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Virtualizing the Cleanroom: An Investigation into Learner Outcomes, Usability, and Technology Acceptance in Immersive Semiconductor Training

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Abstract

Semiconductor manufacturing training is often constrained by high equipment costs, hazardous materials, and limited access to cleanroom facilities. To address these challenges, this study investigates the efficacy of a standalone immersive Virtual Reality (VR) training system designed to support photolithography instruction. Using a single-group pre- and post-test experimental design with 10 electrical engineering students, the study evaluated within-subject changes in conceptual knowledge and self-efficacy while examining technology acceptance and usability. Results indicated that the VR intervention yielded significant improvements in both knowledge ($p < .001$, $d = 1.86$) and self-efficacy ($p < .05$, $d = 0.77$), positioning the system as a valid environment for procedural skill acquisition. Furthermore, regression analysis supported the Technology Acceptance Model (TAM), revealing that Perceived Ease of Use significantly predicted Perceived Usefulness ($R^2 = .895$). However, findings also highlighted a significant negative correlation between cognitive load and system usability ($r = -.85$), suggesting that high mental workload can diminish user acceptance and sense of agency. These findings suggest that while VR is a powerful tool for specialized engineering education, instructional designers must prioritize interaction simplicity and cognitive load management to ensure technology acceptance and learning effectiveness.

Introduction

Semiconductor manufacturing and microfabrication are foundational to modern technologies, yet training in these domains remains constrained by high equipment costs, hazardous materials, and limited cleanroom access [1]. Photolithography, in particular, requires learners to master a tightly sequenced set of procedures involving chemical handling, ultraviolet exposure, and precision alignment, leaving little room for trial-and-error learning. As a result, students often encounter these processes through static instruction or brief supervised practice, which may limit conceptual understanding, procedural confidence, and readiness for real cleanroom environments.

Immersive virtual reality (VR) has emerged as a promising instructional modality for addressing these challenges by enabling learners to practice complex procedures in safe, repeatable, and resource-efficient environments. Prior research in industrial operations training demonstrates that VR systems can significantly enhance learner engagement and training effectiveness, particularly when users perceive the system as useful and aligned with task demands. In industrial contexts, perceived usefulness has been shown to directly influence engagement and learning outcomes, suggesting that learners are more likely to invest cognitive effort when VR training is perceived as practically valuable rather than merely novel [2]. These findings highlight VR's potential to support procedural skill acquisition in high-risk, high-cost domains such as semiconductor manufacturing.

However, learning effectiveness alone does not guarantee the successful adoption of VR systems in educational settings. Technology acceptance research consistently emphasizes the importance of usability and perceived ease of use in shaping learners' attitudes and perceptions of usefulness [2, 3]. Extensions of the Technology Acceptance Model (TAM) to immersive and dynamic learning environments show that perceived ease of use is a critical antecedent to perceived usefulness, particularly in complex VR systems that require learners to interact with unfamiliar interfaces while simultaneously processing instructional content [4]. When interaction demands are high, cognitive resources may be diverted away from learning tasks, reducing both system acceptance and instructional effectiveness.

This issue is especially salient in immersive VR training for technically demanding procedures. While VR environments can enhance realism and presence, they can also impose substantial cognitive load through complex interactions, sensory richness, and multitasking requirements. Research in VR-based industrial and educational training suggests that elevated cognitive load can negatively affect usability perceptions, sense of control, and overall satisfaction, even when learning gains are observed [5]. Consequently, understanding how usability, cognitive load, and technology acceptance interact is essential for designing VR systems that support, not hinder, learning.

Despite growing interest in VR for engineering and industrial education, relatively little empirical research has examined these relationships within the context of semiconductor microfabrication training. Existing VR photolithography studies primarily emphasize technical feasibility or procedural accuracy, with less attention to learner experience, usability metrics, and acceptance models. Moreover, few studies integrate learning outcomes (e.g., knowledge gains and self-efficacy) with validated usability instruments and TAM constructs in a single empirical framework.

To address these gaps, the present study investigates a standalone immersive VR cleanroom training system designed to support photolithography instruction for electrical engineering students. Grounded in usability theory and the Technology Acceptance Model (TAM), this research examines not only whether VR training improves conceptual knowledge and self-efficacy, but also how perceived ease of use, perceived usefulness, usability, and cognitive load shape learners' overall experience. By integrating learning outcomes with acceptance and usability measures in a highly technical training domain, this study aims to contribute empirical evidence to the design and implementation of effective VR-based laboratory education. The following questions guided this study:

RQ1: To what extent does the immersive VR cleanroom training intervention improve electrical engineering students' conceptual knowledge of photolithography and their self-efficacy in performing microfabrication tasks?
RQ2: Does Perceived Ease of Use (PEOU) predict Perceived Usefulness (PU) within the context of a highly technical VR training simulation, and how does this relationship align with the Technology Acceptance Model?
RQ3: What is the relationship between the system's perceived usability (SUS scores), the learners' cognitive load, and their overall satisfaction with the training experience?

Literature Review

Virtual Reality and STEM Education

Virtual reality (VR) is increasingly used in STEM education to create immersive, interactive environments that make abstract and complex concepts easier to understand. Across K–12 and higher education, VR supports 3D visualization of invisible or hard-to-access phenomena, such as micro-scale material structures, engineering mechanisms, and scientific processes, thereby improving conceptual clarity and spatial reasoning [6, 7, 8, 9]. VR laboratories and simulations allow students to conduct experiments and practice procedures safely, overcoming constraints of time, cost, and equipment while enhancing practical skills and bridging theory–practice gaps [6, 7, 10, 11]. Studies and reviews report that well-designed VR experiences tend to increase student motivation, engagement, and perceived usability, often with equal or better learning outcomes compared with traditional slides or physical models, and with lower perceived workload [12, 13, 14, 15]. In engineering and science courses, VR has been used for mechanism exploration, materials testing, and introductory STEM lessons, showing gains in self-efficacy, problem-solving, and application of concepts [7, 8, 11, 14, 16]. VR is also being developed for inclusive STEM learning, supporting students in rural areas, learners with disabilities, and students with autism spectrum disorders through customizable environments and scaffolded virtual learning spaces [17, 18, 19, 20]. At the same time, research emphasizes that the educational impact of VR depends heavily on pedagogical alignment and instructional design; effective applications integrate clear learning objectives, appropriate guidance, and opportunities for active, inquiry-based learning rather than relying on immersion alone [9, 12, 21, 22].

Photolithography in Microfabrication

Photolithography is a core microfabrication technique used to transfer precise geometric patterns onto a substrate, forming the basis of modern integrated circuits, MEMS, microbatteries, microfluidics, and lab-on-chip devices [23, 24, 25]. It is typically taught through a blend of conceptual instruction and carefully scaffolded hands-on activities, so that students understand both the physics/chemistry and the practical workflow of pattern transfer. In high school and early undergraduate settings, instructors often use simplified polymer experiments where students prepare microscale "silhouettes" or pattern silicon wafers with custom masks, linking the steps of coating, exposure, and development to topics such as photochemistry, reaction kinetics, and polymer chemistry [26, 27]. At universities with cleanroom access, students may complete structured lab modules that mirror industrial processes, including photoresist application and metrology, radiometric characterization of exposure systems, alignment and overlay, linewidth measurement, and image evaluation with microscopes, sometimes in multi-course sequences from introductory to advanced microlithography [28, 29]. Where full-scale facilities are unavailable or too costly, low-cost setups and custom alignment/UV exposure tools allow hands-on practice of optical lithography, microcontact printing, and embossing using basic equipment, making the topic accessible from middle school to college and in two-year programs [30, 31]. More recently, virtual reality and simulation-based environments have been integrated into photolithography teaching to let students rehearse complex cleanroom procedures, develop operational proficiency, and reduce the risk of damaging expensive equipment, often with documented gains in task accuracy, reduced procedural errors, and increased learner confidence [32, 33, 34]. Across these approaches, modern curricula emphasize step-by-step visualization of the process, explicit discussion of optical and chemical parameters, and alignment with broader learning goals in nanotechnology and materials education [29, 34, 35].

Methodology

A. System Design and Development

The proposed system is a standalone virtual reality (VR) training application developed to support procedural learning in cleanroom photolithography, a domain characterized by high equipment cost, hazardous materials, and a steep learning curve for novice users. The system was designed with the Unity Game Engine and evaluated on the Meta Quest Pro, with full compatibility across other Meta Quest standalone headsets. This hardware choice prioritizes accessibility, portability, and ease of deployment in educational settings, allowing trainees to begin practicing with minimal setup or technical support while maintaining sufficient tracking fidelity for precise interaction.

Photolithography involves handling flammable solvents, UV exposure, and complex multi-step equipment operation, typically taught through a combination of written lab manuals, instructor demonstrations, and limited supervised practice. These constraints significantly restrict opportunities for repetition and error-based learning. The VR system addresses this gap by providing a controlled environment where learners can safely perform the complete process repeatedly, make mistakes without serious consequence, and develop procedural fluency prior to entering the physical cleanroom.

A central design goal was to achieve high visual and interaction fidelity, where it directly supports learning and transfer. All equipment, tools, and spatial layouts were manually modeled by the development team to match the real cleanroom laboratory on campus using Blender. Once modeled, the object texture is baked into a 2K resolution map and exported as an FBX to be imported into the Unity Game Engine. This includes the mask aligner, spin coater, hot plates, the fume hood, and surrounding environment. Assets were created using reference photography and physical measurements to preserve scale, proportions, and operational affordances. Visual fidelity is not treated as an aesthetic goal alone, but as a pedagogical mechanism to ensure spatial familiarity and reduce cognitive dissonance when transitioning from virtual to physical training.

Figure 1. Participants during the study sessions

To support both usability and performance on standalone hardware, the simulation employs multiple lighting profiles that dynamically shift throughout the training experience. Instructional phases use dimmed lighting to reduce environmental salience and draw attention to the information hub and tutorial content, while procedural phases restore brighter, realistic lighting that mirrors cleanroom conditions. Lighting transitions act as implicit cues that signal shifts between learning, assessment, and active task execution. All lighting is precomputed using baked lightmaps and reflection probes, ensuring stable frame rates while preserving realistic shadows and material response. (see **Figure 2**)

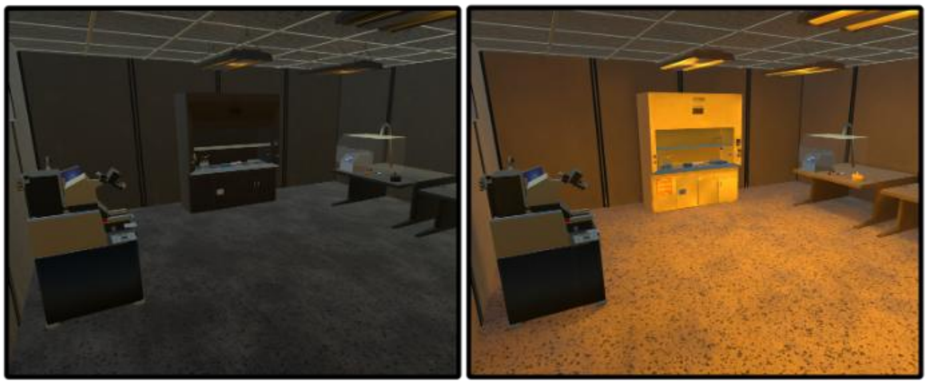

Figure 2. Different lighting profiles (left) is for tutorial/quiz steps, and (right) is for when the user is actually doing the tutorial steps on their own

Interaction fidelity is implemented using the UltimateXR software development kit (SDK), which enables object-specific hand poses, physics-based manipulation, and context-aware interactions. When users grasp tools such as spray bottles, tweezers, or alignment knobs, their virtual hands assume natural poses tailored to each object. This reduces abstraction and supports embodied learning by reinforcing correct motor patterns. The system also integrates multiple locomotion profiles, including smooth locomotion with vignetting and teleportation with snap turning, allowing users to select the mode that best balances comfort and immersion. These options are toggled directly within the information hub, allowing for setting changes to accommodate individual differences in motion tolerance and prior VR experience.

The primary contribution of the system's instructional design is the unified information hub, which centralizes guidance, feedback, progress tracking, and assistance within a single, persistent interface. Prior iterative designs of this simulation using distributed instructional displays including TVs and tablets were found to disrupt the user's workflow and increase cognitive load in past heuristic evaluations. The information hub addresses this by remaining accessible at all times and organizing content into clearly defined panels. Users can view their current section and step, overall progress, elapsed time, and score, with real-time visual and audio feedback reinforcing correct actions or highlighting safety violations. Color-coded borders and score animations provide immediate, intuitive cues without interrupting task flow. (see **Figure 3**)

Figure 3. (left) shows the old TV/tablet instructional format which we overhauled after past heuristics. (right) shows our new info center implementation as well as a hand pose of when the info center is grabbed and adjusted by the user.

The hub also integrates tutorial videos, short formative quiz questions, and step-by-step instructions. Each module section begins with a video demonstration, followed by a low-stakes conceptual check. Users may attempt these questions multiple times, receiving corrective feedback and explanations before proceeding to hands-on practice. This structure reflects established scaffolding principles, supporting novice learners while allowing guidance to be gradually withdrawn when the user switches from practice to test mode. These two mirrored training modes support both learning and assessment. Practice mode provides full tutorials videos, explicit step guidance, and object highlighting, while testing mode removes these features, requiring users to rely on a virtual clipboard analogous to real lab manuals and documentation. Because the underlying process, scoring, and interaction logic remain constant, but guidance features are removed, differences in performance can be attributed to learner retention rather than overly significant system variation. (see **Figure 4**)

Figure 4. Instructional content on the info center. (left) shows a tutorial video with a neutrally colored border. (center) shows a correct quiz answer with green border feedback and (right) shows an incorrect quiz answer with red border feedback

An integrated AI assistant, NOVA, is accessible through the hub as an optional support tool during practice mode. Using speech-to-text and text-to-speech, learners can ask procedural or conceptual questions during training without leaving the simulation. NOVA's animated states—idle, listening, processing, and speaking—provide transparency into system behavior and reinforce the user's sense of control while still having access to guided support.

Finally, the system records detailed interaction logs and eye-tracking data to support assessment and instructional refinement. These analytics enable instructors to review learner performance, identify common errors, and explore attention patterns during safety-critical steps. While the photolithography module represents a domain-specific contribution, the information hub, interaction framework, and dual-mode training structure are intentionally designed to generalize to other laboratory and procedural training contexts, positioning the system as a transferable model for immersive, learner-centered VR education.

B. Participants

A total of 10 students majored in Electrical Engineering over the Fall 2025 semester in a mid-west university. The participants were selected using convenience sampling, due to accessibility and availability to participate in the study. All 10 participants were male (100%), with ages ranging from 20 to 27 years old. The participant pool was predominantly White/Caucasian (n = 8, 80%), with the remaining distribution consisting of one African American (10%) and one Middle Eastern (10%) participant. In terms of prior VR exposure, half of the cohort (50%) reported previous experience using VR for entertainment. Conversely, prior usage for educational purposes was minimal, with only one participant (10%) reporting experience in an informal learning context.

C. Experiment Protocol

The study commenced with formal orientation and the acquisition of informed consent from all participants. Following this, a pre-intervention survey was administered to capture demographic data, baseline knowledge, and perceived self-efficacy.

To mitigate technical barriers, participants were then introduced to the VR controllers, the headset, and the operations of the VR, so as to be familiar with the corresponding operations in the VR. Once they felt comfortable operating in the VR, they transitioned to the official VR-based semiconductor microfabrication training. This training consisted of three distinct segments: two guided practice sessions, which included scaffolded facilitation in VR and on-site assistance, followed by a final evaluation session. During the evaluation, all on-site assistance and in-system hints were removed to assess independent performance.

Immediately following the VR experience, a post-intervention survey was administered to reassess knowledge and self-efficacy, while also measuring system usability, cognitive load, and technology acceptance.

This entire study process could be referred to in Figure 5 below:

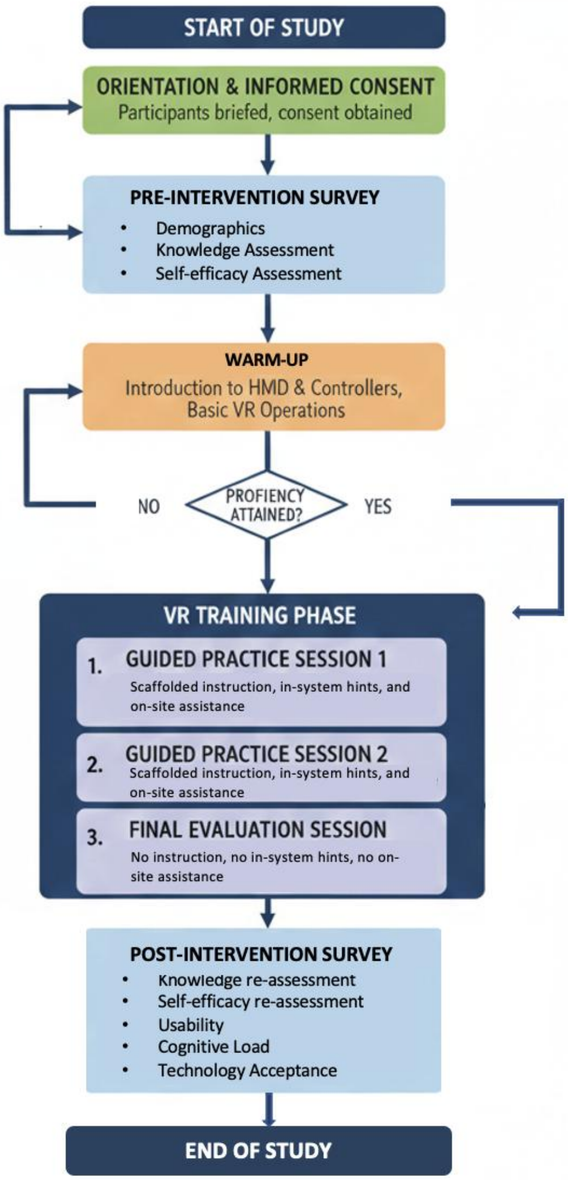

Figure 5. Study procedure

D. Data Instrumentation and Sources

The study employed a pre- and post-test experimental design with 10 electrical engineering students to data collection, utilizing validated scales and expert-designed assessments.

Self-efficacy was measured using Self-Efficacy for Learning Performance items in the Motivated Strategies for Learning Questionnaire (MSLQ) [36]. This instrument has demonstrated high internal consistency, with a reported Cronbach's alpha of .93. Within the current sample, the internal reliability was calculated at Pre-Lab (before): $\alpha = 0.94$ and Post-Lab (after) $\alpha = 0.98$. Both values are well above the commonly accepted threshold of 0.70, indicating excellent internal consistency among the self-efficacy questions for both the pre- and post-surveys.

Knowledge quiz questions were created by the subject experts in understanding students' knowledge in the semi-conductor microfabrication process, The assessment consisted of 11 items, including 5 multiple-choice questions, 3 open-ended questions and 3 sequencing tasks, scored out of a total of 29 points. Example items included questions such as, "what is this machine?", "please reorder the sequence of photolithography process."

Usability was measured via System Usability Scale (SUS) [37], with historical Cronbach Alpha reported to be .91 [38] (Bangor et al., 2008), indicating a high-level of reliability. Within the current sample, the internal reliability was calculated at $\alpha = 0.83$. This is well above the standard 0.70 threshold, indicating good internal consistency among the SUS items.

Cognitive load was measured using NASA TLX [39], with intraclass correlation coefficients (ICC) reported ranging between 0.71 and 0.81, indicating excellent reliability [40]. Internal consistency for the Cognitive Load scale was evaluated, yielding a Cronbach's alpha of 0.80, indicating good reliability.

Technology acceptance was assessed using the Technology Acceptance Model (TAM) [41], which has demonstrated psychometric reliability, with reported reliability exceeding .90 [42]. Within the current sample, the TAM demonstrated excellent internal reliability for the overall scale ($\alpha = 0.99$), as well as for both the Perceived Ease of Use ($\alpha = 0.97$) and Perceived Usefulness ($\alpha = 0.99$) subscales. These values well exceed the standard 0.70 threshold, indicating strong internal consistency among the items.

E. Data Analysis

Pre-and-post self-efficacy and knowledge quiz were analyzed utilizing paired-sampled t-test. SUS was analyzed using the recommended calculation methods by [43]. NASA TLX score was reported as descriptive statistics to interpret the overall trends of the data. A Pearson correlation was also conducted to understand the relationship between SUS and TLX scores. TAM was calculated using a standard scale scoring process [41], then a simple linear regression was conducted to determine if Perceived Ease of Use (PEOU) predicts Perceived Usefulness (PU).

Results

Paired-samples *t* tests were conducted to examine changes in knowledge and self-efficacy following the VR training intervention. Participants showed significant improvements in both outcomes.

Knowledge Test Performance

Knowledge scores increased significantly from pretest ($M = 15.65$, $SD = 5.30$) to posttest ($M = 22.25$, $SD = 2.76$), $t(9) = 5.87$, $p < .001$, 95% CI [4.06, 9.14], $d = 1.86$. On average, participants improved by 6.60 points, corresponding to a 42.2% gain relative to the pretest mean. The effect was very large (Cohen, 1988), indicating that the VR training substantially enhanced participants' knowledge. (**Figure 6**)

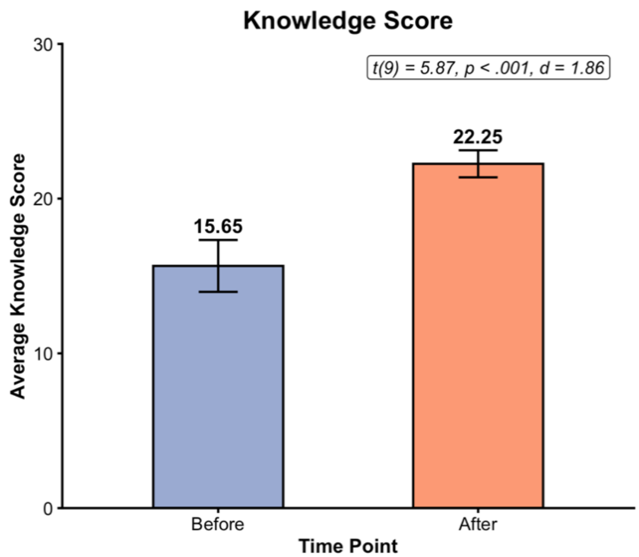

Figure 6. pre- and post- knowledge scores

Self-efficacy

Self-efficacy also increased significantly from pretest (M = 4.04, SD = 0.70) to posttest (M = 4.58, SD = 0.62), $t(9) = 2.83$, $p < .05$, 95% CI [0.11, 0.97], d = 0.89. The mean increase of 0.54 points represents a 13.3% improvement relative to the pretest mean, reflecting a large effect and a meaningful gain in participants' confidence following the VR training. Figure 7 depicts pre- and post-intervention self-efficacy ratings. (see **Figure 7**)

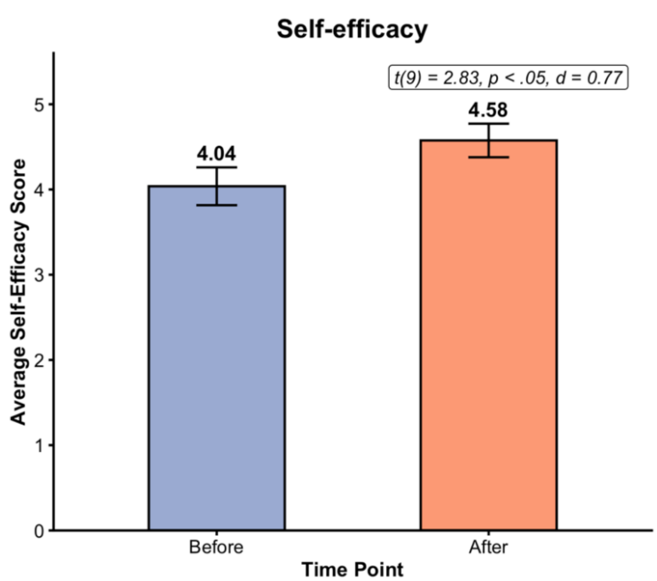

Figure 7. pre- and post- self-efficacy ratings.

Usability

A quantitative analysis was conducted to evaluate participants' perceptions of the XR Cleanroom training system. This analysis examined descriptive statistics for perceived usability and overall satisfaction, as well as the statistical relationship between these two variables.

Perceived usability was measured using the System Usability Scale (SUS), which yields a score from 0 to 100. Overall satisfaction was measured using a single-item "Overall Rating" question (measured on a 7-point scale).

The mean SUS score was 73.00 (SD = 14.62), indicating an above-average usability rating. The overall rating was high, with a mean of 5.70 (SD = 0.67) and a median of 6.0. Detailed descriptive statistics are presented in **Table 1**.

Table 1: Descriptive Statistics for SUS Score and Overall Rating (N = 10)

Variable	**Mean**	**Std. Dev. (SD)**	**Median**	**Min**	**Max**
SUS Score	73.00	14.62	73.75	47.5	95.0
Overall Rating	5.70	0.67	6.0	4.0	6.0

To investigate the relationship between perceived usability and user satisfaction, a Pearson product-moment correlation was performed. The analysis revealed a strong and positive correlation between the SUS score and the overall rating, r(8) = .608, p = .062. Although the effect size (r) indicates a strong association where higher perceived usability relates to higher overall ratings, this result was not statistically significant at the .05 level, likely due to the small sample size (N=10).

To further examine the predictive power of usability on user ratings, a simple linear regression was performed with SUS score as the independent variable and overall rating as the dependent variable.

The results indicated that the overall model approached significance but did not meet the standard threshold, F(1, 8) = 4.70, p = .062. The SUS score explained 37.0% of the variance in overall rating (R^2 = .370, Adjusted R^2 = .291).

The SUS score was found to be a positive predictor of overall rating (b = 0.028, p = .062). For every 10-point increase in the SUS score, the model predicts a 0.28-point increase in the overall rating. Figure x shows the scatter plot with a regression line. The wide gray area shows why the p-value (0.062) wasn't quite significant due to a small sample size. (see **Figure 8**)

Figure 8. Scatter Plot with Regression Line

Technology Acceptance Model (TAM)

A simple linear regression was conducted to determine if Perceived Ease of Use (PEOU) predicts Perceived Usefulness (PU). The model was statistically significant, $F(1, 8) = 67.84$, $p < .001$, accounting for 89.5% of the variance in Perceived Usefulness ($R^2 = .895$).

Perceived Ease of Use was a significant positive predictor of Perceived Usefulness ($b = 0.85$, $p < .001$). (see **Table 2** and **Figure 9**). These findings support the core hypothesis of the Technology Acceptance Model (TAM), suggesting that as users perceive the system to be easier to use, their perception of its usefulness increases substantially.

Table 2: Regression Analysis for Perceived Ease of Use (PEOU) predicting Perceived Usefulness (PU)

Predictor	***B***	***SE***	***t***	***p***
(Constant)	1.22	0.59	2.08	.071
Perceived Ease of Use (PEOU)	0.85	0.10	8.24	< .001

Note. $R^2 = .895$, Adjusted $R^2 = .881$, $F(1, 8) = 67.84$, $p < .001$.

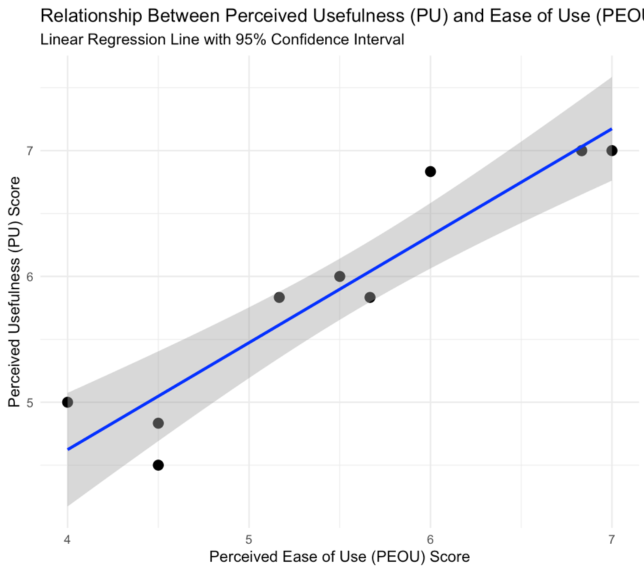

Figure 9. Scatter Plot with Regression Line

Cognitive Load Relationships

Cognitive load was strongly and negatively correlated with system usability (SUS), $r = -.85$, $p = .002$, indicating that greater mental effort during the VR session was associated with lower perceived usability. Cognitive load was also negatively correlated with technology acceptance ($r = -.65$, $p = .041$) and agency ($r = -.66$, $p = .039$), suggesting that higher perceived cognitive demands were associated with lower acceptance of the system and a reduced sense of control. (see **Figure 10**)

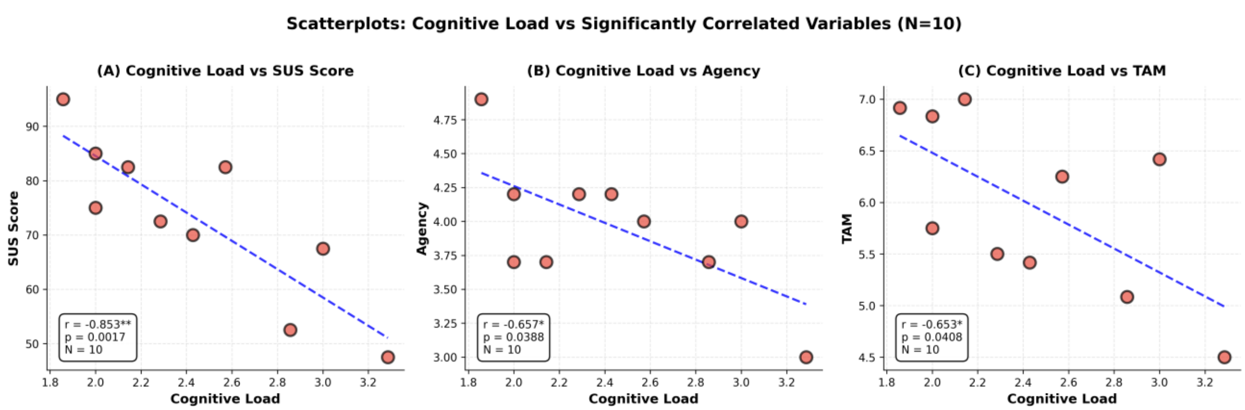

Figure 10. Cognitive load vs. Significantly correlated variables

Discussion and Implications

Discussion of the Empirical Results

Our findings of significant gains in knowledge and self-efficacy align with a growing body of research on VR-based training that reports improvements in performance, confidence, and behavioral intention in complex industrial and technical contexts [2, 44]. Prior studies of VR-supported industrial and collaborative learning environments indicate that perceived usefulness and intention to use VR are positively associated with learning performance. This evidence supports our interpretation that the observed increase in self-efficacy reflects a substantive learning-related outcome rather than a purely attitudinal response [2, 44, 45].

The finding that higher System Usability Scale (SUS) scores are significantly correlated with, and predictive of, overall system ratings is consistent with a broad body of Technology Acceptance Model (TAM) and VR acceptance research, which consistently demonstrates that perceived ease of use and usability strongly influence user attitudes and behavioral intentions [2, 4, 33, 43, 45, 46]. Across clinical, aviation, and maritime VR applications, ease of use has been shown to affect perceived usefulness, enjoyment, attitudes, and intention to use, either directly or indirectly [3, 4, 33, 43]. When SUS is treated as a proxy for usability, the positive relationship observed between SUS and overall system ratings in this study aligns well with these established patterns.

Our results show that Perceived Ease of Use (PEOU) positively predicts Perceived Usefulness (PU) reflect the core relationship proposed by TAM and has been robustly replicated in VR learning and training contexts. Examples include dynamic and aviation-focused VR learning environments [46], industrial operations training [2], maritime engine room simulators [3], VR training systems incorporating self-efficacy and immersion [43], and hybrid TAM–UTAUT models applied to medical training [33]. Collectively, these studies confirm that when VR systems are perceived as easier to use, learners are more likely to view them as useful, a pattern that is directly mirrored in our findings [2, 3, 33, 43, 46]. Although some VR-specific models report weaker or non-significant PEOU-to-PU relationships when tasks are inherently simple or systems are intrinsically easy to use [47], the significant relationship observed in this study is consistent with the dominant trend in the literature.

The observed association between greater mental effort, higher perceived cognitive demands, and lower usability, acceptance, and sense of control is also broadly consistent with existing research. Studies on VR workload indicate that elevated mental workload can hinder the effectiveness and enjoyment of VR training, highlighting the importance of managing cognitive load through careful design [48]. Extended VR acceptance models further emphasize that usability, comfort, and pragmatic system qualities are key determinants of perceived ease of use and, subsequently, downstream acceptance constructs [33, 43, 47]. Excessive mental effort or cognitive demand can undermine these relationships. Research incorporating additional experiential factors, such as presence, cybersickness, and interaction complexity, demonstrates that negative user experiences, such as discomfort or excessive challenge, can reduce perceived usefulness and intention to use, even when core TAM pathways remain valid [43, 47, 48]. Accordingly, our findings provide an explicit illustration of how cognitive overload can erode the TAM constructs (PEOU, PU, attitude, and intention) that support technology acceptance.

Overall, this study extends existing literature by integrating usability (as measured by SUS), cognitive load, and learning-related self-efficacy within a highly technical training domain, photolithography, that has only recently begun to receive attention in VR training research [1, 2].

Implications for Educational Practice
Our results reveal several important educational implications regarding the design and implementation of immersive virtual reality (VR) for teaching complex STEM skills.

The significant gains in knowledge and self-efficacy observed in this study position the VR system as a legitimate skills-training environment. This finding aligns with prior research on cleanroom microfabrication VR and other industrial and clinical VR training systems that demonstrate improvements in procedural accuracy, safety awareness, and learner confidence [12, 33, 49, 50, 51]. From an educational perspective, these results support the use of VR as a core pre-laboratory or practicum component for hazardous, costly, or highly sequenced procedures, such as photolithography, rather than as a supplementary motivational tool.

The strong influence of System Usability Scale (SUS) scores and Perceived Ease of Use on overall system ratings and Perceived Usefulness indicates that technology acceptance constructs are closely intertwined with educational value. Prior reviews of immersive VR in STEM education and skills training similarly emphasize that ease of interaction and low-friction interfaces are prerequisites for meaningful learning outcomes [12, 50, 52, 53, 54]. Educationally, this suggests that VR instructional design must treat interaction simplicity, clear guidance, and error-tolerant interfaces as integral components of pedagogy. When these elements are lacking, learners may disengage or avoid productive struggle, thereby undermining learning potential.

The finding that increased mental effort and higher perceived cognitive demands are associated with reduced usability, acceptance, and sense of control is consistent with existing evidence showing that immersive VR can elevate cognitive load and, when poorly structured, even hinder learning [52, 55]. At the same time, prior research highlights that an appropriate level of challenge is necessary to promote transfer and higher-order skill development [52, 56].

Several instructional implications follow this balance. First, scaffolding and worked examples should be front-loaded within VR environments and gradually faded as learners develop procedural fluency. Second, VR learning sessions should remain short and tightly focused, as meta-analytic evidence indicates that the strongest learning effects occur in brief, skill-oriented VR activities [55, 57]. Third, sensory richness should be deliberately aligned with instructional goals, while extraneous visual or interactive elements that consume cognitive resources without supporting learning should be minimized [52].

Taken together, these findings suggest that immersive VR for photolithography can serve as a powerful tool for developing procedural competence and learner confidence when usability is high and cognitive load is carefully managed. Critically, interaction design and cognitive load management should be treated as central instructional levers rather than afterthoughts, ensuring that immersion enhances, rather than competes with, learning.

Limitations and Future Research Directions
While this study represents a significant advance in our understanding of the potential for VR in STEM education, it is not without its limitations. First, the primary limitation of this study is the small sample size (N = 10) and the reliance on a single-group pre- and post-test design. Because

the study lacked a control group receiving traditional instruction, the significant knowledge and self-efficacy gains observed cannot definitively prove that the VR intervention is superior to conventional methods. Rather, these results establish the system's baseline viability for skill acquisition. The lack of statistical significance in certain correlations likely reflects a Type II error (false negative) due to the limited sample rather than the absence of a true relationship. These findings should be interpreted with caution until validated by future studies with larger cohorts. Second, this experiment was conducted over a short period, encompassing only one one-hour session in VR. Future research should examine longitudinal learning impacts and transferability of conceptual gains. Third, this experiment was conducted with a highly homogeneous group consisting of only ten male students [(100% male, 80% Caucasian). This lack of demographic diversity severely restricts the generalizability of the usability, cognitive load, and technology acceptance findings. Future studies need larger and more diverse samples to test significance across broader populations.

Conclusion

This study provides empirical evidence supporting the efficacy of a standalone Virtual Reality (VR) Cleanroom training system for semiconductor microfabrication. The results demonstrate that a single VR intervention can yield substantial within-subject educational benefits, with participants exhibiting significant improvements in both conceptual knowledge and self-efficacy following the simulation. These findings confirm that the VR simulation successfully bridges the gap between abstract theory and procedural confidence, positioning the system as a legitimate skills-training environment rather than merely a technological novelty.

Theoretically, the findings robustly support the Technology Acceptance Model (TAM), confirming that perceived ease of use is a critical predictor of perceived usefulness. The data indicate that technical usability is a foundational requirement for learner engagement, as higher usability scores are strongly correlated with overall user satisfaction. Conversely, the significant negative relationship between cognitive load and system usability suggests that a high mental workload associated with navigating the interface can diminish the user's sense of agency and acceptance.

Consequently, the educational impact of VR is inextricably linked to its design quality. Instructional designers must treat interaction simplicity as a pedagogical variable; when cognitive demands are too high, they compete with learning resources. Effective VR environments must therefore carefully balance immersion with cognitive load management through scaffolded guidance and minimized extraneous visual elements.

While these results are promising, the study's limitations, specifically the small sample size and participant homogeneity, warrant cautious interpretation. Future research should aim to validate these findings with larger, more diverse cohorts and investigate the longitudinal retention of skills. Ultimately, this research affirms that when usability is high and cognitive load is effectively managed, immersive VR can transform the training landscape for specialized engineering fields.

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