Designing for Transfer: Developing a Skill-Based Simulation Using Learning Engineering Design Frameworks

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ABSTRACT

As simulation-based training becomes increasingly vital to workforce development, there is a growing need to design digital learning experiences that intentionally support skill transfer from virtual to physical contexts. This paper presents a use case in which a skill-based simulation game was developed for novice, pre-hire pipefitters using a learning engineering framework grounded in cognitive task analysis and game design methodologies. The simulation aims to prepare learners for a complex pipefitter assembly task by targeting decision-making, sequencing, and spatial reasoning skills in a virtual environment prior to engagement in a multimodal, hands-on mock-up. The full training sequence includes three components: (1) the digital simulation game, (2) a classroom assembly mock-up using 3D printed components, a 3D model, and an augmented reality (AR) app that scaffolds performance and reinforces procedural knowledge, then 3) full mock-up pipefitter assembly. This paper outlines the iterative design process, including cognitive fidelity mapping, learner persona development, learning objectives alignment, and integration of game mechanics to support engagement and practice for the digital simulation game. Special attention is given to how learning engineering principles were used to align instructional intent with user experience design, ensuring that learners could rehearse key decisions and procedural logic in the simulation prior to applying them in the physical assembly. Early usability feedback and expert reviews suggest that the simulation game effectively primes learners for the cognitive demands of the mock-up activity, offering promising implications for future skill-based training design in skilled trades. The paper concludes with lessons learned and future directions for expanding multimodal transfer-focused training systems.

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INTRODUCTION

In today's rapidly evolving industrial landscape, the need for simulation-based training systems that build real-world readiness has intensified—particularly in skilled trades like maritime pipefitting where the growing skills gap demands training that cultivates higher-order cognitive skills such as decision-making, spatial reasoning, and adaptive problem-solving (Fiore et al., 2010; Hoffman & Militello, 2012). While simulation technologies show promise for fostering such macrocognitive functions, a major challenge lies in supporting transfer which is the ability to apply virtual learning to physical tasks (Barnett & Ceci, 2002; Salas et al., 2009). This paper presents a use case where a skill-based simulation game was designed to help novice, pre-hire pipefitters practice decision-making and spatial strategies in a structured digital environment, prior to hands-on mock-up tasks. Rooted in learning engineering frameworks (Goodell & Kolodner, 2023) and game design principles (Gee, 2005), this training approach addresses both cognitive and procedural demands. The three-part sequence includes: (1) a digital simulation of realistic pipe assembly, (2) a classroom mock-up with 3D printed parts, visual models, and an AR guidance app, and (3) a final full mock-up requiring real-world synthesis of skills. Drawing on the Learning Engineering Design Framework (Goodell & Kolodner, 2023), cognitive task analysis (Crandall, Klein, & Hoffman, 2006), and macrocognitive theory, the simulation system integrates multimodal tools (digital, physical, and AR) to develop not just procedural proficiency but also cognitive flexibility and situational awareness (Endsley, 2017; Hegarty, 2004). The following sections outline the design process, simulation features, and early evaluation findings that show potential for improving cognitive readiness and transfer in novice pipefitters.

USE CASE: PIPEFITTER SIMULATION TRAINING SEQUENCE

Target Learners and Context

The simulation-based training sequence was developed for novice pre-hire pipefitters enrolled in an industrial maritime training program at a regional community college. These learners typically enter the program with little to no prior experience in pipefitting and face steep cognitive and procedural learning curves. The demands of the trade require not only manual skill but also proficiency in blueprint interpretation, spatial configuration of parts, precise measurements, and procedural adherence within complex, safety-critical environments such as ship compartments. Traditional instructional approaches, focused heavily on rote task demonstration and isolated practice, have not adequately prepared trainees for these multidimensional requirements. To address this gap, a multimodal simulation framework was developed using principles of macrocognition and learning engineering to scaffold novice learners through progressively complex training stages.

Training Sequence Overview

The training system comprises a three-part sequence that blends digital, augmented, and physical modes of learning. Each component is designed to reinforce core cognitive and procedural skills, promote decision-making under constraints, and prepare learners for real-world application.

Digital Simulation Game

The sequence begins with an interactive simulation game that introduces learners to fundamental pipefitting tasks through decision-making scenarios and procedural sequences. In this game, learners must select appropriate pipe components, visualize correct orientations, and assemble parts in a virtual environment that mirrors real-world constraints (e.g., confined space, measurement tolerances). Immediate feedback mechanisms and scaffolded challenges promote cognitive rehearsal of expert-like behaviors, including error-checking, sequencing, and spatial estimation. As detailed in Johnson (2023), this game is informed by a cognitive task analysis of expert pipefitters and integrates game mechanics such as visual affordances, hint systems, and adaptive challenge levels.

Classroom Mock-Up Activity Using 3D Printed Parts, 3D Models, and Augmented Reality

Building on virtual practice, the second phase introduces physical materials. Learner's transition into a hands-on mock-up activity using custom 3D printed PVC pipe components and visual references from a 3D model. An AR application, which was designed to overlay spatial guidance and part selection tips, provided step-by-step scaffolds while capturing data on accuracy and timing. This hybrid space blends physical motor actions with continued cognitive support, helping learners apply what they practiced virtually while managing real-world spatial and tactile constraints. The AR tool also highlighted procedural lapses and suggests corrections, reinforcing performance alignment with professional standards.

Full Pipefitter Assembly Task

The final stage is a high-fidelity physical task in which learners complete a full pipefitting assembly with minimal guidance from their instructor measuring metal pipes, cutting, tacking, and grinding the components together. This task simulates a realistic shipboard environment and requires independent application of blueprint interpretation, component layout, and precise measurements on a metal mock-up. Learners must demonstrate sequencing efficiency, decision accuracy, and compliance with dimensional specifications which are hallmarks of both cognitive readiness and procedural mastery. The task serves as a culminating assessment, where instructors observe learners' ability to self-regulate and execute under realistic constraints.

Learning Objectives Across the Sequence

The pipefitter simulation sequence targets four key cognitive learning outcomes critical to novice performance and long-term transfer: 1) decision-making, 2) sequencing, 3) spatial reasoning, and 4) procedural accuracy, all strong predictors of skill acquisition and workplace success (Chi et al., 1988). Decision-making is developed through tasks that require selecting components, choosing assembly paths, and adapting to errors thus mirroring real-world demands in maritime trades where judgment under uncertainty is vital (Zsambok & Klein, 1997). These decision points are guided by expert heuristics gathered via cognitive task analysis. Sequencing is reinforced by having learners practice arranging steps in logical order, essential for avoiding errors that can cause system failures. Structured practice supports procedural fluency and retention (Schneider & Stern, 2010), helping learners internalize expert workflows. Spatial reasoning, critical for interpreting layouts and transforming 2D blueprints into 3D systems, is supported through visualization tools, AR overlays, and mock-ups. These scaffold spatial cognition, which is predictive of STEM success (Uttal et al., 2013), with AR serving as a cognitive amplifier (Radu, 2014). Procedural accuracy is emphasized throughout, focusing on alignment, measurement, and integrity. High-fidelity simulations and real-time feedback help encode correct behavior and reduce error rates (Issenberg et al., 2005). Together, these objectives form a cognitive blueprint for building expertise, with the training system's multimodal structure ensuring each target is reinforced and transferable to real-world tasks.

SIMULATION GAME DESIGN PROCESS

Designing an effective simulation game for novice pipefitters required a rigorous alignment of cognitive learning objectives with user experience, gameplay dynamics, and instructional design principles. The simulation game was conceived not simply as an engaging digital tool, but as a cognitive rehearsal environment engineered to foster key decision-making, sequencing, and spatial reasoning skills prior to physical mock-up practice. Guided by the Learning Engineering Design Framework (Goodell & Kolodner, 2023) the design process incorporated insights from task analysis, learner personas, and macrocognitive modeling to ensure a high level of instructional and cognitive fidelity (see Figure 1 below).

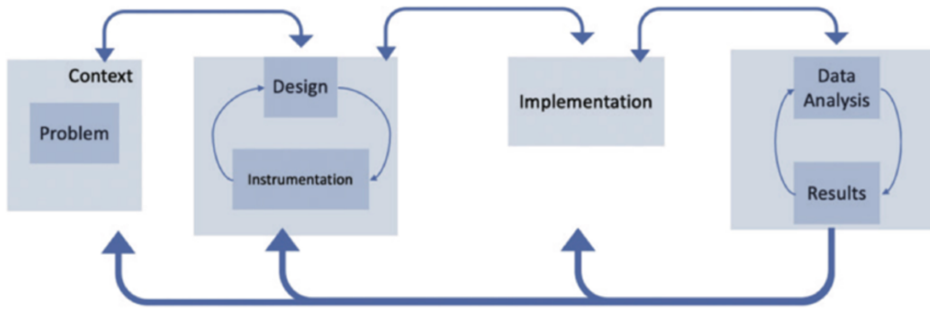

Figure 1. The learning engineering design framework model. We used this model to guide the research and design of the pipefitter simulation game.

Learning Objectives to Game Mechanics Mapping

At the core of the simulation's design was the strategic mapping of learning objectives to in-game actions and mechanics. The game was developed to simulate realistic pipefitting decisions such as sequencing assembly steps, choosing correct pipe components, and adjusting for environmental or spatial constraints which are common challenges in shipboard compartments. Each game mechanic was carefully linked to a cognitive function. For example, the act of sequencing pipe connections within confined digital workspaces mirrored real-world expectations and required learners to consider dependencies and operational order (See Figure 2, below). Gameplay elements such as rotating and aligning virtual fittings, checking for system integrity, or responding to virtual errors served to reinforce attention to procedural accuracy and decision-making under constraints. This approach ensured that learners had the opportunity to develop error recognition and correction strategies, which are critical in skilled trades (van der Meij & de Jong, 2006).

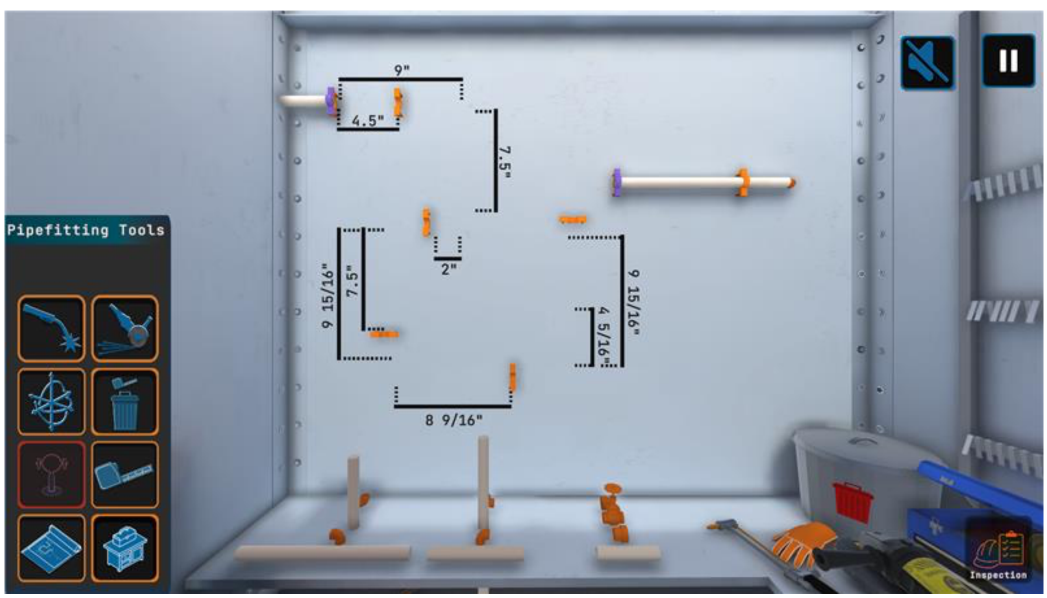

Figure 2. Example Pipefitter Simulation digital workspace aligned to cognitive and learning engineering frameworks.

Cognitive Fidelity Mapping

A key objective of the design was to maximize cognitive fidelity, decision points, and constraints encountered in the real-world pipefitting assembly task. This goes beyond surface-level realism and targeted the mental demands of expert performance. Cognitive fidelity was achieved by embedding authentic task logic into the gameplay, such as interpreting a simplified digital blueprint, sequencing pipe elements according to flow direction, and making measurement-based decisions using simulated rulers and grid snapping tools (see Figure 3, below).

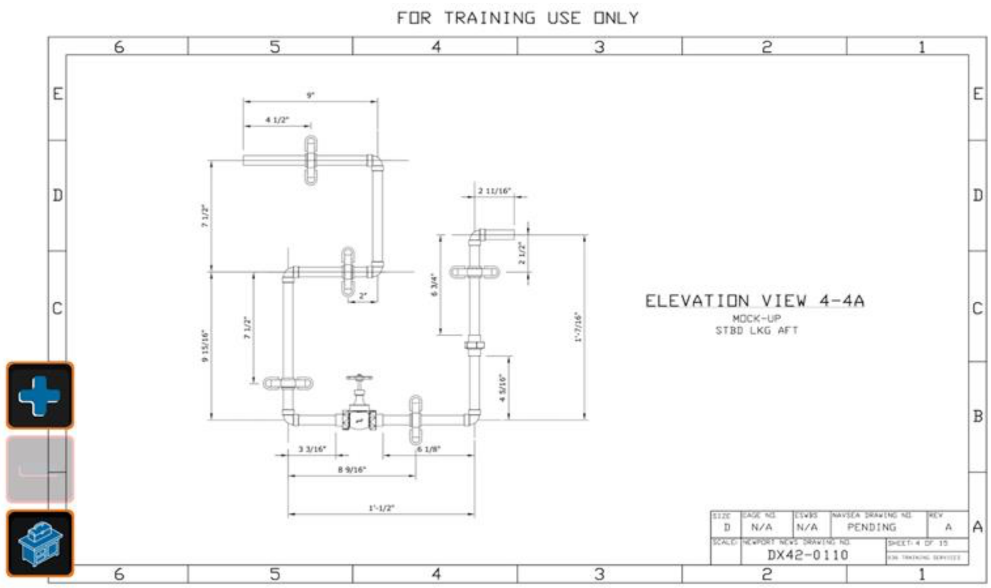

Figure 3. Example Pipefitter Simulation blueprint replicating real-world assembly operations for novice pre-hire trainees.

Unlike high-fidelity physical simulators that replicate every surface detail, the digital simulation focused on replicating the cognitive terrain of the task, specifically where learners must anticipate spatial misalignment, respond to constraints like pipe length or fitting compatibility, and maintain awareness of task objectives across multiple steps. This fidelity ensured that learners were not simply playing a game but mentally rehearsing the decisions and problem-solving sequences used by experienced pipefitters (Gray, 2017).

Learner Persona Development and UX Design Integration

Informed by qualitative data from community college instructors, early-stage apprentices, and cognitive task analysis interviews, the design team developed learner personas that reflected the realities of pre-hire pipefitting trainees. These consisted of namely, low exposure to technical drawings, limited experience with spatial manipulation, moderate digital literacy, and strong motivation for workforce entry. These personas shaped both the user experience (UX) and instructional design strategy, leading to key decisions around accessibility, scaffolding, and interface layout. The simulation was built to minimize cognitive load through intuitive navigation, tablet-friendly drag-and-drop mechanics, and a clean workspace modeled after real-world mock-up benches. Embedded instructional supports including a contextual glossary, just-in-time hints, and reflective prompts at level completion were integrated to reinforce procedural knowledge and promote metacognition without interrupting immersion. Visual checklists and formative feedback loops helped learners track progress and internalize step-by-step procedures (see Figure 4, below). This personalized, learner-informed design not only enhanced usability but also increased learner independence and reduced frustration during gameplay, aligning with principles of cognitive load theory and effective learning experience design (Sweller et al., 2019).

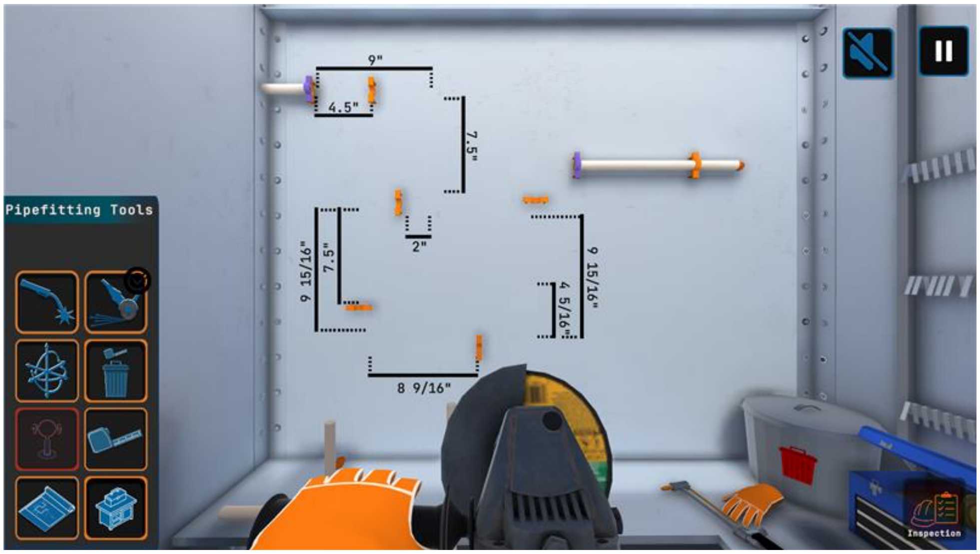

Figure 4. Users receive options for "inspections", see far right button icon, to help track progress and mimic real-world operations for a Quality Assurance inspector to check assemblies.

MULTIMODAL TRANSFER DESIGN: FROM DIGITAL TO PHYSICAL

The learning engineering design of the pipefitter training sequence places deliberate emphasis on multimodal transfer, which refers to the progression of skills and knowledge from a digital simulation to embodied practice in physical settings. While simulation games provide a low-risk environment to rehearse cognitive skills, translating that knowledge into hands-on proficiency requires instructional scaffolds that extend across modalities. To address this, the training design integrates a physical mock-up activity phase that bridges virtual learning with real-world task execution in the training classroom before trainees complete the formal mock-up assembly with metal pipes and other equipment.

The physical mock-up activity phase was engineered to mirror the digital experience while introducing new tactile and kinesthetic challenges (see Figure 5 below). Using 3D printed PVC pipe parts and scale-accurate models of a pipefitting workspace, trainees were given the opportunity to reapply the decisions and task sequences they practiced virtually. The components used, designed from CAD models aligned with shipyard standards, allow learners to physically manipulate pipe segments, fittings, and connectors to complete partial or full assemblies. The 3D printed pipe parts were designed by laser scanning the actual pipe pieces trainees manipulate in the physical assembly mock-up at the community college.

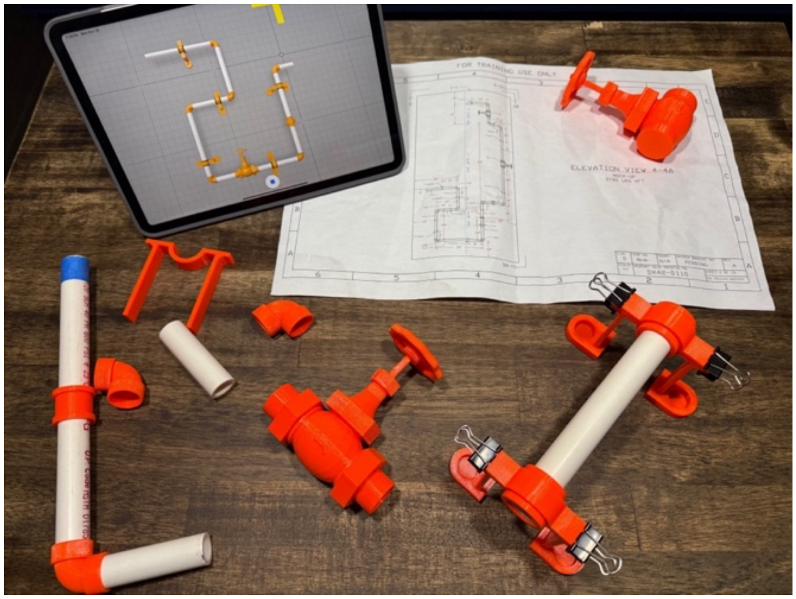

Figure 5. The integrated Pipefitter training activity embeds the learning engineering model and framework to provide trainees skill transfer practice.

Augmenting this physical interaction is a custom-built augmented reality (AR) app designed to scaffold learners through key decision points. When learners scan a blueprint or object marker with a tablet, the AR system overlays step-by-step procedural prompts, spatial placement indicators, and error-checking feedback on the physical components as a quality assurance inspection (which also mimics operational procedures within the industrial environment). The AR interface does not replace the cognitive demands of the task but enhances learners' ability to self-monitor and adjust their actions in real time. By projecting performance-relevant information directly into the workspace, AR tools serve as cognitive scaffolds that reduce working memory load while reinforcing previously practiced simulation content (Dunleavy, et al., 2009). As such, the AR app supports not only procedural recall but also attention to measurement precision, part orientation, task sequencing, and even an assessment tool for instructors on trainee performance and knowledge progression.

Crucially, the sequence of instruction was designed to optimize the conditions for transfer-appropriate processing, which posits that transfer is more likely when cognitive processes engaged during training closely resemble those required during real-world application (Morris, et al., 1977). After initial exposure and rehearsal in the digital simulation, learners transition to the physical mock-up with a clear structure: (1) pre-briefing and part orientation, (2) guided AR-based practice, and (3) unguided independent assembly. This gradual release of responsibility ensures that learners are not only exposed to relevant cues and constraints but also have repeated opportunities to retrieve and reapply procedural steps from memory. The AR feedback mechanisms act as midpoints in this transition reinforcing decision-making accuracy without becoming a crutch. The overall intentional layering of modalities: simulation, augmented guidance, and physical task execution ensures that learners engage in cognitive rehearsal, kinesthetic manipulation, and adaptive problem-solving. This design reflects current best practices in instructional transfer design and supports the development of trainees who are cognitively and procedurally prepared to meet the real-world demands of maritime pipefitting.

EVALUATION AND FEEDBACK

The design and development of the pipefitter simulation and training sequence followed an iterative, evidence-based process shaped by ongoing evaluation and stakeholder feedback. Multiple rounds of formative assessment, including usability testing, expert review, and early learner performance tracking were conducted to ensure that the system not only met instructional design goals but also effectively supported novice learners in transferring cognitive skills to real-world pipefitting tasks. The evaluation process was structured around three core areas: 1) usability testing and observations, 2) cognitive task alignment, and 3) early indicators of transfer readiness.

Usability Testing and Observations

The usability testing and observations component engaged two primary user groups: novice pre-hire trainees from a regional community college pipefitting program and experienced journeyman pipefitters who served as subject matter experts (SMEs). A total of eighteen novice trainees interacted with both early prototypes and final versions of the simulation game and the AR-assisted mock-up activities. Meanwhile, six expert pipefitters participated in think-aloud walkthroughs and detailed evaluations of the simulation's technical and cognitive fidelity. Novices consistently reported high levels of engagement and found the simulation's interface intuitive and helpful. Visual prompts, contextual feedback, and the gradual increase in task complexity were cited as features that supported their understanding and progression. However, some trainees encountered difficulties with component rotation and spatial alignment, particularly when transitioning from digital environments to physical mock-ups. In response, the development team implemented design refinements that included enhanced rotational guides, color-coded part labels, and scaffolded tutorials focused on spatial orientation.

Simultaneously, the SMEs provided in-depth commentary on the realism of the simulation's decision-making elements. They affirmed the authenticity of the assembly logic and praised the simulation for including cognitively demanding scenarios, such as selecting among competing component options, interpreting flow direction, and anticipating downstream effects of incorrect configurations. This feedback was essential in ensuring that the system maintained both learner usability and trade-relevant fidelity. The alignment between expert expectations and novice learner needs created a balanced training environment that promoted both accessibility and realism.

Cognitive Task Alignment Review

An essential component of the evaluation involved reviewing the alignment between the simulation's embedded decision points and the cognitive demands of actual pipefitting tasks. Drawing from cognitive task analysis (CTA) protocols, each game module was analyzed against expert workflows to verify that learners were engaging in appropriate sequencing, judgment, and error correction activities. Reviewers examined whether learners had to interpret constraints, resolve part mismatches, and make forward-looking planning decisions. These are cognitive hallmarks of expert trades performance. This review validated the instructional intent of the game. All core procedural steps including blueprint reading, component selection, part rotation and placement, and final validation were present and mapped closely to the real-world pipefitting workflow. The AR component further strengthened this alignment by providing real-time prompts during mock-up activities that paralleled the virtual training logic. Importantly, SMEs noted that the cognitive demands were appropriately scaled for novices, supporting progressive development rather than overloading the learner at early stages.

Early Indicators of Transfer Readiness

Finally, the evaluation team analyzed early indicators of transfer readiness by collecting and comparing quantitative performance data across all three phases of the training sequence: the digital simulation game, the AR-guided mock-up, and the culminating full physical assembly. Learner performance was measured using four main indicators: task completion time, accuracy of component placement, frequency of sequencing errors, and the number of instructor interventions required. The data revealed clear improvements between the pre- and post-simulation phases. Average error rates dropped significantly from 38% to 14%, while the average number of instructor interventions per learner declined from 5.2 to 1.8. Task completion times also improved substantially, decreasing from an average of 34.5 minutes to 21.3 minutes. These quantitative findings are visually represented in the Performance Improvements from Pre- to Post-Simulation graph (see Figure 6 below), which highlights the measurable gains in learner efficiency, independence, and procedural accuracy following engagement with the simulation sequence.

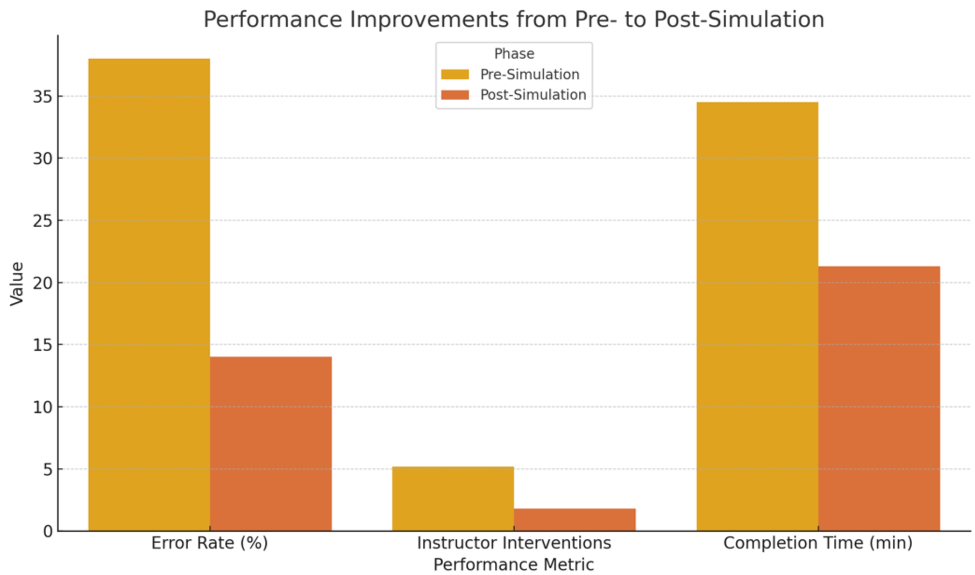

Figure 6. Performance improvements from pre-to-post simulation

Further qualitative observations supported these findings. Learners who began their training with the digital simulation displayed stronger self-correction behaviors during the mock-up phase and demonstrated a greater degree of independence during the final full assembly. They hesitated less during decision points, selected parts with more confidence, and engaged more fluently with blueprint navigation. Notably, trainees who used the AR app during hands-on activities were better able to identify and resolve mismatches independently, often referring to the app's guidance prompts before seeking instructor help. These behavioral shifts suggest a meaningful transfer of cognitive strategies from virtual to physical environments.

These findings are consistent with previous studies that have linked well-aligned simulation environments to improvements in procedural performance and reduced error frequency (Issenberg et al., 2005; Salden et al., 2006). Moreover, learners who used the AR app during mock-up training showed stronger self-correction behavior and greater independence by the final task. These early findings indicate that the multimodal sequence beginning with a cognitively rich simulation and followed by scaffolded hands-on practice effectively primes novice learners for the demands of real-world pipefitting tasks. Ongoing iterations and longitudinal assessments will continue to refine this model, but initial evaluations confirm that the simulation is both usable and instructionally effective in promoting cognitive skill transfer.

SUMMARY AND FUTURE DIRECTIONS

While the development and preliminary evaluation of the pipefitter simulation training sequence show promising outcomes for cognitive engagement and procedural transfer, several limitations remain that present opportunities for future refinement and research. First, the current use case was tested with a relatively small group of learners in a single pre-hire training context. Broader validation is necessary across diverse learner populations, instructional contexts, and levels of prior experience to generalize findings. Additionally, while usability testing and initial performance data support the alignment of simulation tasks with cognitive demands, a more robust longitudinal evaluation is required to assess the durability of learning and long-term transfer effectiveness in real-world settings.

Future development efforts will focus on building out additional levels and branching scenarios within the digital simulation to support adaptive progression. These enhancements will enable learners to encounter a wider range of challenge types including complex blueprint variations, task disruptions, and material substitutions to better reflect the unpredictability of work environments. Incorporating adaptive learning mechanisms will allow the system to respond dynamically to learner performance, personalizing support and challenge levels in real time. This positions the platform for future alignment with joint cognitive systems (JCS) informed frameworks, enabling more intelligent forms of human-system interaction grounded in cognitive engineering principles.

Another critical next step is the integration of analytics and performance dashboards to support both instructors and learners. By tracking user actions, timing, error types, and decision paths, the system can generate rich data profiles that inform instructional interventions, learner self-assessment, and system improvement. These analytics can also support workforce readiness metrics and competency-based progression models long considered a growing demand in industry-aligned training programs. Looking forward, the design principles and learning engineering framework piloted in this pipefitting simulation can be extended to other skilled trades such as electrical work, welding, and HVAC. These domains share similar cognitive and procedural structures and would benefit from simulation environments that support decision rehearsal, spatial reasoning, and error recovery in low-risk digital settings. Scaled deployment will also require modularization of content, integration with learning management systems (LMS), and further testing in hybrid and remote learning formats. Beyond trades, the framework holds significant promise for other high-consequence industries such as advanced manufacturing, where operators must interact with automated systems, interpret sensor data, and manage production workflows under time constraints. Simulation-based training could support troubleshooting, machine calibration, and predictive maintenance tasks, especially when integrated with digital twin and IIoT platforms.

In the defense sector, similar approaches could be used for training maintainers, technicians, and logistics personnel who must operate within complex systems that require procedural accuracy and situational adaptability. For instance, adaptive simulation environments could support mission rehearsal for equipment setup, field repairs, or supply chain adjustments (training scenarios where decision-making under stress and joint task coordination are vital). Healthcare also presents a strong parallel, particularly in domains like surgical tech, emergency medical services, or biomedical equipment repair, where simulation can be used to build cognitive fluency in diagnostic sequences, procedural protocols, and human-technology interaction. In all sectors, designing simulations that focus not only on procedural compliance but also on developing macrocognitive skills, such as situation awareness, problem-solving, and communication, can significantly improve both training outcomes and workplace readiness. Lastly, longitudinal research will be essential to understand the impact of this multimodal training sequence on transfer performance over time. Future studies should investigate not only immediate post-training assessments but also delayed retention, transfer to unfamiliar tasks, and on-the-job performance indicators. As simulation systems grow more adaptive and data-rich, they hold significant promise for advancing the science of human performance in complex, collaborative environments.

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