



Immersive learning factories for promoting experiential manufacturing education and STEM competency development

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ABSTRACT

Modern manufacturing systems have become increasingly complex and require a skilled workforce, demanding innovative educational approaches to bridge theoretical knowledge and practical skills. This VR approach addresses STEM education challenges by fostering experiential, competency-based learning by investigating how immersive VR can enhance learner engagement, motivation, and learning in engineering education settings. We propose the use of learning factories as an approach to close the gap between theoretical knowledge and practical skills. Immersive Learning factories integrate Virtual Reality (VR) technologies as an experiential learning approach to support engineering education and manufacturing workforce development. Based on the LEAD Factory at Graz University of Technology, a fully immersive VR environment was developed to simulate real-world assembly and layout planning tasks. This virtual learning factory includes multiple layout configurations, interactive tools, and a “Build Your Own Factory” feature for custom workflow design, providing a specific training case. This descriptive study involving 30 participants evaluated the system’s effectiveness across four key domains: creativity in layout design, usability, learning motivation, and cognitive load. Results show that participants (67 %) were able to deliver high-quality functional designs and reported high usability scores (mean SUS = 83.9), strong intrinsic motivation (mean interest = 5.9/7), and low average cognitive load (mean NASA-TLX = 4.44/20). In conclusion, participants were able to independently design functional layouts, engage meaningfully with the tasks, and complete them with minimal frustration. These findings not only suggest that VR-immersed learning factories are an effective, scalable, and engaging platform for industrial education and skills development but also provide valuable evidence on how immersive environments can foster motivation and reduce cognitive load in technical engineering education.

1. Introduction

As the complexity of global manufacturing systems increases, the demand for a highly skilled technical workforce is higher than ever. At the same time, demographic shifts across the Organization for Economic Co-operation and Development (OECD) countries, marked by an aging workforce and prolonged careers, further amplify this need (Wolf & Siedl, 2021). However, many educational programs in engineering and production-related fields struggle to keep pace with rapidly evolving industrial technologies and work practices. A critical skills gap persists, with employers reporting difficulty finding workers with the necessary competencies for modern manufacturing roles (Abele et al., 2017; Tisch & Metternich, 2017a, 2017b).

Learning factories have emerged as an effective pedagogical model for bridging this gap. These are physical educational environments (setups) that simulate real industrial workflows, enabling students to gain hands-on experience with production processes in a controlled, reflective setting (Cachay et al., 2012; Tisch et al., 2016). They support realistic forms of education and training by integrating physical tasks, teamwork, and process design, thus aligning educational outcomes with workforce requirements. However, physical learning factories come with limitations: high infrastructure costs, constrained accessibility, and limited flexibility in scaling training to larger or remote groups.

Meanwhile, there is a substantial growing interest in leveraging digital technologies to support learning and education (Zawacki-Richter & Latchem, 2018). Thus, immersive technologies such as Virtual Reality

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(VR) are being explored as alternatives or supplements to physical training environments, to address their natural limitations. Recent work has underscored both the potential and the challenges of using immersive VR for effective learning, highlighting key design considerations to optimize presence, engagement, and learning outcomes (Makranksy & Petersen, 2021; Parong & Mayer, 2018). VR provides a highly engaging, interactive, and cost-efficient platform that can simulate complex systems, offer immediate feedback, and promote experiential learning across time and space (Makranksy et al., 2021; Wohlgenannt et al., 2020). In manufacturing education, VR can replicate production lines, assembly stations, and logistics scenarios while allowing learners to make decisions, perform tasks, and see the consequences of their actions immediately.

However, to assess the effectiveness of VR scenarios in manufacturing, it is critical to investigate the outcomes resulting from such training, particularly in the form of performance, engagement, perceptions, and cognitive load. Specifically, performance, referred to as the observable outcomes of learning that demonstrate a learner's ability to apply conceptual and procedural knowledge to specific tasks or problems, can be operationalized as levels of innovative factory layout designs. Factory layout designs can serve as evidence of learners' ability to apply engineering, manufacturing, and systems-thinking concepts to create layouts that are not only functional but also demonstrate originality, efficiency, and adaptability. Such designs provide insights into students' problem-solving skills, which are essential for optimizing production efficiency in modern manufacturing environments (Abulrub et al., 2011), and serve as tangible indicators of how learners transfer conceptual and procedural knowledge to authentic engineering tasks (Zhang et al., 2025). Second, assessing usability, the extent to which a system can be used by specific users to achieve intended purposes, is a critical determinant of learning effectiveness because it directly influences learners' ability to engage cognitively and emotionally with instructional content (Radianti et al., 2020). A useable and engaging VR interface encourages active exploration, experimentation, and reflection, all of which contribute to meaningful learning (Mikropoulos & Natsis, 2011). Third, measuring motivation to learn in a VR learning factory is vital, as motivation, the internal process that initiates, directs, and sustains goal-oriented behavior in learning contexts, is a key determinant of persistence, effort, and self-regulation in technology-enhanced learning environments (Khan, T. et al., 2019). Finally, understanding cognitive load provides evidence of the mental effort required during learning, informing the design of VR learning experiences that balance immersion with information processing capacity (Juliano et al., 2022). Thus, performance, engagement, motivation, and cognitive load offer a comprehensive view of the pedagogical effectiveness and user experience of VR learning factories in preparing learners for Industry 4.0 manufacturing contexts. Accordingly, this paper presents the development and evaluation of a VR-based learning factory modelled after the LEAD Factory at Graz University of Technology. The virtual system supports full assembly training, error-based feedback, and custom factory layout creation via a "Build Your Own Factory" tool. It was designed to facilitate a structured learning progression, from guided tasks to independent system design, within a virtual industrial environment.

To evaluate the effectiveness of our approach, in terms of a VR learning factory's learning effect, the study investigates the following research questions.

1. What were students' levels of innovative factory layout designs?
2. How did students perceive their engagement with the VR learning factory in terms of its usability?
3. What were the students' levels of motivation to learn in the context of the VR learning factory?
4. What were the students' levels of cognitive load when learning in the context of the VR learning factory?

With these questions, we measure the level of innovation of the students' designs (RQ1), a more concrete and problem- and systems-thinking-based learning outcome compared to recall of knowledge (Makranksy et al., 2019; Sweller, 1994). Additionally, we investigate three learner-centered factors that are necessary for the scalability of immersive education, namely usability (RQ2), motivation (RQ3), and cognitive load (RQ4). By combining these two perspectives, we aim to gain a comprehensive understanding of whether the VR learning factory enables accessible, effective, and productive learning of complex engineering tasks. Our results build on and contribute to current discourse in educational technology by providing empirical evidence on how immersive environments can be designed and evaluated to support constructivist and competency-based learning goals in higher education.

2. Background

2.1. Skills shortage and educational gaps in manufacturing

The industrial landscape is undergoing rapid transformation due to increasing automation, globalization, and digitalization. These changes have created a growing need for qualified personnel who possess not only technical knowledge but also the ability to navigate complex systems, collaborate in teams, and think critically (Abele et al., 2017). At the same time, economic growth and changing industrial demands require manufacturing systems to adapt rapidly. This shift brings with it an urgent need for well-educated engineers and skilled production workers. However, traditional educational approaches often fail to provide learners with the practical, systems-oriented, and collaborative competencies required in modern manufacturing environments (Abele et al., 2017; Cachay et al., 2012).

Despite efforts to modernize curricula, many engineering and vocational education programs fall short in cultivating real-world competencies. A persistent disconnect exists between theoretical instruction and hands-on application, resulting in graduates who may understand production principles in abstraction but lack experience in applying them in realistic settings. This disconnect poses risks not only to productivity but also to safety and innovation.

Simultaneously, learners increasingly expect technology-enhanced educational experiences. Over the past century, both technological advances and generational changes have driven a transition from traditional to interactive learning; this is especially the case among Generation Y, characterized as digital natives who favor engaging, technology-rich educational experiences (Pirker et al., 2016). At the same time, scholars in the educational technology domain have emphasized that immersive learning environments can bridge such theoretical-practical gaps by promoting spatial reasoning, problem-solving, and engagement (Makranksy et al., 2021). This study contributes to these efforts within a manufacturing education context.

VR offers a cost-effective and accessible opportunity to create immersive learning environments, tackling challenges across various disciplines. By enhancing visualization, spatial reasoning, and collaboration, VR supports discovery-based learning, corrects misconceptions, and could boost motivation and self-efficacy (Oje et al., 2023).

2.2. Learning factories and VR in education

Learning factories are educational settings designed to replicate real production environments and have emerged as a response to the described educational gap. A learning factory is a physical or virtual environment that simulates a real industrial production environment, used for training, teaching, and research (Abele et al., 2017). These environments integrate physical machinery, workflows, and teamwork, allowing learners to develop technical and social competencies in a structured setting (Tisch et al., 2016). The concept is grounded in experiential and action-oriented, as well as problem- and competency-based learning models, and often involves real product

manufacturing tasks. Learning factories are supported by didactic frameworks such as the Learning Factory Curriculum Guide, which emphasizes progressive learning levels from macro (infrastructure) to micro (task) design (Tisch et al., 2016). Throughout the past decades, the learning factory concept has evolved into a mature pedagogical framework supported by empirical studies and design models fostering core competencies in industrial and manufacturing engineering, systems thinking, process optimization, and digital manufacturing (Abele et al., 2024). While highly effective, physical learning factories are expensive to build and operate, often require significant space, and are not always accessible to all learners (Tisch et al., 2017).

Parallel to the growth of learning factories, immersive technologies, and particularly VR, have been increasingly adopted in educational settings across disciplines. VR can offer advantages such as safety, cost savings, location independence, and immersive engagement. In educational contexts, it enhances student motivation, concentration, and learning outcomes (Conrad et al., 2024; Makransky et al., 2019; Sattar et al., 2019).

Prior research has applied VR in medical, architectural, and engineering education, with measurable gains in motivation, spatial understanding, and knowledge retention (Acevedo et al., 2024; Akbulut et al., 2018; Chirico et al., 2016; Zhang et al., 2024). Such studies show that VR allows learners to explore 3D environments, interact with simulated tools and machines, and learn by doing, and that VR increases learner motivation, enhances retention, and can be particularly effective for spatial and procedural knowledge (Chirico et al., 2016; Conrad et al., 2024; Makransky et al., 2021; Pirker et al., 2021). However, most of this work either lacks a unified system design or does not assess immersive learning key outcomes such as intrinsic motivation or cognitive load (Makransky et al., 2019). Furthermore, careful instructional design was identified to be critical to avoid excessive cognitive load and ensure effective learning (Jensen & Konradsen, 2017; Makransky et al., 2019; Radianti et al., 2020). Based on the previous work, it was determined that, while prior research has demonstrated VR's potential for enhancing motivation and engagement across disciplines (Conrad et al., 2024; Radianti et al., 2020), only a few studies have integrated immersive VR into manufacturing learning factories with empirical evaluations of learner outcomes. For instance, Riemann and Metternich (2022) argued that VR-based learning factories can offer authentic training without the logistical and financial challenges of physical setups. However, most implementations remain either theoretical or limited in scope, lacking empirical evaluation of user outcomes like usability, motivation, or workload.

2.3. Implications for the study and preliminary work

This study addresses the identified gaps through a structured, empirical analysis aligned with educational goals and investigation of applied problem-solving (RQ1), usability (RQ2), motivation and engagement (RQ3), and cognitive load (RQ4). A Learning Factory is about developing competency in process design and systems optimization (Tisch et al., 2016), which is measured by the quality and variability of factory layout designs created by the students, testing the VR system's ability to facilitate higher-order engineering thinking beyond just memorizing facts. High system usability is necessary for any educational technology, particularly immersive VR, to prevent disorientation and frustration. Intrinsic motivation – specifically interest and perceived competence – is investigated, due to its strong correlation with deeper processing and knowledge retention in STEM context (Makransky et al., 2021). VR poses a risk of high cognitive load. Thus, it needs to be ensured that the VR environment is not a hindrance but still serves as a pedagogical facilitator.

In 2022, our initial comparative study (n = 20) evaluated the effectiveness of an HMD-based VR training against a desktop computer-based module for developing digital competence. Participants in both groups completed identical theoretical and practical exercises, with the

only difference in the delivery platform (HMD vs desktop), and then answered standardized questionnaires on system usability (SUS), motivation (QCM), knowledge acquisition, and action performance. Results showed that VR achieved usability scores comparable to the desktop setup, with both being in a “good-excellent” range. Motivation levels did not differ significantly overall, though VR users found the practical task significantly easier to complete. Specifically, preliminary inferential analysis using independent samples t-tests indicated that the observed effect sizes for motivation were small, suggesting that either the effect is negligible or that the study was statistically underpowered to detect a meaningful difference in motivation between the two modalities. In knowledge gains, desktop participants outperformed VR, whereas in terms of action performance, VR had a slightly higher average score.

Despite the intentionally small, exploratory study size (n = 20), it provided valuable insights in indicating that VR is an equally viable alternative to traditional computer-based instruction, matching or exceeding desktop training on key usability, motivational, and performance metrics. In addition, it highlighted the need for the current descriptive study (n = 30) to systematically assess the core user experience factors (usability, load, motivation) before proceeding to a larger, adequately powered comparative effectiveness trial.

2.4. Theoretical framework: Experiential Learning Theory

This study is grounded in Kolb's Experiential Learning Theory (ELT), which posits that learning is a process whereby knowledge is created through the transformation of experience (Kolb, 1984). According to this model, effective learning involves a cyclical interaction between four stages (Kolb, 1984). First, in the *concrete experience* stage, learners engage in direct interaction with tasks or environments. In the *reflective observation* stage, learners review and reflect on that experience. Then, in the *abstract conceptualization* stage, learners form new ideas or adapt to existing ones, and in the *active experimentation* stage, learners apply what they learned to new situations.

Recent research in educational psychology supports the effectiveness of VR in fostering Kolb's experiential learning cycle, particularly in STEM education contexts (Oje et al., 2023). The learning experiences afforded by the VR learning factory naturally guided learners to the stages presented in Kolb's model. Specifically, students begin with concrete experience by performing realistic assembly tasks in the immersive environment. They receive feedback on errors and completion times, prompting reflective observation. The layout planning tool enables students to engage in abstract conceptualization as they design new configurations to solve production challenges. Finally, they conduct active experimentation by testing their custom layouts in VR and interpreting performance outcomes. This design-and-test loop in the VR factory aligns with the active experimentation phase, carefully balancing engagement with cognitive demands as suggested by Makransky and Petersen (2021), thus reinforcing deep learning.

This iterative cycle not only reinforces learning through feedback but also allows students to navigate between guided and self-directed tasks. The combination of immersive simulation and constructive layout design makes the system particularly well-suited to experiential learning principles. As students engage in the four stages of experiential learning, they also engage in critical learning processes such as diverging, assimilating, converging, and accommodating, each of which can be supported through different elements of the system. For example, as students engage in group work, open discussions, and creative activities, they engage in diverging learning processes moving from concrete experiences to reflective observation. Similarly, as students engage in more structured learning activities, they engage in assimilating processes, moving from abstract conceptualization to reflective observation. Then, as students engage in practical application tasks, they undergo converging processes, transitioning from abstract conceptualization to active experimentation. Finally, as students engage in real-world challenges and design tasks, they enact accommodating

processes, moving from concrete experiences to active experimentation. In summary, by providing a structured and flexible learning loop, the VR LEAD Factory supports competency development not only in procedural industrial and manufacturing engineering knowledge but also in problem-solving, critical thinking, and systems understanding, which are the core goals of experiential technical education. Situating this study within Kolb's framework, this study aims to contribute to a growing body of research that leverages immersive technology not just for demonstration, but for meaningful cognitive transformation through reflective and applied learning.

3. Virtual reality learning factory design

The present study addresses this gap by designing and exploring a VR-based learning factory (Fig. 1 bottom) built upon the physical LEAD Factory at Graz University of Technology (Fig. 1 top) that combines simulation of realistic production processes with student-driven design and planning. The LEAD factory (Lean, Energy Efficiency, Agility and Digitalization), a learning factory for academic and industrial engineering education, was established in 2014 and is built around the production and assembly of a market-available scooter (Karre et al., 2017).

In over 30 training modules for the LEAD topics, participants produce scooters in three distinct states, ranging from a suboptimal initial state to an advanced lean state and a fully optimized digital state (see e. g., Wolf et al., 2022). As inherently implemented in the learning factory concept, the main limitations of the LEAD factory include the spatial bind to one layout at a time involving changeover efforts and restricting the representable learning scenarios and its product reuse and disassembly processes resulting in tiresome, repetitive processes for the employees after or sometimes even between the practical sessions. To overcome these limitations, a VR-based system was developed that can host several states at a time and does not require physical product disassembly (Herstätter et al., 2024).

Virtual Reality (VR) is defined as a computer-generated, three-dimensional representation of a real or fictional environment, that gives users a pervasive sense of presence and enables them for real-time interaction with the computer-generated environment (Pila et al., 2021). In Milgram and Kishino's Reality-Virtuality Continuum, VR is

positioned at the Virtual Environment extremity (Milgram & Kishino, 1994). This distinguishes VR by its requirement to completely substitute the user's physical surroundings with synthetic sensory input to achieve deep technological immersion (Berg & Vance, 2017). VR is characterized by stereoscopic, head-tracked displays and multi-sensory feedback, all designed to create an illusion of being experientially present in an alternative digital space (Radianti et al., 2020; Steuer, 1992).

The VR learning factory system includes (a) a digital twin of the LEAD Factory's physical production processes, (b) a realistic virtual replica of the real layout states: current, lean, and digital (Fig. 1), (c) modular VR training scenarios that simulate real assembly with tool interaction and digital performance tracking as well as factory and process planning tasks, and (d) a custom layout planner ("Build Your Own Factory") that exports user-designed configurations into VR without changeover times. The goal of this VR implementation is to simulate the experience of a real-world learning factory while leveraging the benefits of virtual environments, such as cost efficiency, safety, flexibility, and accessibility.

The system includes four layout states, each simulating a different production philosophy. These layouts are visually and functionally distinct and can be changed in virtual reality in seconds. They allow learners to explore the impact of design changes on task flow, assembly time, and quality. Users can switch between layouts via an in-VR interface, also enabling comparative analysis, as shown in Fig. 1.

- Premade Current State: Reflects the unoptimized, baseline configuration of the physical factory.
- Premade Lean State: Integrates lean manufacturing principles, such as flow, balanced operation, reduced part transport and improved ergonomics.
- Premade Digital State: Includes digital feedback tools like sensors and real-time production data.
- Custom State: Imports user-designed layouts created via an external layout planner tool.

3.1. Learning architecture and actions

The VR learning factory was developed using the Unity 3D game

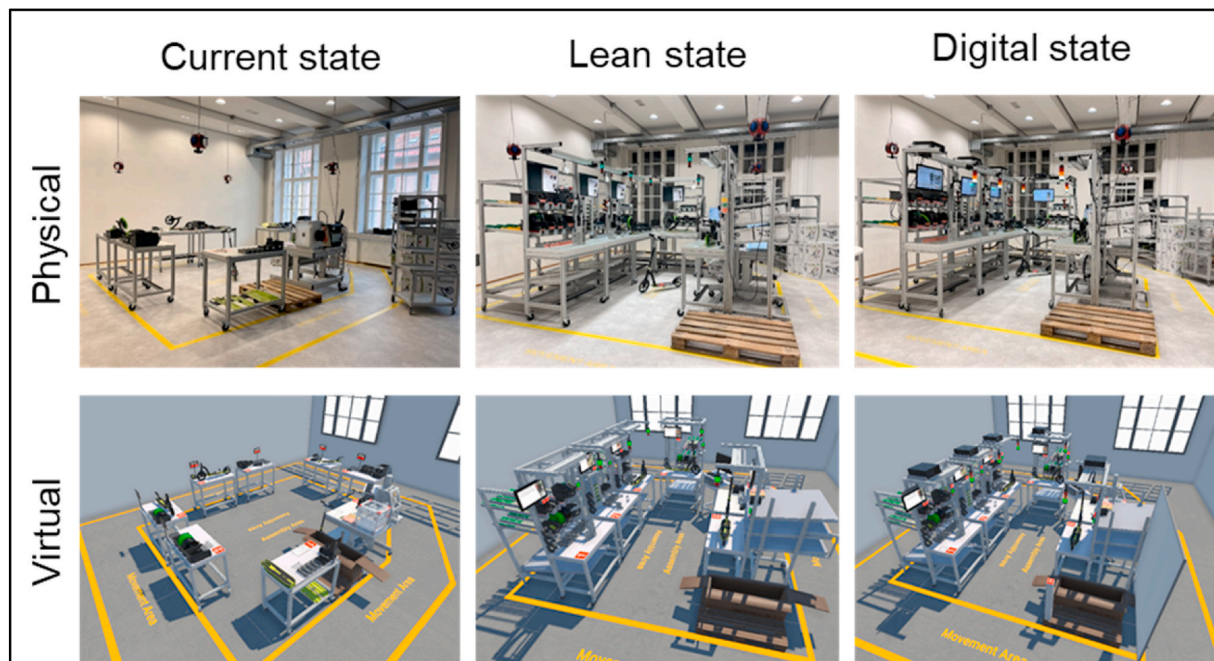


Fig. 1. The three states of the LEAD Factory (physical - top and virtual - bottom).

engine, deployed with Meta VR hardware. The system follows an object-oriented architecture that replicates core components of the physical LEAD Factory (Fig. 2), including workstations, tools, parts, assembly sequences, and instructions. All components were modelled in 3D and programmed to allow interactions such as grabbing, picking, and placing of parts, using tools (e.g., screwdrivers, torque wrenches), interpreting visual guides, and responding to system feedback (e.g. on errors, or final performance evaluation).

The system allows students to train on pre-defined layouts and then create and test their own factory, thus covering both instructional and exploratory learning modes within a fully immersive VR environment. Learners use VR controllers to grab, move, and place parts and tools. The system uses haptic and visual cues to guide learners. For example, outlines on parts indicate interaction readiness, and real-time prompts show the correct tool or part orientation. Interaction design is based on best practices for immersive learning environments and aims to promote engagement and self-guided learning (Makransky et al., 2021; Wohlgenannt et al., 2020).

This includes (1) independent state transitions between layouts, (2) visual cues for objects when selectable, (3) snap guidance outlining parts when aligned correctly, (4) task guidance by paper or screen prompts for each assembly step, (5) faulty assembly option where scoters can be finished with missing parts, incorrect screwing, or in incorrect assembly sequence leading to required disassembly and rework, and (6) an error feedback option, where incorrect actions trigger vibration and messages.

All actions are tracked and timestamped, allowing assessment of efficiency and process accuracy. Fig. 3 shows examples of the visual guidance cues implemented in the system. Lastly, the software is developed in a modular way, allowing educators to adjust configurations or expand the software with new modules as needed, making it future-proof and highly adaptable.

3.2. Build Your Own Factory: layout planning tool

A key feature of the system is the “Build Your Own Factory” module. This tool allows users to create a layout by balancing assembly activities and workload in the line assigning them to workstations, positioning workstations, and assigning tasks. The final workstation setting and layout can be exported to a file, which is then loaded into the VR environment. This feature was developed as a Java-based desktop tool integrated with the VR system, ensuring that for all potential settings the final layout starts with all parts and tools needed per workstation. Thus, users can test the performance of their own state without any effort needed and virtually assemble products immediately, as the set-up time is close to zero students can test various layouts in one training run. The feature was directly derived from a training scenario in the physical learning factory, that requires students to change the physical factory’s layout, tiresome and time-consuming, allowing them to test only one

layout per session. A quality report is generated at the end, detailing assembly time, workstation load, and any errors to enable evaluation of the different layout’s performances.

3.3. Pilot testing and preliminary evaluation

Unlike previous efforts that focus on isolated aspects of learning (e.g., VR assembly or layout planning), this system provides a unified, immersive learning experience. Thus, this represents a step forward from previous implementations by integrating factory simulation, layout planning, and real-time performance feedback into a single, immersive platform. The goal is not just to replicate existing factory features, but to extend learning possibilities that offer immediate feedback, simulation of multiple factory states, and adaptive training scenarios. A pilot study was implemented to test the feasibility and effectiveness of the VR solution as compared to a desktop solution, as described in Section 2.3. This particular study goes deeper by investigating how 30 students engaged with this system across four learning dimensions, using both quantitative and qualitative data to assess usability, motivation, cognitive load, and the effectiveness of layout design. Our results deliver new knowledge and design principles to inform both the design of VR-based training systems and the pedagogy of manufacturing education.

4. Methods

This descriptive study investigated how learners engaged with the VR LEAD Factory across four learning dimensions: factory design, usability, motivation, and cognitive load. An approach was used, incorporating quantitative scales, qualitative feedback, and performance data extracted from the system, that aligns with best practices in VR learning research (Makransky et al., 2019; Makransky & Petersen, 2021). The initial comparative evaluation described in Section 2.3 provided the methodological base for our current study’s design, guiding the measures, test metrics, and analytical procedures in the VR learning factory context.

The study took place at Graz University of Technology and involved 30 participants. This threshold aligns with conventional guidance in statistics and social sciences, where $n = 30$ is often treated as the minimum sample size for approximating a normal distribution under the Central Limit Theorem (CLT) (Lumley et al., 2002; Wilson Van Voorhis & Morgan, 2007). In educational and behavioural research, a sample of 30 or more participants is typically regarded as sufficient to provide stable estimates of means and variances (Johanson & Brooks, 2009). Participants were recruited via internal email lists and in other lectures at the institute and volunteered without compensation. No prior experience with the LEAD Factory setup and processes was required. All participants signed informed consent forms and received a short orientation on how to use the VR equipment. The average age of participants

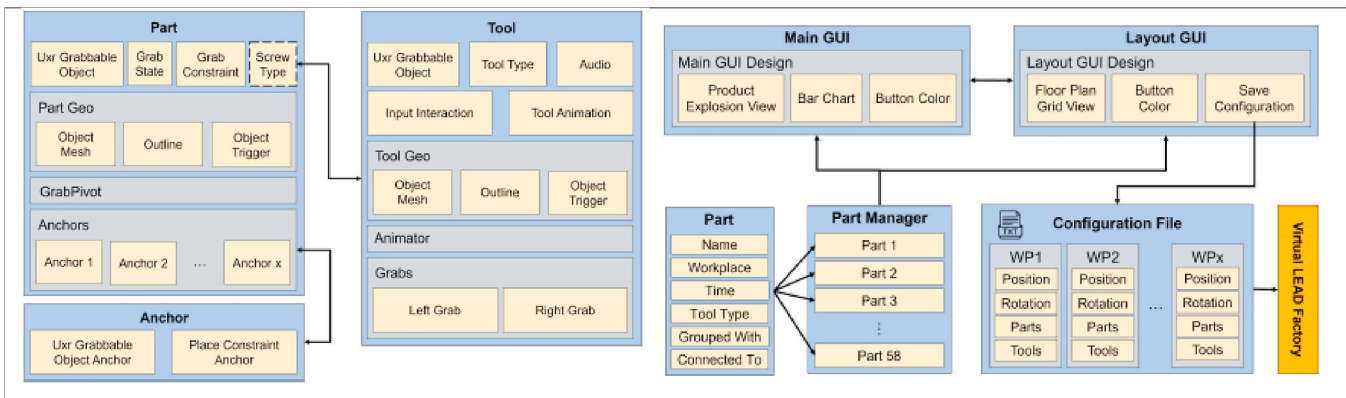


Fig. 2. Unity object (left) and “Build Your Own Factory” Java architecture (right) of the VR Lead Factory.

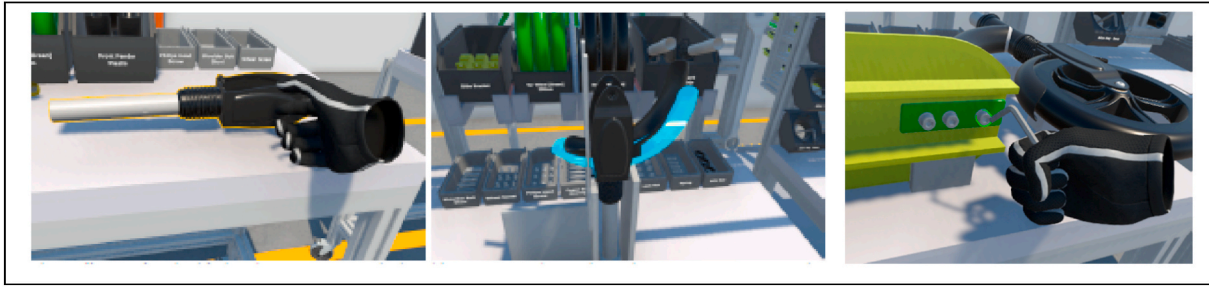


Fig. 3. Visual cues for grabbing (yellow), placing (blue), or screwing (green) parts.

was 27.1 years (SD 3.58), most of them were male (73 %), engineering students (67 %) predominantly in their late bachelor studies or early master studies and early-career professionals (33 %). While the sample size is modest ($n = 30$), it aligns with similar exploratory VR studies in higher education (e.g., Makransky et al., 2021) and is sufficient to detect trends in usability, workload, and motivation. Furthermore, the sample size is further justified by the homogeneous population.

Based on a prior self-assessment on a 5-point Likert scale, a great overall interest in XR and digital technologies could be observed, characterizing the participant group largely as digital natives. Despite this high interest and prior exposure/experience with computer aided technologies, participants on average showed low prior experience with VR, highlighting the need for effective system onboarding. Interest in gaming was inconspicuous (see Table 1).

4.1. Procedures and data collection

The exploration followed a within-subject design. As shown in Fig. 4, participants completed a structured three-stage process including (1) a pre-session briefing with a calibration of hardware, a demographic questionnaire, introduction to the LEAD factory concept and declaration of consent, (2) a general testing session in VR to become familiarized with the technology, (3) an introduction in the test scenario and task description, continued by working on the tasks. In the structured and independent task work participants first experience the current state of the LEAD factory while getting familiar with the overall controls and the scooter assembly. Second followed a VR session performing guided assembly in the “Lean” and “Digital” states. This was followed by the key phase, an independent systems design: the design of an own optimized assembly scenario in VR using the “Build Your Own Factory” tool on the PC and experiencing it afterwards in VR. In the debrief, participants could experience other layouts and aspects of the virtual LEAD factory on own guidance and motivation, before filing a post-session questionnaire gathering data on usability, motivation, cognitive load, and open-ended feedback. One full session lasted approximately 90–120 min.

Usability was assessed by measuring the perceived ease of use on the 10-item System Usability Scale – SUS (Brooke, 1996). The motivation was evaluated by the Questionnaire on Current Motivation - QCM, which includes interest, perceived competence, challenge, and anxiety using 7-point Likert items (Rheinberg et al., 2001). To conclude on the task complexity and cognitive load, we used the 0-20-point scale for six dimensions of the NASA Task Load Index - NASA-TLX (Hart & Staveland, 1988). Data about different aspects - such as cycle time, number of

workstations, number of boxes/tools, or layout design - of the student-developed layout was gathered in layout log files, partly manually by the instructor and partly automated by the system. Finally, we discussed the results from these log files and asked for additional open-ended feedback. This study design adhered to common standards in VR educational research, combining validated instruments (SUS, QCM, NASA-TLX) with behavioral data capture to triangulate learner experience and outcomes (Makransky et al., 2019, 2021; Makransky & Mayer, 2022). Although the SUS, QCM, and NASA-TLX are well-established, validated measures, the initial self-assessment survey was validated as part of this study to ensure that the measure was appropriate to our context and was producing valid data, and the details of the validation process are provided in Section 4.3.

4.2. Data scoring and analysis

In this study, quantitative data were analyzed using descriptive statistics and frequency distributions to address the four research questions. Validity and reliability of the data analysis were ensured by adhering to the established scoring procedures of the chosen validated instruments (SUS, QCM, NASA-TLX), minimizing scoring bias. Objective performance data regarding the layout designs (e.g. layout functionality, cycle time and component count) was extracted directly from the system log files to minimize the potential for error by subjective observation. Collected data was interpreted using established, peer-reviewed benchmarks (e.g. Bangor et al. for SUS, and Prabawari et al. for NASA-TLX normalization) to maximize robustness and comparability for the chosen study design. The logged data for RQ1, regarding the layouts developed by students included the number of workplaces (WP), the cycle time, the average part boxes per WP, part boxes total, and average as well as total numbers for the required tools (per WP). To understand variability, minimum and maximum values were observed, and additionally, the layouts were compared visually. A higher range in workplaces indicates more variability in the different layouts, thus indicating, with high likelihood, more innovative layouts. Cycle times and tools are values that can serve as good indicators for the efficiency of the developed layout.

For rigor and operationalization, the evaluation of the layouts was structured around two tiers: Functional Design and High-Quality Design. Both objective system data as well as expert-based qualitative assessment were used for classification. As of definition of design quality, a functional design is successfully meeting the minimum viable criteria for production. This required that the scooter assembly process could be completed from start to finish without generating errors that prohibit completion of the scooter. A functional design was further classified as high-quality design if it robustly demonstrated advanced competency by meeting key optimization criteria, consisting of efficiency (minimized cycle time), process balance (minimized time difference between highest and lowest load workstations) and lean principles (strategic assignment of parts, tools and positioning of workstations).

For RQ 2, the System Usability Scale (SUS) was used, following the standard procedure (range 0–100) and interpreting it according to

Table 1
Participant initial self-assessment results.

Self-assessment	Mean	Standard deviation
Overall interest in XR	4.2	0.95
Overall interest in digital technologies	4.5	0.76
Prior experience with VR	2.2	1.27
Prior experience with computer-aided technologies	3.8	1.11
Interest in gaming	2.9	1.53

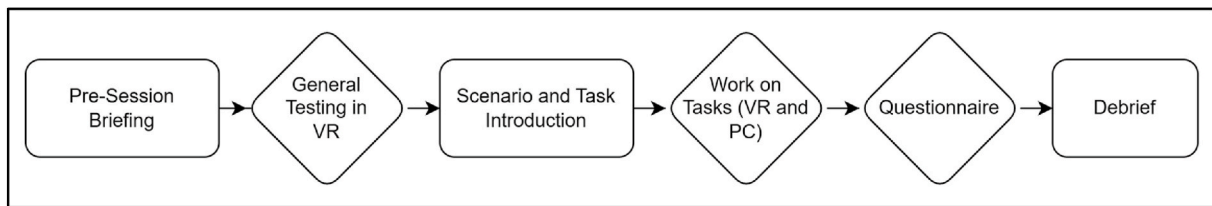


Fig. 4. Testing procedure.

Bangor et al. (2009), with values over 68 indicating above-average usability and scores above 80.3 corresponding to an “Excellent” usability rating. Motivation, as assessed in RQ 3, was assessed by using the questionnaire on current motivation (QCM) by Rheinberg et al. (2001), evaluating the four aspects, including interest, probability of success, challenge and anxiety, each measured on a 7-point scale. Calculating the subscale enabled overall motivational profiles of the participants to be obtained. Lastly regarding RQ 4, the cognitive load, recorded NASA-TLX scores for the dimensions of mental, physical, and temporal demand, performance, effort, and frustration were averaged (unweighted, as the Raw TLX was used) to yield a total workload score between 0 and 20. Normalization to a scale from 0 to 100 allows for closer interpretation as values under 30 are considered low to medium, and values above 80 are considered high (Prabawari et al., 2019).

4.3. Validity, reliability, and ethical considerations

The validity and reliability of the study were established through multiple measures. First, a pilot study was conducted to ensure the clarity, feasibility, and appropriateness of the learning environment, the educational activity, and the research instruments and procedures, as described in Section 2.3. Content validity was strengthened by having a subject matter expert review the assessments and any survey questions that were not based on previously validated scales. To ensure reliability in the evaluation of student work, a second independent rater scored the final factory design projects. Any discrepancies in the ratings were then resolved in a group discussion. The performance of layout designs was evaluated based on quantitative data derived from the system’s log, including the layout functionality (e.g. assembly order feasibility, deviation from calculated takt-time, task distribution, necessary tools on the workplaces, necessary parts on each workplace), and implemented process optimizations (cycle-time balance, ease of assembly, number of workplaces, optimization of material flow).

Regarding the ethical considerations, the University does not have an institutional review board; however, this study adhered to the ethical principles outlined in the Belmont Report and the Declaration of Helsinki to ensure the protection of participants’ privacy and confidentiality. The data collection activities were conducted as part of normal educational practices aligned with the course objectives. All data were treated with strict confidentiality; that is, no names or identifying information were recorded, and participants were assigned anonymous codes for analysis. The data analysis was conducted only after the semester had concluded and final grades had been submitted. All findings are reported in aggregate form to ensure that no individual participant can be identified. The study also involved informed consent by the participants.

5. Results

5.1. Student factory designs

Results are presented according to the four core dimensions of immersive learning effectiveness: learner creativity and problem-solving (layout design), perceived usability, intrinsic motivation, and cognitive workload. These dimensions align with prior frameworks evaluating

immersive learning environments (Makransky et al., 2021). A major task consisted of participants creating their own factory layouts on a desktop tool based on Java. Their layout was then transferred to the virtual setup, and they tested directly in VR. Resulting layout designs were analyzed based on efficiency (number of workplaces and cycle time), balance (time difference between high-and low-load workplaces), and number of tools and boxes used in the layout. Fig. 5 gives an overview of the variety of developed layouts.

Experiences of previous exercises conducted in our physical setting usually yielded only 3–4 different layout variants, so for the VR setup, a much higher layout variety (with no duplication) was observed. Design quality was generally high. Most participants (67 %) achieved functional layouts that also met high-quality optimization criteria, though balance and task distribution varied. About 33 % of users failed to achieve fully balanced workloads across stations, leading to partially effective, but still functional designs. Reliability and validity were ensured by a dual-method approach, where objective metrics from the log files, as well as qualitative metrics evaluated by two experts, were considered. Open-ended student feedback indicated high learning satisfaction and contextual understanding of the benefits VR offers in such tasks, as the following statements indicate:

“Seeing my design in VR and then testing it made it feel like real engineering.”

“I liked the freedom to try and optimize something myself, not just follow instructions.”

“It was difficult to balance the layout without direct feedback during the planning.”

“It was interesting to see how a small change in layout affected the timing and effort.”

These findings reinforce the value of exploratory design in VR learning environments, supporting the premise that interactive control enhances learner engagement and creative agency.

5.2. Perceived usability levels

System usability was measured using the SUS (System Usability Scale), which yielded positive results. An average SUS score of 83.92/100 points (SD 8.73) was measured, which, according to Bangor et al. (2009), determines a good to excellent system usability (see Table 2).

Overall, 60 % of the participants scored above 80 points, indicating high usability, and 90 % scored above the usability benchmark of 68 points. According to students’ answers, the system’s intuitive interaction design and visual guidance were key contributors to these high usability scores. Nevertheless, as some students also indicated that they needed to learn a lot before they could get going, onboarding and initial training could still be improved, e.g., through better instructions, tutorials, or an in-VR walkthrough at startup. This could add additional benefits to the training as it puts the learning curve for VR usage before the actual training.

However, overall participant feedback shows that 90 % agreed the system was easy to use, 87 % felt confident using the system, and 83 % would like to use the system frequently. This was supported by the open-ended feedback as participants highlighted the ease of grabbing and

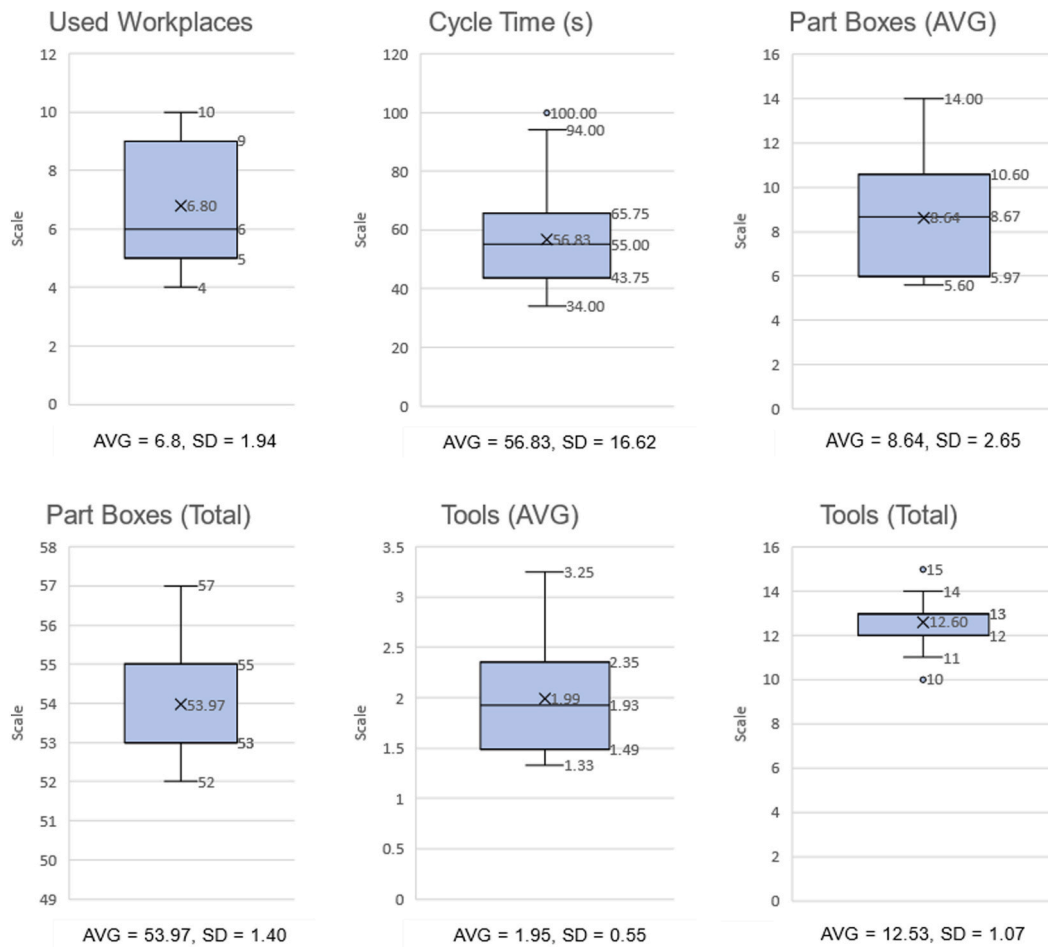


Fig. 5. Variation of different layout aspects (Boxplots).

Table 2
SUS scores and item breakdown.

ID	Question	Average	SD
S1	I think that I would use this system frequently.	2.53	0.92
S2	I found the system unnecessarily complex.	3.67	0.54
S3	I thought the system was easy to use.	3.37	0.60
S4	I think that I would need the support of a technical person to be able to use this system.	2.77	1.15
S5	I found the various functions in this system were well integrated.	3.43	0.56
S6	I thought there was too much inconsistency in this system.	3.77	0.42
S7	I would imagine that most people would learn to use this system very quickly.	3.37	0.66
S8	I found the system very cumbersome to use.	3.80	0.40
S9	I felt very confident using the system.	3.30	0.59
S10	I needed to learn a lot of things before I could get going with this system.	3.57	0.62
Score		83.92	8.73

placing items, although noting occasional tracking issues and the need for clearer layout instructions.

5.3. Motivation to learn

The analysis of the QCM data, covering interest, probability of success, challenge, and anxiety, revealed that participants expressed strong interest and a sense of competence (probability of success) during tasks. Specifically, the interest subscale was used as the self-report measure of intrinsic motivation, which aligns with psychometric guidelines where

this dimension is considered the core component of enjoyment and intrinsic drive. This finding is supported by students' feedback, such as: "It felt like I was doing something real, not just playing. I actually cared if it worked."

The high interest score, coupled with the high probability of success, indicates a compelling, autonomy-supportive learning experience. The moderate challenge score suggests the task was engaging but not overwhelming and the safe environment of a learning factory minimizes the fear of making failures, enhancing the learning experience even more (see Table 3), also backed by the low value for anxiety.

The alignment between high interest and low anxiety highlights the value of psychologically safe environments in immersive learning, a factor that significantly impacts learning persistence and self-efficacy (Makranksy & Mayer, 2022).

5.4. Experienced cognitive load

Overall cognitive load fell in the medium range, according to the NASA-RTLX score (see Fig. 6). The RTLX workload overall was rated with 4.44/20, equalling a value of 22.2/100. According to established

Table 3
Motivation scores by dimension.

Category	Average	Standard Deviation
Anxiety	1.42	0.58
Challenge	4.17	0.92
Probability of Success	6.03	0.41
Interest	5.87	0.64

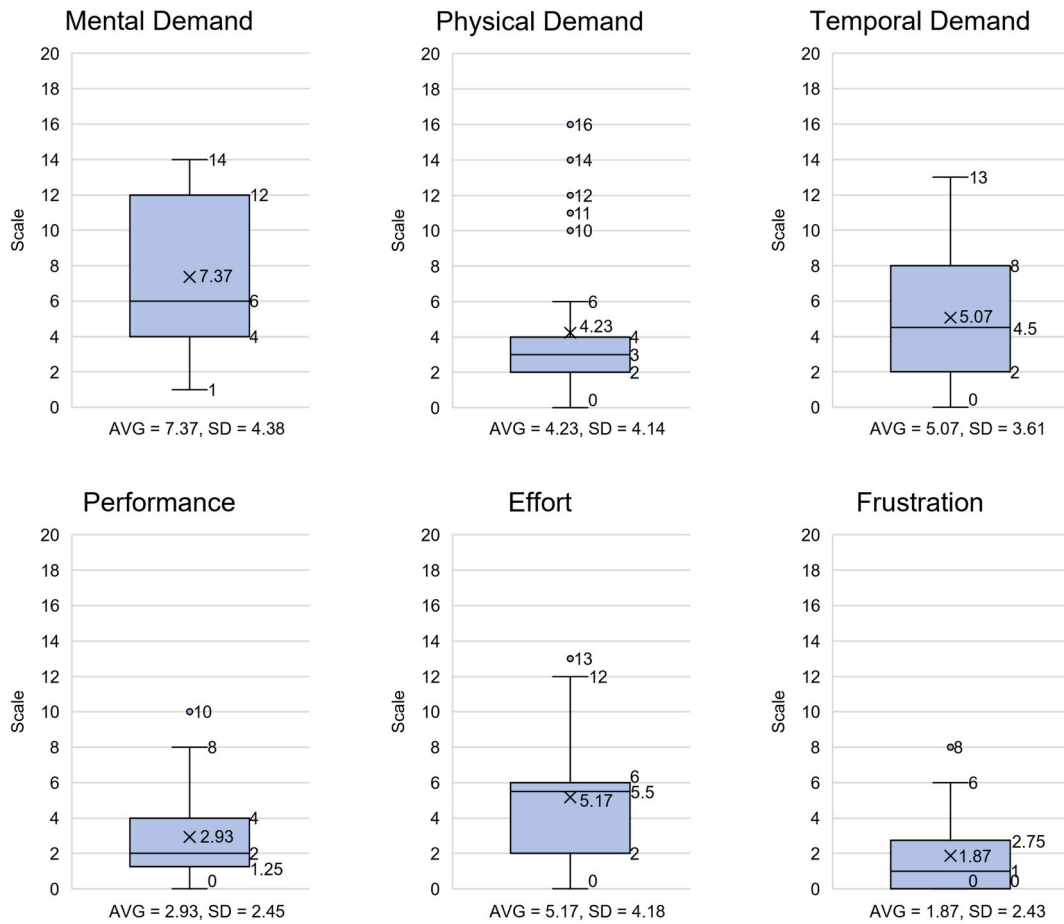


Fig. 6. NASA TLX results.

benchmarks (Prabaswari et al., 2019), this is considered a low to medium workload – representing a desirable outcome for a complex, simulation-based system like the VR learning factory. Analysing the subscales indicates successful instructional design. In general, participants rated the mental demand higher (AVG = 7.37, SD = 4.38), than the physical demand (AVG = 4.23, SD = 4.14). While this is not surprising, given the low weights and speeds involved, a significant number of outliers indicates that the physical demand is very individual, also depending on how good the headset fits the person's physical traits (e.g. headband, lens width). The relatively highest value in mental demand indicates that the task required substantial mental processing, planning and decision-making, aligning with the higher-order planning skilled required for our factory layout design. At the same time a moderate effort value (AVG = 5.17, SD = 4.18) suggests that participants invested the necessary cognitive resources.

Temporal demand (AVG = 5.07, SD = 3.61) shows that there is no specific "stress" test or stressful event present in the experiment, this was expected. A very positive value could be determined for frustration (AVG = 1.87, SD = 2.43), which was evaluated as the least demanding load, indicating that the participants experienced only little frustration during the use of the VR system and showing that the moderate mental effort was not translated into negative affective load. In terms of performance (AVG = 2.93, SD = 2.45), which has an inverted scale, participants showed satisfaction with their own performance. The low overall TLX score, therefore, should not be interpreted as a lack of challenge, but rather as an indication of effective instructional scaffolding within a demanding technical domain.

6. Discussion

The results of this study support the effectiveness of a VR-enhanced learning factory in promoting both cognitive and motivational aspects of engineering education. The system was not only technically functional and immersive, allowing participants to design their own factory layouts, but also demonstrated educational value based on usability, motivation, and workload metrics. From an educational technology standpoint, this study advances our understanding of how immersive learning environments can be implemented and assessed in complex, applied domains such as manufacturing. The findings confirm that VR can support key pedagogical objectives such as learner agency, engagement, and manageable cognitive effort.

Regarding the first research question investigating students' ability to design factory layouts, most users met the general criteria for effective layout design (cycle time, balance, number of workplaces), although only a minority created optimally balanced lines. The ability to conceptualize, design, and test layouts independently reflects a strong level of engagement and applied learning. This shows that the system facilitated not only technical engagement but also higher-order planning skills. This supports findings by Tisch et al. (2016), who emphasized the importance of hands-on, reflective learning in manufacturing education. In terms of layout design, the variety compared to regular physical training was enormous. While usually there would be one variation per team (consisting of up to 5 people), with the tested solution, there was one variation per person.

The second research question evaluated the system's level of usability. Based on our findings regarding the average SUS score of 83.9, we determined that it exceeded the standard benchmark of 68 and indicates high usability, suggesting that the interface was easy to learn and

use. Students felt confident and enjoyed working in the environment, consistent with research by Ko et al. (2020), who found that visual guidance and task-oriented feedback increase positive user experience in VR systems. This result also indicates that the developed virtual prototype, despite its early stage and room for improvement, has already reached a mature level.

The third research question evaluated students' motivation to learn in the context of the learning factory. Motivation scores were high across all QCM dimensions. Especially the high score on the interest subscale, that depicts the intrinsic motivation within the QCM framework, along with a high perceived probability of success (competence), reinforces the core motivational potential of the system.

These are key factors associated with deeper learning - supporting findings from Conrad et al. (2024), Makransky et al. (2021) and Sattar et al. (2019), who reported that VR learning increases engagement and curiosity. The ability to interact, explore, and experiment likely contributed to this intrinsic engagement. The relatively low anxiety (fear of failure) suggests that learning factories, and especially the virtual environment, provided a safe space for exploration and iterative learning.

Finally, the fourth research question evaluated students' potential cognitive load. With the highest evaluated NASA-TLX score being 7.37, the system imposed a moderate but manageable load. This is desirable, as excessive cognitive load can hinder learning, while too little can lead to disengagement (Sweller, 1994). Most participants found the tasks mentally stimulating but not frustrating. These results suggest the VR factory hits a pedagogical sweet spot of being challenging, but not overwhelming.

Few existing studies have explored a VR-based learning factory using such a practical approach. Previous implementations either focused on layout simulation and assembly planning (Riemann & Metternich, 2022) or single-task virtual modules (Pirker et al., 2021). This study builds upon prior work by extending the learning factory concept into a fully immersive, multi-featured VR system, contributing empirical evidence across the dimensions of technical performance, user engagement, cognitive effort, and learning output.

The use of a "Build Your Own Factory" feature is also a novel contribution of this study. It supports constructivist learning principles by enabling students to actively create and test their own solutions, rather than passively consume instruction. The dual-platform integration (Java planning tool and VR execution) offers an advanced model of blended digital education. For this application, motivation and usability results match earlier findings by Radianti et al. (2020), Pirker et al. (2021) and Makransky et al. (2019), confirming the potential of VR to foster learner engagement and extending this knowledge by applying it specifically to manufacturing education with a unique design-and-test learning module. This study adds new insight by, in addition to testing the usability, stress load, and engagement levels, observing the impact of VR on the result's variety and layout qualities, offering a more direct measure of the learning applications. Compared to studies in broader education literature, our results reinforce the motivational and cognitive benefits of VR reported by Conrad et al. (2024); Makransky et al. (2019), Makransky and Petersen (2021), and Parong and Mayer (2018) and align with pedagogical goals outlined by Reigeluth (2016) for personalized and experiential learning.

Overall, the findings of this study support the use of immersive VR as an effective method for delivering competency-based manufacturing education as an addition to physical learning in the learning factory environment. Participants demonstrated the ability to navigate complex, authentic tasks and design their own factory layouts, and immediately test it in VR while reporting high usability, strong motivation, and moderate cognitive load.

7. Implications for STEM education

The results of this study highlight several educational benefits of

integrating VR into learning factory models. These findings have practical implications for curriculum design, instructor training, and the broader implementation of immersive technologies in technical education.

The VR LEAD Factory supports experiential learning by allowing students to "learn by doing." While Radianti et al., (2020) highlight the importance of aligning immersive VR designs with pedagogical goals; our "Build Your Own Factory" tool exemplifies this by enabling open-ended problem solving aligned with competency-based learning outcomes. Its immersive interactions, iterative layout designs, and real-time feedback (see Fig. 7), learners progress through Kolb's (1984) cycle of concrete experience, reflection, conceptualization, and experimentation. Thus, this feature promotes student agency, reflection, and problem-solving as foundations of competency-based education.

This aligns directly with the core goals of learning factory pedagogy, which emphasize the development of critical thinking, process design, and problem-solving skills (Tisch et al., 2016). Instead of merely following a scripted sequence or simulation a system, students actively apply principles of assembly flow, workstation balancing, and lean production by planning, designing, and iterating on their own layout ideas. Thus, they are engaging deeply with production planning and control theory and workflow optimization theory, skills difficult to teach in traditional lecture settings. This approach aligns well with constructivist pedagogical concepts and supports the development of industry-relevant skills such as systems thinking, critical analysis, and design-based learning (Reigeluth, 2016), providing insight for educators designing VR-based instruction across STEM fields. The layout design task exemplifies how VR can enable open-ended problem solving, which aligns with educational calls for systems thinking and design-based learning (Pirker et al., 2021; Reigeluth, 2016) and recent recommendations for immersive educational design regarding learner control and cognitive manageability (e.g., Makransky et al., 2019; Radianti et al., 2020).

One of the key strengths of a VR-based learning factory is its ability to reach a larger and more diverse student population. Unlike physical learning factories, which require extensive infrastructure in a designated place, VR environments can be deployed remotely and scaled with relatively low marginal cost. This expands access to high-quality training for students in remote or under-resourced areas and enables institutions to scale up without proportional increases in physical infrastructure. It also opens possibilities for cross-institutional collaboration, hybrid courses, and remote skills training programs. Educators can deploy these environments for pre-training, flipped classroom models, or even entirely virtual labs, especially in contexts where physical space or equipment access is limited.

Beyond manufacturing education, these findings offer preliminary, yet instructive, implications for broader STEM instruction. Due to the inherent constraints of this descriptive, single-session investigation and the necessarily modest sample size employed, the direct extrapolation of these quantitative results (e.g., specific SUS or QCM scores) to the entire heterogeneous STEM domain must be undertaken with considerable circumspection. However, there is compelling evidence to the successful transferability of the underlying VR design principles in facilitating core, applied competencies universally pertinent across technical disciplines. Immersive VR environments such as this prototype are thus posited to actively support the development of competencies that necessitate spatial reasoning, iterative systems design, and real-time critical problem-solving.

This aligns with ongoing calls for more embodied and experiential learning in science and engineering, where traditional labs or workshops are often resource-intensive or inaccessible to all learners (Lindgren & Johnson-Glenberg, 2013). Consequently, the pedagogical model and the corresponding evaluation framework outlined herein may more appropriately be viewed as prototypes and conceptual blueprints for analogous technical applications, rather than empirical generalizations. This is especially the case for small and medium enterprises where the

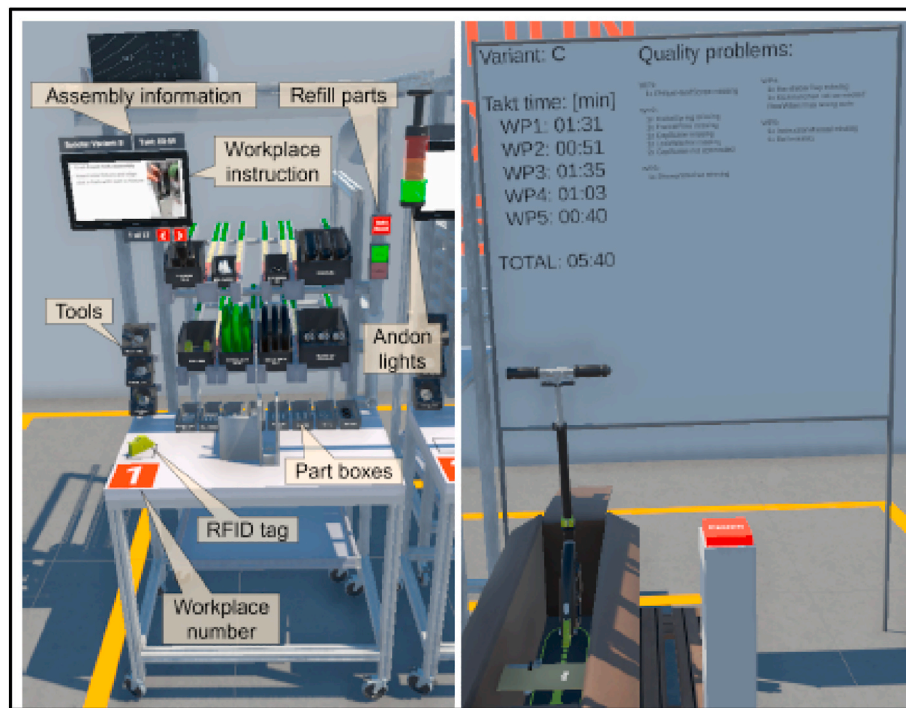


Fig. 7. Workstation in the digital state and cycle time and quality reports from the analytics tool for student feedback.

maintenance of a physical training environment could be unprofitable due to the limited number of workforces using the environment.

While the system is designed for self-guided learning, instructor facilitation remains important. Educators can guide students in reflecting and discussing their layout results, drawing connections to lean manufacturing principles, and interpreting error reports. Additionally, the built-in analytics tools can support formative assessment by tracking performance, error patterns, and decision-making behavior. However, the training instructor's guidance is key to using these tools effectively and to integrating them into the broader instructional learning strategies, realizing the full potential of the VR system. We think that this study offers several important takeaways for engineering educators, instructional designers, and institutions seeking to modernize manufacturing education through immersive technology. However, future iterations could include instructor dashboards or real-time progress monitoring (see Fig. 7), allowing educators to intervene or scaffold learning based on individual student data. This opens doors to adaptive learning and intelligent tutoring integration in VR-based systems and aligns to increasingly emphasized approaches in adaptive learning literature (e.g., Holstein, McLaren, & Alevan, 2019).

8. Conclusion, limitations, and future work

This study demonstrates that immersive VR environments, and particularly VR learning factories, can be integrated into higher education curricula to enhance engagement, promote creativity, and support complex skill development in technical fields. When paired with thoughtful instructional design, they can enrich student learning while making industrial training more accessible, engaging, and effective. This study demonstrated the feasibility and educational value of integrating VR into a learning factory for engineering education. The virtual LEAD Factory enabled learners to engage in realistic assembly tasks, explore different factory configurations, and design their own optimized layouts. The evaluation showed strong usability, high learner motivation, and manageable cognitive load, suggesting that VR can be a powerful tool for training engineers in modern production systems, as well as training the workforce in production settings.

While the findings are promising, several limitations should be acknowledged. The study included a small sample, with one learning factory setup and 30 participants. Although this size aligns with similar exploratory VR studies in higher education, it limits the statistical power required for robust inferential analysis and for detecting small-to-medium treatment effects, thus necessitating the primary use of descriptive statistics. Participants used the system in a single session, so findings are only valid for short-term engagement. Longer-term studies are needed to evaluate effects as knowledge retention, skill transfer, and learning progression. An initial comparative study was conducted under similar conditions, providing insights into relative performance difference, but pre-intervention knowledge or motivation surveys mean that baseline learner factors could not be controlled for in the current study. This exposes findings to variables as the Hawthorne effect (improved performance due to participation awareness) and the novelty effect (high motivation/engagement solely from the adoption of a new technology, like VR). The study took place in a single institution and a specific disciplinary context (manufacturing), constraining the scope of generalization to other applied fields. Therefore, the primary and most robust contribution is situated in the demonstrated technical feasibility and the empirical validation of the system's core design parameters (usability, motivation, and manageable cognitive load) within the narrowly defined context of industrial engineering education. Nevertheless, it is contended that the robust design principles and the rigorous evaluation framework established can effectively inform the development of similar immersive applications across other STEM and applied disciplines.

Prior experience with and exposure to VR varied across participants, which may have influenced usability and performance (positively and negatively), which are susceptible to technology affinity. Lastly, technical constraints in terms of minor interface limitations (e.g., hand tracking and instruction clarity) were noted by users and might have affected the outcome of the study. These factors suggest the need for further technical refinement and broader trials.

However, despite the limitations, the study's findings suggest that the immersive environment successfully enabled hands-on, student-centered learning aligned with real industrial workflows. Thus, the

results support the use of VR as a scalable, immersive alternative or supplement to traditional learning factories. Students were not only able to perform tasks effectively but also expressed high engagement and a sense of ownership over their learning process. Regarding learning outcomes, students' layout performance demonstrated both enhanced creativity (as the elaborated layouts included a higher share of change and variation compared to the initial system, similar to physical LF trainings) and practical understanding. These results validate the use of VR not only as a simulation platform but also as a facilitator of deep, experiential learning and align with broader educational goals of promoting applied, autonomous, and reflective learning in engineering education.

Future research could explore how repeated use impacts learning, retention, and skill transfer in longitudinal effects, as previously suggested by Radianti et al. (2020), and Makransky and Petersen (2021). Future studies should also control for confounding variables such as the Hawthorne effect and the novelty effect by using a longitudinal multi-group design with pre- and post-tests to test for equivalence. Planned additions to the application also include the integration of a multi-user VR for team-based planning and production tasks, the usage of advanced analytics on data logs to personalize learning and assess decision-making patterns in real time, and the extension of curricular coverage of the VR learning factory model in sustainable product design and production planning tasks. A future comparative study might measure transfer of skills from the VR environment to physical factory environments or explore team-based learning in multi-user VR scenarios as emerging priorities in educational technology research. As the cost and accessibility of VR hardware continue to improve, immersive learning factories can become a core component of next-generation engineering education. They offer a unique opportunity to blend cognitive, psychomotor, and affective learning domains in a unified, engaging format.

CRedit authorship contribution statement

Matthias Wolf: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Conceptualization. **Patrick Herstätter:** Writing – original draft, Validation, Project administration, Methodology, Investigation. **Marvin Rantschl:** Visualization, Software, Investigation. **Christian Ramsauer:** Supervision, Resources, Funding acquisition. **Alejandra J. Magana:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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