**Robotics Laboratory During COVID-19: Challenges and Future Directions for Extended Reality-enabled Laboratories**

Sara Masoud

Industrial and Systems Engineering, Wayne State University

[saramasoud@wayne.edu](mailto:saramasoud@wayne.edu)

Meina Zhu

Learning Design and Technology, Wayne State University

[meinazhu@wayne.edu](mailto:meinazhu@wayne.edu)

Jeremy Rickli

Industrial and Systems Engineering, Wayne State University

jlrickli@wayne.edu

Ana Djuric

Engineering Technology, Wayne State University

ana.djuric2@wayne.edu

**Abstract**

Laboratory sessions are essential to engineering education, especially for understanding abstract concepts. Expensive laboratory equipment and machines pose challenges to institutions aiming to offer accessible, hands-on learning opportunities. Moreover, the emerging trend of online engineering education faces critical challenges in how to satisfy laboratory learning requirements. With the rapid rate at which information and communication technologies advance the popularization of computer-embedded devices, education systems need to continuously innovate to promote education methods that leverage the latest technological features. Extended reality (XR) technologies enhance interactive virtual environments with an accurate resemblance to physical reality. These technologies enable students to examine the various bodies that compose the environment from different perspectives through simulated and sensory data. The principles of intermediate awareness and direct cognition are the essential advantages of immersive technologies. Learners are granted direct interaction without depending on second-hand accounts, which results in the regression of unique primary data. The application of extended reality in various paradigms, like problem-based learning, exploratory learning, and distance learning, has provided fertile ground to advance learning. Construction engineering education and coaching have adopted immersive technologies, including desktop-based immersive, 3D game-based, and modeling (BIM)-enabled XR. Specifically, XR can be considered as a pedagogical model for simulation-based learning. In this work, five robotics laboratory sessions prior to and during COVID-19 are reviewed, and major challenges are highlighted. Following these comparisons, XR-enabled solutions are discussed to address these challenges and alleviate the workload for both students and instructors.

**Introduction**

Laboratory sessions are essential to engineering education, especially for understanding abstract concepts (Jagodziński & Wolski, 2015). The expensive cost of laboratory equipment and machines poses challenges to institutions. Moreover, the emerging trends of online engineering education face challenges regarding laboratory sessions. With the rapid rate at which information and communication technologies advance the popularization of computer-embedded devices, education systems need to innovate to promote quality education mediated by the latest technological features (De Mello & Gobara, 2014).

Extended reality (XR) technologies enhance interactive virtual environments with a seemly accurate resemblance to physical reality. These technologies enable students to examine the various bodies that compose the environment from different perspectives through simulated/sensory data (Nubi & Vincent, 2020). The principles of intermediate awareness and direct cognition are the essential advantages of immersive technologies. Learners are granted direct interaction without depending on second-hand accounts, which results in the regression of unique primary data (Nubi & Vincent, 2020). The application of extended reality in various paradigms like problem-based learning, exploratory learning, and distance learning has provided fertile ground for learning. Construction engineering education and coaching have adopted immersive technologies, including desktop-based immersive, 3D game-based, and modeling (BIM)-enabled Extended Reality (Nubi & Vincent, 2020). Specifically, XR can be considered a pedagogical model for simulation-based learning (Nubi & Vincent, 2020).

The COVID-19 pandemic has sped up the transformation phase for manufacturing laboratories. The constant threat of a partial or complete lockdown has pushed many educators to distance themselves from relying on physical laboratories and think outside the box on delivering hands-on experience through remote and virtual laboratories. XR technology, one of the top trending educational technologies (Bui, 2020), is one viable alternative to the expensive cost of laboratory equipment during and after the COVID-19 pandemic. In the context of learning, while virtual reality (VR) can be used as a complementary teaching method to further enhance the learning experience, augmented reality (AR) can provide a virtual extension to the physical learning space, enabling valuable yet physically impossible or time-consuming actions (Thiede et al., 2017; Tsovaltzi et al., 2010; McCusker et al., 2018). AR has been considered as effective in education by making learning more interactive, dynamic, and engaging (Akçayır & Akçayır, 2017; Lee, 2012) and enhancing learning outcomes (Ong et al., 2008). Prior research has found that AR improves learners' skills and knowledge in diverse science subject areas, including engineering education (Parras-Burgos et al., 2020). XR has been applied to enhanced learning in many different fields, such as projects and manufacturing processes (Liarokapis et al., 2004), electronic engineering (Martin-Gutierrez et al., 2012), architecture (Fonseca et al., 2014), and mathematics (Salinas et al., 2013).

**Literature Review**

Laboratories have been used for development, research, and education since late 1800s in the United States. The first two categories focus on answering specific questions, determining design parameters, and extending the students’ body of knowledge beyond what they have learned within classrooms. The third category, education, is critical to transferring theoretical knowledge while gaining practical experience and skill sets (Balamuralithara & Woods, 2009), specifically in the fields of automation and robotics. Educational automation and robotics laboratories can be defined as purely hands-on, remote, and virtual modes, as shown in Figure 1.

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Figure 1: Categories of educational laboratories

The categorization of educational laboratories is defined based on whether the learner and asset are co-located and whether the experiments are conducted using physical assets or digital replicas. Hybrid laboratories are created if any combinations among these categories happen. These hybrid laboratories are the results of the growing educational demands to combine the benefits of different modes (Viegas et al., 2018).

**Hands-on laboratories:** Hands-on laboratories are designed to enable students to manipulate, observe, explore, and think about science using concrete materials, guided by a present educator. These laboratories can be further classified as onsite (i.e., built in a fixed location) and mobile (i.e., cars and trucks) laboratories. Lack of hands-on experience in manufacturing processes is one of the most crucial competency gaps in manufacturing education (Ssemakula et al., 2006). The excessive cost associated with maintaining a modern manufacturing laboratory makes it complex for educational institutions to provide challenging yet realistic experiences for students. Learning factories are one of the best realizations of hands-on laboratories in manufacturing education, where a practice-based engineering curriculum is integrated with analytical and theoretical knowledge (Lamancusa et al., 1997). Although learning factories have been proven to be capable of balancing theoretical concepts with physical facilities for product realization in an industrial-like setting, the high costs of setting up such facilities have led to non-uniform hands-on experience for the students in different universities (Ssemakula et al., 2006). Due to the high costs associated with hands-on laboratories, remote and virtual laboratories have been gaining interest among educators even before COVID-19. The onset of COVID-19 and the introduction of Industry 4.0 technologies such as industrial internet of things (IIoT) and XR have significantly sped up the integration of remote and virtual learning laboratories.

**Virtual Laboratories:** virtual laboratories are designed to teach students the fundamentals, while hands-on laboratories enable students to manipulate the systems and better understand the process of parameter tunning for systems. Virtual laboratories are developed as an online format and are designed to reduce the costs of hands-on laboratories by reducing the equipment, space, and maintenance costs associated with hands-on laboratories. Virtual laboratories usually rely heavily on high-fidelity simulations and game engines to deliver realistic representations of physical systems.

Traditionally, simulations have been used in the design phase in manufacturing to save time and resources. Nowadays, high-fidelity simulations models are used to better understand the behaviors of certain products and/or processes in different scenarios. High-fidelity simulations can support proof of concept and design, reduce the integration costs by replacing physical assets with digital ones, shorten the design to delivery time, and optimize robotic and automated production systems. For example, Tecnomatix software's robotics and automation simulation solutions can be used to: 1) design complete work cells, 2) plan, simulate, and optimize robotic operation paths, and 3) program robots and automation offline (SIEMENS, 2022).

XR is an umbrella term covering a spectrum of computer-generated immersive environments such as VR, AR, and augmented virtuality (AV) over the reality-virtuality continuum (Tunur et al., 2021). Virtual reality immerses users fully in an entirely virtual world created at the intersection of immersive technologies and high-fidelity simulations. While users lose their connections with the real world in VR, AR improves user experiences in the real world by augmenting virtual objects and superimposing information on the real-world environment. On the other hand, AV falls between VR and AR by augmenting real objects in virtual environments. Industrial automation and robotic operations training are ideal candidates for XR immersive training environments due to the expense and safety considerations of physical robotic laboratories and has been the focus of multiple research studies.

Successful implementation of XR technologies in an education and training setting relies on achieving suitable levels of immersion and presence. Immersion is a user’s perception of being present in a non-physical (i.e., VR) or pseudo non-physical (i.e., AR and AV) environment. Immersion is achieved by integrating technologies such as head mounted displays, room scaling systems, haptic/tactile feedback, and smartphones into non-physical environments. These technology exchange sensory input from reality with digitally generated signals, such as images and sounds (Freina & Ott, 2015). Presence is the subjective reaction of the user due to experiencing immersion in an altered environment (Slater, 2003). If successfully implemented, XR environments orchestrate harmonized exchange of information among its components (i.e., hardware and software) in order to provide immersion and presence for users. Though XR and industrial automation research and education have been a focus of prior research, the Computing Community Consortium held a Content Generation for Workforce Training workshop [CA2VES workshop document] in 2019 that identified limitations to current XR, VR, and AR systems. Limitations include: 1) understanding the level of realism needed for diverse types of training and 2) development of XR interaction and visualization techniques directly relevant to training (such as where and how tasks are to be performed).

Using XR devices to improve programming of manufacturing work cells based on industrial robots was investigated to visualize robot paths and execute path preplanning checks of a robot cell (Neves et al., 2018). A VR simulator for teaching robotics has been developed and evaluated where users are able to create trajectories while implicitly defining reference points. The VR simulator assists users in task execution, improving visualization, and reducing the time spent on the trajectory planning tasks (Dos Santos et al., 2017). AR assisted a Human Operator to learn complex tasks in robot programming. (Domingues et al., 2009) presented a decentralized software and network architecture for collaborative teleoperation based on scaled mixed reality.

**Remote Laboratories:** Remote laboratories are set up to provide different avenues for sharing skills and resources among students to improve the learning experience (Cotfas et al., 2015). Remote laboratories deviate from hand-on ones due to the distance between the experimenter and where the experiment is taking place. Given the recent advances in robot manipulators and tactile-feedback systems, remote laboratories are becoming more common in educational settings.

IIoT enables remote control of machines and robots through wireless communications and integration of low-cost sensors, hardware, software, edge computing, and storage systems (Gilchrist, 2016). In addition to facilitating advanced analytics and optimal operational decisions, IIoT can enable teleoperation. Teleoperation represents the ability to operate equipment or machines from a distance (Fong & Thorpe, 2001). Telerobotic, a specific form of teleoperation, focuses on the remote control of a robot. Telerobotic, where human intelligence pairs with robots’ capabilities such as repetition, manipulation, and precision, can be achieved by utilizing a streaming wide range of data retrieved by sensors implemented in a robot’s environment (Fong & Thorpe, 2001). Offline and/or real-time autonomy can be realized by processing these data. Although teleoperation roots back to the 1950s, the interest in teleoperations has surged significantly due to the COVID-19 pandemic as teleoperation platforms are designed for situations that are too dangerous, uncomfortable, limiting, repetitive, or costly for humans (Murphy, Gandudi, & Adams, 2020). Remote laboratories are usually built upon teleoperation in manufacturing, where learners learn to remotely operate a machine or robot in pseudo real-time. Another technology that improves the quality of remote laboratories is digital twinning. Digital twins are high-fidelity simulations that are connected to the actual assets through IIoT. In manufacturing, the main benefits of digital twins can be summarized as reducing risks as well as safer hands-on and remote training of operators (Hernandez-de-Menendez et al., 2020).

From a pedagogical perspective, hand-on, virtual and remote laboratories have their own strengths and weaknesses. Hands-on laboratories not only foster interactions, collaboration, and socialization but also enable students to learn through trial and error. The main disadvantages of hands-on laboratories are limiting students to the laboratory, whether onsite or mobile, requiring active supervision, restrictive time budgets available to each student, and high maintenance costs. On the opposite extreme to hands-on learning, virtual learning relies on virtual representations of the physical assets. As a result, the main advantage of virtual laboratories is their capability of promoting learning through trial and error in a safe environment, even with very limited supervision. Virtual laboratories eliminate restrictive time budgets as students can go through the simulated experiments at any time. In addition, virtual laboratories have much smaller maintenance and upkeep costs as it is much more affordable to create a new digital copy of a robot than to buy a new one. The main disadvantage of virtual laboratories is their limitations in helping students to gain necessary skill sets. The main advantage of remote laboratories is their capability to facilitate distant-learning programs. In addition, they can relax the restrictive time budgets of hands-on laboratories due to their flexibility. Although not as good as hands-on laboratories in terms of educational effectiveness, they can provide better environments for gaining skills compared to virtual laboratories and deliver the same level of learning in terms of controlling robots and machines as hands-on laboratories. Similar to hands-on laboratories, one of the main disadvantages of remote laboratories is their high maintenance and upkeep costs. In addition, socialization usually is not practiced in remote laboratories (Hernández-de-Menéndez et al., 2019). Both remote and virtual laboratories outperform hands-on laboratories in terms of accessibility, reproducibility, as well as safety.

**Case Study and Proposed Approach**

In robotics education, it is not only critical for students to handle hardware equipment, but it also is a substantial learning goal of robotics programs. As a result, many efforts have been made to meet COVID-19 safety regulations while providing a seamless transition from hands-on laboratories to virtual/remote ones without sacrificing learning quality.

Here, we compare the impact of hands-on and remote/virtual hybrid laboratories. In this study, students have gone through safety and offline programming modules in either hands on or hybrid modes. While the second group (20 students) has taken these modules in a hands-on format, the first group (15 students) has experienced these modules through remote/virtual hybrid laboratories. All other factors, such as materials covered in each module and instructor, are fixed in this experimental design. Safety and offline programming modules are selected to evaluate the impact of the hands-on versus remote/virtual hybrid laboratories on cognitive learning outcomes in terms of knowledge and skill gains, respectively. Figure 2 illustrates the students grades over different topics and mode of learning.

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Figure 2: Students performance over topic (offline programming VS safety) and model of learning ( hands-on VS hybrid)

First, the impacts of the topics and modes of learning are evaluated using Welch Two Sample T-test as displayed in Table 1. We compare the mean performance of the students over different topics (Off-line Programming VS Safety), hypothesizing there is a significant difference on the mean score of the student based on the topic of learning. Next, we study the mode of learning (Hybrid VS Hands-on). We hypothesize there is a significant difference on the mean score of the students based on their mode of learning.

Table 1: Welch Two Sample T-test of Students’ performance on the topics and learning modes

|  |  |  |  |
| --- | --- | --- | --- |
|  | T-value | Degree of Freedom | P-value |
| Topic (Off-line Programming VS Safety) | 0.070 | 28.0 | 0.944 |
| Mode (Hybrid VS Hands-on) | 3.292 | 67,7 | 0.001 |

Table 1 illustrates that although the T-test fails to reject the first null hypothesis studying the impact of the topic on students’ performance at a significance of 0.05, it does reject the second null hypothesis. The results of the second Welch Two Sample T-test confirms the model of learning have a significant impact on students’ performance. Furthermore, we study whether the mode of learning can significantly impact both knowledge and skills gains. As a result, two additional Welch Two Sample T-tests were conducted where, the first experiment focused on knowledge gain by comparing the impacts of modes of learning on students’ performances in the “Robotics Safety” module, while the second one concentrated on skill gain (i.e., psychomotor skills gain) through studying the “Offline Programming” module as shown in Table 2.

Table 2: Welch Two Sample T-test on Students’ performance on offline programming and safety modules in hybrid and hands-on laboratory sessions

|  |  |  |  |
| --- | --- | --- | --- |
|  | T-value | Degree of Freedom | P-value |
| Skill Gain | 3.0941 | 30.997 | 0.002 |
| Knowledge Gain | 1.4559 | 20.804 | 0.080 |

Offline programming has been a significant technological advancement for industrial robots/cobots, allowing quicker deployment at a lower initial cost. Offline programming has become an essential part of planning and designing any industrial robots/collaborative robots system, as it significantly reduces programming time compared to the tradition point-to-point programming Comparing the performance of students attending these two alternative laboratories illustrates that students significantly (α=0.01) perform better when they learn through hands-on experience (p-value =0.002 in a Welch Two Sample t-test with an approximate degree of freedom of 30).

The same design of the experiment is applied to the safety module. The Welch Two Sample t-test fails to identify any significant difference within the performance of the student groups taking the course with the hybrid and hands-on laboratories (p-value =0.080 with an approximate degree of freedom of 20).

While our analysis illustrates that there is no significant difference on knowledge gain among different laboratories, it highlights a significant gap in skill gain. To address this, we propose an immersive learning alternative to reduce the gap between the existing hands-on and distance learning approaches. Here, we present an immersive learning environment based on three levels of immersion using the Unity game engine.

**The XR–enabled Laboratories:** In a VR–enabled laboratory, immersive technologies such as HTC Vive and Leap Motion are equipped with realistic physics-based models and accurate gesture recognition algorithms to enable interaction with a teach pendant in the virtual world as illustrated in Figure 3. This laboratory provides virtual scenes where the user interacts with a virtual robot as well as a virtual teach pendant. The immersive technology required for this platform includes HTC Vive and Leap Motion. The HTC Vive utilizes multiple stations and trackers in order to provide room scaling capability. As a result, the physical movements of users can be directly translated to the virtual environment. Leap Motion will be integrated into the HTC Vive to model the movement of the user’s hands in the virtual environment. These immersive technologies will be integrated with the XR training environment, where the user will be using a virtual teach pendant with his/her virtual hands to interact with the virtual robots through a Mixed Reality toolkit. To provide a better sense of interaction, a replica or 3D printed shell of a robot teach pendant, tracked with an HTC Vive tracker, will be provided to the user. As a result, while the user is going through a module (e.g., jog a robot using joint and Cartesian coordinate systems) within the virtual environment, his/her hands can experience how to work with a teach pendant.

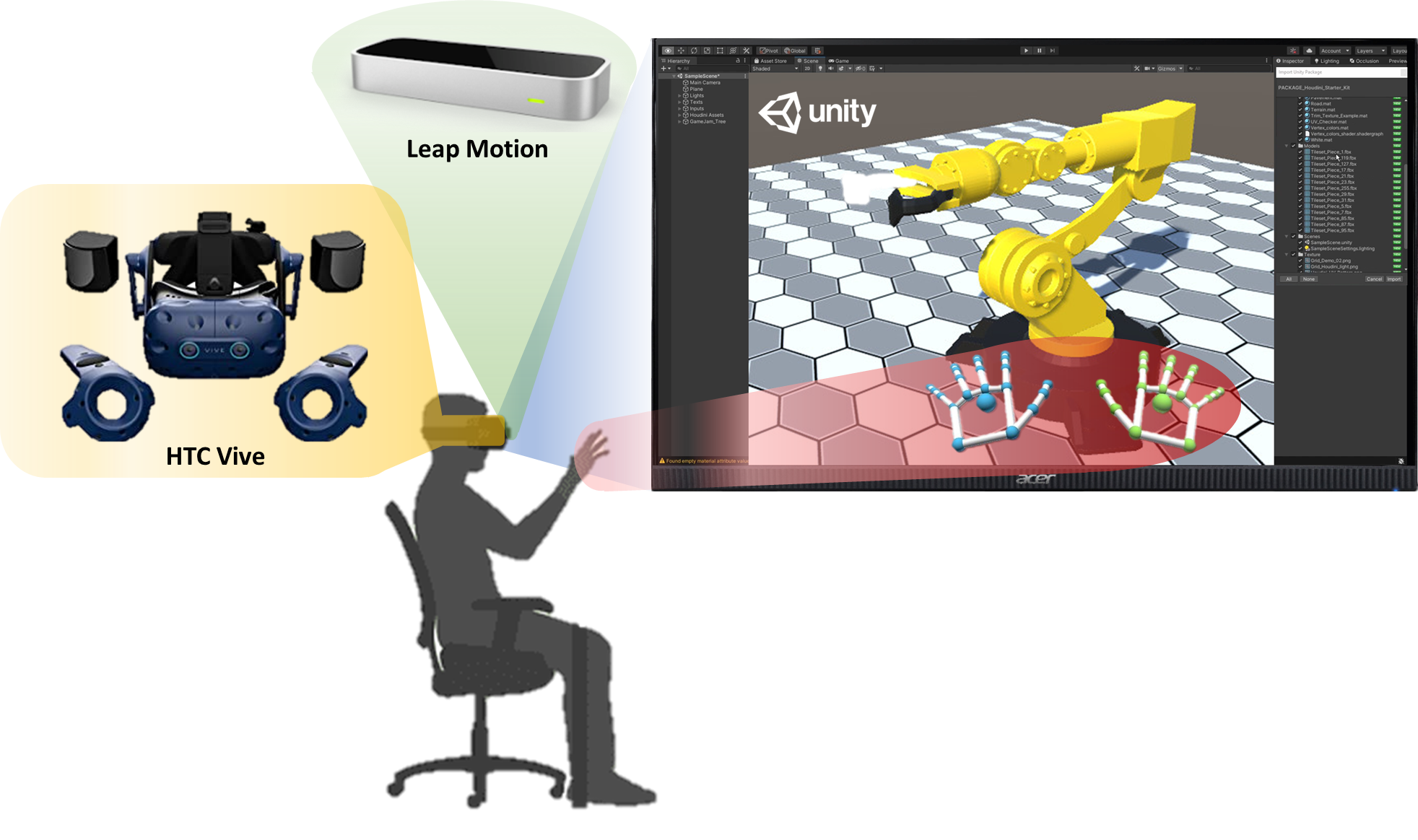


Figure 3: A demonstration of the proposed VR-enabled laboratory

Although the proposed approach relies on VR technology due to its affordability compared to AR, it is possible to implement similar laboratories using AR. In a AR-enabled laboratory, students can potentially rely on technologies such as Microsoft HoloLens II, smart phones, or tablets to visualize the augmented models of the robotic arm and use their hands to control a virtual teach pendant. In addition, the proposed virtual asset can be connected to the actual asset (the real robotic arm) to remotely control the physical asset.

**Challenges and Future Directions**

Although the proposed approach has the potential to enable hands-on learning experiences through remote/virtual hybrid laboratories, there are some challenges that should be recognized:

**Development Challenges**

**Physics-based Modeling:** Physics-based modeling is a major part of our proposed XR training environment as it is responsible for a realistic representation of all assets (i.e., robots), whether dynamic or static. Unity game engine and PC developer’s kit can be utilized to implement physics-based modeling components within the learning space.

* In real-time rendering, most common in interactive environments such as ours, the 3D images are calculated at an extremely high speed so that it looks like the scenes, which consist of multitudes of images, occur in real-time when users interact with the XR environment (Sherman & Craig, 2018). Unity’s Sprite Renderer can functionalize the rendering process.
* Physics engines are software designed to enable computers to create real-world physics phenomena (e.g., gravity and fluid dynamics) and apply them to 3D objects in XR environments and/or other 3D renderings to visualize how those objects interact in the digital world. Any physics engine should be able to simulate a variety of physical systems (e.g., rigid body dynamics, soft body dynamics, and fluid dynamics), apply those systems to 3D objects and environments, and work in tandem with other engines to create a cohesive experience. Unity’s built-in 3D physics engine (i.e., Nvidia PhysX engine integration) can satisfy these needs.
* The last part of physics-based modeling is the robot kinematics engine which is in charge of robot kinematics modeling and motion planning. These functions will be implemented via the integration of Robotics PC Developer's Kit, a powerful tool that enables high-performance communication of information and instructions between a PC and robot controller, and Unity game engine.

**Learning Component Adaptation:** One of the main benefits of this proposed remote/virtual hybrid laboratory setting is its capability in separating mastery of technical equipment from the acquisition of functional skills. To do so, it is critical to provide information and expose students to the equipment in an adaptable setting. So that, the students have the freedom to learn about the equipment and skill sets at their own pace.

* The adaptation learning component utilizes deep learning algorithms to customize the immersive environment based on user’s personal behavior and related parameters. This customization includes calibration of users input signals delivered by the user interface and personalization of course materials based on real-time evaluation of user’s performance (Vaughan et al., 2016). Recurrent neural networks, especially exogenous Long-short Term memory (LSTM) models, have shown excellent performance in time-series data analysis and signal processing as those are the input format provided by user interface (Guo et al., 2018). The adaptation learning component will be implemented via Unity ML- Agents toolkit (Nandy & Biswas, 2018), which is built on the open-source library TensorFlow (Abadi et al., 2016).
* The development of such an XR immersive and interactive training environment can be computationally exhaustive as the environment should be dynamically updated to present real-time reactions to the user’s continuous actions. In addition, no fixed frequency can be defined for the physics-based model reconditioning given the dynamicity of robots. Updating the learning environment at a high frequency (i.e., every second) for all six modules may sound like a potential solution, but it is not computationally advisable as it puts too much pressure on the computational units and drains the battery life of the XR technologies.
* To address this issue, a logic module will be designed to implement Dynamic Data Driven Applications Systems (DDDAS) (Blasch, 2018). DDDAS not only relies on sensory data to monitor the performance of the system in real-time but also relies on these data to dynamically optimize the measurement process in a feedback control loop. To do so, the Logic module will employ a statistical algorithm such as ensemble Kalman filter, Particle filter, and Bayesian models to optimize the run-time measurements of the user interface as well as the reconditioning of the developed physics-based model.

**Implementation Challenges**

**Availability/Cost of VR Headsets:** VR headsets range anywhere between a few dollars to hundreds. Given the need for higher levels of immersion and interaction, the less affordable VR systems are a better fir for the proposed platform. As a result, the implementation costs for the proposed virtual/remote laboratory setting can be a problem. If the purchase of the VR equipment is placed on the students, it may impact the quality of learning specifically for the students from lower-income back-grounds. But it is notable that the proposed systems can potentially replace the need to purchase actual robots. A solution would be for the schools to invest in buying VR systems instead of robots and lend the students the VR set up in case of remote laboratories.

**Cyber Sickness:** VR may cause cyber sickness due to the sense of immersion and presence. Cyber sickness differs from motion sickness as the user immersed in VR can be stationary and experience cyber sickness due to a compelling sense of motion caused by changes of visual imagery (Hale & Stanney, 2002). As a result, the higher the level of immersion and interaction is, the more likely it is for the user to suffer from cyber sickness. But there are ways to alleviate or remove the potential of cyber sickness. Porcino et al. (2017) introduced guidelines to minimize cyber sickness levels in head-mounted display systems. Stauffert et al. (2018) has identified field of view, duration, and latency, while Kwok et al. (2018) recognized acceleration, and navigation speed as the main factors impacting cyber sickness levels. Given these identified factors, a potential future research direction can be predicting the onset of cyber sickness even before occurring.

**Conclusion**

Although essential, hands-on learning imposes some challenges on educational systems due to its high costs of implementation and maintenance. At the same time, the COVID-19 pandemic illustrates that there is a need to deliver the same quality of learning through remote and virtual laboratories. Comparing the current practices of remote and virtual laboratories to the hands-on ones shows that although the current practices can deliver the same level of learning quality in terms of knowledge gain, the same cannot be said for skill gain. Comparing the performance of students attending these two alternative laboratories illustrates that students significantly (*α=0.01*) perform better when they learn through hands-on experience (p-value =0.002 in a Welch Two Sample t-test with a degree of freedom of 30) when skill gain is required. Here we picture the future of remote/virtual laboratories by relying on VR technology and deep learning.

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