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ADOPTION AND USAGE OF AUGMENTED REALITY-BASED VIRTUAL LABORATORIES TOOL FOR ENGINEERING STUDIES

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ABSTRACT

Aim/Purpose	The study seeks to utilize Augmented Reality (AR) in creating virtual laboratories for engineering education, focusing on enhancing teaching methodologies to facilitate student understanding of intricate and theoretical engineering principles while also assessing engineering students' acceptance of such laboratories.
Background	AR, a part of next-generation technology, has enhanced the perception of reality by overlaying virtual elements in the physical environment. The utilization of AR is prevalent across different disciplines, yet its efficacy in facilitating Science, Technology, Engineering, and Mathematics (STEM) education is limited. Engineering studies, a part of STEM learning, involves complex and abstract concepts like machine simulation, structural analysis, and design optimization; these things would be easy to grasp with the help of AR. This restriction can be attributed to their innovative characteristics and disparities. Therefore, providing a comprehensive analysis of the factors influencing the acceptance of these technologies by students - the primary target demographic – and examining the impact of these factors is essential to maximize the advantages of AR while refining the implementation processes.
Methodology	The primary objective of this research is to develop and evaluate a tool that enriches the educational experience within engineering laboratories. Utilizing Unity game engine libraries, digital content is meticulously crafted for this tool and subsequently integrated with geo-location functionalities. The tool's user-friendly interface allows both faculty and non-faculty members of the academic institution to establish effortlessly the virtual laboratory. Subsequently, an as-

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	sessment of the tool is conducted through the application of the Unified Theory of Acceptance and Use of Technology (UTAUT2) model, involving the administration of surveys to university students to gauge their level of adaptability.
Contribution	The utilization of interactive augmented learning in laboratory settings enables educational establishments to realize notable savings in time and resources, thereby achieving sustainable educational outcomes. The study is of great importance due to its utilization of student behavioral intentions as the underlying framework for developing an AR tool and illustrating the impact of learner experience on various objectives and the acceptance of AR in Engineering studies. Furthermore, the research results enable educational institutions to implement AR-based virtual laboratories to improve student experiences strategically, align with learner objectives, and ultimately boost the adaptability of AR technologies.
Findings	Drawing on practice-based research, the authors showcase work samples and a digital project of AR-based Virtual labs to illustrate the evaluation of the adaptability of AR technology. Adaptability is calculated by conducting a survey of 300 undergraduate university students from different engineering departments and applying an adaptability method to determine the behavioral intentions of students.
Recommendations for Practitioners	Engineering institutions could leverage research findings in the implementation of AR to enhance the effectiveness of AR technology in practical education settings.
Recommendations for Researchers	The authors implement a pragmatic research framework aimed at integrating AR technology into virtual AR-based labs for engineering education. This study delves into a unique perspective within the realm of engineering studies, considering students' perspectives and discerning their behavioral intentions by drawing upon previous research on technology utilization. The research employs various objectives and learner experiences to assess their influence on students' acceptance of AR technology.
Impact on Society	The use of AR in engineering institutions, especially in laboratory practicals, has a significant impact on society, supported by the UTAUT2 model. UTAUT2 model assesses factors like performance, effort expectancy, social influence, and conditions, showing that AR in education is feasible and adaptable. This adaptability helps students and educators incorporate AR tools effectively for better educational results. AR-based labs allow students to interact with complex engineering concepts in immersive settings, enhancing understanding and knowledge retention. This interactive augmented learning for laboratories saves educational institutions significant time and resources, attaining sustainable learning.
Future Research	Further research can employ a more comprehensive acceptance model to examine learners' adaptability to AR technology and try comparing different adaptability models to determine which is more effective for engineering students.

Keywords	augmented reality, engineering studies, next-generation technology, virtual laboratory

INTRODUCTION

The impact of digitization on the realm of education continues to expand, affecting educational establishments across different disciplines and at every educational tier. The process of digitalizing education has garnered increased attention, particularly considering the COVID-19 crisis, necessitating adaptations in pedagogical approaches to address emerging circumstances (Li & Lalani, 2020), making e-learning the preferred way of learning for the majority of students. In addition, the e-learning platforms within academic institutions play a crucial role in the dissemination of educational materials, managing student learning advancement, and providing opportunities for students to engage in e-learning modules (Najmul Islam, 2013). Students can engage and visualize material more effectively using e-learning. Traditional pedagogical approaches often prioritize direct instruction, providing a solid foundation of knowledge. The incorporation of digital learning tools and technological advancements can serve to augment these strategies, thereby enriching learning through heightened visual engagement and interactive components.

This study helps to explore digital tools to optimize educational outcomes, leading to suboptimal learning outcomes. In engineering, it is crucial to visualize the concepts to understand the topic thoroughly. Visualizing engineering concepts based on texts and two-dimensional figures in textual books is tough. For instance, within the mechanical engineering curriculum, manufacturing processes continue to be presented as static 2D images or basic animations on presentation slides without providing additional interaction opportunities for students in many institutions. Engineering is a discipline that heavily depends on laboratory instruction as a fundamental element in imparting practical skills. Such skills are required to cater to the ever-growing industry (Seifan et al., 2020). Physical laboratories have a shortage of resources because of a greater number of students enrolled. Due to this reason, they are grouped to perform experiments, which leads to a lack of customized learning and can make it more difficult for students to attain desired learning objectives. Augmented reality (AR) technology plays a major role in addressing these issues. It enables students with hands-on laboratory experience for everyone, highlighting the impact and need of remote technology for effective learning (Achuthan et al., 2021; Cooper & Ferreira, 2009).

AR incorporates digital data into the physical environment, positioning it in proximity to actual settings along the virtuality spectrum. The virtuality spectrum ranges from the real environment to the virtual environment, with AR and Augmented Virtuality (AV) in between, respectively. The transitional region between real and virtual environments, known as mixed reality, encompasses different degrees of blending virtual and real-world elements (Milgram & Kishino, 1994)

AR is gaining popularity across various industries, increasingly supported on digital platforms, and gaining wider acceptance within society. The market size of AR within the training and education sector shows substantial expansion, with forecasts suggesting an increase from $18.25 billion in 2023 to $30.19 billion in 2024, demonstrating a compound annual growth of 65.4% (Business Research Company, 2023). On the contrary, it is still not frequently used for tactile experiments performed in laboratories. Laboratories and practicals are the only means of having hands-on experiences in traditional learning. Yet, it is impossible to incorporate all engineering concepts in one lab and cater to a large crowd at once due to limited resources. Due to its superior capabilities in areas such as informatization, visualization, intelligence, and convenience, AR-based teaching is poised to supplant traditional teaching methods.

This paper introduces a study involving the application of AR technology in establishing a simulated laboratory environment to improve the dissemination of conventional engineering educational content. The primary objective of this initiative is to present a virtual AR laboratory for engineering education, which is constructed on a user-friendly AR platform, facilitating its integration into daily laboratory sessions by students and educators. These virtual laboratories exist within a digital realm where students engage with various engineering models, select specific modules, and observe their functionalities up close, fostering interactive learning experiences. It serves to demonstrate visually intricate processes and theories, enabling enhanced student engagement with educational content. An AR tool is incorporated for this purpose. It serves to visually illustrate complex processes and concepts, facilitating increased student involvement with the educational material. The tool's only dependency is an Android mobile device equipped with a camera. For AR to function, students must align their device cameras with specific printed materials featuring square patterns or images referred to as markers. Different markers are utilized in the laboratory to display diverse three-dimensional models, utilizing the device's Global Positioning System (GPS) to position the models accurately within the provided laboratory space.

A study is systematically conducted among a cohort of university engineering students, with the primary objective being to thoroughly evaluate the AR Virtual Lab learning efficacy and adaptability. The assessment is conducted through the utilization of the Unified Theory of Acceptance and Use of Technology (UTAUT2) framework (Venkatesh et al., 2012), offering empirical data to ascertain the tool's usability and its incorporation into the learning process. Drawing upon the elements of the UTAUT2 framework, which serve as a foundation for assessing the behavioral inclinations of students towards embracing AR laboratories, a set of five hypotheses, based on the impact of performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation are formulated to help identify the factors that influence engineering students' adoption of AR for learning. The overarching aim is to discern the extent to which said tool contributes to the enhancement of students' learning outcomes, as well as to gain insight into the perceptions held by the students regarding the seamless integration of these AR laboratories within their academic curriculum.

LITERATURE REVIEW

The advantages of utilizing e-learning environments for students and higher education institutions encompass cost savings in physical teaching and learning infrastructure, facilitation of the digitalization of course materials for seamless sharing and accessibility of learning resources at any time and from any location, as well as the incorporation into the worldwide educational landscape (Pham et al., 2019). E-learning is widely used in the education sector, and the recent progress in this field involves the integration of AR learning, which proves to be highly successful in delivering immersive and interactive educational experiences. AR garnered significant interest due to its efficacy as a valuable tool for delivering educational material (Bower et al., 2014; Radu & Schneider, 2019). This highlights the need for advancement in AR learning.

Looking over the medical research, the findings of Nugroho et al. (2022) indicate a significant impact of COVID-19, thus necessitating the exploration of alternative learning approaches in light of constraints. AR emerges as a promising solution to facilitate active and independent learning in the given context. The review reveals that AR technologies offer immersive and interactive learning experiences, which have the potential to enhance anatomy education. Similar efforts could be taken to make progress in engineering studies to minimize the cost of resources and ensure sustainability in educational settings.

The study conducted by Manyilizu (2023) evaluating the effectiveness of a virtual laboratory holds significance for individuals involved in the instruction and/or acquisition of engineering concepts, regardless of access to physical laboratories, if they have information and communication technology (ICT) resources. In addition to addressing the current shortage of physical laboratory resources and staff, virtual laboratories eliminate the necessity for students to wait in queue to perform the practical. A similar study is depicted in Figure 1.

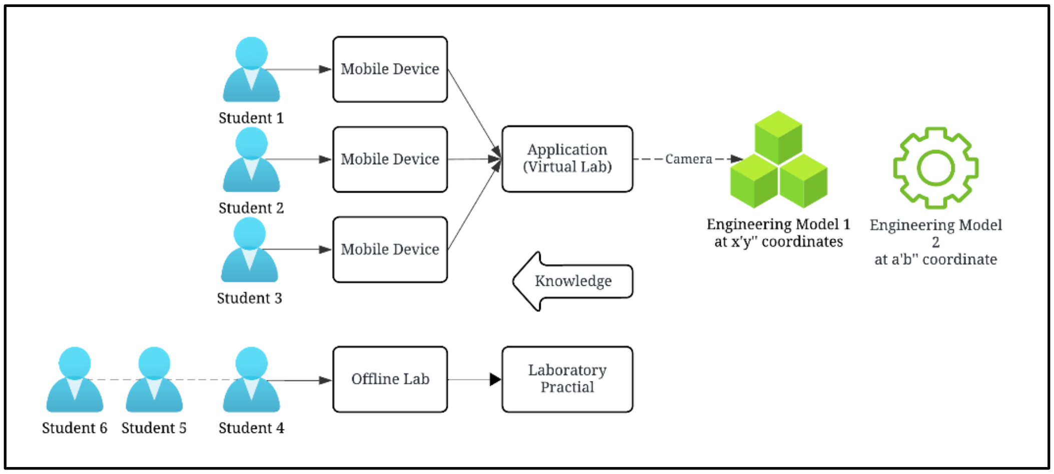

Figure 1. Comparative study of AR and non-AR learning

The scenario in Figure 1 delineates the distinction between conventional laboratory experiments conducted in physical settings and virtual laboratory experiments, focusing on underlining and exploring the crucial requirement for the availability and utilization of virtual laboratory infrastructures. Students 1, 2, and 3 engage in the virtual AR lab, which is established utilizing markers, enabling them to utilize the application to engage with various models and conduct experiments simultaneously. Conversely, Students 4, 5, and 6 utilize the physical laboratory. While Student 4 partakes in the laboratory experiment, Students 5 and 6 are required to form a queue and await their turn due to the equipment being in use, leading to increased time consumption. Furthermore, a research study (Jacob et al., 2020) was carried out at the University of Mumbai involving 300 students divided into two groups of 180 students each. One group was provided with an AR learning application while the other group followed traditional learning methods; the group utilizing the AR learning application exhibited significant enhancements.

The incorporation of AR within the realm of engineering education highlights its effectiveness in enhancing students' understanding of abstract concepts through 3D visualization and interactive learning experiences for electronics engineering (Tuli et al., 2022). Highlighting the scarcity of laboratory resources, Tuli et al. (2022) use markers for spawning and rendering 3D models for different electronic circuits. Students can interact with the circuits and perform laboratory practicals on them. A pilot study on students using the AR app showed that the students using it performed better than the other group. In conclusion, there is a need to focus on implementing AR as a large-scale teaching tool. The findings from this study suggest that AR intervention improves students' educational achievement and learning mentality.

The study conducted by T. L. Tan et al. (2024) investigates the factors affecting AR technology adoption in Vietnamese higher education using customer behavior theory. The study builds a model to analyze the impact of learner experience on various goals and AR adoption. A mixed-methods approach is used, with quantitative data from a survey of 200 students and qualitative data from interviews with four lecturers. Results show convenience and immersive experiences significantly impact academic, social, and practical goals, influencing AR adoption. The study offers insights for institutions to enhance student experiences and promote AR adoption, aiding digital transformation in education.

Pogodaev et al. (2020) examined the use of marker and marker-less AR technologies and software with practical applications in teaching electrical engineering disciplines. The methodology involves creating 3D models of electrical objects like electromagnetic relays and electric motors, using AR to enhance the learning experience. The study by Grodotzki et al. (2023) demonstrated the use of cube-based markers for rendering the 3D models.

The markers are printed cutouts of patterns or images on which the 3D models can be rendered. Different markers are utilized in the laboratory to display diverse three-dimensional models. Figure 2 shows the various markers that can be used for rendering the 3D models. The leftmost marker is of definite contrast, which the tracker easily recognizes. The middle marker consists of an image with a border, and the rightmost marker is an image that the Image tracker can also recognize.

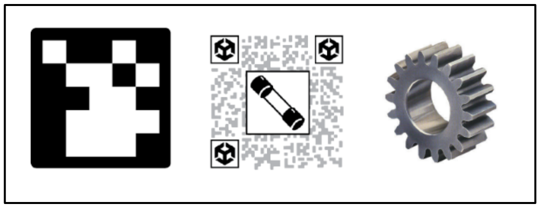

Figure 2. Examples of different types of AR markers

The study by El Barhoumi et al. (2022) discusses AR in Architecture, Engineering, Construction, and Operation (AECO) and focuses on the challenge of accurately placing 3D models in AR environments. Different types of markers (QR codes, printed photos, etc.) were tested as AR scene triggers, requiring detectability in the real world. Comparing the accuracy and stability of different AR placement methods, such as marker-based and marker-less approaches, using various SDKs like AR Core and Vuforia. It also discusses the use of the Trimble SiteVision system for improving the placement accuracy of 3D models.

Q. Tan et al. (2015) delve into the exploration of AR in the realm of mobile learning, with a specific emphasis on the identification of objects based on location and the presentation of digital content corresponding to tangible entities. The research conducted by Kleftodimos et al. (2023) and Nguyen et al. (2018) exemplifies the application of Location-Based AR, which relies on geographical coordinates and the digital compass of mobile devices. These scholarly inquiries serve as valuable resources for the creation of a virtual immersive laboratory within educational environments and offer insights into the integration of GPS technology with AR.

The study conducted by Tiwari et al. (2024) delves into the effects of an AR system, known as EDINAR, on the academic performance of students studying engineering drawing. A cohort of 392 first-year engineering students participated in the study, with the students being split into two groups – one utilizing conventional teaching methods and the other employing the AR application. Noteworthy discoveries from the study include the superior performance of students utilizing EDINAR compared to those employing traditional techniques, showcasing enhancements in spatial cognition and theoretical comprehension. The study underscores the capacity of AR technology to enrich educational outcomes within engineering drawing curricula, establishing a basis for future research endeavors investigating the broader educational applications of AR and its harmonization with other emergent technologies.

To gain insight into the usability and feasibility of e-learning tools, a comprehensive examination was carried out by Opriş et al. (2019), Udeozor et al. (2023), and Stechert and Yengui (2022), who conducted surveys and research aimed at analyzing student behavior through a range of methodologies including quantitative and various graphical analysis techniques. Utilizing theoretical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), several researchers like Bourgonjon et al. (2010) have recognized elements such as 'observed ease of usage' and 'observed utility,' along with 'entertainment' (Beavis et al., 2015) as crucial factors that impact the integration of educational games. Similar theories can be used for AR adaptation as well. The Theory of Planned Behavior (TPB) is relevant to the Unified Theory of Acceptance and UTAUT2 as it provides foundational insights that have been incorporated into the latter model (Venkatesh et al., 2012). TPB's components, such as behavioral intentions, subjective norms, and perceived behavioral control, align with UTAUT2's elements, like social influence and facilitating conditions (Ajzen, 1991). Moreover, UTAUT2 extends beyond TPB by integrating factors such as hedonic motivation, price value, and habit, enhancing its predictive power and applicability in technology adoption studies (Dwivedi et al., 2019; Venkatesh et al., 2012). The use of UTAUT2 in this study is justified as it provides a detailed understanding of various determinants impacting AR adoption, making it particularly suitable for analyzing engineering students' intentions to use AR in education (Tamilmani et al., 2019). The hypothesis formation in this study also reflects previous work by incorporating elements recognized in TAM and UTAUT frameworks, ensuring a solid theoretical foundation and alignment with existing research (Faqih & Jaradat, 2021; Venkatesh et al., 2003).

METHOD

The focus of this study is to develop a tool that enhances the learning experience in engineering laboratories. By providing a visual representation of difficult procedures and ideas, this tool encourages students to engage more actively with the educational material. The development of digital content for this tool is done using Unity game engine libraries using a C# programming environment, later integrated with geo-location capabilities. The tool is easy to use for both faculty and non-faculty members of the institution to set up the virtual lab. The tool is then evaluated using a UTAUT2 model, which is done by surveying university students and determining their adaptability.

SYSTEM OVERVIEW

This study proposes an application for visualizing engineering concepts of the real world with the help of markers, which are identified through a camera and estimated by GPS. The development of the system is all done with Unity. The system's operational phases include image input, tracking, 2D image recognition, GPS coordinate estimation, and visualization, where it processes color and depth image data from the camera and compares it with Unity's marker library. Mapbox API combined with ARCore accurately tracks the model's position in real-time within the physical environment and synchronizes the information using GameSparks. GameSparks is the database that is used to store the coordinates. The database has three attributes: latitude, longitude, and model, which dynamically update when the user decides to place a particular model at a fixed coordinate. The models are later augmented at the coordinate with the help of the device's GPS. Figure 3 illustrates the proposed system's conceptual flow as described in this study.

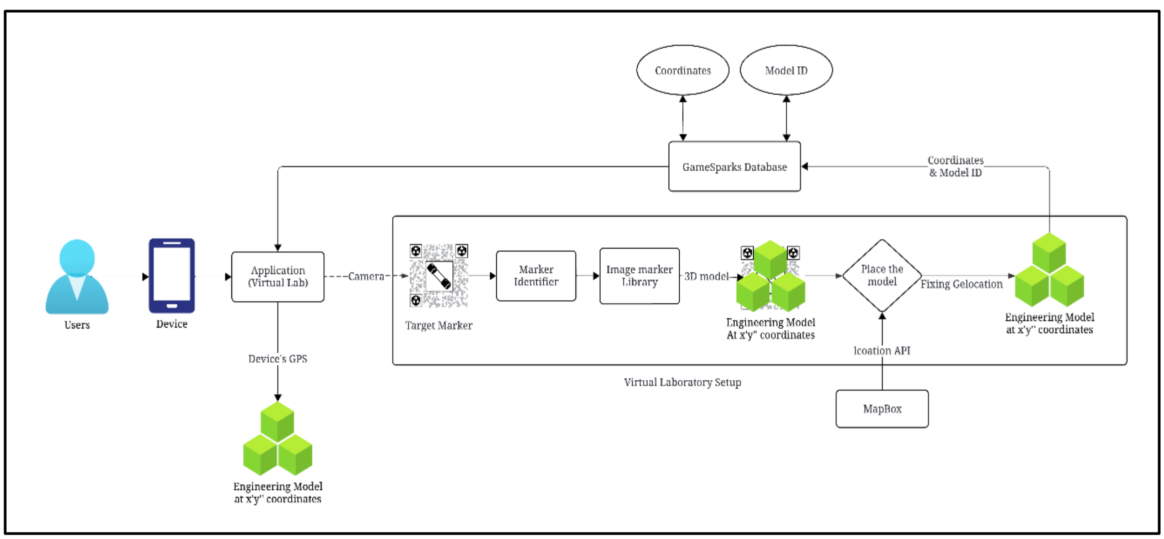

Figure 3. System overview

MARKER IDENTIFICATION

Markers are printed/digital images of a fixed dimension, as seen in Figure 3. In this application, markers act as a trigger to render 3D AR models. Markers provide a valuable method for establishing a specific location within a Scene to localize AR content, with Mixed and Augmented Reality Studio (MARS) utilizing marker tracking functionalities from ARFoundation to enable the development of content capable of recognizing and aligning with a marker's pose. To begin image marker tracking, one must first assemble markers or images and store them in a library, which is then utilized by the MARS Session GameObject to identify any specified markers present in the physical environment being explored by the device.

Figure 4 shows the complete flow of marker identification. The input is taken in real-time from the camera. The image tracking is done by Unity AR Foundation's Tracked Image Manager. It scans the marker by converting it into a binary image, and the frame is identified. Image features are extracted through contour abstraction to be able to identify the image. Simultaneously, the positions and orientations of the marker relative to the camera are calculated. Equation (1) determines the position and orientation of the marker derived for each pixel ***i***.

$$P_i = K \cdot [R \mid t] \cdot X_i \qquad (1)$$

where P_i represents the 2D image coordinate of a pixel i on the marker, while X_i denotes the corresponding 3D world coordinate. The intrinsic camera matrix K encapsulates parameters like focal length and distortion, governing the mapping between 3D points and 2D image coordinates. The extrinsic matrix $[R \mid t]$ combines rotation (R) and translation (t) information, defining the camera's orientation and position in space. By utilizing camera calibration, we determine these matrices, enabling precise projection from 3D to 2D space.

The marker image is matched with the prefab to the marker image through the XR Reference Image Library, which contains a collection of reference images that the tracker uses for detection. Once the prefab to render is identified, the 3D object is aligned with the marker using P_i. Rendering of the 3D object happens simultaneously, and the 3D object is spawned on the marker in real time. Each detected image has a tracking state, which provides additional information about tracking quality. An image that goes out of view may not be removed, but its tracking state will likely change.

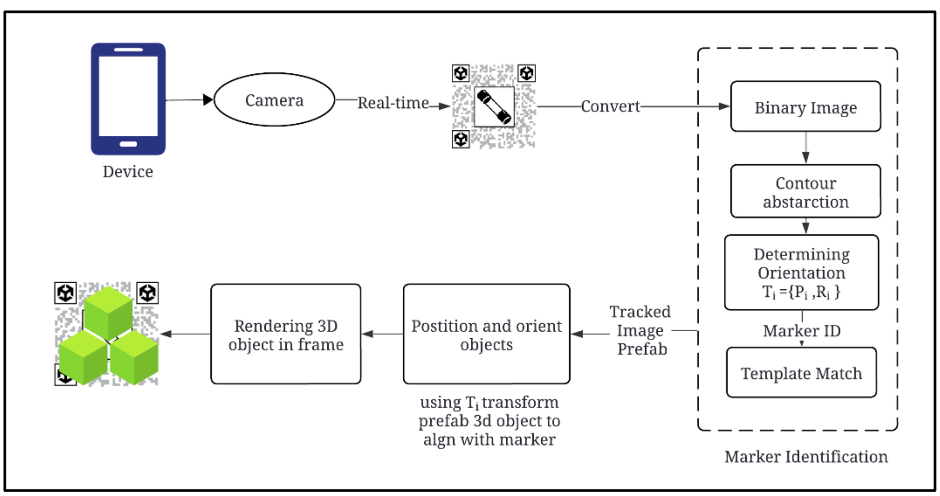

Figure 4. Marker identification

GEO-MAPPING 3D OBJECTS

Unity 3D and AR Core are employed to position AR objects at specific GPS coordinates. Unity Camera needs to be aligned with the true north for the object to show up in the right place. Mapbox

Map SDK is used to quickly access and interact with the Maps, Geocoding, and Directions services. Mapbox's location API is configured with Unity. It utilizes AR Position deltas and GPS Position deltas to determine the angle representing the deviation from the AR camera to the actual north direction. Mapbox also helps in reducing the AR object drifting that occurs with AR Core. GameSparks is used to store the coordinates and model ID. It uses NoSQL, consisting of a collection and added events of the app to read, write, and delete from the server. Three attributes are *LAT* for latitude, *LON* for longitude, and *ID* for model ID. When the user hits the place button, the GameObject, i.e., the rendered 3D model, is checked against its model ID and recorded. Simultaneously, the location data from Mapbox records all the data and stores it in the cloud database. When the app starts, the data is queried immediately from the cloud, and the models are rendered at their respective coordinates. Figure 5 portrays the entire flow of the procedure to fix the coordination of 3D objects, as mentioned above.

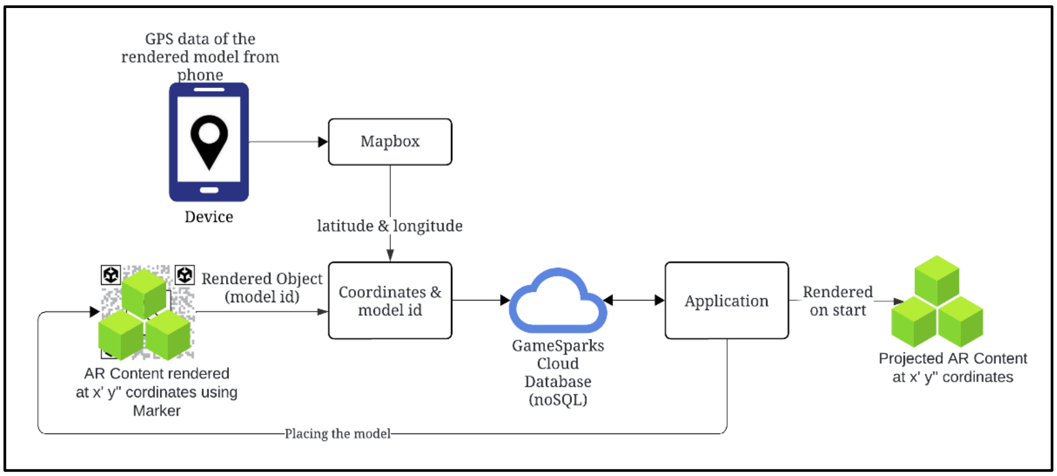

Figure 5. Geo-mapping 3D model

Modelling

Markers of various types are specifically tailored for distinct engineering prototypes. These prototypes are typically available in fbx, glb, and prefab file formats and can be effortlessly imported into the assets library or constructed within the editor. Each prototype comprises an infographic canvas for information display and a coordinate canvas to indicate its current position. All prototypes are equipped with audio sources, scripts, and animations through the utilization of the Unity Game Engine. The illustration in Figure 6 depicts the scene containing the prefab prototype alongside two infographic canvases.

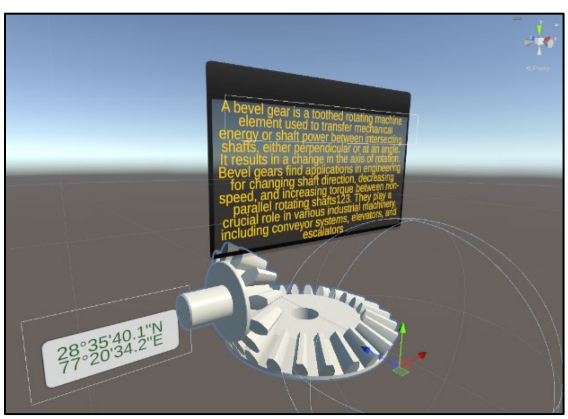

Figure 6. Bevel gear model with infographic canvas

PERFORMANCE EVALUATION

Three hundred engineering students from Pune University engaged in a research survey endeavor focusing on the utilization of AR in learning, as well as providing feedback regarding the implementation of an AR tool for the establishment of a virtual AR laboratory. Data collection is facilitated through an online questionnaire, which is divided into two distinct sections: the first aimed at assessing the adaptability of AR learning, and the second sought feedback specifically related to the tool.

ADAPTABILITY MEASURING METHOD

The extended UTAUT2 model is employed to evaluate the features influencing the adaptability of AR tools to set up a virtual AR laboratory for engineering education. Originally conceived by Venkatesh et al. (2003), the UTAUT model serves as the base for the UTAUT2 framework introduced. This updated model by Venkatesh et al. (2012) incorporates additional elements such as hedonic motivation, price value, and habit, expanding upon the original UTAUT model, which integrated various established theories, including the Technology Acceptance Model (TAM), Motivational Model, Theory of Planned Behavior, Innovation Diffusion Theory, Theory of Reasoned Action, Model of PC Utilization, and Social Cognitive Theory.

The UTAUT2 posits that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (H) directly impact an individual's intention Behavioral Intentions (BI) to utilize technology, while FC, HM, PV, and H directly influence usage. In this study, an adapted iteration of the UTAUT2 framework is employed to analyze the determinants influencing the inclination of engineering students to participate in AR learning. The UTAUT2 framework comprises PE, EE, FC, SI, and HM, all of which contribute to the computation of BI.

Performance Expectancy (PE) relates to the degree to which a person observes that the utilization of a specific technology will empower them to carry out a particular task. This could include improvements in understanding, engagement, and knowledge retention of AR learning compared to traditional learning methods (Venkatesh et al., 2003). As a result, the hypothesis H1 can be articulated as follows:

> **H1:** The impact of Performance Expectancy on students' intentions to utilize AR for educational purposes will be significant.

Effort Expectancy (EE) denotes the perception of the level of ease connected with the utilization of a technological system like AR. Research indicates that technologies perceived as easy to use are more likely to be adopted by students (Venkatesh et al., 2003). Consequently, the hypothesis posits as:

> **H2:** Effort Expectancy will exert a substantial impact on the inclinations of students toward incorporating AR for educational purposes.

Social Influence (SI) is characterized as the degree to which a person observes the endorsement of AR technology by influential figures in their social circle (Venkatesh et al., 2003). Studies have found that the opinions of peers and educators can significantly impact students' technology adoption decisions (Taylor & Todd, 1995; Venkatesh et al., 2003). This includes peer recommendations, instructor support, and the perceived norms within the engineering community regarding the use of AR for learning and practical applications. Thus, it is anticipated that:

> **H3:** Engineering students who perceive greater Social Influence from peers, instructors, and industry professionals regarding the use of AR in engineering education will have a higher intention to use AR.

Facilitating Conditions (FC) refers to the confidence in the presence of suitable infrastructure to strengthen the adoption of AR technology (Venkatesh et al., 2003). In the realm of AR education, this might encompass the provision of assistance, training, or competencies necessary to navigate the AR. Therefore, it is envisaged that:

> **H4:** The impact of Facilitating Conditions on students' willingness to engage with AR technology for educational objectives will be noteworthy.

Hedonic Motivation (HM) is described as the pleasure or satisfaction derived from the utilization of technology (Venkatesh et al., 2012). Consequently, it is anticipated that this factor will significantly influence students' inclination toward utilizing AR for educational purposes. Therefore, hypothesis H5 suggests that:

> **H5:** Hedonic Motivation will yield a notable impact on students' intent to utilize AR for learning purposes.

Behavioral Intentions (BI) denote the expected possibility of a person adopting a new technology (Venkatesh et al., 2012). BI plays a crucial role in understanding the acceptance and practical implementation of innovative technology.

SURVEY

The design of the questionnaire focused on identifying the factors influencing students' intentions to use AR in engineering education. An online survey questionnaire is employed for this purpose, gathering demographic information, AR experiences, and students' perceptions calculated on six entities based on the UTAUT2 model in Appendix A.

The questionnaire, derived from the UTAUT2 model, was selected due to its widespread acceptance and validation as a technology acceptance model. The entities were evaluated utilizing a 6-point Likert scale from 'Strongly Disagree' to 'Strongly Agree.' The decision to use a 6-point Likert scale was based on its perceived ability to enhance distinction and dependability compared to a 5-point scale.

The process of data collection and analysis involves multiple stages with student participants. Initially, participants are required to finish the online questionnaire to assess their views of AR learning in engineering studies before engaging with the tool. The completion of the questionnaire involved 300 students, as indicated in Appendix B. It demonstrates the variation in students with different engineering disciplines and academic years. This helps to cover the spectrum of types of engineering students. With the quantitative study done with the questionnaire and data collection, a preliminary investigation employing partial least squares Structural Equation Modelling (SEM-PLS) is conducted to ascertain the factors influencing the behavioral inclinations of engineering students toward the utilization of AR-based virtual labs, as outlined in the adapted UTAUT2 framework.

COMPARATIVE STUDY

Three hundred engineering students from Pune University participated in a research endeavor aimed at assessing the efficacy of AR learning. The research mentions the sample size in Appendix B. This was done by dividing the students into two groups of 150 each. One group engaged in practical exercises using an AR-enabled virtual lab, while the other group followed traditional methods for useful tasks. A faculty member performs the same task, and the time taken by the faculty to perform the practical is recorded as the ideal time to complete the practical. Similarly, the time of completion is recorded for each student, and an average mean is recorded for both groups. A test was administered to measure the knowledge acquired from these practical sessions, and the outcomes were compared between the two groups. The faculty of the mechanical engineering department formulated a set of ten questions, outlined in Appendix C, to assess the student's comprehension of various concepts. The evaluation of the test was overseen by faculty members from the mechanical engineering department. This study seeks to determine the effectiveness of the AR virtual lab tool in facilitating knowledge acquisition through AR.

RESULTS

The lab must be set up, the models that are required for the lab can be preloaded in the app, and the markers can be easily set up. Once the setup is done, the students can easily interact with the models at the specific location in the virtual lab. For demonstration, a Fusebox and a Bevel gear model are set up using the application.

Figure 7 presents the application's screenshot, a model of a Fusebox and a Bevel gear rendered on their respective markers. The UI on the screen consists of four buttons, each having its own functionality. The models can be rotated with < and > buttons present on the top corners. The information button pops up the infographic canvas to get information on the respective model, and the place button fixes the position and coordinates of the model, which pops up a canvas consisting of the current coordinates.

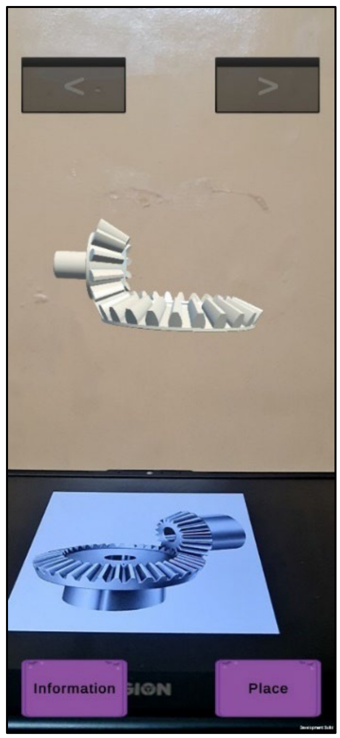

Figure 7. Bevel gear placed on a marker

Figure 8 shows the Infographic and coordinate canvas that popped up. These canvases are hierarchically children of the prefab model and are configured together. Users can toggle this infographic canvas on and off based on their preferences.

Figure 9 shows the alert message that pops up when you press the Place Button. Once the coordinates are fixed, the model can be accessed without the marker in that same location. The model then renders in runtime as soon as you start the app. The previously fixed model can be seen independently without the marker in the frame. Likewise, students can access these models without any marker.

Figure 8. Bevel gear model with infographics and coordinates

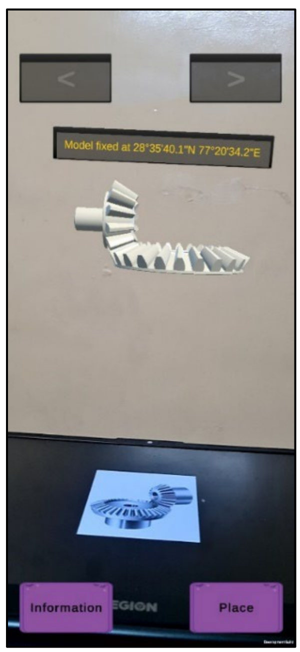

Figure 9. The alert message of the model is placed

These results show us the convenience provided by AR learning apps compared to traditional ways of learning. Engineering institution faculties can just set up these labs in an allocated room, and since it is virtual, it does not require any resources, nor does it take up any space in the real world. Based on the practical that is to be performed, the faculty can change the models based on the experiment they need to conduct on that day and change them for the next practical. The students can get better visualization and an immersive experience by flattening the learning curve and understanding concepts easily through the tool. Based on feedback taken on the tool, the students were told to rate the experience of the AR virtual lab from 1 to 5.

Figure 10 demonstrates that 44% of the 300 students provided a rating of '5' on a scale ranging from 0 to 5. In contrast, 33% and 9% of the students rated the virtual lab as '4' and '3' respectively. This illustrates the level of satisfaction among the students towards the AR virtual lab, with approximately 77% expressing a positive sentiment and the remaining 9% holding a neutral stance toward the tool.

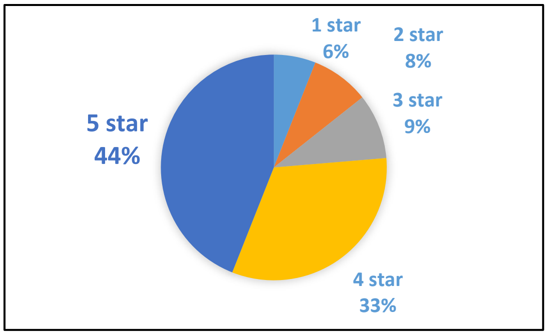

Figure 10. Rating of proposed AR Virtual Lab tool

The assessment model is designed to assess the dependability and accuracy of the utilized entities. Illustrated in Table 1, the Cronbach's alpha values, serving as indicators of internal consistency reliability of the assessment entities, exceeded the minimum threshold of 0.6 (Hair et al., 2017). This demonstrates that the assessment entities exhibit robust local uniform dependability, suggesting favorable associations among items meant to measure identical entities.

Based on the responses provided by the cohort of students, the mean is computed based on the responses corresponding to their respective question IDs. To ensure the dependability and validity of our measurement tools, we analyzed various crucial metrics: Factor Loadings, Average Variance Extracted (AVE), Cronbach's Alpha, Composite Reliability (CR), and the Heterotrait Monotrait Ratio (HTMT). These metrics aid in evaluating the caliber of our constructs and their associated items (Hair et al., 2017).

The assessment of Factor Loading entails gauging the correlation between each observed variable and its latent construct. Loadings exceeding 0.7 are deemed satisfactory, indicating a robust relationship between the items and the construct.

AVE gauges the extent of variance explained by a construct versus that attributed to measurement error, as illustrated in Equation 2.

$$AVE = \frac{\sum(Factor\ Loading^2)}{n} \qquad (2)$$

where n represents the number of items associated with the specific latent construct. AVE exceeding 0.5 signifies that the construct elucidates more variance than measurement error.

Cronbach's alpha (α) evaluates the internal consistency of items on a scale computed using Equation 3.

$$\alpha = \frac{N.\bar{c}}{\bar{v}+(N-1).\bar{c}} \qquad (3)$$

where N denotes the number of items, $\bar{c}$ is the average covariance between item pairs, and $\bar{v}$ is the average variance. Values surpassing 0.7 signify acceptable reliability.

Composite Reliability (CR) scrutinizes the reliability of latent constructs and is determined as shown in Equation 4. CR values should exceed 0.7 to signify robust reliability.

$$CR = \frac{(\sum Factor\ Loading)^2}{(\sum Factor\ Loading)^2+\sum(1- Factor\ Loading^2)} \qquad (4)$$

Ensuring the validity, high AVE, and factor loadings indicate good convergent validity, meaning the items are well-correlated with their respective constructs. High Cronbach's alpha and CR indicate that the items reliably measure the constructs, ensuring the reliability of the data.

Table 1. Reliability and validity

Entities	Question ID	Mean	Standard deviation	Factor loading	AVE	Cronbach's alpha	CR
Performance Expectancy	PE1	4.36	0.89	0.864	0.842	0.935	0.996
	PE2	4.01	1.01	0.902			
Effort Expectancy	EE1	4.39	0.90	0.883	0.730	0.862	0.896
	EE2	4.73	0.95	0.826			
Social Influence	SI1	4.38	0.91	0.813	0.609	0.757	0.832
	SI2	4.71	1.01	0.746			
Facilitating Condition	FC1	4.51	1.12	0.790	0.749	0.855	0.911
	FC2	3.86	1.27	0.935			
Hedonic Motivation	HM1	4.09	0.86	0.936	0.864	0.927	0.950
	HM2	3.98	1.09	0.923			
Behavioural Intentions	BI1	3.34	1.16	0.867	0.713	0.831	0.881
	BI2	4.33	1.47	0.821			

Moreover, the entities' validity is ascertained through the assessment of convergent and discriminant, as suggested by Hair et al. (2017). As displayed in Table 1, the factor loadings for each survey question and the average variance calculated for each entity (AVE) exceeded the recommended thresholds of 0.708 and 0.5, respectively. Furthermore, the Heterotrait-Monotrait ratio (HTMT) presented in Table 2, a measure of discriminant validity, is observed to be below the recommended maximum value of 0.9 (Gold et al., 2001). These findings confirm that the model meets the discriminant and convergent validity requirements, thus establishing the entities and items as both valid and reliable.

Table 2. Heterotrait-Monotrait ratio (HTMT), a discriminant validity count

	BI	EE	FC	HM	PE	SI
Efforts expectancy (EE)	0.372					
Facility condition (FC)	0.556	0.366				
Hedonic motivation (HM)	0.763	0.339	0.501			
Performance Expectancy (PE)	0.566	0.374	0.789	0.577		
Social influence (SI)	0.430	0.506	0.411	0.460	0.599	

Following the confirmation of entity validity and reliability through the measurement model, the subsequent step involved assessing the structural model. This included evaluating the coefficient of determination (R^2) and the significance of path coefficients (B) (Hair et al., 2017). Before conducting these analyses, a check is conducted on the model to ensure the absence of convergence problems (Hair et al., 2017). Results indicated that all entities exhibited Variance Inflation Factor (VIF) values below 3, the suggested limit, showing the absence of multicollinearity. The relationships between the entities were then examined through the analysis of path coefficients and their impact on the model, as illustrated in Figure 11.

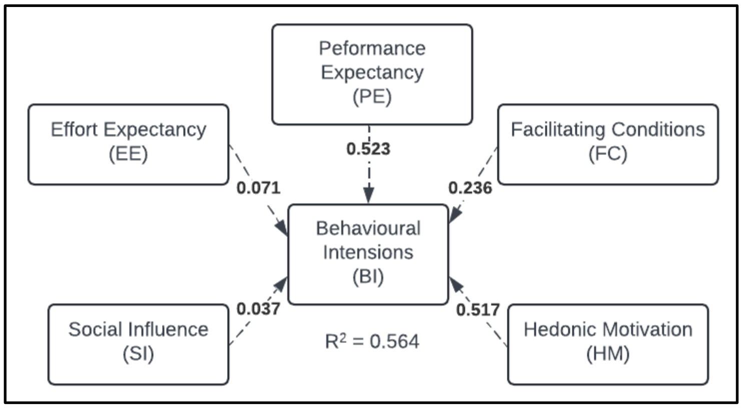

Figure 11. Structural equation prediction model

The proportions of variance explained by PE, EE, SI, FC, and HM in students' intentions to embrace AR for learning were 0.523, 0.071, 0.037, 0.236, and 0.517, respectively, as depicted in Figure 11. PE was observed to be 52.3 % of the variance in students' intentions to use AR tools for learning, which can be attributed to their expectations that using AR tools will improve their learning performance. Only HM and PE had a noteworthy positive impact on students' inclination to utilize AR for engineering education, supporting H1 and H5. Hence, Hypotheses H2, H3, and H4 were refuted, positing significant influences of EE, SI, and FC on students' intentions to adopt virtual AR labs for learning. Lack of endorsement from peers and instructors might affect students' willingness to use AR tools. The perceived difficulty in using AR tools could deter students from adopting them. With $R^2 > 0.2$, the adapted UTAUT2 model is deemed suitable for this behavioral study as per Hair et al. (2017), accurately predicting a 51.6% variance in engineering students' behavioral intentions to utilize the AR-based virtual lab tool for learning. The findings of this study indicate a noticeable positive shift in the students' performance expectancy, suggesting a potential enhancement in their learning trajectory. Furthermore, the results highlight a significant increase in hedonic motivation, emphasizing the pleasure-driven aspect that collectively contributes to fostering effective learning outcomes.

Comparative Study Results

The present study seeks to assess the effectiveness of AR virtual laboratories compared to conventional physical laboratories regarding improving students' hands-on knowledge acquisition. Two cohorts – Group 1 and Group 2 – consisting of 150 students each, engaged in hands-on sessions on different gears utilizing AR virtual labs and traditional laboratories, respectively. After these sessions, both cohorts underwent a standardized evaluation to measure their comprehension, with outcomes presented in Table 3. Group 1, utilizing AR virtual labs, attained an average score of 8.83 marks with a standard deviation of around 1.19, while Group 2, utilizing traditional laboratories, acquired an average score of 7.06 marks with a standard deviation of 1.50. The optimal time for experimenting was observed to be 10 minutes and 15 seconds. It was noted that the average time taken by Group 1 was 11 minutes and 25 seconds, whereas Group 2 recorded an average time of 25 minutes and 12 seconds. These findings indicate that students utilizing AR virtual laboratories demonstrated a higher efficiency in experiment execution than those using traditional laboratory setups, resulting in significant time and resource savings.

The average score for Group 1 is 8.83, whereas the average score for Group 2 is 7.06. This superior mean score for Group 1 implies that AR virtual labs exhibit greater efficacy in enhancing students' practical knowledge and performance, thereby corroborating hypothesis H1.

The results indicate that students in Group 1, who were exposed to AR virtual labs, exhibited slightly superior performance on average compared to their peers in Group 2, who worked in traditional laboratory environments. Despite the narrower standard deviation in Group 1 suggesting a somewhat lesser degree of variability in performance, both groups displayed similar levels of consistency in their practical educational outcomes. These findings highlight the potential of AR virtual laboratory tools in enriching practical learning, potentially attributed to their immersive and interactive characteristics, which have a higher capacity to engage students than traditional approaches.

Table 3. Comparative study on the use of AR tool

Research groups	Sum of marks	Number of students	Mean (marks)	Standard deviation	Average time taken	Ideal time taken
Group 1: Students performing practicals in AR virtual laboratory	1325	150	8.83	1.19	11 minutes 25 seconds	10 minutes 15 seconds
Group 2: Students performing practicals in traditional laboratory	1059	150	7.06	1.50	25 minutes 12 seconds	

CONCLUSION

This paper aimed to present an approach that utilizes AR in Engineering Education. A geo-location-based AR app has been developed to promote sustainable education. AR learning cuts down on resources and space required, making the process of learning eco-friendly. Virtual AR labs are set up using an app that is economically friendly for educational institutions and even provides students with an immersive way of learning. Complex models like a Boeing turbine are quite expensive to accommodate in college, yet they can have a 3D model of the turbine within the virtual lab, and students can see it working and have hands-on experience. Also, the institute would be free of those expenses. The use of AR Learning modules is fruitful and beneficial for both educational institutions to provide better learning and for students to grasp knowledge effectively and sustainably and shape the future of digital learning.

The outcomes of the quantitative data analysis from the research revealed that among various entities considered, only Performance Expectancy (PE) and hedonic motivation (HM) had a statistically significant impact on students' intentions to use AR-based tools for engineering education. This implies that the groups of students involved in this study prioritize enjoyment and fun experienced through AR interaction as the key determinant for their adoption of AR-based labs in engineering education.

In the future, a qualitative study could potentially be conducted with a larger group of students. Furthermore, a comparative study could be implemented within an engineering college, comparing a cohort of students engaging in practical exercises using AR applications with another group following traditional methods. This study would involve administering tests to assess the level of knowledge acquisition. Additionally, an assessment of the feedback provided by faculty members and educational institutions regarding the utilization of the AR applications is recommended. Employing a more robust acceptance model would enable learners to examine the adaptability of AR technology.

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APPENDIX – RESEARCH SURVEY

Appendix A. Questionnaire used in the study

Entities	Question ID	Questions
Performance Expectancy (PE)	PE1	I would find AR Labs valuable for learning engineering practical
	PE2	Using AR apps specifically developed for the purpose of educating individuals on fundamental engineering principles would likely enhance my understanding and proficiency in the field of engineering.
Effort Expectancy (EE)	EE1	Interaction with AR apps aided for engineering would be easy to understand
	EE2	Engineering skills would developed, from the AR app
Social Influence (SI)	SI1	College faculties will be supportive of the use of AR learning
	SI2	Would recommend AR learning to my peers
Facilitating Condition (FC)	FC1	My university would provide the necessary support for using AR learning
	FC2	Using AR is suitable with the way I learn
Hedonic Motivation (HM)	HM1	I enjoy learning about AR
	HM2	The engagement provided by AR for learning engineering concepts is fun
Behavioural Intentions (BI)	BI1	I would like to use AR-based virtual laboratories in our university is made available
	BI2	Post utilization of the virtual lab, I would use them in the near future, if I have to perform any engineering practical

Appendix B. Sample data of participants

		Frequency	Percentage
Department	Mechanical Engineering	165	55%
	Industrial and Production Engineering	60	20%
	Electronics and Telecommunication Engineering	45	15%
	Instrumentation and Control Engineering	30	10%
Year	Second Year	75	25%
	Third Year	90	30%
	Final Year	135	45%
Familiarity with AR	Yes	189	63%
	No	111	37%
Use of smartphones for studies	Always	150	50%
	Often	75	25%
	Sometimes	60	20%
	Rarely	15	5%

Appendix C. Questionnaire for practical assessment

Question ID	Purpose	Question	Marks
Q1	Basic understanding	What is the basic function of gears in a mechanical system?	1
Q2	Types of gears	Which of the following is a type of gear with straight teeth used for parallel shafts?	1
Q3	Gear ratios	How does a higher gear ratio affect the output gear?	1
Q4	Practical application	What happens when you change the gear ratio in a gear system?	1
Q5	Observations and Analysis	What observation might you make about a gear setup with high efficiency?	1
Q6	Mechanical advantage	What does mechanical advantage in a gear system refer to?	1
Q7	Real-world application	Which type of gear is commonly used in clocks for precise timing?	1
Q8	Troubleshoot	If you encounter excessive friction in your gear system, what should you check first?	1
Q9	Experiment design	What is an essential step to ensure accurate results in your gear test experiment?	1
Q10	Critical thinking	Based on test results, which change might improve the performance of a gear system?	1

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