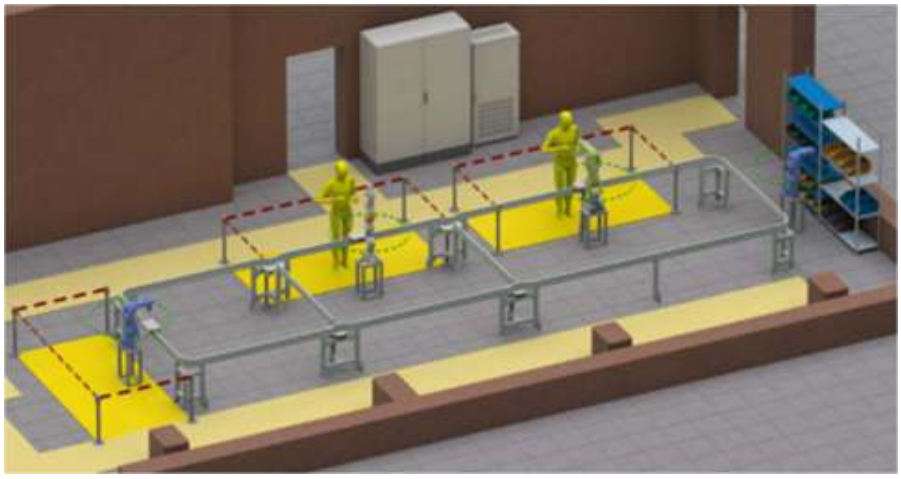

**Fig. 2 .** CAD drawing of the BO Smart Factory.

A total of four industrial robots is in use in the BO Smart Factory, two of which can be operated collaboratively. One of these collaborative robots is a model from the manufacturer FANUC with the type of designation CR-7iA/L. This robot is particularly suitable for assembly and handling tasks involving small components with a maximum payload of up to 7 kg. The FANUC robot has a maximum reach of 911 mm and an axis speed of up to 1,000 mm/s [5]. The second collaborative robot is a KUKA LBR iiwa R800 [6], which is used at the second assembly station. With a maximum reach of 800 mm and a payload of 7 kg, the technical specifications of this robot are comparable to those of the FANUC model. However, the assemblies are fed in and out by non-collaborative industrial robots. The use of robots from different manufacturers results in increased variance in the control and automation components used. The robot controller used for the FANUC CR-7iA/L is the R-30iB Plus. This has a Gigabit Ethernet interface and is designed for use in the Industrial Internet of Things (IIoT). The KUKA LBR iiwa 7 R800 is equipped with the KUKA Sunrise controller, which provides USB, Ethernet, and V/I interfaces. The robot workstations are connected via a rail system from the manufacturer MonTrac. This system is characterized by its compact design and high flexibility, reliability, and efficiency. With the help of so-called "TracSwitch" modules, the track can be distributed from one to two tracks or vice versa. The “TracSwitch” elements are used at the four junctions of the production line and enable the specific selection of the direction of travel. The shuttles used to transport components and assemblies reach travel speeds of up to 55 m/min with a maximum payload of 30 kg. The rail system itself has no separate control unit or communication interfaces of its own.

# 3 Assembly Line

In addition to the BO Smart Factory, there is a purely manual production line located in building C1. The assembly line is part of the meso level. The line comprises a total of four workstations and an additional pre-assembly workstation. Figure 3 presents the structure of the assembly line.

**Fig. 3.** Structure of the assembly line.

The workstations are ergonomically designed but have no direct connection to a higher-level control system. The statuses within the assembly are visualized using a traffic light system from the manufacturer WERMA.

The cloud-based WeASSIST [7] system from WERMA is used for this purpose, which serves to record, monitor, and display process and status information. The use of such a visual assistance system increases the transparency of manual assembly processes and supports structured human-machine interaction. In particular, the system enables standardized feedback on malfunctions, processing statuses, and support requirements without overloading the assembly process with complex control systems. WeASSIST thus represents a low-threshold approach to the gradual digitization of manual production systems.

# 4 RC Car

The product manufactured in the BO Smart Factory and on the assembly, line is a conventional RC car model from the HPI brand called Jumpshot ST Flux [8]. The RC Car is the on the micro level and delivers the interaction at the product application layer.

**Fig. 4.** HPI Jumpshot ST Flux on the campus of Bochum University of Applied Sciences.

For a detailed analysis of the RC car, it was completely disassembled and systematically broken down into its individual components. Figure 5 shows a complete overview of all identified individual parts. Based on this product disassembly, the necessary quantity, assembly, and structural parts lists were derived, which form the basis for a structured representation of the product in the digital model. In total, the RC car consists of 132 different individual parts.

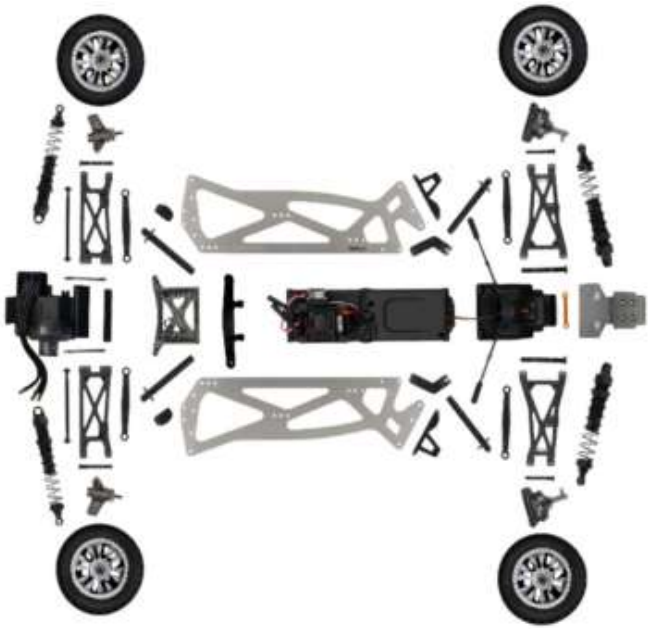

**Fig. 5.** Disassembled RC car.

Parallel to the physical product disassembly, a process-oriented analysis of the assembly processes was carried out. For this purpose, a Supplier-Input-Process-Output-Customer (SIPOC) map was created, in which both the relevant process steps and the associated assembly times were recorded. The time recordings were carried out in accordance with the REFA methodology and ensure a standardized and reproducible collection of process times. The structural and temporal data obtained in this way form the essential input information for the digital twin. Based on this data, standardized workflows (standard work) were derived, which form the basis for uniform and reproducible execution of the assembly processes. Linking the product structure, process model, time data, and standard work enables a realistic representation of the assembly processes, which serves as the basis for simulation, analysis, and optimization within the BO Smart Factory. Linking the product structure, process model, and time data enables a realistic representation of the assembly processes, which serves as the basis for simulation, analysis, and optimization within the BO Smart Factory.

## 5 Digital Twin

The RC car is assembled in two consecutive production stages. In the first stage, the drive unit and the RC unit are assembled in the BO Smart Factory. In the second production stage, the remaining components are assembled at manual workstations. To implement the digital twin, both the BO Smart Factory and the manual assembly line were modeled and mapped in Siemens Tecnomatix. Figures 6 and 7 show the respective digital twins of the two production areas.

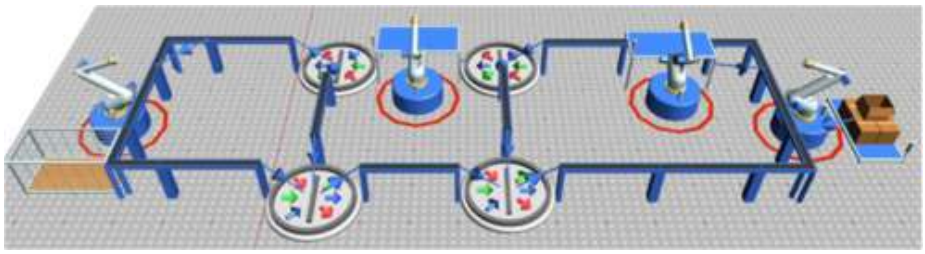

**Fig. 6.** Digital twin of the BO Smart Factory.

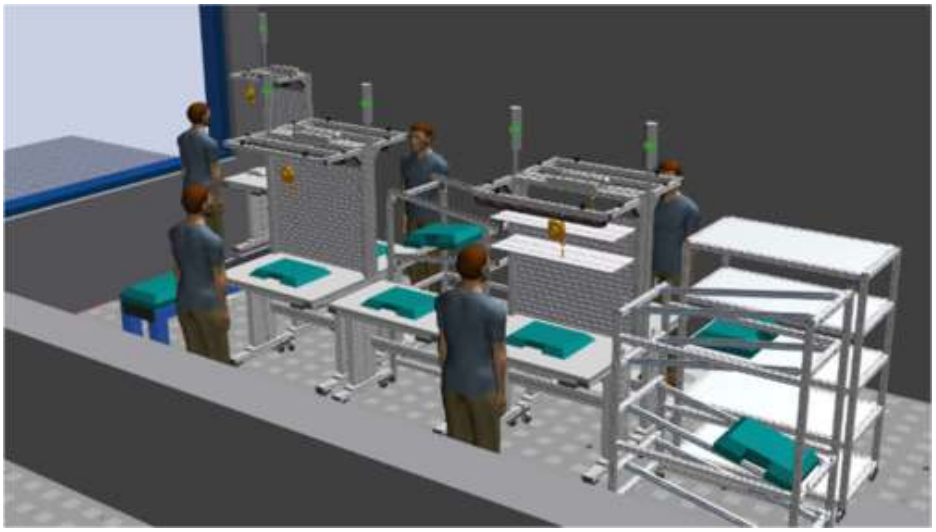

**Fig. 7.** Digital Twin Assembly Line.

The two digital twins of the BO Smart Factory and the assembly line enable a consistent digital representation of the hybrid production structure. They form the basis for the analysis, simulation, and evaluation of assembly and material flow processes using realistic time, resource, and layout data. Building on the digital twins, data analytics methods are used to systematically evaluate production-relevant key figures. This includes analyses of cycle times, throughput times, and resource utilization based on time data recorded in accordance with REFA. In addition, digital twins enable the identification of potential bottlenecks and the evaluation of different production and layout scenarios using simulation-based data analyses. Other use cases include the analysis of variant diversity, the investigation of downtime and waiting times, and the derivation of initial performance-related key figures, for example as a preliminary stage to Overall Equipment Effectiveness (OEE). By combining digital twins and data analytics, cause-and-effect relationships can be made transparent and well-founded, data-based decisions can be made on process design and optimization. In the context of the learning factory, these use cases also enable the practical teaching of analytical methods and promote understanding of data-driven optimization approaches in hybrid production systems.

## 6 Extended Reality (XR)

To visualize and interact with the digital twins, the universities in Bochum and Gelsenkirchen use extended reality (XR) technologies, which include augmented reality (AR), virtual reality (VR), and mixed reality (MR), which is part of the micro level, too. These technologies enable an immersive and interactive representation of the digital twins of the BO Smart Factory and the assembly line and facilitate online exchange between the two universities. The use of XR makes complex production and process relationships spatially tangible and provides lasting support for understanding layout structures, material flows, and assembly processes. Particularly in the didactic context of the learning factories at the Bochum and Gelsenkirchen locations, XR helps to convey abstract planning and simulation models in a clear manner and to establish a close link between the real production environment and the digital twin. In addition, XR-supported access to digital twins opens up new possibilities for interactive

teaching and learning formats, such as virtual tours, simulation-based scenario analyses, and collaborative planning tasks, thus supporting the training of data- and model-based skills in line with Industry 4.0.

## 7 Conclusion and Results

The learning and teaching concept presented by the BO Smart Factory and the assembly line at the Bochum and Gelsenkirchen university locations show how real production systems can be holistically mapped and analyzed using digital methods. The combination of automated and manual production areas creates a realistic hybrid production environment that integrates different characteristics of modern manufacturing systems. The model-based mapping of production systems as digital twins forms the central basis for simulation-supported analyses, data-based evaluations, and continuous optimization approaches. In conjunction with data analytics methods, process metrics can be systematically recorded, analyzed, and made available for informed decision-making processes. The derivation of standard work based on structured products and process data further contributes to the reproducibility and transparency of assembly processes. The complementary use of extended reality technologies expands the functionality of digital twins with an immersive and interactive component and supports both technical analyses and didactic objectives. Overall, the concept presented enables close integration of real production, digital twins, data analytics, and XR, thus representing a future-oriented learning environment that specifically prepares students for data- and model-based tasks in Industry 4.0-compliant production systems.

The learning factory concept described in this article was implemented with students for the first time last semester and evaluated as part of a systematic course evaluation. The results show a very high level of acceptance and perceived relevance of the concept: the dimensions of interest (M = 1.2) and significance for future career (M = 1.4) achieved excellent ratings on a scale with 1.0 as the best score. In addition, qualitative feedback from participants underscores the high practical relevance, topicality, realism, and variability of the learning environment, with individual students rating the internship as the best of their academic career to date. The high level of professional relevance results from the consistent alignment of the learning factory concept with real industrial processes and the promotion of practical, interdisciplinary skills that are directly transferable to professional fields of application in industry. Against the backdrop of these results, it can be assumed that the program will continue to enjoy a high level of acceptance over the next three years and have a lasting positive effect on the motivation, learning success, and perceived professional relevance of the participants.

## Glossary

Digital twins:
Digital twins are virtual representations of physical objects, processes, or systems that are linked to their real-world counterparts via bidirectional data connections. They are used for continuous condition monitoring, scenario simulation, and analysis and optimization of system behavior throughout the entire life cycle.
Data analysis:
Data analysis refers to the methodical process of systematically collecting, cleaning, transforming, evaluating, and interpreting data with the aim of identifying patterns, correlations, and insights and making them usable to support scientifically sound decision-making processes.
Smart Factory:
The smart factory describes a highly digitized and networked production environment in which physical production resources, information systems, and actors interact with each other via cyber-physical systems to control and continuously optimize production processes in an adaptive, data-driven, and largely autonomous manner.

XR – Extended Reality:
Extended Reality (XR) is an umbrella term for immersive technologies that extend or completely replace the perception of the real environment with digital content. These include virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), which are used in various forms to enable interaction between real and virtual elements.

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# Next-Generation Learning Factory Center: Concepts and Infrastructure

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**Abstract.** The Learning Factory Center of the Department of Industrial Engineering, Faculty of Engineering, Chiang Mai University, Thailand, was established in 2019 serves as a hub for education and research in advanced manufacturing aligned with Industry 4.0 and the emerging Industry 5.0 paradigm. Its primary mission is to strengthen students' practical skills, support collaborative research with industry, and provide a realistic testbed for innovative manufacturing concepts. The Learning Factory Center emphasizes immersive and realistic production experiences through the integration of automation technologies, robotics, artificial intelligence, simulation systems, and comprehensive data analytics. The Learning Factory Center incorporates state-of-the-art technologies that replicate the core functions of modern industrial facilities. Key components include an automated storage and retrieval system (ASRS), a robotic assembly station, and an automated palletizing system, all of which are centrally monitored and controlled through a supervisory control and data acquisition (SCADA) system. In 2025, the Learning Factory Center will be further expanded with additional equipment and learning spaces, integrating augmented reality (AR), virtual reality (VR), and a battery pack assembly station featuring a collaborative robot (Cobot) and an automated guided vehicle (AGV) equipped with a robotic manipulator. These developments represent a progression toward a fully developed the Learning Factory Center that leverages digital twin technology, the Internet of Things (IoT), data analytics, and cyber-physical systems (CPS) within a smart manufacturing environment. Overall, the Learning Factory Center plays a vital role as a hands-on learning platform for students, a research hub for faculty and the university, and a training center for industrial upskilling and reskilling.

**Keywords:** Learning Factory, Industrial 4.0, Smart Manufacturing.

## 1 Introduction

The transition of industry 4.0 toward smart manufacturing, the industrial sector faces significant challenges related to advanced technologies, automation systems, and real-time data integration. Developing a workforce with skills aligned to these demands has therefore become a critically important issue. The concept of the learning factory has gained international recognition as a practice-oriented learning platform that bridges theory and real-world application within environments that closely resemble actual industrial factories [1]. It enhances technical competencies, system-oriented problem-solving skills, and interdisciplinary collaboration through structured, practice-oriented learning factory environments [2]. By incorporating real industrial workpieces, tools, and production scenarios into training activities, learners can directly observe, analyze, and optimize manufacturing processes, leading to deeper conceptual understanding and practical proficiency [3]. Moreover, Learning Factories play a vital role in supporting lifelong learning, applied research, and technology transfer from academic institutions to industry [4]. Consequently, the establishment and development of learning factories constitute a necessary mechanism for strengthening industrial competitiveness and sustainably producing a high-quality workforce [5].

## 2 Concept of the Learning Factory Center

The transformation of manufacturing systems in the era of Industry 4.0 has significantly reshaped the roles of engineers and researchers. Their responsibilities are no longer limited to specialized technical expertise; instead, they must be capable of integrating multidisciplinary knowledge, designing complex manufacturing systems, analyzing data, and effectively linking advanced technologies with real industrial applications. In response to these demands, the Learning Factory Center has been developed to serve as a learning ecosystem that systematically integrates education, research, and industrial engagement. The proposed framework is derived from established learning factory concepts, particularly the mini-factory approach presented in [3], which emphasizes practice-oriented and industry-relevant learning environments. Building upon this foundation, the framework adapts and extends these principles to support a structured competency progression within an integrated education–research–industry ecosystem aligned with Industry 4.0 requirements. Fig. 1(a) illustrates the conceptual framework of the Learning Factory Center, emphasizing a progressive pathway for enhancing learners' skills and competencies. The framework consists of the following stages:

*Communicate:* Learners develop fundamental competencies in engineering communication, interdisciplinary teamwork, and human–machine interaction. These skills form a critical foundation for working in smart factories, which require effective coordination among personnel, technologies, and large volumes of data.

*Invent:* This stage focuses on idea generation and creative problem-solving. Learners apply knowledge in automation systems, robotics, and artificial intelligence to develop innovative concepts or solutions that address real manufacturing challenges. This phase promotes systems thinking and experiential learning through hands-on experimentation.

*Design:* Serving as the core of the Learning Factory Center concept, this stage emphasizes holistic manufacturing system design. Learners engage in activities ranging from design needs analysis and equipment selection to process planning, component development, and control system implementation. This approach aligns with the design paradigm shown in the lower part of Fig. 1(a), which spans from raw materials to prototype development.

*Profession & Innovation:* This stage elevates learning from an academic context to professional practice and innovation. Learners apply their accumulated knowledge to develop research outputs, innovations, or practical solutions that can be directly implemented in industrial settings.

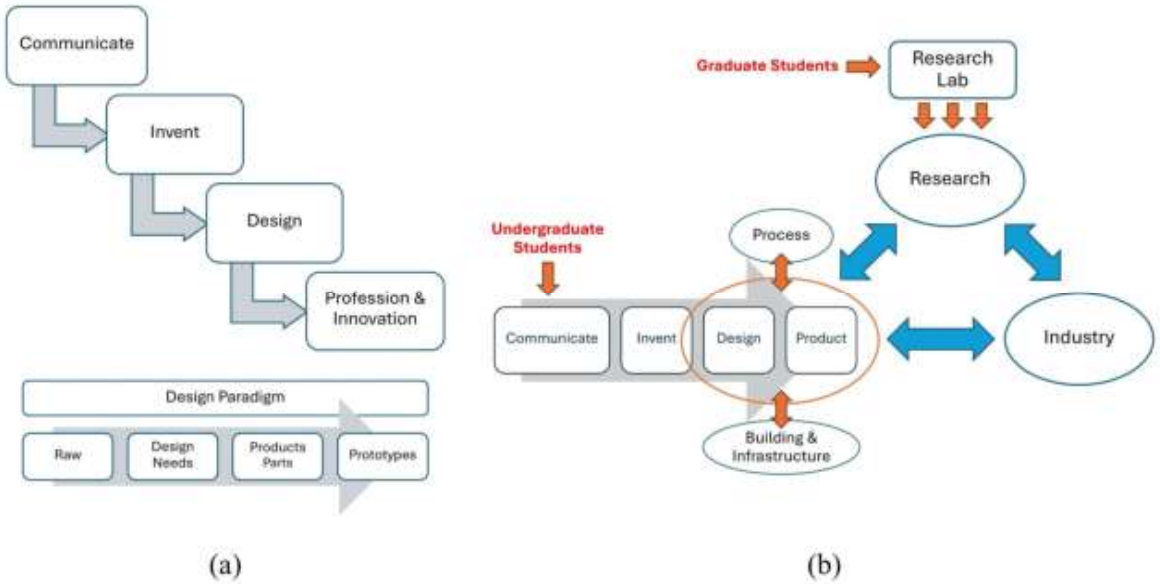


**Fig. 1.** (a) The conceptual framework (b) Ecosystem of the Learning Factory Center

Beyond the conceptual framework, the development of an integrated ecosystem for education, research, and industrial collaboration is equally essential to the Learning Factory Center. Fig. 1(b) presents the system architecture of the Learning Factory Center, which connects undergraduate students, graduate students, research laboratories, and industrial partners in a continuous and interactive loop. In the educational dimension, undergraduate students engage in the learning process through the sequential stages of Communicate, Invent, Design, and Product within the Learning Factory Center environment. This environment is supported by both physical infrastructure (buildings and facilities) and manufacturing processes that enable hands-on, practice-oriented learning. At this level, students gain a comprehensive understanding of manufacturing systems, from conceptualization to final product realization. Graduate students, on the other hand, play a bridging role between education and research laboratories by conducting research that builds upon the Learning Factory Center platform. Research activities are not isolated from teaching; rather, they are integrated into the same ecosystem, allowing research outcomes to be continuously transferred back into educational activities and prototype manufacturing system development. Industry partners play a crucial role as providers of real-world problems, technology users, and co-developers of innovation. Through active knowledge and data exchange with both educational and research components, industry engagement ensures that the Learning Factory Center remains relevant and aligned with actual industrial needs. This structure enables the Learning Factory Center to function as a concrete interface connecting universities and industry.

Overall, the proposed Learning Factory Center advances the state of the art by operationalizing a competency-oriented learning factory framework within a systematically integrated, industry-connected physical–digital ecosystem, thereby strengthening the transferability and scalability of learning factory implementations in Industry 4.0 contexts.

## 3 Infrastructure of the Learning Factory Center

The Learning Factory Center is designed as a prototype facility for learning and experimentation in modern manufacturing systems, with a total area of approximately 240 square meters. The internal layout and workflow planning are arranged to closely reflect real industrial production processes, covering stages from raw material storage and assembly to material handling, data management, and system control through digital platforms. The infrastructure of the center is divided into two main areas, Zone A and Zone B shown in Fig. 2. Each zone has distinct roles and functions, they are fully integrated to enable seamless collaboration and system-level operation.

**Fig. 2.** The infrastructure and areas of the Learning Factory Center

Zone A of the Learning Factory Center is designed as a demonstration area for automated manufacturing systems. Its core component is a small-scale Automated Storage and Retrieval System (ASRS), which serves as the central hub for storing workpieces, raw materials, and semi-finished components. Although the ASRS is scaled appropriately for an educational environment, it retains the same structure and operating principles as those employed in real industrial facilities. Within the same area, two industrial robots with a payload capacity of approximately 3 kilograms are installed for assembly tasks. These robots are well suited for pick-and-place operations and the assembly of small components. They are deployed in a modular assembly workstation where the sequence of operations and assembly configurations can be flexibly adjusted according to learning objectives or experimental requirements. The representative product used in the Learning Factory Center is a worm gear reducer. This product is designed to be disassembled into multiple subcomponents, such as the top cover, front cover, housing body, and various internal parts. The selection of this type of product enables learners to clearly understand the concept of step-by-step assembly processes, ranging from component storage and handling to assembly, inspection, and preparation for delivery. After the assembly process is completed, the finished products are transferred to an automated palletizing system. This system employs one industrial robot with a payload capacity of

approximately 16 kilograms to arrange the products on pallets according to predefined patterns. The palletizing system enables a comprehensive simulation of end-of-line processes, demonstrating the complete workflow from individual components to finished products ready for shipment. All equipment and subsystems in Zone A are monitored and controlled through a Supervisory Control and Data Acquisition (SCADA) system, which serves as a centralized platform for visualizing machine status, material flow, and operational data. Users can monitor the production process in real time and modify operating conditions or system configurations from a single interface.

Zone B of the Learning Factory Center is designed as a learning and experimentation area for Human–Robot Collaboration (HRC). The main workstation in this zone is a battery assembly station, which represents a manufacturing process that requires both the precision of robots and the flexibility of human operators. At this station, humans work collaboratively with a collaborative robot (Cobot) to perform various battery assembly tasks, such as component placement, fastening, inspection, and final assembly. This station design allows learners to gain practical insight into safety concepts, task allocation, and the design of production processes in which humans and robots can operate together efficiently and safely. Once the battery assembly process is completed, the system is connected to an Automated Guided Vehicle (AGV) equipped with a robotic arm for material handling. The AGV collects assembled products from the assembly station and transports them autonomously to the storage area. It performs both loading and unloading operations automatically. The AGV then delivers the completed products to the ASRS located in Zone A, demonstrating the integrated and coordinated operation between the two zones. Similar to Zone A, all systems in Zone B are monitored and controlled through the SCADA platform. This enables users to obtain a comprehensive view of material flow and production status throughout the entire manufacturing process, from initial assembly to final storage. From the perspective of training and workforce development, the AR, VR, and MR stations within the Learning Factory Center are designed to support training for new personnel, reskilling to adapt to evolving technologies, and upskilling for experienced workers. Trainees can begin by learning the fundamentals of automated manufacturing systems, robotic operation, automated storage systems, and SCADA-based control in a virtual environment. They can then progressively transition to hands-on training with real systems. VR and MR technologies enable the design of diverse training scenarios, such as simulating machine failures, practicing troubleshooting in production lines, or adjusting system parameters without affecting actual operations. AR technology, on the other hand, enhances on-site training by providing real-time guidance and contextual information. This integrated approach reduces learning time, increases operator confidence, and supports workforce development for readiness in digital and Industry 4.0 manufacturing environments. In addition, the center is equipped with five high-performance computers used for system simulation, data analysis, production process design, and the development and optimization of control systems. The integration of digital infrastructure with real manufacturing systems enables the Learning Factory Center to effectively bridge theoretical learning with practical implementation.

## 4 Conclusion

The Learning Factory Center demonstrates the critical role of smart manufacturing infrastructure in supporting systematic workforce development for Industry 4.0. By integrating real production systems with comprehensive digital technologies—such as automation, industrial robots, Cobot, ASRS, AGVs, SCADA, and AR/VR/MR—the center provides a learning environment that closely mirrors actual industrial settings. This infrastructure supports both formal education and the upskilling or reskilling of industrial personnel through hands-on training and simulation-based learning. The integration of physical and digital systems effectively bridges theory and practice, enhancing workforce readiness for advanced manufacturing technologies.

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