

Markerless augmented reality remote laboratory for computer networks education in hybrid learning: a quasi-experimental study

Muhammad Dominique Mendoza^{1,2}, Wan Ahmad Jaafar Wan Yahaya², Sriadhi¹, Nur Azlina Mohamed Mokmin², Fahmy Syahputra¹, Elsa Sabrina³, Erita Astrid⁴, Olnes Yosefa Hutajulu⁴

¹Information Technology and Computer Education Study Program, Department of Electrical Engineering Education, Faculty of Engineering, Universitas Negeri Medan, Medan, Indonesia

²Centre for Instructional Technology and Multimedia, Universiti Sains Malaysia, Gelugor, Malaysia

³Department of Family Welfare Education, Faculty of Engineering, Universitas Negeri Medan, Medan, Indonesia

⁴Electrical Engineering Study Program, Department of Electrical Engineering Education, Universitas Negeri Medan, Medan, Indonesia

Article Info

Article history:

Received Feb 3, 2026

Revised Aug 25, 2026

Accepted Sep 4, 2026

Keywords:

Augmented reality
Computer networks education
Hybrid learning
Niantic Lightship
Remote laboratory

ABSTRACT

This study evaluates a markerless augmented reality (AR)-based remote laboratory for supporting hybrid learning in a computer networks course. Conventional remote laboratory approaches based on two-dimensional network simulations may provide flexible access but offer limited spatial interaction with networking components. To address this limitation, a markerless AR remote laboratory was developed using the Niantic Lightship Geospatial Browser, enabling students to place, connect, and configure virtual routers, switches, and end devices within their physical surroundings. A quasi-experimental design was conducted over one academic semester (14 weeks) with 120 undergraduate students, comprising an experimental group using the AR-based remote laboratory ($n=60$) and a control group using a conventional two-dimensional network simulation environment ($n=60$). Learning outcomes, usability, engagement, interaction logs, and qualitative feedback were collected and analyzed. The experimental group achieved higher post-test scores than the control group (82.45 ± 6.31 vs. 74.18 ± 7.02 , $p < 0.001$), with a large between-group effect (Cohen's $d=1.25$). The AR group also reported higher engagement and learning confidence, while interaction logs indicated shorter task completion times and fewer configuration attempts. These findings suggest that markerless AR can provide a promising approach for supporting spatial interaction and experiential quality in remote computer networks laboratory activities within hybrid learning environments.

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Corresponding Author:

Muhammad Dominique Mendoza

Information Technology and Computer Education Study Program

Department of Electrical Engineering Education, Faculty of Engineering, Universitas Negeri Medan

St. Willem Iskandar, Pasar V Medan Estate, Percut Sei Tuan, North Sumatra, Indonesia

Email: aenaen@unimed.ac.id

1. INTRODUCTION

Engineering education relies heavily on laboratory exercises to provide students with hands-on practical experience [1]. However, traditional labs are resource-intensive—equipment is costly and lab access time is limited for the growing number of students [2]. In the post-COVID era, many institutions have adopted hybrid learning models where courses (including labs) are delivered in a mix of face-to-face and

online formats [3]. This shift has made remote laboratory solutions increasingly important for ensuring all students can engage in experiments regardless of location. Indeed, hybrid lab classes have become the norm since 2021, allowing off-campus students to participate through internet-based platforms [4]. The challenge is that translating the rich, hands-on nature of in-person lab work to remote settings is difficult [5]. Students appreciate the flexibility of remote labs but report drawbacks such as lower cognitive engagement, less instructional support, and weaker peer interaction compared to on-campus labs [6]. A key limitation of many remote and virtual laboratories is the lack of physical interactivity, resulting in a weak representation of real-world experimental conditions [7]. In other words, conventional remote labs often feel less immersive because they only imitate the real lab through computer interfaces, without the tactile and spatial cues of being in the lab [8]. As noted by Asare *et al.* [9], virtual labs suffer from a lack of direct contact between the student and the laboratory equipment. For example, a recent hybrid lab implementation found that a minority of students (about 5–10%) disliked the absence of in-person activity in the remote lab experience [10]. These observations underscore the need for remote lab solutions that can better approximate the hands-on, immersive nature of physical laboratories.

Augmented reality (AR) offers a promising approach to enhance remote laboratory experiences by overlaying interactive virtual objects onto the real world [11]. Unlike virtual reality (VR), which immerses the user in a fully synthetic environment, AR preserves the real-world context and augments it with digital content [12]. This means students at home could use a smartphone or tablet to see virtual lab equipment superimposed on their actual desk or room, interacting with it as if it were physically present. Markerless AR technology, in particular, has become highly accessible in recent years [13]. Markerless AR eliminates the need for fiducial markers or quick response (QR) codes by leveraging device sensors and computer vision techniques, such as simultaneous localization and mapping (SLAM), to detect surfaces and accurately anchor 3D content in real-world environments [14]. The advent of development frameworks like Apple's ARKit and Google's ARCore has made markerless AR available on hundreds of millions of iOS and Android devices. Leveraging these technologies, it is now feasible to create an AR-enhanced remote lab that students can use at home without any dedicated hardware beyond their mobile device [15].

Prior studies in educational technology suggest that AR can significantly improve student engagement and learning outcomes [16]. AR has been shown to facilitate better visualization of abstract concepts, increase motivation, and improve performance by providing interactive, spatial learning experiences. In the context of labs, researchers such as Alnagrat *et al.* [17] have explored AR and related extended reality (XR) approaches to restore a sense of "physical" interaction for remote learners. For instance, Lizano-Sánchez *et al.* [18] introduced the concept of an augmented remote laboratory (ARL), which allowed students to perform remote electronics experiments with AR overlays on real equipment.

However, the positive effects reported in AR-supported learning should be interpreted with consideration of the potential novelty effect. Students who encounter an AR-based laboratory for the first time may initially demonstrate higher engagement or motivation because of the unfamiliar and interactive nature of the technology. Such an effect may not necessarily represent a sustained educational benefit after prolonged exposure. Therefore, the effectiveness of AR-supported laboratory learning should be considered in relation to both immediate learning and engagement outcomes and the potential for sustained effects over longer periods. Longitudinal studies are needed to determine whether the observed benefits are maintained after prolonged exposure to AR-based laboratory environments.

Despite the growing body of research on AR-supported laboratory learning, several gaps remain. Existing AR laboratory studies have predominantly focused on electronics and other engineering applications, while the application of markerless AR to computer networking laboratories remains insufficiently explored. Moreover, previous approaches have often relied on physical laboratory equipment or marker-based interaction, which may limit flexibility for students participating remotely from different physical environments. There is also limited empirical evidence combining learning outcomes, usability, engagement, and interaction efficiency when evaluating markerless AR-based remote laboratories in hybrid computer networks education. These gaps highlight the need for a more flexible remote laboratory approach that combines markerless spatial interaction with computer networking activities while providing comprehensive evidence of its educational effectiveness.

To address these gaps, this study develops and evaluates a markerless AR-based remote laboratory for a computer networks course in a hybrid learning environment. The system integrates real-world spatial scanning and virtual network devices through the Niantic Lightship Geospatial Browser, enabling students to place, connect, and configure virtual routers, switches, and end devices within their physical surroundings. A quasi-experimental design is employed to compare students using the AR-based remote laboratory with those using a conventional remote laboratory approach. The study makes three main contributions to the literature. First, it extends AR-based remote laboratory research into the domain of computer networking by implementing markerless spatial interaction with virtual networking equipment, thereby addressing an

underexplored application domain. Second, it provides an empirical basis for understanding how spatially anchored AR can support remote laboratory activities in a hybrid learning context without requiring physical network equipment at the learner's location. Third, it contributes a multidimensional evaluation framework by examining learning outcomes, usability, student engagement, and interaction efficiency, providing evidence that can inform the design and evaluation of future AR-supported remote engineering laboratories. Accordingly, this study aims to determine whether the proposed AR-based remote laboratory can improve students' learning performance and laboratory experience compared with conventional remote laboratory methods.

The research objectives are therefore to: i) develop a functional markerless AR application that supports computer networking laboratory activities, including network topology assembly, virtual cabling, and device configuration and ii) evaluate its effectiveness in a hybrid learning environment by examining learning outcomes, usability, student engagement, and interaction efficiency compared with a conventional remote laboratory approach.

2. RELATED WORK

2.1. Augmented reality in engineering education

The use of AR in engineering and technical education has expanded rapidly, driven by AR's ability to create interactive and visual learning experiences [19]. By overlaying digital information or 3D models onto the real world, AR enables students to visualize complex concepts that are otherwise abstract or invisible. For example, AR applications can display virtual circuit components, machinery, or molecular structures in a classroom, allowing learners to explore them from different angles and in context [20]. This interactive visualization can improve spatial reasoning and facilitate the comprehension of engineering principles. AR is also credited with promoting active learning, as students participate in manipulating virtual objects or data, which aligns with constructivist and experiential learning approaches.

AR implementations in education can be broadly categorized into marker-based and markerless AR. Marker-based AR relies on predefined visual targets, such as QR codes or fiducial images, which are detected by the device camera to anchor virtual content relative to the marker's position. However, this approach depends on physical printed markers or objects, and previous research has identified limitations associated with marker detection in certain learning environments [21]. In contrast, markerless AR eliminates the need for printed targets by utilizing sensor data, including camera input, gyroscopes, and depth sensing, to understand the environment and position virtual objects in real-world space [22]. Markerless AR applications can anchor digital content by analyzing feature points, surfaces, or GPS coordinates, thereby eliminating the need for fiducial-based object tracking systems [23]. Advances in mobile AR toolkits have further increased the accessibility of markerless AR, as demonstrated by Apple's ARKit and Google's ARCore, which support plane detection and motion tracking on modern smartphones [24].

The distinction between marker-based and markerless AR has important implications for educational implementation, but neither approach is universally superior. Marker-based approaches provide predefined reference points that can support stable and controlled placement of digital content, making them suitable for structured learning activities in which virtual content needs to be aligned with specific physical locations. However, their dependence on physical markers may reduce flexibility when students participate from different environments. Markerless AR, in contrast, allows virtual objects to be anchored directly to surfaces or spatial features within the learner's environment [22]–[24]. This characteristic is particularly relevant to remote and hybrid learning, where students may use different physical spaces and personal mobile devices. Nevertheless, markerless AR may also be affected by environmental conditions, device capabilities, surface characteristics, and tracking stability. Therefore, the suitability of marker-based or markerless AR depends on the learning context, task requirements, and desired interaction characteristics. In the context of remote and hybrid laboratory learning, markerless AR offers a potentially suitable approach because it reduces dependence on dedicated physical markers while allowing virtual laboratory components to be positioned and manipulated within the learner's environment.

In summary, AR offers several pedagogical advantages for engineering education: it enables interactive visualization of equipment and phenomena, supports learning-by-doing in safe virtual environments, and can increase student engagement and motivation by adding interactive or immersive elements to lessons [25], [26]. As the technology matures, AR is becoming increasingly user-friendly and scalable. The distinction between marker-based and markerless AR is therefore an important design consideration, with markerless approaches offering greater flexibility for learning activities conducted across different physical environments [27]. Nevertheless, existing research has largely emphasized AR as a tool for visualization, conceptual understanding, and general learning support. Comparatively less attention has been given to the use of markerless AR as an interactive environment for conducting complete remote engineering laboratory activities that require students to manipulate multiple technical components and understand their

spatial relationships. This limitation is particularly relevant to computer networking education, where students need to visualize and configure interconnected devices and network topologies. Therefore, further investigation is needed into how markerless AR can be integrated into remote laboratory activities to provide both spatial interaction and meaningful hands-on learning experiences in hybrid engineering education.

2.2. Remote laboratories in engineering education

Remote laboratories are online platforms that allow students to perform laboratory experiments without being physically present in the laboratory [28]. They typically either offer remote access to real physical equipment through internet-controlled instruments and cameras or replicate experimental activities using software-based virtual simulations. The initial development of remote laboratories was motivated by the need to overcome resource constraints associated with traditional hands-on laboratories [29]. Compared with traditional laboratories, remote laboratories provide greater flexibility, continuous availability, and increased accessibility for students with geographical or physical constraints [30]. These advantages are particularly relevant to hybrid and blended learning models, in which students may need to participate in laboratory activities from both on-campus and off-campus locations [31].

However, remote laboratory approaches differ considerably in the degree of physical interaction and authenticity they provide. Remote laboratories that provide access to real physical equipment can preserve some characteristics of authentic laboratory work, but they remain dependent on the availability, maintenance, and scheduling of institutional equipment. In contrast, software-based virtual simulations provide greater scalability and accessibility because students can access simulated environments without sharing physical hardware. Nevertheless, simulated environments may provide a less authentic representation of physical laboratory conditions and may offer fewer opportunities for students to develop spatial and procedural understanding. Thus, existing approaches involve a trade-off between accessibility and flexibility on the one hand and physical authenticity and interaction on the other.

Over the course of their development, remote laboratories have matured such that, when carefully designed, they can achieve learning outcomes comparable to those of traditional in-person laboratory experiences. Previous studies have shown that students using remote or virtual laboratories can achieve conceptual understanding and laboratory skills comparable to those developed in traditional settings, particularly when supported by appropriate pedagogical scaffolding such as pre-laboratory tutorials and guided instruction [32], [33]. Remote laboratory environments commonly provide web-based interfaces through which students can adjust experiment parameters, view live data or video feeds, and observe real-time responses from laboratory equipment [34]. These findings demonstrate that physical presence is not always necessary for achieving conceptual learning outcomes. However, comparable learning outcomes do not necessarily indicate comparable learning experiences, particularly when laboratory tasks require spatial understanding and direct manipulation of multiple technical components.

Furthermore, remote laboratories present educational and social challenges, as students may experience reduced engagement and motivation when laboratory interfaces lack immersive features [35]. Students operating equipment remotely interact through computer interfaces rather than physically manipulating devices, which can make the laboratory experience feel abstract and disconnected from real-world practice [36]. Another limitation is that remote labs often simplify or virtualize certain aspects of experiments [37]. Purely software-based simulations may overlook real-world imperfections such as noise, latency, and component variability, resulting in a less authentic learning experience [38]. These limitations are particularly relevant in engineering education, where students are expected to develop not only conceptual knowledge but also practical and procedural competencies through interaction with technical systems.

The comparison of these approaches indicates that the central challenge is not simply providing remote access to laboratory activities, but maintaining meaningful interaction and experiential quality while preserving the flexibility of remote learning. Conventional remote laboratories effectively address accessibility and resource constraints, but their interface-based interaction may limit spatial understanding and experiential authenticity. Conversely, remote access to physical equipment can provide greater authenticity but remains constrained by institutional hardware and laboratory availability. This creates a need for approaches that can combine the accessibility of remote laboratories with richer spatial interaction without requiring students to have direct access to physical laboratory equipment.

AR provides a potential approach to addressing this limitation by allowing virtual laboratory components to be anchored within the learner's physical environment. Unlike conventional two-dimensional remote laboratory interfaces, AR can provide spatially grounded representations that students can observe and manipulate from multiple perspectives. However, the effectiveness of AR in this context depends on whether it can support meaningful laboratory procedures rather than merely provide visual representations. This issue is particularly important for computer networking education, where students need to understand

the spatial and functional relationships among routers, switches, end devices, and network connections. Therefore, integrating markerless AR with remote laboratory activities represents a potential approach for addressing the spatial and interaction limitations of conventional remote laboratories while maintaining the flexibility required for hybrid learning.

2.3. Hybrid learning in engineering labs

Hybrid learning, which combines face-to-face and online instruction, has become increasingly common in engineering education, a trend significantly accelerated by the COVID-19 pandemic [39]. When campuses worldwide were closed or operated at reduced capacity, engineering programs were compelled to adopt remote solutions to ensure the continuity of laboratory instruction [40]. In the post-pandemic era, many institutions have adopted hybrid instructional models in which some students participate in on-site laboratory sessions while others engage remotely, either synchronously or through asynchronous access to laboratory materials.

Implementing hybrid laboratories at scale remains challenging because effective hybrid laboratory design requires more than simple live streaming or data sharing. Recent studies by Fabian *et al.* [41] emphasizes that laboratory activities must be redesigned to maintain engagement and achieve comparable learning experiences for both on-site and remote students in post-pandemic hybrid learning environments. This indicates an important distinction between providing access to laboratory content and providing an equivalent laboratory learning experience. While online access can improve flexibility, remote students may not receive the same opportunities for physical interaction, spatial exploration, and immediate collaboration that are available to students participating on campus.

Furthermore, research on student experiences in hybrid engineering labs reveals both advantages and persistent challenges [42]. Hybrid formats can provide students with greater flexibility in accessing laboratory activities and allow participation from different locations. However, the benefits of flexibility may be accompanied by reduced cognitive engagement and social interaction when remote students rely primarily on computer-mediated interfaces. A study by Chen *et al.* [43], on remote course delivery similarly highlighted challenges associated with interaction and communication, suggesting that students participating remotely may find it more difficult to discuss problems and obtain immediate assistance compared with face-to-face learning. These findings indicate that hybrid laboratory environments require intentional design strategies to support not only access but also engagement, interaction, and a sense of participation.

A key challenge in hybrid laboratory settings is therefore ensuring that remote and on-site students can achieve comparable learning experiences and outcomes [44]. If on-campus students can physically interact with laboratory equipment while remote learners are limited to observation, simplified simulations, or two-dimensional interfaces, differences in learning opportunities may emerge. Existing approaches have attempted to address this problem through take-home laboratory kits, remote access to physical equipment, and virtual laboratory environments. However, each approach has limitations. Take-home equipment can improve physical interaction but increases logistical and equipment requirements, whereas remote access to institutional equipment remains dependent on laboratory infrastructure and availability. Virtual simulations offer greater scalability but may provide weaker spatial and experiential representations of real laboratory activities.

These differences highlight a continuing gap in hybrid engineering laboratory design: how to provide remote students with meaningful, spatially grounded interaction while retaining the flexibility and scalability of online participation. AR provides a potential solution because it can situate digital laboratory components within the learner's physical environment rather than restricting interaction to conventional two-dimensional interfaces. Nevertheless, the application of markerless AR to hybrid engineering laboratories remains insufficiently explored, particularly for laboratory activities that require students to understand spatial relationships among multiple technical components.

In this context, the use of markerless AR may provide an intermediate approach between physical laboratory participation and conventional remote simulation. Rather than attempting to fully reproduce a physical laboratory or simply provide remote access to existing equipment, markerless AR can allow virtual equipment to be spatially anchored in the learner's environment and manipulated from different viewpoints. This capability is particularly relevant to computer networking laboratories, where understanding the relationships among routers, switches, end devices, and network connections is an important component of practical learning. Therefore, investigating markerless AR within a hybrid computer networks laboratory can address an unresolved issue in the existing literature by combining remote accessibility with spatially grounded laboratory interaction.

2.4. Augmented remote laboratory for remote labs: state of the art and gaps

Considering the inherent limitations of remote laboratories, particularly the lack of physical presence and immersive interaction, researchers have focused on the use of AR and VR technologies to

improve the effectiveness of remote laboratory environments. By overlaying virtual elements onto real laboratory setups or onto the student's environment, AR can provide a form of mediated hands-on experience for remote users. However, existing AR-based remote laboratory approaches differ substantially in terms of laboratory domain, interaction mechanism, dependence on physical equipment, and degree of spatial interaction.

Andújar *et al.* [45] introduced an ARL for electronics experiments, representing an early attempt to incorporate AR into remote laboratory activities. Students could interact with a video representation of a physical laboratory experiment enhanced with virtual control panels and overlays. The study demonstrated that AR could increase immersion and provide learning experiences that could surpass those offered by conventional laboratory approaches. However, the system remained closely connected to a physical laboratory setup and was developed specifically for electronics experiments. Thus, while the study established the potential of AR for enhancing remote laboratory experiences, it did not address how markerless AR could support laboratory activities that require students to construct and manipulate spatial relationships among multiple virtual technical components.

Odeh *et al.* [46] developed another remote AR laboratory approach for engineering education, focusing on electronic circuit experiments. Their system combined a live representation of physical laboratory hardware with virtual components and connections, allowing students to interact remotely with circuit configurations. This approach provided a richer representation of physical laboratory procedures than conventional remote interfaces and helped students develop confidence in transitioning to real hardware. Nevertheless, the approach depended on access to physical laboratory equipment and remained focused on electronics. Consequently, its implementation may be less flexible for learners who participate remotely without direct access to institutional laboratory infrastructure.

Tuli *et al.* [47] subsequently developed an AR learning environment for electronics laboratory experiments in which students used a tablet to access virtual components and interactive instructions. Their results showed that the AR group achieved higher post-test performance and more positive attitudes than the control group, providing further evidence of the potential of AR to support laboratory learning. However, the approach used marker-based AR, requiring physical markers in the learning environment, and was again implemented in electronics education. Therefore, although the study demonstrated improvements in learning outcomes and student attitudes, it did not establish whether markerless AR could provide similarly effective spatial interaction for computer networking laboratory activities.

The comparison of these studies reveals both common findings and important differences. All three studies demonstrate the potential of AR to improve interaction, engagement, or learning outcomes in laboratory-based learning [45]–[47]. However, their approaches differ in the way virtual content is connected to the physical laboratory environment. Andújar *et al.* [45] and Odeh *et al.* [46] relied more directly on remote interaction with physical laboratory equipment, whereas Tuli *et al.* [47] provided a more virtualized AR laboratory experience using marker-based interaction. These differences reflect a trade-off between physical authenticity, technological flexibility, and scalability. Approaches connected to physical equipment can provide greater authenticity but remain dependent on laboratory infrastructure, while marker-based virtual AR can reduce hardware requirements but still requires predefined physical markers.

Another limitation concerns the laboratory domains investigated in previous studies. The reviewed AR remote laboratory studies have primarily focused on electronics experiments [45]–[47]. Although electronics and computer networking both involve technical systems and component relationships, networking laboratories require students to understand different types of spatial and functional relationships, including the arrangement of routers, switches, end devices, and network connections. Therefore, findings from electronics-based AR laboratories cannot be assumed to transfer directly to computer networking education.

These limitations indicate that the potential of AR-based remote laboratories has not yet been fully explored in computer networking education, particularly through markerless spatial interaction. A markerless approach can eliminate dependence on predefined physical markers and allow virtual networking devices to be anchored directly within students' physical surroundings. This capability may provide a more flexible way to represent and manipulate network topologies while maintaining the accessibility required for remote and hybrid learning.

Accordingly, the present study extends previous AR remote laboratory research in three respects: i) it applies markerless AR to a computer networks laboratory rather than the electronics-focused contexts that dominate previous studies [45]–[47], ii) it uses spatial scanning and anchoring to allow virtual networking equipment to be positioned within learners' physical environments without requiring dedicated physical markers or direct access to laboratory hardware, and iii) it evaluates the resulting learning environment across multiple dimensions, including learning outcomes, usability, student engagement, learning confidence, and interaction efficiency. This positioning allows the present study to move beyond demonstrating that AR can

enhance laboratory learning and instead examine how a markerless AR-based remote laboratory can function as a scalable and spatially interactive approach for hybrid computer networking education.

3. SYSTEM DESIGN

3.1. System architecture and augmented remote laboratory application

The proposed remote laboratory was developed as a markerless AR application using the Unity 3D engine and mobile AR technologies. The system employed ARCore for Android and ARKit for iOS to support environmental plane detection and spatial tracking on students' mobile devices. Vuforia was optionally integrated for specific object-recognition use cases, while the primary interaction mode remained markerless. The application simulated common networking equipment and laboratory components through low-polygon but visually representative 3D models, including routers, switches, end devices, and network cables.

In the system architecture, ARCore and ARKit provided device-level environmental tracking and plane detection, while the Niantic Lightship Geospatial Browser was used to obtain and manage spatial scan and mesh data for establishing the scanned environment in which virtual networking devices were positioned. Vuforia was optionally integrated for specific object-recognition functions and was not required for the primary markerless AR workflow.

The AR application enabled students to place and anchor virtual networking devices onto detected real-world surfaces and examine them from multiple viewpoints. Interactive functions allowed users to power on virtual devices, access configuration interfaces, establish valid network connections through virtual cabling, and execute basic networking commands such as "ping" through a lightweight simulation engine. These functions were designed to support laboratory activities that required students to construct and configure network topologies within their physical surroundings. To support initial familiarization with the system, guided AR-based tutorials were incorporated during the orientation phase. These tutorials introduced students to basic operations such as device placement, virtual cabling, and configuration. The guided tutorials were disabled during assessment activities to allow students to perform laboratory tasks independently and reduce reliance on instructional prompts.

Prior to full deployment, the application underwent needs analysis and pilot testing involving networking instructors and a small group of volunteer students to assess its alignment with laboratory activities. Iterative refinements were subsequently made, particularly to improve device selection and command interaction. The application was designed to operate on common student-owned mobile devices that met the minimum ARCore or ARKit requirements. Loaner tablets were provided by the institution when necessary to support participation in the experimental group.

3.2. Spatial scanning and augmented remote laboratory workflow

The AR testing interface, including the finalized site scan and generated 3D mesh used throughout the implementation, is presented in Figure 1. The spatial scanning and mesh retrieval were performed using the Niantic Lightship Geospatial Browser, enabling real-world spatial data to be incorporated into the remote laboratory environment. The scanned environment provided the spatial basis for positioning virtual networking devices within the learner's physical surroundings. This process allowed virtual devices to be anchored to spatial features of the scanned environment rather than being presented solely within a conventional two-dimensional simulation interface.

The virtual networking devices shown in Figure 2 illustrate two types of network equipment used in the AR-based laboratory activities. Figure 2(a) presents a virtual switch, which enables students to explore device connectivity and construct network topologies by connecting multiple virtual devices within the scanned physical environment. Figure 2(b) presents a virtual router, which allows students to examine routing functions and configure communication between different network segments. Both devices can be positioned and interacted with through the AR interface, providing a spatially anchored representation of networking equipment. These virtual devices support subsequent laboratory activities, including network topology construction, device configuration, virtual cabling, and connectivity testing.

3.3. Laboratory learning tasks

The AR-based remote laboratory was designed to support laboratory activities commonly performed in a computer networks course. The learning tasks focused on network topology construction, device configuration, and connectivity testing. Students interacted with virtual routers, switches, and end devices within the spatially scanned environment and used virtual network cables to establish connections among the devices.

The laboratory activities included exercises such as local area network (LAN) configuration, static routing, and client-server setup. For example, in a routing exercise, students placed virtual router and PC

models within the AR environment, connected them using virtual cables, and configured routing tables through the AR interface. These activities required students to construct and modify network topologies while observing the spatial relationships among the virtual networking components.

The AR environment also supported basic network verification through simulated connectivity testing, including the use of “ping” commands. This allowed students to configure network devices and evaluate whether the resulting topology and connections functioned as intended. The learning tasks were designed to maintain the core procedural requirements of conventional computer networks laboratory activities while introducing spatial interaction through markerless AR.

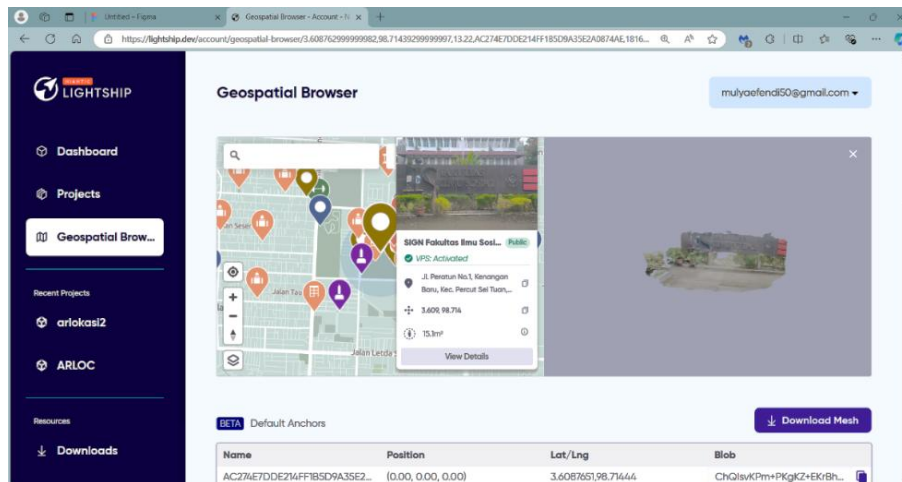


Figure 1. Testing interface of the Niantic Lightship Geospatial Browser showing the finalized site scan and the corresponding 3D mesh used in the experiment

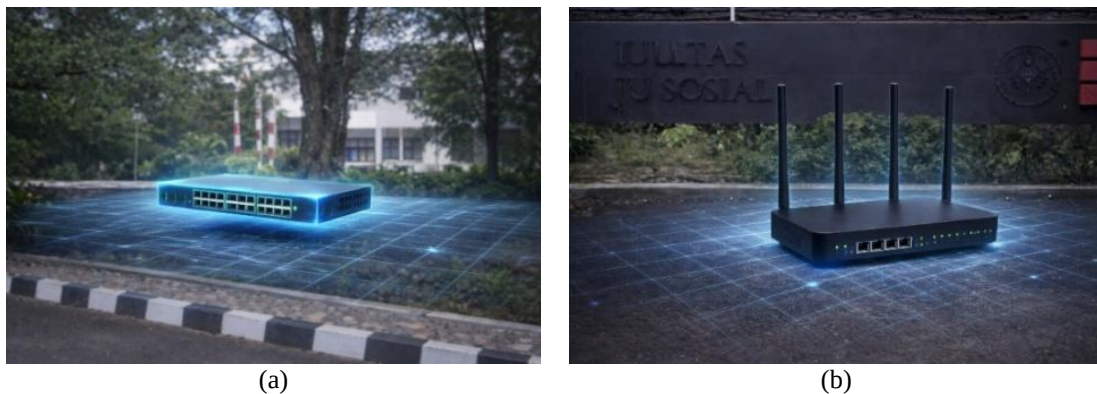


Figure 2. AR-based network laboratory assets: (a) virtual switch placement and (b) virtual router placement within the scanned physical environment

4. METHOD

4.1. Research design and participants

This study adopted a quasi-experimental design to evaluate the effectiveness of a markerless AR-based remote laboratory in a computer networks course [48]. The study was conducted in the Informatics and Computer Engineering Program at Universitas Negeri Medan, Indonesia, during a core computer networks course. A total of 120 third-year undergraduate students from two consecutive cohorts participated in the study. All participants had prior foundational knowledge of computer networking concepts.

Participants were assigned by class section to an experimental group using the AR-based remote laboratory (n=60) and a control group using conventional remote laboratory methods (n=60) to minimize treatment contamination. Individual random assignment was not feasible because the intervention was implemented within existing class sections. Both groups were taught by the same instructor, followed the

same course content and laboratory curriculum, and completed equivalent laboratory activities over the same academic semester.

The independent variable was the laboratory condition, consisting of the markerless AR-based remote laboratory for the experimental group and the conventional remote laboratory condition for the control group. The primary dependent variable was learning performance, measured through students' post-test scores, with pre-test scores used to assess baseline knowledge. Additional outcome measures included perceived usability, student engagement, learning confidence, interaction behavior, and qualitative feedback.

At the time of implementation, the AR application was stable and compatible with common student-owned mobile devices meeting the minimum ARCore or ARKit requirements. Institutional support was provided through loaner tablets when necessary to ensure participation in the experimental group. The overall research procedure, including the stages of research implementation, data collection, and data analysis, is summarized in Figure 3.

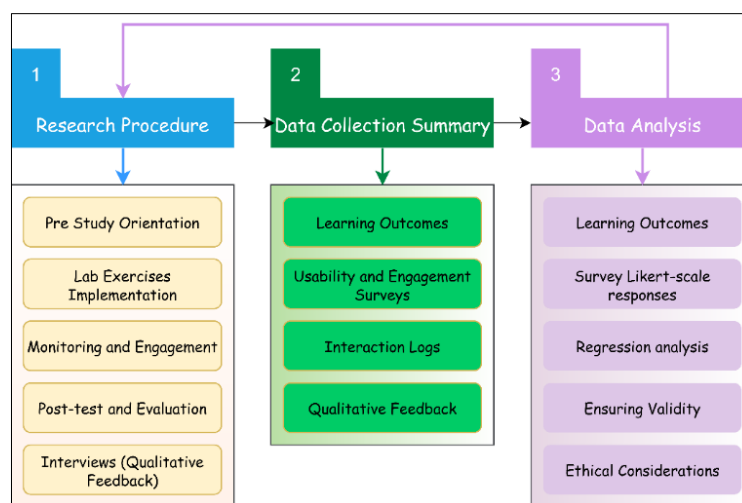


Figure 3. Method overview

4.2. Research procedure

The study was conducted over one academic semester (14 weeks) as part of the regular computer networks laboratory activities. Both groups followed the same laboratory curriculum and completed equivalent learning tasks, while the experimental group used the markerless AR-based remote laboratory and the control group used a conventional two-dimensional network simulation environment. The research procedure consisted of pre-study orientation, laboratory implementation, monitoring and engagement assessment, post-test and evaluation, and qualitative interviews.

4.2.1. Pre-study orientation

In the first week, the experimental group received an orientation on installing and using the AR remote laboratory application, including a live demonstration of device placement, virtual cabling, and basic configuration conducted via video conferencing in a hybrid setting. Students were allowed to explore the system in a sandbox mode. The control group received a parallel orientation focused on conventional remote lab tools and written laboratory guidelines. During this phase, a pre-test was administered to both groups to assess baseline knowledge of core networking concepts, consisting of multiple-choice, short-answer, and basic practical diagnostic tasks.

4.2.2. Lab exercises implementation

From weeks 2 to 12, students completed weekly laboratory exercises aligned with the course curriculum, targeting competencies such as LAN configuration, static routing implementation, and basic client-server setup. The experimental group performed these activities using the AR-based remote laboratory, enabling flexible participation across locations.

During scheduled lab sessions, instructional support was provided via video conferencing and online chat, and students could share AR screens or screen recordings to demonstrate their configurations. In contrast, the control group used a conventional remote laboratory condition based on two-dimensional

network simulation using Cisco Packet Tracer or an equivalent network simulation tool. Students performed the same laboratory activities as the experimental group, including topology construction, device configuration, and connectivity testing, but without markerless AR-based spatial interaction or spatially anchored virtual networking devices.

Both groups worked individually or in small teams of two to three students in accordance with course policies. Experimental group students occasionally shared an AR-capable device during in-person meetings or worked individually before consolidating results, while control group teams collaborated primarily through video conferencing while using the network simulator. Equivalent levels of instructional guidance were provided to both groups throughout the intervention, despite differences in the technological platforms used.

4.2.3. Monitoring and engagement

Process data were collected throughout the laboratory sessions. With student consent, the AR application recorded interaction data such as the time taken to complete each laboratory task and the number of configuration attempts required to establish network connectivity. For the control group, corresponding information was obtained from simulator activity reports and student self-reports. At the midpoint of the semester, a short survey was administered to both groups to assess student engagement and confidence in performing the laboratory activities. The survey also served to identify major issues during the intervention. Feedback was used to make minor procedural adjustments. For example, during week 3, some students in the AR group experienced difficulty placing multiple devices within a limited physical space. They were therefore advised to use larger surfaces or the floor when creating larger network topologies.

4.2.4. Post-test and evaluation

During weeks 13–14, a post-test was administered to both groups to assess learning outcomes following the laboratory intervention. The post-test followed the same general structure as the pre-test while emphasizing practical problem-solving scenarios related to network configuration. The experimental group additionally completed the System Usability Scale (SUS) to evaluate the perceived usability of the AR application. Both groups completed a lab experience survey measuring engagement, enjoyment, and perceived learning. The survey included AR-specific items for the experimental group and equivalent tool-focused items for the control group. Open-ended questions were also included to obtain additional feedback about the laboratory experience.

4.2.5. Interviews (qualitative feedback)

To gain deeper insights into students' laboratory experiences, 10 students from each group were randomly selected for short interviews or focus group discussions, ensuring representation of high-, medium-, and low-performing students. The discussions were conducted via video calls, recorded, and transcribed for qualitative analysis. For the experimental group, the interviews focused on students' experiences using AR, including what they liked, challenges they encountered, and suggestions for improvement. The control group was asked about their experiences with the conventional laboratory approach, including challenges encountered and aspects of the learning experience that they perceived as lacking. The resulting qualitative data were subsequently analyzed to provide contextual insights into the quantitative findings.

4.3. Data collection summary

Several types of data were collected and analyzed, including:

a. Learning outcomes

Learning outcomes were assessed using students' pre-test and post-test scores. The pre-test was administered before the laboratory intervention to establish baseline knowledge, while the post-test was administered at the end of the intervention to assess learning performance. Students' laboratory assignment grades were also collected as complementary performance indicators, with each laboratory activity evaluated through graded reports or practical checks.

b. Usability and engagement surveys

SUS scores from the AR group, and custom engagement survey responses from both groups (using Likert-scale items such as "I found the lab activities engaging" or "I felt frustrated during the labs"). The SUS was used as a standardized measure of overall perceived usability. However, because SUS provides a global usability score, it does not capture all dimensions of the user experience, such as cognitive workload, detailed interaction quality, or specific usability problems. Therefore, the SUS results should be interpreted as an overall indicator of perceived usability rather than a comprehensive usability assessment. Future studies could complement SUS with more detailed usability and workload measures, such as ISO 9241-based

usability measures or the NASA Task Load Index (NASA-TLX), to provide a broader assessment of usability and cognitive demand.

c. Interaction logs

For the experimental group, the AR application recorded interaction data during the laboratory activities, including task completion time, the number of configuration attempts, recorded errors, and interaction events. For the control group, corresponding information was obtained from simulator activity reports and student self-reports of task completion time when equivalent application-level logs were unavailable. Because the two laboratory platforms generated interaction data through different logging mechanisms, the interaction measures were not statistically normalized or treated as fully equivalent measures across groups. Task completion time was retained in minutes, while configuration attempts, errors, and interaction events were retained as recorded counts. Simulator activity reports and self-reported time-on-task were used for the control group when corresponding application-level data were unavailable.

Accordingly, these measures were interpreted as complementary indicators of interaction patterns and task performance rather than as directly equivalent measurements across the two laboratory conditions. This distinction was considered when interpreting the interaction results and is acknowledged as a methodological limitation of the cross-platform comparison.

d. Qualitative feedback

Qualitative data were obtained from open-ended responses in the lab experience survey and from interviews or focus group discussions conducted with selected students from both groups. The qualitative data provided contextual information about students' laboratory experiences, including perceived benefits, challenges, engagement, collaboration, and learning confidence.

The collected measures served complementary purposes within the evaluation framework. Pre-test scores were used to establish baseline knowledge, while post-test scores represented the primary measure of learning performance. Laboratory assignment grades provided a complementary indicator of practical task performance. Interaction logs were used to characterize students' task behavior and interaction efficiency, whereas survey measures captured perceived engagement, learning confidence, and usability. Qualitative interview and open-ended survey data were used to contextualize and explain patterns observed in the quantitative findings. Thus, the measures were not treated as interchangeable outcomes but as complementary sources of evidence for evaluating the AR-based remote laboratory.

4.4. Data analysis

The collected data were analyzed using quantitative and qualitative techniques. Quantitative analyses were used to examine differences in learning performance, engagement, and interaction-related measures between the experimental and control groups, while qualitative analysis was used to identify themes that provided contextual insights into students' laboratory experiences.

4.4.1. Learning outcomes

An independent-samples t-test was conducted to compare post-test scores between the experimental and control groups and determine whether a significant difference in learning performance existed after the intervention [49], [50]. Paired-samples t-tests were conducted within each group to examine improvements from pre-test to post-test, with the significance level set at $p < 0.05$ [51]. Assumptions of normality and homogeneity of variance were evaluated before conducting the parametric tests. When these assumptions were not fully satisfied, the Mann–Whitney U test was used as a non-parametric verification of between-group differences [52].

4.4.2. Survey Likert-scale responses

Likert-scale responses were treated as ordinal data and analyzed using non-parametric procedures for between-group comparisons. Engagement ratings were compared between the experimental and control groups using the Mann–Whitney U test. SUS scores, which provide a single overall usability score for each participant, were summarized using descriptive statistics, including the mean and standard deviation, and interpreted against established SUS benchmarks.

4.4.3. Regression analysis

Simple linear regression analysis was employed to examine whether the use of AR (coded as AR=1, control=0) significantly predicted post-test performance. The effect size of the regression model was assessed using Cohen's f^2 , which quantifies the proportion of explained variance relative to unexplained variance and is calculated as $f^2 = R^2 / (1 - R^2)$. Based on the obtained $R^2 = 0.13$, the resulting was $f^2 = 0.149$, indicating an effect size close to the conventional medium-effect threshold.

4.4.4. Qualitative data analysis

Qualitative data were analyzed using thematic analysis. Two researchers independently coded interview transcripts and open-ended survey responses, after which the codes were discussed and consolidated into key themes, including perceived presence in AR, technical challenges, collaboration and communication, and learning confidence. Selected representative quotations were used to support and contextualize the quantitative findings.

4.4.5. Ensuring validity

Several procedures were implemented to support the validity and reliability of the findings. Established instruments, including the SUS and standard test questions reviewed by networking faculty were used to support content validity. The instructor responsible for grading laboratory assignments was blinded to students' group membership; laboratory reports were anonymized and mixed before grading to minimize potential grading bias. For the quantitative data, the internal consistency of the custom survey scales was assessed using Cronbach's alpha. The engagement scale yielded a value above 0.80, indicating good internal consistency. For the qualitative data, multiple researchers independently coded the data and compared their results to improve coding reliability. Inter-coder agreement was high after initial minor differences were discussed and resolved.

4.5. Ethical considerations

Informed consent was obtained from all participants, and participation in the study had no impact on course grades, as all laboratory activities and assessments were part of the standard curriculum. Students were allowed to opt out of data usage, anonymity was strictly maintained in all reporting, and no identifying information was disclosed. To ensure fairness, the control group received the standard instructional approach and was provided with an introduction to the AR system after the study concluded.

5. RESULTS

This section evaluates the effectiveness of the proposed AR-based remote laboratory, with a focus on learning outcomes, usability, engagement, and interaction efficiency in a hybrid learning environment. The results highlight the system's potential to support immersive, scalable, and context-aware remote laboratory experiences in computer networking education.

5.1. Learning outcomes comparison

The evaluation of learning outcomes demonstrates that the AR-based remote laboratory produced stronger academic improvements compared to the conventional remote laboratory approach across key assessment indicators. Under the AR-supported learning condition, students achieved higher post-test scores, reflecting improved conceptual understanding and practical competence in computer networking tasks. In contrast, although the control group also exhibited learning gains, their overall performance improvement was more modest. Statistical analysis confirmed that the difference in post-test performance between the two groups was significant, indicating the effectiveness of the AR-supported laboratory in enhancing learning within a hybrid instructional environment. Table 1 summarizes the comparative pre-test and post-test results for both groups, with all values reported as mean scores with standard deviations based on 60 participants per group.

Table 1. Comparison of pre-test and post-test scores between groups

Group	N	Pre-test mean (SD)	Post-test mean (SD)	<i>p</i> -value	Cohen's <i>d</i>
Experimental (AR-based remote lab)	60	64.32 (7.41)	82.45 (6.31)	<0.001	1.25
Control (conventional remote lab)	60	65.01 (7.12)	74.18 (7.02)	<0.001	

As shown in Table 1, the experimental group increased its mean score from 64.32 (SD=7.41) in the pre-test to 82.45 (SD=6.31) in the post-test, representing an improvement of 18.13 points. In comparison, the control group increased from 65.01 (SD=7.12) to 74.18 (SD=7.02), corresponding to an improvement of 9.17 points. Thus, the gain observed in the AR group was nearly twice that of the control group. The relatively similar pre-test scores between the two groups (64.32 and 65.01) also indicate comparable baseline performance at the descriptive level.

The *p*-values below 0.001 indicate statistically significant improvements from pre-test to post-test within both groups. This suggests that both laboratory approaches supported students' learning during the

intervention. However, the substantially larger gain observed in the experimental group indicates a stronger improvement under the AR-supported learning condition. The higher post-test performance of the experimental group may be associated with the spatially anchored interaction provided by the markerless AR environment, which allowed students to visualize and interact with virtual routers, switches, and end devices within their physical surroundings. Such interaction may have supported students in understanding network configurations and performing laboratory procedures more effectively than the conventional remote laboratory interface.

These findings are directly relevant to the research objective of evaluating the effectiveness of the markerless AR-based remote laboratory in a hybrid computer networks course. The higher post-test score and greater learning gain observed in the experimental group provide empirical support for the potential of the AR-based remote laboratory to enhance students' conceptual understanding and practical competence. Nevertheless, because the study employed a quasi-experimental design, the findings should be interpreted as evidence of the effectiveness of the overall AR-supported laboratory intervention rather than as definitive evidence that AR technology alone caused the observed improvement.

5.2. Usability and engagement results

The evaluation of usability and student engagement indicates that the AR-based remote laboratory provided a more favorable learning experience compared to the conventional remote laboratory approach. Students in the experimental group reported higher levels of perceived usability, engagement, and learning satisfaction throughout the laboratory sessions. The SUS results suggest that the AR application achieved a high level of usability, exceeding commonly accepted benchmarks for educational systems. Additionally, engagement survey responses reveal that AR-supported activities enhanced students' motivation and confidence during laboratory tasks within the hybrid learning setting.

Table 2 summarizes the usability and engagement results for both groups, with values reported as mean scores and standard deviations. As shown in Table 2, the experimental group reported a higher mean engagement score (4.31 ± 0.52) than the control group (3.62 ± 0.61), indicating a more favorable level of engagement during the AR-supported laboratory activities. The experimental group also reported higher learning confidence, with a mean score of 4.28 ± 0.49 compared with 3.57 ± 0.58 in the control group. The differences of 0.69 points in engagement and 0.71 points in learning confidence suggest that students using the AR-based remote laboratory experienced greater engagement and confidence when performing the laboratory activities.

Table 2. Usability and engagement evaluation results

Measure	Group	Mean (SD)
SUS	Experimental (AR-based remote lab)	82.6±7.8
Engagement score	Experimental (AR-based remote lab)	4.31±0.52
	Control (conventional remote lab)	3.62±0.61
Learning confidence	Experimental (AR-based remote lab)	4.28±0.49
	Control (conventional remote lab)	3.57±0.58

Note: engagement and learning confidence were measured using a 5-point Likert scale (1=strongly disagree, 5=strongly agree).

The experimental group obtained a mean SUS score of 82.6 ± 7.8 . This score indicates a high level of perceived usability of the AR application and suggests that students were generally able to interact with the system effectively during the laboratory activities. Because the SUS was administered only to the experimental group, the usability score is interpreted as an evaluation of the AR application's usability rather than as a direct comparison between the two laboratory approaches.

Taken together, the higher engagement and learning confidence scores, combined with the high SUS score, indicate that the AR-based remote laboratory provided a favorable learning experience. The spatial interaction with virtual networking devices may have contributed to this result by allowing students to visualize and manipulate network components within their physical surroundings. These findings are relevant to the research objective of evaluating the effectiveness of the AR-based remote laboratory not only in terms of learning outcomes but also in terms of students' learning experience in a hybrid environment. However, the engagement and learning confidence measures were based on self-reported responses and should therefore be interpreted cautiously, as students' perceptions may have been influenced by their familiarity with digital technologies or the novelty of the AR experience.

5.3. Interaction log analysis

Interaction log analysis was conducted to examine the efficiency and behavioral patterns of students while performing laboratory activities. The analysis focused on task completion time, configuration attempts,

and the number of interaction events recorded during each laboratory session. These indicators provide complementary evidence of how students interacted with the AR-based and conventional remote laboratory environments. Table 3 presents the comparison of interaction log metrics between the experimental and control groups.

Table 3. Interaction log metrics comparison

Metric	Experimental (AR-based remote lab)	Control (conventional remote lab)
Task completion time (minutes)	24.6±4.8	31.2±5.6
Configuration attempts	3.1±1.2	5.4±1.7
Interaction events per session	42.8±6.3	26.5±5.9

As shown in Table 3, students in the experimental group completed laboratory tasks in a shorter average time than those in the control group (24.6±4.8 minutes versus 31.2±5.6 minutes). This represents a difference of 6.6 minutes, indicating that students using the AR-based remote laboratory were able to complete the assigned tasks more efficiently. The experimental group also required fewer configuration attempts, with an average of 3.1±1.2 attempts compared with 5.4±1.7 attempts in the control group. The lower number of attempts suggests that students using the AR environment may have experienced less trial-and-error behavior when configuring network devices.

Interestingly, the experimental group recorded a higher number of interaction events per session (42.8±6.3) than the control group (26.5±5.9). Rather than indicating lower efficiency, this pattern suggests that students in the AR environment engaged more actively with the virtual laboratory components while completing their tasks in less time. The combination of more interaction events, shorter task completion time, and fewer configuration attempts indicates a more active and potentially more structured interaction pattern. In the AR environment, students could directly manipulate spatially anchored virtual routers, switches, and other network components, which may have encouraged more frequent exploratory interactions while reducing unsuccessful configuration attempts.

These findings are relevant to the research objective of evaluating the interaction efficiency of the markerless AR-based remote laboratory. The results suggest that spatially anchored AR may support laboratory task execution by enabling students to interact directly with virtual networking devices and visualize their spatial relationships. The reduced completion time and configuration attempts, together with the higher interaction frequency, provide complementary evidence that the AR environment supported both active exploration and more efficient task completion.

However, the interaction metrics should be interpreted with some caution. The AR application generated system-based interaction logs, whereas the control group relied on simulator activity reports and, in some cases, self-reported task time. Therefore, the interaction events and task completion times may not have been captured through completely equivalent mechanisms across the two conditions. Consequently, the observed differences should be interpreted as evidence of different interaction patterns between the laboratory environments rather than as definitive evidence that the AR system is intrinsically more efficient. Further studies using standardized automated logging procedures across both conditions would provide stronger evidence for comparing interaction efficiency.

5.4. Regression analysis results

A simple linear regression analysis was conducted to examine whether participation in the AR-based remote laboratory was associated with students' post-test performance. The AR-based remote laboratory was coded as 1, whereas the conventional remote laboratory was coded as 0. Table 4 presents the regression coefficients and model summary for post-test scores.

Table 4. Simple linear regression results for post-test scores

Predictor	B	SE	β	<i>t</i>	<i>p</i> -value
Constant	41.72	4.18	-	9.98	<0.001
AR-based remote lab (0=control, 1=AR)	8.27	2.71	0.36	3.05	0.003

Note: model summary: $R^2=0.13$, adjusted $R^2=0.12$

As shown in Table 4, participation in the AR-based remote laboratory was positively associated with post-test performance ($B=8.27$, $\beta=0.36$, $t=3.05$, $p=0.003$). The positive regression coefficient indicates that students in the AR condition were predicted to obtain post-test scores approximately 8.27 points higher than

students in the control condition, on average. The standardized coefficient ($\beta=0.36$) indicates a positive association between the laboratory condition and post-test performance, while the p -value below 0.05 indicates that this association was statistically significant.

The model produced an R^2 value of 0.13 and an adjusted R^2 of 0.12, indicating that the laboratory condition accounted for approximately 13% of the variance in students' post-test performance. Although this represents a relatively modest proportion of explained variance, the result provides additional statistical evidence that the type of laboratory environment was associated with differences in learning performance. The remaining variance may reflect other factors not included in the model, such as students' prior knowledge, individual learning characteristics, engagement, or other instructional factors.

These findings are relevant to the research objective of evaluating the effectiveness of the AR-based remote laboratory in supporting students' learning outcomes. The regression analysis complements the descriptive comparison presented in Table 1 by showing that the AR-based laboratory condition was significantly associated with higher post-test performance. However, because the study employed a quasi-experimental design and the regression model reported in Table 4 includes the laboratory condition as the predictor, the result should be interpreted as a significant association rather than definitive evidence of a causal effect of AR technology. Further analysis incorporating baseline pre-test scores and other relevant covariates would provide stronger evidence regarding the independent contribution of the AR-based laboratory to post-test performance.

5.5. Qualitative findings

Qualitative analysis of interview responses and open-ended survey feedback revealed consistent themes supporting the quantitative results. Students in the experimental group reported a stronger sense of presence and improved spatial understanding when using the AR-based remote laboratory, which helped them visualize network topologies and device relationships more clearly. Participants also expressed increased learning confidence and engagement, noting that the ability to interact with virtual devices in real-world environments made laboratory tasks more intuitive. These qualitative insights help explain the observed improvements in learning outcomes, usability, and interaction efficiency within the hybrid learning context.

6. DISCUSSION

6.1. Comparison with previous studies and interpretation of findings

The findings of this study provide empirical evidence that a markerless AR-based remote laboratory can support learning in a hybrid computer networks course. The experimental group achieved a higher post-test mean score than the control group (82.45 ± 6.31 versus 74.18 ± 7.02), with a large between-group effect size (Cohen's $d=1.25$). Both groups demonstrated significant improvement from pre-test to post-test, indicating that conventional and AR-supported laboratory activities were both capable of supporting student learning. However, the greater improvement observed in the AR group suggests that the spatially interactive laboratory environment provided additional educational value beyond the conventional two-dimensional simulation approach.

This finding is consistent with previous studies that have reported positive effects of AR in laboratory-based engineering education. For example, Tuli *et al.* [47] found that students using an AR learning environment for electronics laboratory experiments achieved higher learning outcomes and more positive attitudes than students using a conventional approach. Similarly, Andújar *et al.* [45] and Odeh *et al.* [46] demonstrated the potential of AR-supported remote laboratories to improve interaction and provide richer laboratory experiences. The present study extends these findings to computer networks education, where students must understand the relationships among routers, switches, end devices, and network connections. In this context, the ability to position and manipulate virtual networking devices within a physical environment may provide a more spatially meaningful representation of network topology than a conventional two-dimensional interface.

The interaction results provide further evidence supporting this interpretation. Students in the AR group completed laboratory tasks in a shorter average time than those in the control group (24.6 ± 4.8 versus 31.2 ± 5.6 minutes) and required fewer configuration attempts (3.1 ± 1.2 versus 5.4 ± 1.7). At the same time, the AR group recorded more interaction events per session (42.8 ± 6.3 versus 26.5 ± 5.9). This combination suggests that students interacted more actively with the laboratory environment while completing tasks with fewer unsuccessful configuration attempts. The result is consistent with research indicating that AR can facilitate interactive visualization and active engagement in engineering learning [19], [25], [26], [53]. In the present context, spatially anchored virtual devices may have helped students perceive the relationships among networking components and construct network topologies more intuitively.

The engagement and learning confidence findings also support the potential educational value of the AR-based laboratory. The experimental group reported higher engagement scores than the control group (4.31 ± 0.52 versus 3.62 ± 0.61) and higher learning confidence (4.28 ± 0.49 versus 3.57 ± 0.58). These findings are broadly consistent with previous research suggesting that interactive and immersive technologies can enhance student engagement and perceived learning effectiveness [16], [25]. The mean SUS score of 82.6 ± 7.8 further indicates that students generally perceived the AR application as usable. Together, these results suggest that the spatial interaction provided by the AR environment may have contributed not only to learning performance but also to a more favorable laboratory experience.

The regression analysis provides additional support for the relationship between laboratory condition and learning performance. Participation in the AR-based laboratory was positively associated with post-test performance ($B=8.27$, $\beta=0.36$, $t=3.05$, $p=0.003$), while the model explained 13% of the variance in post-test scores ($R^2=0.13$). The corresponding Cohen's f^2 of 0.149 indicates an effect close to the conventional medium-effect threshold. These findings strengthen the evidence that the AR-supported laboratory condition was associated with better learning performance. However, because the study used a quasi-experimental design and the intervention involved differences in interaction mode and learning support, the findings should be interpreted as evidence of the effectiveness of the overall AR-supported laboratory intervention rather than as evidence of an isolated causal effect of AR technology.

Overall, the findings extend previous AR laboratory research in two important ways. First, they demonstrate the application of markerless AR to computer networks education, an area that has received comparatively less attention than electronics-based laboratory applications [45]–[47]. Second, they show that spatially anchored virtual networking devices can be integrated into remote laboratory activities without requiring students to have direct access to physical networking equipment. Thus, the contribution of the present study lies not only in the use of AR, but in demonstrating how markerless spatial interaction can be incorporated into a remote computer networks laboratory and evaluated across learning performance, engagement, usability, and interaction behavior.

6.2. Implications for hybrid learning in computer networks education

The findings of this study demonstrate that the AR-based remote laboratory can support hybrid learning by enabling flexible, location-independent laboratory activities while maintaining meaningful experiential learning. Through spatial scanning and anchoring enabled by the Niantic Lightship Geospatial Browser, students were able to interact with virtual network devices within their own physical surroundings rather than being restricted to a conventional two-dimensional simulation interface. This spatial interaction provides an alternative way to represent network devices and topologies in remote laboratory activities and may help address the limited spatial representation commonly associated with conventional remote laboratory environments.

From a pedagogical perspective, the findings suggest that markerless AR can complement conventional laboratory approaches in computer networks education. Students were able to construct network topologies, connect virtual devices, and perform configuration activities without requiring physical networking equipment at their location. This provides greater flexibility for students participating remotely while retaining interactive elements of laboratory practice. The higher engagement, learning confidence, and interaction measures observed in the AR group suggest that spatially anchored virtual devices may contribute to a more interactive laboratory experience within a hybrid learning setting.

The approach also has practical implications for institutions seeking to extend access to networking laboratory activities beyond the physical campus. Because the proposed laboratory uses students' mobile devices and virtual networking components, laboratory activities can be conducted across different physical environments without requiring access to dedicated networking hardware. However, successful implementation still depends on factors such as device compatibility, available physical space, students' familiarity with AR interaction, and the design of appropriate laboratory tasks. Therefore, markerless AR is best considered as a complementary approach for extending hybrid laboratory learning rather than a complete replacement for physical networking laboratories.

6.3. Limitations and future research

Despite the positive findings, several limitations should be considered when interpreting the results. First, the study was conducted with 120 undergraduate students from a single university and within one computer networks course. Therefore, the findings may not be directly generalizable to students from other institutions, educational levels, or engineering disciplines. Replication across different institutions, courses, and learner populations is needed to examine the robustness of the observed effects.

Second, the intervention was conducted over one academic semester (14 weeks), and the study primarily assessed learning outcomes and student experiences within the intervention period. Although the

results indicate positive learning and engagement outcomes, the possibility of a novelty effect cannot be completely excluded. Students may have initially responded positively to the unfamiliar and interactive nature of AR. Longer-term and longitudinal studies are therefore needed to determine whether the observed benefits are sustained after prolonged exposure to markerless AR laboratory environments.

Third, usability was primarily assessed using the SUS, which provides a standardized measure of overall perceived usability but does not capture all dimensions of user experience or cognitive workload. Future studies could complement SUS with more comprehensive usability and workload measures, such as ISO 9241-based measures or NASA-TLX, to examine specific aspects of interaction, efficiency, and cognitive demand.

Finally, the effectiveness of the AR laboratory may depend on contextual and technical factors, including device compatibility, available physical space, students' familiarity with AR interaction, and the design of laboratory tasks. These factors may influence students' ability to position and manipulate multiple virtual devices and may therefore affect the generalizability of the findings to other learning environments. Future research should investigate these factors systematically and consider larger multi-institutional samples, longitudinal designs, and comparisons with different types of remote laboratory platforms. Such studies would provide stronger evidence regarding the sustained educational value and scalability of markerless AR-based remote laboratories in engineering education.

7. CONCLUSION

This study examined the effectiveness of an AR-based remote laboratory for computer networking education within a hybrid learning environment. By comparing an experimental group using a markerless AR system with a control group employing conventional remote laboratory tools, the results demonstrate that the AR-supported approach significantly improves learning outcomes, usability, engagement, and interaction efficiency. Students using the AR-based laboratory achieved higher post-test scores, completed tasks more efficiently, and showed reduced configuration errors, indicating stronger conceptual understanding and procedural accuracy.

Furthermore, the integration of spatial scanning and anchoring through the Niantic Lightship Geospatial Browser enabled context-aware interaction with virtual network devices within students' physical environments. The findings suggest that this approach can provide a flexible and scalable alternative for laboratory activities conducted across different physical locations, supporting the use of markerless AR-based remote laboratories in hybrid computer networks education.

ACKNOWLEDGMENTS

The authors would like to express their sincere appreciation to Universitas Negeri Medan and Universiti Sains Malaysia for establishing and supporting the collaborative research framework under the Implementing Arrangement between the Informatics and Computer Education Study Program, Electrical Engineering Study Program, Culinary Education Study Program, Faculty of Engineering, UNIMED, and the Centre for Instructional Technology and Multimedia, USM. The authors also gratefully acknowledge the academic and technical contributions of lecturers and researchers from both institutions who were involved in the development, implementation, and evaluation of the AR-based remote laboratory system.

FUNDING INFORMATION

This research was conducted under a joint research collaboration framework between Universitas Negeri Medan and Universiti Sains Malaysia, as stipulated in the Implementing Arrangement on Collaboration in Joint Research (No. 9276/UN33.5/KS/2025). The research and publication activities were financially supported by Universitas Negeri Medan, under institutional research funding allocated through the Faculty of Engineering. All research-related expenses were administered in accordance with the applicable regulations and research governance policies of Universitas Negeri Medan and the Republic of Indonesia.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Muhammad	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Dominique Mendoza														
Wan Ahmad Jaafar	✓	✓		✓				✓		✓	✓	✓		
Wan Yahaya														
Sriadhi	✓									✓		✓		✓
Nur Azlina Mohamed Mokmin		✓		✓			✓			✓	✓	✓		
Fahmy Syahputra		✓				✓		✓	✓	✓	✓	✓		
Elsa Sabrina	✓	✓		✓		✓				✓	✓			
Erita Astrid	✓		✓	✓				✓		✓	✓		✓	✓
Olnes Yosefa Hutajulu	✓			✓				✓		✓				

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, MDM, upon reasonable request.

REFERENCES

- [1] M. Anwar, Y. Rahmawati, N. Yuniarti, H. Hidayat, and E. Sabrina, "Leveraging Augmented Reality to Cultivate Higher-Order Thinking Skills and Enhance Students' Academic Performance," *International Journal of Information and Education Technology*, vol. 14, no. 10, pp. 1405–1413, 2024, doi: 10.18178/ijiet.2024.14.10.2171.
- [2] X. Zhang, "Internet of Things and Cloud Computing-Powered Virtual Laboratories for Enhanced STEM Education," *Journal of The Institution of Engineers (India): Series B*, vol. 106, pp. 1767–1776, Dec. 2025, doi: 10.1007/s40031-024-01192-y.
- [3] M. T. Qamar, A. Malik, J. Yasmeen, M. Sadiq, and M. Ajmal, "Incorporating face-to-face and online learning features to propose blended learning framework for Post-COVID classrooms in India," *Asian Association of Open Universities Journal*, vol. 19, no. 1, pp. 70–87, 2024, doi: 10.1108/AAOUJ-08-2023-0097.
- [4] N. Noradila, "The Effectiveness of Learning Programming Language Online: Student Perceptions and Performance," *Journal of Technology and Operations Management*, vol. 16, no. 1, pp. 25–37, 2021, doi: 10.32890/jtom2021.16.1.3.
- [5] S. H. Chen, "Learning lab skills online: Lessons from implementing video-based instruction for a remote biotechnology lab," *Biochemistry and Molecular Biology Education*, vol. 50, no. 6, pp. 633–640, 2022, doi: 10.1002/bmb.21667.
- [6] D. J. Rosen and A. M. Kelly, "Working together or alone, near, or far: Social connections and communities of practice in in-person and remote physics laboratories," *Physical Review Physics Education Research*, vol. 18, no. 1, 2022, doi: 10.1103/PhysRevPhysEducRes.18.010105.
- [7] A. J. A. Alnagrat, R. C. Ismail, and S. Z. S. Idrus, "The Opportunities and challenges in virtual reality for virtual laboratories," *Innovative Teaching and Learning Journal*, vol. 6, no. 2, pp. 73–89, 2023, doi: 10.11113/itlj.v6.91.
- [8] B. Aruanno, F. Tamburrino, P. Neri, and S. Barone, "Virtual Reality Laboratory for Engineering and Material Science Immersive Learning," *Computer Applications in Engineering Education*, vol. 33, no. 3, 2025, doi: 10.1002/cae.70041.
- [9] S. Asare, S. K. Amoako, D. K. Biilah, and T. B. Apraku, "The Use of Virtual Labs in Science Education: a Comparative Study of Traditional Labs and Virtual Environments," *International Journal of Science Academic Research*, vol. 04, pp. 6563–6569, 2023.
- [10] M. Lundquist and A. Aguanno, "Here and There: A Novel Hybrid Remote/In-Person College-Level Science Lab Model at a Small, Primarily Undergraduate Institution," *Journal of College Science Teaching*, vol. 53, no. 3, pp. 205–210, 2024, doi: 10.1080/0047231X.2024.2338038.
- [11] H. Hidayat *et al.*, "Metacognitive Awareness Determination through Technology: A Problem-Solving Android Gamification App," *International Journal of Information and Education Technology*, vol. 14, no. 8, pp. 1099–1108, 2024, doi: 10.18178/ijiet.2024.14.8.2138.
- [12] J. Dudley, L. Yin, V. Garaj, and P. O. Kristensson, "Inclusive Immersion: a review of efforts to improve accessibility in virtual reality, augmented reality and the metaverse," *Virtual Reality*, vol. 27, no. 4, pp. 2989–3020, 2023, doi: 10.1007/s10055-023-00850-8.
- [13] T. A. Syed *et al.*, "In-Depth Review of Augmented Reality: Tracking Technologies, Development Tools, AR Displays, Collaborative AR, and Security Concerns," *Sensors*, vol. 23, no. 1, 2023, doi: 10.3390/s23010146.
- [14] P. G. Ruiz, "Advances in the Use of Fiducial Markers for Positioning Tasks with Cameras," Ph.D. Thesis, Universidad de Cordoba, 2025.
- [15] S. Ubale, "Real-time Ai-augmented reality for mobile learning: advancing educational technology," *International Journal of Research in Computer Applications and Information Technology (IJRCAIT)*, vol. 7, no. 2, pp. 2686–2696, 2024, doi: 10.34218/ijrcait_07_02_204.

- [16] T. Booyoesen, "Exploring the Impact of Augmented Reality on Student Engagement and Learning Outcomes in Science Education," *Journal Educational Verkenning*, vol. 4, no. 4, pp. 25–32, 2023, doi: 10.48173/jev.v4i4.183.
- [17] A. Alnagrat, R. C. Ismail, S. Z. S. Idrus, and R. M. A. Alfaqi, "A Review of Extended Reality (XR) Technologies in the Future of Human Education: Current Trend and Future Opportunity," *Journal of Human Centered Technology*, vol. 1, no. 2, pp. 81–96, 2022, doi: 10.11113/humtech.v1n2.27.
- [18] F. Lizano-Sánchez, L. F. Paniagua-Orozco, D. Ureña-Corella, M. Jiménez-Romero, and C. Arguedas-Matarrita, "Development, Use, and Educational Impact of Remote Laboratories in Natural Sciences: A Scoping Review," *Laboratories*, vol. 3, no. 3, p. 21, 2026, doi: 10.3390/laboratories3030021.
- [19] E. Abbasi, "The impact of emerging educational technologies, including artificial intelligence and augmented reality, on the improvement of practical skills learning," *Educational Technology Research and Development*, vol. 74, pp. 875–895, Apr. 2026, doi: 10.1007/s11423-025-10578-8.
- [20] A. Fombona-Pascual, J. Fombona, and R. Vicente, "Augmented Reality, a Review of a Way to Represent and Manipulate 3D Chemical Structures," *Journal of Chemical Information and Modeling*, vol. 62, no. 8, pp. 1863–1872, 2022, doi: 10.1021/acs.jcim.1c01255.
- [21] Y. M. Huang, A. Y. Cheng, and T. T. Wu, "Analysis of Learning Behavior of Human Posture Recognition in Maker Education," *Frontiers in Psychology*, vol. 13, 2022, doi: 10.3389/fpsyg.2022.868487.
- [22] J. Seetohul, M. Shafiee, and K. Sirlantzis, "Augmented Reality (AR) for Surgical Robotic and Autonomous Systems: State of the Art, Challenges, and Solutions," *Sensors*, vol. 23, no. 13, 2023, doi: 10.3390/s23136202.
- [23] J. Cao, K. Y. Lam, L. H. Lee, X. Liu, P. Hui, and X. Su, "Mobile Augmented Reality: User Interfaces, Frameworks, and Intelligence," *ACM Computing Surveys*, vol. 55, no. 9, pp. 1–36, 2023, doi: 10.1145/3557999.
- [24] R. Gudlavalleti, A. Pandey, M. Malviya, S. Gandhi, and M. Kasar, "A Comparative Study of Interior Designing Using Markerless Augmented Reality," *International Journal of Innovative Research in Technology*, vol. 9, no. 2, pp. 470–474, 2022.
- [25] S. Olbina and S. Glick, "Using Integrated Hands-on and Virtual Reality (VR) or Augmented Reality (AR) Approaches in Construction Management Education," *International Journal of Construction Education and Research*, vol. 19, no. 3, pp. 341–360, 2023, doi: 10.1080/15578771.2022.2115173.
- [26] N. Suhail, Z. Bahroun, and V. Ahmed, "Augmented reality in engineering education: enhancing learning and application," *Frontiers in Virtual Reality*, vol. 5, 2024, doi: 10.3389/frvir.2024.1461145.
- [27] S. Vashisht, "Exploration of Markers in Augmented Reality: Methodologies and Applications," in *2nd International Conference on Intelligent Cyber Physical Systems and Internet of Things, ICoICI 2024 - Proceedings*, 2024, pp. 1082–1086, doi: 10.1109/ICoICI62503.2024.10696631.
- [28] C. Xie, C. Li, S. Sung, and R. Jiang, "Engaging Students in Distance Learning of Science With Remote Labs 2.0," *IEEE Transactions on Learning Technologies*, vol. 15, no. 1, pp. 15–31, 2022, doi: 10.1109/TLT.2022.3153005.
- [29] D. May, B. Morkos, A. Jackson, N. J. Hunsu, A. Ingalls, and F. Beyette, "Rapid transition of traditionally hands-on labs to online instruction in engineering courses," *European Journal of Engineering Education*, vol. 48, no. 5, pp. 842–860, 2023, doi: 10.1080/03043797.2022.2046707.
- [30] M. Ogunsola-bande, "Alternatives to Traditional Physical Science Laboratory Experiences: A Review," *West African Journal of Open & Flexible Learning*, vol. 12, no. 2, pp. 165–200, 2024.
- [31] M. P. Akhil and R. Lathabhavan, "Hybrid/blended learning approach in higher education institutions (HEIs): a bibliometric analysis," *Learning Organization*, vol. 32, no. 6, pp. 1011–1030, 2025, doi: 10.1108/TLO-01-2023-0016.
- [32] M. M. Musagalievich, A. Y. Çelik, A. M. Rashidkyzy, M. B. Talgatkyzy, N. M. Abdyzhaparovna, and T. Z. Iliyaskyzy, "Laboratory Affordances for Early-Stage Pedagogical Content Knowledge Development in Chemistry Teacher Education: A Comparative Qualitative Case Study in Kazakhstan and Türkiye," *Education Sciences*, vol. 16, no. 4, p. 645, 2026, doi: 10.3390/educsci16040645.
- [33] V. K. Kolil and K. Achuthan, "Virtual labs in chemistry education: A novel approach for increasing student's laboratory educational consciousness and skills," *Education and Information Technologies*, vol. 29, no. 18, pp. 25307–25331, 2024, doi: 10.1007/s10639-024-12858-x.
- [34] A. Mikroyannidis *et al.*, "FORGE: An eLearning framework for remote laboratory experimentation on FIRE testbed infrastructure," in *Building the Future Internet through FIRE: 2016 FIRE Book: a Research and Experimentation based Approach English*, 2017, pp. 521–560, doi: 10.1201/9781003337447-20.
- [35] D. Moyaki, N. Hunsu, D. May, A. Paul, P. Irukulla, and C. Gomillion, "Usability Evaluation of Virtual Reality Laboratories in Biomedical Engineering Education," *Biomedical Engineering Education*, vol. 6, pp. 235–259, Jul. 2026, doi: 10.1007/s43683-025-00210-9.
- [36] S. Alsaleh, A. Tepljakov, A. Kose, J. Belikov, and E. Petlenkov, "Relmagin Lab: Bridging the Gap Between Hands-On, Virtual and Remote Control Engineering Laboratories Using Digital Twins and Extended Reality," *IEEE Access*, vol. 10, pp. 89924–89943, 2022, doi: 10.1109/ACCESS.2022.3199371.
- [37] R. L. Mariz, R. E. Z. De Oliveira, and D. C. Cavalieri, "Cloud-based remote laboratory for teaching modern control systems: enhancing practical learning through interactive simulations," *Cogent Engineering*, vol. 13, no. 1, p. 2639213, Dec. 2026, doi: 10.1080/23311916.2026.2639213.
- [38] Y. Jiang *et al.*, "A Step-by-Step Guide to Creating a Robust Autonomous Drone Testing Pipeline," *arXiv Preprint*, 2025, doi: 10.48550/arXiv.2506.11400.
- [39] J. Singh *et al.*, "Online, Hybrid, and Face-to-Face Learning Through the Eyes of Faculty, Students, Administrators, and Instructional Designers: Lessons Learned and Directions for the Post-Vaccine and Post-Pandemic/COVID-19 World," *Journal of Educational Technology Systems*, vol. 50, no. 3, pp. 301–326, 2022, doi: 10.1177/00472395211063754.
- [40] A. Al-Zoubi, E. S. Cristobal, F. R. Shahrouy, and M. Castro, "The Middle East Higher Education Experience: Implementing Remote Labs to Improve the Acquisition of Skills in Industry 4.0," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 982–991, 2024, doi: 10.1109/TLT.2023.3341490.
- [41] K. Fabian, S. Smith, and E. Taylor-Smith, "Being in Two Places at the Same Time: a Future for Hybrid Learning Based on Student Preferences," *TechTrends*, vol. 68, no. 4, pp. 693–704, 2024, doi: 10.1007/s11528-024-00974-x.
- [42] Y. Zhang, C. Stöhr, S. S. Jämsvi, J. Kabo, and J. Malmqvist, "Student Experiences of Hybrid and Online Engineering Labs in a Logic Control Course," *Computer Applications in Engineering Education*, vol. 33, no. 3, 2025, doi: 10.1002/cae.70032.
- [43] V. Chen, A. Sandford, M. LaGrone, K. Charbonneau, J. Kong, and S. Ragavaloo, "An exploration of instructors' and students' perspectives on remote delivery of courses during the COVID-19 pandemic," *British Journal of Educational Technology*, vol. 53, no. 3, pp. 512–533, 2022, doi: 10.1111/bjet.13205.
- [44] G. Anoop *et al.*, "Adapting Instructional Labs for Remote Delivery During the COVID-19 Pandemic: A Review of Strategies, Outcomes, and Perceptions," *Computers in Education Journal*, vol. 14, no. 4, 2025, doi: 10.18260/B34C-90-25648.

- [45] J. M. Andújar, A. Mejias, and M. A. Marquez, "Augmented reality for the improvement of remote laboratories: An augmented remote laboratory," *IEEE Transactions on Education*, vol. 54, no. 3, pp. 492–500, 2011, doi: 10.1109/TE.2010.2085047.
- [46] S. Odeh, S. A. Shanab, M. Anabtawi, and R. Hodrob, "Remote augmented reality engineering labs," in *IEEE Global Engineering Education Conference, EDUCON*, 2012, pp. 1–6, doi: 10.1109/EDUCON.2012.6201162.
- [47] N. Tuli, G. Singh, A. Mantri, and S. Sharma, "Augmented reality learning environment to aid engineering students in performing practical laboratory experiments in electronics engineering," *Smart Learning Environments*, vol. 9, no. 1, 2022, doi: 10.1186/s40561-022-00207-9.
- [48] H. Na, K. B. S. Willet, and C. Kim, "Investigating the impact of AR technologies on geometric learning in primary school: A comparison between marker-based and markerless AR," *British Journal of Educational Technology*, vol. 56, no. 6, pp. 2502–2521, 2025, doi: 10.1111/bjet.13584.
- [49] C. K. Assuah, G. K. Mantey, and L. Osei, "The Effect of Think-pair-share Learning on Junior High School Students' Achievement in Algebraic Expressions: Pre-test-Post-test Non-equivalent Control Group Design," *Asian Journal of Probability and Statistics*, vol. 20, no. 2, pp. 46–55, 2022, doi: 10.9734/ajpas/2022/v20i2418.
- [50] Ilham *et al.*, "The Effect of a Six-Week Intervention Using Small-Sided Games (SSG), Ladder Drill, and Dynamic Balance on Agility of Young Futsal Players; [Вплив шеститижневої інтервенції з використанням ігор неповними складами (ІНС), тренувань з координаційною драбиною та динамічної рівноваги на спритність юних футзалістів]," *Physical Education Theory and Methodology*, vol. 25, no. 5, pp. 1237–1247, 2025, doi: 10.17309/tmfv.2025.5.23.
- [51] S. Craig, P. Stark, C. B. Wilson, G. Carter, S. Clarke, and G. Mitchell, "Evaluation of a dementia awareness game for undergraduate nursing students in Northern Ireland: a Pre-/Post-Test study," *BMC Nursing*, vol. 22, no. 1, 2023, doi: 10.1186/s12912-023-01345-2.
- [52] A. Sumeer, F. Ullah, S. Khan, R. Khan, and W. Khan, "Comparative Analysis of Parametric and Non-Parametric Tests For Analyzing Academic Performance Differences," *Policy Research Journal*, vol. 3, no. 8, pp. 55–62, 2025, doi: 10.5281/zenodo.16751260.
- [53] M. D. Mendoza *et al.*, "Enhancing Computational Thinking Skills through Markerless Augmented Reality and GPS-Supported Learning in Computer Networking," *International Journal of Information and Education Technology*, vol. 16, no. 2, pp. 330–344, 2026, doi: 10.18178/ijiet.2026.16.2.2506.

BIOGRAPHIES OF AUTHORS



Muhammad Dominique Mendoza    is a lecturer in the Information Technology and Computer Education Study Program, Faculty of Engineering, Universitas Negeri Medan (UNIMED), Indonesia. His research interests include immersive learning media, augmented and virtual reality, educational games, learning assessment, and AI-based chatbot applications. He can be contacted at email: aenaen@unimed.ac.id.



Professor Dr. Wan Ahmad Jaafar Wan Yahaya    is the Deputy Vice Chancellor (Student Development Affairs and Alumni) at Universiti Sains Malaysia (USM), Penang. He holds a Ph.D. in Multimedia Education from the University of Leeds, United Kingdom, and has extensive experience in educational technology and multimedia education. His research interests focus on multimedia education and instructional technology. He can be contacted at email: wajwy@usm.my.



Sriadhi    obtained his Ph.D. in Multimedia Education from Universiti Sains Malaysia, Malaysia. He is a professor in the Information Technology and Computer Education Study Program at Universitas Negeri Medan, Indonesia. His research interests focus on ICT in education, multimedia learning, e-learning, and virtual laboratory development. He can be contacted at email: sriadhi@unimed.ac.id.



Ts. Dr. Nur Azlina Mohamed Mokmin    is an associate professor at the Centre for Instructional Technology and Multimedia, Universiti Sains Malaysia (USM), and serves as deputy director of Research, Innovation, and Community. Her research interests include artificial intelligence in education, virtual and augmented reality, instructional multimedia, and assistive technologies. She can be contacted at email: nurazlina@usm.my.



Fahmy Syahputra    is an academic and educational technology practitioner whose research focuses on augmented reality (AR), virtual reality (VR), artificial intelligence (AI), and information systems in education. His interests include digital learning innovation, intelligent systems, and technology-based academic services. He can be contacted at email: famybd@unimed.ac.id.



Elsa Sabrina    holds a master's degree in Engineering Education and a doctoral degree from Universitas Negeri Padang, Indonesia. She is a lecturer at the Faculty of Engineering, Universitas Negeri Medan, Indonesia. Her research interests include vocational technology education, decision-making systems, and engineering systems. She can be contacted at email: elsasabrina@unimed.ac.id.



Erita Astrid    is a lecturer and researcher at the Faculty of Engineering, Universitas Negeri Medan, Indonesia. She earned her bachelor's degree in Electrical Engineering from Universitas Andalas and her master's degree from National Sun Yat-Sen University, Taiwan with a research focus on optimization of power systems and renewable energy. Her research contributions aim to improve the efficiency and sustainability of power system using artificial intelligence optimization. She can be contacted at email: eritaastrid@unimed.ac.id.



Olnes Yosefa Hutajulu    is a lecturer in the Electrical Engineering and Engineering Profession Programs at Universitas Negeri Medan (UNIMED), Indonesia, and is currently pursuing a doctoral degree in Electrical Engineering at Universitas Gadjah Mada (UGM). His research interests include power electronics, renewable energy, solar power generation, internet of things for energy conservation, solid-state transformers, and virtual laboratory development. He can be reached at email: olnes.hutajulu@unimed.ac.id.